Little, Jeremy Keenan (2015) ***A song of fire and water: will climate change interacting with fire affect the distribution of vegetation in the Australian Wet Tropics?*** **PhD thesis, James Cook University.**

A song of fire and water:

will climate change interacting with fire affect the distribution of vegetation in the Australian Wet Tropics?

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Submitted February 2015

For the degree of Doctor of Philosophy

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Acknowledgements

One does not accomplish great things without the physical, mental and spiritual support of others.

I wish to thank Steve Williams, Steve Turton, Will Edwards, Jeremy Vanderwal and Chris Johnson of James Cook University (JCU) and David Bowman of University of Tasmania for various supervisory roles throughout my candidature. You have each taught me many things. Special thanks to Steve Williams and to Will Edwards for taking the risk and agreeing to take me on. I wish to thank David Bowman, Lynda Prior and Grant Williamson of the University of Tasmania for an insightful, rewarding and thoroughly enjoyable collaboration. I also wish to thank James Maloney (JCU) and Beth Crase (NUS) for friendly technical advice. I acknowledge the team support from members of the Centre for Tropical Biodiversity and Climate Change (JCU), including Alex Anderson, Luke Shoo, Robert Puschendorf, Collin Storlie and Scott Parsons.

I am grateful for access to country, which was granted by the traditional custodians of the lands of the Wet Tropics, Eungella and McIlwraith Range. On ground fieldwork was gratefully permitted by the Queensland Parks and Wildlife Service (QPWS) and the Australian Wildlife Conservancy. Thanks also to those agencies for ‘trying’ not to burn my weather stations. I also wish to thank Roger Stevens (Mt Spurgeon) and Peter Mann-Jones (via QPWS; Mt Windsor) for access to historic weather data. I thank Andrew Hedges (QPWS) and Ellen Weber from Wet Tropics Management Authority, for advice and encouragement. I thank Graham Harrington, Matt Bradford and David Hilbert from CSIRO for early discussions, advice and for making available their data. I make a special acknowledgement and thanks to Rupert Russell, whose insight, understanding, passion and knowledge of the tall eucalypt forests of the Wet Tropics has been an inspiration. I had much assistance conducting field work and I wish to thank the following volunteers: Alex Anderson, Sophia Carroll, Rhiannon Dalrymple, Kalu Davies, Christine Eriksen, Samantha Forbes, Emma Ignjic, Pat Macquarie, Andrew Picone, Daniel & Jade Stonggrove, Sian Thomas and especially Maree Grenfell. Special thanks to Alex Anderson for opportunities to expand my work into other bioregions (not included here) and for great adventures on Cape York Peninsula.

Heartfelt thanks to my friends for providing a roof over my head when I needed it, especially Alex Anderson, Scott Parsons and Sam Fox. I am indebted to my family and friends who provided me with personal support. My love, gratitude and thanks go to Carolyn Little, Alan and Lois Little and to Maree Grenfell. Love, thanks and memory also go to the late Magnus and Gwenyth Frendin. My love and appreciation goes to Evie and Rosa Little for being such beautiful sparks of joy. I wish to thank all my friends (you know who you are) and family for the emotional support you have shared throughout my long and arduous candidature. I could not have done it without you. Special thanks go to Maree Grenfell, Nathan Knott, Megan Lewis, Michelle Yates, Andrew Picone, Anita Cali and Jann Crase for love, emotional support, care and encouragement. Much love and deep gratitude goes to Maree Grenfell for enduring some tough, wonderful and unforgettable years, for unwavering support and for carrying me out of the jungle on one leg (I'll save that story for another time), in more ways than one.

As egotistical as this sounds, I also have to thank myself. The road less travelled was a difficult one. I acknowledge the dedication, persistence (stubbornness), grim determination, independence, passion and belief in myself that it could be done, despite the odds.

Thank you to all those of you that believed in me too.
It is accomplished!

This thesis is dedicated to sacred ecology, mother earth and the divine feminine in each of us. May we treat her more gently. I dedicate this thesis to the sacred places of the Wet Tropics that gave me insight and wisdom: Chooreechillum, Wooroonooran, Kahlpahlim, Manjal Dimbi, Wurrmbu, Wundu and Nulbullulal. These names, their landscape and their spirit should be etched into the psyche of all Australians. They will endure within me forever.

Jeremy Little
Cairns, October 2015

Statement of the Contribution of Others

Stipend:

- James Cook University (JCU)
- College of Marine and Environmental Sciences (JCU)
- Centre for Tropical Biodiversity and Climate Change (JCU) (CTBCC)
- Graduate Research School (JCU
- Wet Tropics Management Authority (WTMA)

Supervision:

- Prof. Stephen Williams
- Prof. Steve Turton
- Dr. Will Edwards (part)
- Prof. David Bowman (part)
- Dr. Jeremy Vanderwal (part)
- Prof. Chris Johnson (part)

Funding of Research and Equipment (Chapters 3 and 4):

- Marine and Tropical Sciences Research Facility (MTSRF) via CTBCC
- Queensland Government Department of Premiers and Cabinet
- Wet Tropics Management Authority (WTMA)
- Skyrail Rainforest Foundation

Collaboration with University of Tasmania (UTAS) (Chapter 4):

- Prof. David Bowman, Dr. Lynda Prior, Dr. Grant Williamson (Chapters 4,5)
- Funding- National Climate Change Adaptation Facility (NCCARF)
- Funding- School of Plant Science (UTAS)

Statistical support:

- Lynda Prior (Chapters 4)
- Susan Jacups (Chapters 2,3)
- Rhondda Jones (Chapters 2,5)
- Jeremy Vanderwal (Chapter 2)
- Beth Crase (Chapter 2)

Data Analysis:

- Lynda Prior (Chapter 4)

- Grant Williamson (Chapters 4,5)

Access to Data:

- Bureau of Meteorology
- Geosciences Australia
- Queensland Government
- Wet Tropics Management Authority
- CTBCC
- Graham Harrington and Matt Bradford, CSIRO (Atherton)

Editorial assistance:

- Thesis: Steve Williams, Steve Turton.
- Chapter 4: Lynda Prior, David Bowman

ABSTRACT

Vegetation, fire and climate are intrinsically interrelated phenomena. Changes in one of these elements will affect the others. Climate change poses an immediate threat to ecosystems, affecting both fire regimes and vegetation around the world. Climate change interacting with other stressors pose the greatest threat to species and ecosystems. Hence, fire as an environmental stressor can exacerbate climate change impacts. The synergistic effects of direct climate change impacts and climate-induced shifts in fire regimes have substantial implications for vegetation and the distribution of vegetation types. For example, fire sensitive vegetation globally already only occupies half its potential distribution due to fire. Changes in fire regime have the potential to increase this pressure and induce fire-driven tipping points where vegetation shifts into an alternative stable state.

The Australian Wet Tropics, a world heritage region of international significance, hosts a range of vegetation types, narrow ecotones, fire regimes and climatic variability in close proximity along steep elevation gradients. Broad vegetation types in the region are rain forest, tall eucalypt forest and savanna, which occur along this environmental gradient. Rain forest vegetation dominates the high rainfall coastal ranges and savanna woodlands dominate the drier inland areas, with a narrow band of tall eucalypt forest in between. Fire is a regular occurrence in Australian savanna and accounts for 80% of the fire activity in Australia. Rain forests on the other hand, are unlikely to burn on a regular basis and are characterised by fire sensitive species. Tall eucalypt forests are also sensitive to frequent fire, but infrequent fire can aid the recruitment of its shade-intolerant canopy eucalypt species. Thus, these vegetation types represent a spectrum of fire regimes and fire tolerance along an environmental gradient.

The aim of this thesis was to address the question *'will climate change interacting with fire affect the distribution of vegetation types'?* Fine-resolution vegetation distribution models were developed using topographic, edaphic and climatic variables for current conditions. Complex interactions between vegetation, modelled macroclimate, topography and edaphic factors were detected. These required further exploration to account for the influence of climate relative to other factors, such as fire, competition and vegetation feedbacks. The relative influence of climate and topography on the distributional patterns of vegetation was determined (Chapters 2 and 3) and the potential presence of alternative vegetation states was quantified (Chapter 2). Vegetation feedbacks on microclimate and fire danger were detected (Chapter 3 and 4). Accounting for these complexities in vegetation models is currently a major barrier to making effective predictions of future distributions.

The potential influences of model inaccuracies, alternative vegetation states, spatially interpolated climate models, and inability to account for fire indicated modelling would be unlikely to result in accurate outputs. These complexities were explored to ascertain how they affect current distributions and how climate change might impact them, rather than relying on simple model predictions of distribution under future climates.

A spatial analysis of *in situ* below-canopy micrometeorological and fire danger conditions was assessed from a regional network of monitoring sites within different vegetation types. These were compared with standard meteorological stations and used in an assessment of historic climate and fire danger trends within the region. How spatial climate models related to *in situ* topoclimate conditions was tested. A review of historic trends and potential future trajectories was made and how data may better explain future projections of future climate, fire and vegetation distribution, but no hard evidence could be presented.

Three vegetation types (rain forest, tall eucalypt forest and savanna) were modelled at a fine-resolution with a geospatial residuals autocovariate technique to assess model capacity to accurately predict current vegetation distribution (Chapter 2). Models generally performed well, but were not near perfect despite use of high-resolution data, robust spatial techniques, full data set and known distributions. This result suggested that there were other important variables influencing vegetation distribution. Comparisons of observed and potential vegetation distributions provided insight into landscape patterns and suggested competition and feedbacks between vegetation types within overlapping environmental niches. Alternative stables states of vegetation and stochastic disturbances by fire are mechanisms also likely to be contributing to vegetation distribution and thus affecting model performance. The relative performance of models between vegetation types and occupancy of potential distributions by other vegetation types indicated that savanna was the most stable vegetation type and tall eucalypt forests the least. Tall eucalypt forests, a threatened ecological community, occupied a narrow environmental space between rain forest and savanna. They are exposed to both long-term shade intolerance from rain forest and short-term frequent fire intolerance from encroaching savanna fires. Other vegetation types occupied large areas of the modelled core environmental niche for tall eucalypt forest, which instead occupied sub-optimal environmental conditions with very low probability of occurrence. This suggested that tall eucalypt forests are closer to the edge of their environmental niche than the other communities and are likely to be less resilient to additional threats, such as from climate change or increased fire risk. Combined these threats suggest that tall eucalypt forests could be at risk of ecosystem collapse.

Predictions of species or vegetation distribution under current or future climate scenarios are generally based upon spatial interpolated climate data. However, spatial climate data are based on relatively simple interpolation algorithms, which do not accurately capture the idiosyncrasies of montane meteorology. Spatially interpolated climate has seldom been assessed against actual *in situ* conditions, particularly in complex terrain. The reliability of spatially interpolated climate data in reflecting *in situ* topoclimate conditions relative to vegetation types was tested.

A network of 32 micrometeorological sites along eight transects encompassing rain forest, tall eucalypt forest and savanna was established throughout the Wet Tropics region. Three years of microclimate measurements were made at each site and were compared with parallel data from a nearby official meteorological station (Mareeba). They were also compared with spatially interpolated climate data extracted for each site (Chapter 3). Microclimate showed significant differences between vegetation types along the environmental gradient and with Mareeba. Temperature, for example, decreased along the environmental gradient from savanna at lower elevations, to rain forest at higher elevations. However vegetation was a better predictor of microclimate than topography (up to 99% of overall model performance), suggesting the potential effect of vegetation feedbacks on microclimate conditions. This was consistent with case studies of alternative stable state theory for the region. Interpolated climate variables did not relate well and were generally poor predictors of *in situ* microclimate. Again, vegetation was a better predictor of micrometeorological conditions than spatially interpolated climate, contributing up to 90% of overall model performance. Biota respond to topoclimate conditions, suggesting that spatially interpolated climate data alone is unlikely to reliably predict vegetation distributions under any climate scenarios. Incorporating vegetation type, topographic, edaphic and meteorological data in distribution or bioclimatic modelling will result in more meaningful and realistic models.

Climate and fire interact and can strongly affect vegetation distribution, particularly fire sensitive vegetation. Fire danger is a metric that assesses fire risk as a function of climate. The McArthur's Forest Fire Danger Index (FFDI) was calculated from microclimate data for each of 32 sites within the three vegetation types (Chapter 4). These were compared with parallel FFDI calculated for a key official meteorological station at Mareeba. There was a strong association of the Mareeba FFDI values with those from the three vegetation types, albeit they were substantially lower. FFDI values were significantly different between each vegetation type. Values decreased from more open vegetation (savanna), through to closed vegetation (rain forest), a pattern that was consistent across each transect. Only very rarely would rain forest be flammable, despite being adjacent to highly flammable savannas. These results demonstrated a stronger effect of vegetation type on fire danger (as well as microclimate), compared to topography, consistent with a fire – vegetation feedback, which is associated with alternative stable state theory. However, fire restricts rain forest to half their potential distribution around the globe, suggesting that fire is a stronger influence on vegetation distribution than any microclimatic feedbacks that might suppress fire and prevent it from encroaching into fire-sensitive vegetation.

Distribution models were concluded to be too inaccurate to predict how climate change might influence vegetation distribution at a scale relevant to existing distributions of vegetation and biota because: spatially interpolated climate data does not capture extreme events or accurate represent topoclimate conditions; inability to account for vegetation feedbacks and alternative stable states, and vegetation distribution models using current climate were not perfect. All of these issues complicate the climate - vegetation relationship, making a simple modelling strategy questionable without factoring in these complexities and how climate change might impact them. Other methods were used to assess implications of climate change and fire on vegetation distribution. This was done by assessing recent meteorological trends and determining likely trajectories of change in climate and fire danger at a fine-scale within the region. Variability, extremes and trends in climate and fire danger were identified for two key sites and compared with projected future climate trajectories.

Observed daily meteorological data at Cairns (1890-2010) and Mareeba (1957-2010) were analysed for trends in climate and fire danger, including variability and extremes (Chapter 5). Known relationships between Mareeba climate and fire danger, with those for the three vegetation types (Chapter 3 and 4) were used to extrapolate historic climate and fire danger conditions for those vegetation types. Cairns and Mareeba displayed consistent trends for some variables, but opposing trends for others. There were significant increases in all fire danger trends, including average and extreme FFDI at Cairns between 1890 and 2010, however, few fire danger trends were significant at Cairns between 1957 and 2010. Mareeba had no significant trends(1957-2010), but some noteworthy trends were near-significance. These near-significance trends indicated a possible increase in extreme fire danger, but also a possible decrease in average fire danger conditions. Climatic variables underlying FFDI calculation contributed in varying ways to these results. Temperatures increased at both sites, however, rainfall showed no trend at Cairns, but an increasing trend at Mareeba. Climatic trends for each of the vegetation types were expectedly consistent with trends at Mareeba, but with different values.

Historic climate and fire danger trends were broadly consistent with future climate projections. Intra-regional trend variation may help explain some of the uncertainty and weak climate projections made by coarse projections for the Wet Tropics region. With site-specific intra-regional trend information regional variability can be assessed. Observed climate patterns and trends were not consistent throughout the region and by ‘averaging’ these conditions across the region, as is done with global climate models, the detail, accuracy and certainty of trends is weakened by masking variability. Historic trends provide evidence of some consistent and some divergent climate change trajectories within the region. If increasing extreme FFDI is real and is matched with increased fire occurrence, then this may pose a threat to fire sensitive tall eucalypt forests and rain forests, with implications for fire management practices in these ecosystems.

The potential presence of alternative stable vegetation states and vegetation feedbacks on microclimate and fire danger were quantified for rain forest, tall eucalypt forest and savanna (Chapter 2). The presence of vegetation types existing in disequilibrium with climate and in alternative states suggests that climate change alone is unlikely to drive vegetation change or shift in stable states. However, a potential increase in extreme fire danger conditions could disrupt existing alternative stable states in vegetation to drive vegetation change. This would impact fire sensitive tall eucalypt forests and rain forests. This threat is exacerbated by a legacy of European disturbance and increased vulnerability of forest types. The interaction of multiple stressors, including climate change and fire has the capacity to destabilise vulnerable vegetation, promoting shifts into alternative stable states. Tall eucalypt forests, an already threatened vegetation type, are the most at risk of ecosystem collapse in this region.

Will climate change interacting with fire affect the distribution of vegetation types? Evidence including the relative vulnerability of vegetation types and potential changes in fire danger, suggest that vegetation distributions could change. The tendency is for an expansion of savanna, at the expense of a contraction of tall eucalypt forest and rain forest edges, presumably mediated by fire. But an increase in fire danger alone is not enough. Ignitions are required for changes in fire potential to be realised. Ignition sources, including their frequency, timing and location may be a key stressor to exacerbating climate and fire risk to vegetation. Appropriate fire and ignition management could be used to mitigate this risk. How we manage ignitions and fire in the landscape in consideration of ecosystem risks could affect future vegetation distributions. Appropriate fire regimes in the present may be of greater concern to the resilience, distribution and persistence of vulnerable vegetation in the future, than directly from climate change.

Fire frequency is perhaps more strongly linked to ignitions than to climate directly. The overwhelming majority of ignition sources causing fire frequency are anthropogenic. Arson and perverse fire management actions have the potential to exacerbate potential climate change impacts, to tip the balance and drive change in the distribution of vegetation types, including shifts into alternative vegetation states. The main issue may not be about how climate change and a change in fire danger could affect vegetation, but how fire is managed into the future. Fire managers and agencies must adapt to increased fire danger conditions if they are to prevent potential vegetation change and distributional shifts. Consistent with other national and regional reports, it is suggested that reducing landscape pressures, such as fire, are the best option for mitigating climate change impacts on ecosystems. The message is, never mind the warming, watch out for the fire!

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Prelude

In the summer of 2016, weather events affected two Australian World Heritage Areas in devastating ways. Extreme hot weather and warm oceans caused coral bleaching to 93% of reefs in the Great Barrier Reef World Heritage Area (ARC Centre of Excellence Coral Reef Studies 2016). At the same time, bushfires burnt 124,742 hectares in western Tasmania, including 20,125 hectares of the Tasmania Wilderness World Heritage Area (AFAC 2016), affecting ancient fire-sensitive ecosystems that are unlikely to ever recover (Holtz *et al*. 2015; Bowman 2016; Rickards 2016). Are these isolated extreme events, or is this climate change?

Until recently, scientists were cautious about attributing weather events to climate change, due to uncertainty about direct links. However, science and technology have improved and experts are now more confident about detection and attribution of extreme events to climatic change (Stone *et al*. 2013; Hulme 2014; Hansen 2015; Hansen *et al*. 2016; National Academies of Science Engineering and Medicine 2016; Otto 2016). The signs are that the events this summer were likely to be because of climate change (Mariani & Fletcher 2016).

Climate change is impacting biodiversity and ecosystems throughout Australia (Steffen *et al*. 2009). Some regions and ecosystems are more vulnerable to climate change and are at risk of ecosystem shift or collapse, including alpine areas, montane areas, rainforests, tall eucalypt forests and coral reefs (Hughes 2011; Laurance *et al*. 2011). Assessments of Australian ecosystems at risk using the IUCN red list (Rodríguez *et al*. 2011, 2015; Keith 2013, 2015; Keith *et al*. 2013; Nicholson *et al*. 2015), are indicating that collapse is a real threat to a growing number of ecosystems, including from climate change (Auld & Leishman 2015; Barrett & Yates 2015; Burns *et al*. 2015; English & Keith 2015; Metcalfe & Lawson 2015; Tozer *et al.* 2015; Williams *et al*. 2015). Even protected areas are at risk, including National Parks, National Heritage Areas (Dunlop & Brown 2008; Dunlop *et al*. 2012) and World Heritage Areas (Australian National University 2009).

Climate change impacts are also exacerbated by interactions with other stressors, such as bushfires, extreme weather events, pests and weeds. For example, more intense and frequent fires as a result of climate change are a serious threat to biodiversity, ecosystems and protected areas (Williams *et al.* 2009). Some ecosystems are particularly vulnerable to fire including rainforests, tall eucalypt forests, montane and alpine vegetation. Many of the same ecosystems that are vulnerable to climate changes. However, the interacting effect will be greater than either stressor independently (Nitschke 2006; McAlpine *et al.* 2009; Driscoll *et al.* 2012; Moritz *et al.* 2012; Bennett *et al.* 2013; Parmesan *et al.* 2013; Staudt *et al.* 2013).

The most valuable and outstanding ecosystems of Australia are generally within protected areas, particularly National and World Heritage Areas, but include some of the most vulnerable to climate change and bushfire impacts. An assessment of the implications of climate change for Australia's World Heritage properties in 2009 (Australian National University), found that all were affected by climate change and at risk from further impacts. Nine of Australia’s 12 relevant terrestrial properties are at further risk from more frequent and intense fire as a result of climate change, because of the prominence of fire sensitive vegetation in those properties. These World Heritage Areas are the Wet Tropics of Queensland, Fraser Island, Tasmanian Wilderness, the Gondwana Rainforests of Australia and the Greater Blue Mountains, as well as the Australian Alps National Heritage Area. The single greatest threat to these areas is in the form of catastrophic events, such as bushfire, which could result in widespread damage or collapse. The fires observed in Tasmania this year were consistent with climate change predictions for bushfire risk (Bowman 2016; Mariani & Fletcher 2016). Evolving scientific techniques in attribution of weather events to climate change may retrospectively show that the fire events from the past decade in regions such as the Australian Alps, the Victorian highlands and the Greater Blue Mountains are also a result of climatic change.

What of the future of Australia's World Heritage Areas (Figgis *et al*. 2013) and vulnerable ecosystems? Since first assessed in 2009, very little has been done nationally to address climate change threats to Australia’s World Heritage. On the contrary, further pressures from developments have been proposed for some areas including ports, mining, logging and tourism. If we are to avert or mitigate potential catastrophe, we must be diligent in our management at a national and local scale. Little is known about how climate change interacting with stressors, like fire, will affect the distribution or resilience of vegetation types, ecosystems and areas of high conservation value. The following research aims to explore precisely this.

Plate 1. Wundu: a rain forest clad, steep, coastal mountain range of the Australian Wet Tropics.

CHAPTER 1

General introduction:
climate change, fire, vegetation distribution and the Australian Wet Tropics

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1.1 Introduction: vegetation, fire, climate and change

Vegetation, fire and climate are intrinsically interconnected phenomena (Ryan 1991; Mackey *et al.* 2002). A change or shift in one of these phenomena has direct implications for the others. Climate change poses a threat to vegetation around the world through direct climatic influences, as well as indirect and interacting affects such as altered fire regimes.

Shifts in the distribution of vegetation types have occurred throughout Earth's history, often associated with climatic change (Hill 1994; Cramer *et al.* 2001; Harrison & Prentice 2003; Pickett *et al.* 2004; Kershaw *et al.* 2007b). However, the gradual shift of vegetation boundaries in response to a change in climate is not necessarily how vegetation change might occur. Recent and projected climate change is occurring at an unprecedented rate and is causing observable, often abrupt, shifts in vegetation distribution (Walther *et al.* 2005; Bowman *et al.* 2010; Elliott & Kipfmueller 2011; Tng *et al.* 2011; Bond & Midgley 2012; Corlett & Westcott 2013). These abrupt shifts are likely to be associated with indirect stressors interacting with climate change. How climate change, interacting with other environmental stressors, will affect vegetation is a complex but important area of enquiry given the potential for profound impacts.

The distribution of vegetation globally is influenced by a multitude of factors, most importantly by climate, topography, soil and disturbance regimes such as fire (Walter 1985; Archibold 1995). Temperature, rainfall, humidity, wind, seasonality and solar radiation are climatic variables that affect vegetation in different ways. Climate information is generally a summary of average meteorological conditions over a long period of time. Scales of climate include macroclimate, mesoclimate (regional) and microclimate. Variability and extremes in these variables, which are reflected in daily, seasonal or annual meteorology and micrometeorology conditions are not necessarily reflected in macroclimatic averages. These each affect vegetation distributions. Topography features such as slope, aspect, elevation, hydrology, water availability and orientation to prevailing winds or the coastline also affect vegetation distribution and can interact with climate, result in complex topoclimate systems. These can include orographic rainfall, rainshadow, cloud interception or frost hollows. In complex terrain, these topoclimatic conditions can result in equally complex distributions of plants and communities (Letten *et al.* 2013; Oldfather *et al.* 2016). Soil type associated with underlying geology affects vegetation, where soil properties such as soil moisture, water holding capacity and nutrient availability can influence the types of life forms they support. These factors present direct, indirect and stochastic influences on vegetation distribution (Guisan & Zimmerman 2000; Williams *et al.*, 2012a). Macroclimate, topography, geology and global position (latitude and longitude) are indirect variables; meteorological conditions and soils are direct variables.

Disturbance events or regimes, such as fire, flood, drought, cyclone, landslide and frosts, can influence vegetation in substantial ways. Stochastic effects can have negative impacts on some vegetation types, but may also have positive impacts on others. For example, frequent fire has a negative effect on rain forest vegetation and limits its distribution globally by about half its potential (Bond 2005).

Although the relationships between these elements may be presented in simple terms (Jackson 1968; Ryan 1991), there are often inherent complexities such as vegetation competition or feedbacks. Vegetation types can affect each other through competition, where, under certain circumstances, one vegetation type can encroach and outcompete the other. For example, rain forest species can encroach into adjacent vegetation types and shade out non-rain forest species. If conditions change, so can the competitive advantage of a vegetation type. Often disturbance regimes can interact with this competition and opportunistically reset vegetation change. For example, some vegetation types are resilient or more tolerant of disturbance and can regrow or germinate readily after the event. Some vegetation types such as savanna are naturally flammable and tolerant to fire, whereas other types, such as rain forest are less fire tolerant (Walker 1981; Bond & Midgley 1995; Gill & Zylstra 2005). By the action of repeated fires, savanna can outcompete rain forest in areas where they co-occur.

Vegetation can influence the local environment through feedbacks, by modifying aspects of water, light, soil, microclimate, flammability, pathogens or herbivory, thereby to provide a competitive advantage over other vegetation types (Wilson & Agnew 1992). By influencing local conditions, vegetation feedbacks may then allow that vegetation type to persist under sub-optimal environmental conditions. Thus, in some situations, vegetation can develop along alternative, bistable pathways, with the potential for more than one vegetation type to occupy a given site. These are known as alternative stable states (Beisner *et al.* 2003). This disequilibrium with broader environmental conditions may result in vegetation appearing to have incoherent distributions (Low 2011), complicating climatic and environmental predictions of vegetation distribution. However, changes in environmental conditions, such as by an event, disturbance or regime shift can trigger a switch or tipping point, causing transition to an alternative vegetation stable state (Wilson & Agnew 1992). Co-occurring forest and savanna are one of the most prevalent ecotones in the tropics known to exist in alternative stable states (Oliveras & Malhi 2016), also occurring in temperate regions (Kitzberger *et al*. 2016). Although forest - savanna boundaries may be stabilised by positive vegetation feedbacks, they are also sensitive to shifts in climate and fire regime (Oliveras & Malhi 2016).

Stochastic disturbance regimes, such as fire, can exert a powerful perturbation to otherwise stable vegetation-climate systems. Fire has a pervasive influence on vegetation and, for example, restricts rain forest vegetation to about half its potential global distribution (Bowman 2000; Bond *et al.* 2005; Bowman *et al.* 2009). The multiple complex and interactive effects determining the distribution of vegetation types makes accurate prediction of their distributions difficult (Good *et al*. 2016; Harris *et al*. 2016).

Shifts in climate or disturbance regime can potentially upset stable systems held in balance by vegetation feedbacks. Such shifts can result in vegetation tipping into alternative states and thereby shifts in the distribution of vegetation types. Some vegetation types are more susceptible to induced change (Gonzalez *et al.* 2010), disequilibrium (Svenning & Sandel 2013) or tipping points (Laurance *et al.* 2011a) and may become destabilised (Lloret *et al.* 2012), whereby their structure or distribution is affected or result in a complete transition into an alternative stable vegetation state (Wilson & Agnew 1992; Scheffer *et al.* 2001; Beisner *et al.* 2003; Scheffer 2003; Higgins & Scheiter 2012). A tipping point marks the stage between a resilient ecosystem and one that is at risk of change. Where a whole ecosystem is at risk, this is sometimes called ecosystem collapse (Rodríguez *et al.* 2011; Keith 2013, 2015; Keith *et al.* 2013). Given the potentially catastrophic impact of such transitions and shifts on vegetation types and biodiversity around the world, understanding the nature and drivers of vegetation distribution and change may help to mitigate impacts or identify important climate change refugia (Ashcroft *et al.* 2009; Ashcroft 2010; Keppel *et al.* 2012; Keppel & Wardell-Johnson 2012; Mackey *et al.* 2012; Reside *et al.* 2013, 2014).

Cumulative and widespread physical impacts of anthropogenic disturbance has resulted in degradation of ecosystems and vegetation types around the world (Goudie 2013), exacerbating vulnerability to change. Land management activities have the potential to compromise vegetation types, making them less resilient, unstable and susceptible to shift, landscape traps (Lindenmayer *et al.* 2011) or fire traps (Grady & Hoffmann 2012; Werner 2012; Tepley *et al*. 2016). Anthropogenic land management has the potential to exacerbate or mitigate ecosystem vulnerability to the interacting affects of climate change and fire and may pose a substantial threat to vegetation and entire global landscapes.

Climate change has already been observed in the climate record and future projections reveal a dire situation both globally and locally (IPCC 2013; Allen *et al.* 2014). Climate change has had direct impacts on the global distribution of vegetation (Walther *et al.* 2005; Bowman *et al.* 2010; Elliott & Kipfmueller 2011; Tng *et al.* 2011; Bond &

Midgley 2012; Corlett & Westcott 2013) including within Australia (Donohue *et al.* 2009). Climate change is also causing shifts in global fire regimes (Flannigan *et al.* 2009; Krawchuk *et al.* 2009; Liu *et al.* 2010; Moritz *et al.* 2012; Jolly *et al*. 2015). Climate change has the capacity to affect fire regimes, such as their frequency, interval and intensity, thereby influencing the function, structure, resilience and, potentially, the distribution of vegetation types. Changes in the fire regime are likely to have a more immediate impact on vegetation than climate change directly (Flannigan *et al.* 2000; Flannigan *et al.* 2005). Together, the interaction of climate change with other stressors, such as fire, will have a more profound impact on vegetation and biodiversity than either stressor independently (Nitschke 2006; McAlpine *et al.* 2009; Driscoll *et al.* 2012; Moritz *et al.* 2012; Bennett *et al.* 2013; Parmesan *et al.* 2013; Staudt *et al.* 2013).

Fire is an integral component of shaping the structure, function and distribution of global ecosystems and vegetation types (Bond *et al.* 2005; Bowman 2005; Le Page *et al.* 2008; Bowman *et al.* 2009; Krawchuk *et al.* 2009; Shlisky *et al.* 2009; Moritz *et al.* 2010; Whitlock *et al.* 2010; Krawchuk & Moritz 2011; Li *et al.* 2012; Krawchuk & Moritz 2014). Although many plants and vegetation types have evolved fire tolerance (Midgley & Bond 2011), others are fire sensitive and are substantially constrained by the presence of fire (Bond *et al.* 2005). Globally, fire activity restricts fire-sensitive rain forests to half their potential range (Bond *et al.* 2005) and maintains fire-sensitive forests and savannas in alternative stable states (Hirota *et al.* 2010; Hirota *et al.* 2011; Staver *et al.* 2011). Around 20% of global vegetation types are considered fire sensitive and of these, 70% are already exposed to altered fire regimes (Shlisky *et al.* 2009). Of all the elements influencing the distribution of vegetation types around the world, fire is an element that is one of the most readily manipulated by humans and has the capacity for the most profound influence on global vegetation in the short-term (Bowman & Haberle 2010; Bowman *et al.* 2011; Hantson *et al.* 2014; Kitzberger *et al*. 2016). Fire-induced tipping points can drive abrupt change of vegetation into alternative stable states (Clarke & Lawes 2013; Pausas 2015). Predicted climate-induced shifts in fire regimes thus have potentially catastrophic implications for vegetation locally and globally.

Mapping and predicting species or community distributions is important for many reasons in contemporary land management, planning, conservation and research, including assessment of potential climate change impacts (Franklin 2009). Many distribution model techniques are available for explaining or predicting vegetation distributions (Peng 2000; Austin 2002; Dirnböck *et al.* 2002; Miller & Franklin 2002; Segurado & Araujo 2004; Elith *et al.* 2006; Ferrier & Guisan 2006; Lawler *et al.* 2006; Austin 2007; Elith & Graham 2009; Elith & Leathwick 2009; Franklin 2013; Scheiter *et al.* 2013). However, model distributions can be highly variable between different techniques (Lawler *et al.* 2006; Araújo & New

2007) and generate a high degree of uncertainty (Buisson *et al.* 2010). Vegetation modelling techniques are generally based on geographic and climatic predictor variables and seldom, if ever, incorporate stochastic perturbations such as fire, which are ideally required for accurate vegetation models (Thonicke *et al.* 2001). Modelling techniques that include fire regimes or fire spread often undertake a separate model approach or are associated with coarse scale dynamic global vegetation models (Keane *et al.* 2004; Keane *et al.* 2013). Therefore, predictive vegetation models that incorporate fire are not generally of fine enough scale to detect the detailed landscape-scale patterns of vegetation boundaries and distributions. Given that shifts in fire regimes are predicted with climate change (Flannigan *et al.* 2009; Krawchuk *et al.* 2009; Liu *et al.* 2010; Moritz *et al.* 2012), understanding how a change in fire regime may affect vegetation distribution, is perhaps more important than understanding the direct influence of climate alone. To understand the potential impacts of climate change on vegetation distribution it is imperative to ensure that robust model predictions accurately reflect current vegetation distributions and incorporate the relative influences of geographic, climatic and pyric disturbance regimes as predictive inputs. In the absence of suitable distribution model techniques at a fine scale, a multi-disciplinary approach may be required to investigate how climate change might influence fire regimes and vegetation.

To accurately assess the potential impact of climate change interacting with fire on the distribution of vegetation currently requires consideration of multiple complexities associated with their relationships. Consideration needs to be given not only to simple climatic, geographic or edaphic influences on vegetation, but also the influence of stochastic disturbances and potential interactions between climate change and disturbance regimes. The potential influence of vegetation feedbacks, alternative stable states, health and resilience also requires assessment to determine the vulnerability to climate change and fire.

Australia has been identified as being one of the countries most vulnerable to climate change impacts (Williams *et al.* 2012). Potential impacts in Australia are diverse due to its size, diversity of global ecoregions, climatic zones and national bioregions. Assessments of potential climate change impacts in Australia, particularly to terrestrial ecosystems, have identified key vulnerable regions, ecosystems and threatening processes (Howden *et al.* 2003; Hughes 2003; Dunlop & Brown 2008; Steffen *et al.* 2009; Hughes *et al.* 2010; Hughes 2011; CSIRO & Bureau of Meteorology 2015). A recurring theme in these reports is the likely impact of increased fire activity with climate change and its affect on vulnerable ecosystems, vegetation types and biota. Another recurring theme is that to understand how climate change will impact these key vulnerable regions or ecosystems and to prepare adaptation or mitigation responses, requires a more detailed, regional focus and analysis (Hughes 2011; Low 2011; Williams & Crimp 2012; Williams *et al.* 2012; CSIRO

& Bureau of Meteorology 2015). Ideally this should take a multi-scaled whole-of-ecosystem approach (Lindenmayer & Franklin 2002), such as proposed by Mackey *et al.* (2002) for the Victorian Central Highlands. Following these principles, the focus of this study is to determine the impact of climate change and fire on the vegetation of one of world's most biologically important, yet vulnerable regions, the Australian Wet Tropics of Queensland.

1.2 Vegetation, fire, climate and change in the Australian Wet Tropics

This study focussed on the nexus between vegetation, fire and climate and the implications of climate change on this dynamic. The mountainous Wet Tropics region of northeastern Australia includes the Wet Tropics World Heritage Area and is an ideal natural laboratory to study this dynamic. Mountainous tropical regions can have a range of vegetation types, narrow ecotones, fire regimes and climatic zones in close proximity along elevation gradients. This makes them valuable and important for climate change research (Peterson *et al.* 1997; Malhi *et al.* 2010), but also incredibly vulnerable to other change processes (Laurance *et al.* 2011a). The Australian Wet Tropics region is no different and has been identified as being highly vulnerable to climate change (Hilbert *et al*. 2001b; Howden *et al.* 2003; Hughes 2003; Williams *et al*. 2003b; Dunlop & Brown 2008; Steffen *et al.* 2009; Hilbert 2010; Hughes *et al.* 2010; Hughes 2011; Low 2011; Williams & Crimp 2012; Williams *et al.* 2012b; Hilbert *et al.* 2014; CSIRO & Bureau of Meteorology 2015; McInnes *et al.* 2015).

The Australian Wet Tropics is dominated by rain forest and savanna broad vegetation types, with bands of tall eucalypt forest types in between. Climate change is predicted to cause declines in rain forest (-56.5%) and tall eucalypt forest (-41.0%) distribution, but a substantial increase in the distribution of savanna (+160.7%) (eucalypt woodlands, eucalypt open woodlands and tropical eucalypt woodlands/ grasslands) (Hilbert & Fletcher 2012). The mechanism that will most likely drive these changes, is fire (Hughes 2003; Steffen *et al.* 2009; Hughes 2011; Low 2011; Williams *et al.* 2012b; Pausas 2015). Specifically, it is the frequency (and intensity) with which fires occur in savanna vegetation, encroaching into adjacent, more fire-sensitive, vegetation types. Fire already significantly restricts the potential distribution of rain forest (Bowman 2000) and tall eucalypt forest, which is evident as neither of these communities occupy their predicted distribution in Australia (Hilbert & Fletcher 2012).

Australia is one of the most fire prone countries on earth (Bradstock *et al.* 2002; Bradstock *et al.* 2012b). Australia is also a model system for the study of pyrogeography (Bowman & Murphy 2010), as it contains a broad spectrum of fire regimes, vegetation types and climatic zones (Bradstock 2010; Murphy *et al.* 2013). It is also the driest habitable continent on earth and much of the contemporary biota have evolved to cope with high aridity and fire tolerance associated with broad climatic change (Gill *et al.* 1981; Hill 1994; White 1994; Kershaw *et al.* 2002; Mooney *et al.* 2012). Early Australian vegetation was once dominated by rain forest, but with increased aridity and fire activity the vegetation has evolved, with much of its ancestry from Gondwana rain forest lineages (Hill 1991, 1994, 2004; Kershaw *et al.* 1991). Rain forest vegetation now occupies only 0.5% of the Australian landmass (National Land & Water Resources Audit 2002), the largest remaining area being the Australian Wet Tropics. This statistic demonstrates the extent to which aridity and fire have constrained this vegetation type. Australia is now dominated by sclerophyllous vegetation types that have evolved aridity and fire tolerances, with only small areas of remaining rain forest (Beadle *et al.* 1981; Keast 1981; Read 1987; Groves 1994; Hill 1994; Specht & Specht 1999; Department of the Environment and Water Resources 2007).

There is little signature of early anthropogenic influence on fire regimes in Australia and their impact on vegetation types (Kirkpatrick 1994; Kohen 1995; Benson & Redpath 1997; Enright & Thomas 2008; Mooney *et al.* 2011) and Indigenous influences on vegetation were not as profound or widespread as some claim (Rolls 1981; Flannery 1994; Gammage 2011). Interpretation of the natural state of vegetation in Australia is complicated by the sheer extent of disturbance, deforestation and degradation that has occurred since European arrival (Benson 1991; Flannery 1994; Kirkpatrick 1994; Powell 1994; Kohen 1995; Benson & Redpath 1997; Bowman 2001; Turton 2008). These European disturbances include a widespread increase in the frequency and area burnt by fire (Enright & Thomas 2008; Bowman & Haberle 2010; Mooney *et al.* 2011). Today, altered fire regimes in Australia are mainly caused by unplanned fires (81%) (Thackway *et al.* 2008), mostly as a result of arson (Willis 2004; Beale & Jones 2011). These altered fire regimes have the potential to cause transformation of ecosystems (Williams *et al.* 2012b). Post-European land and fire management in Australia have been claimed to have caused the development of landscape traps (Lindenmayer *et al.* 2011), whereby vegetation is maintained in a degraded and compromised state at a landscape scale. Some vegetation types, once degraded, become less resilient to climate- or fire-induced tipping points (Laurance *et al.* 2011a) and could be destabilised (Lloret *et al.* 2012) with transition into an alternative stable state of vegetation (Wilson & Agnew 1992; Scheffer *et al.* 2001; Beisner *et al.* 2003; Scheffer 2003; Higgins & Scheiter 2012). Landscape traps driven by fire may be considered a fire trap (Grady & Hoffmann 2012; Werner 2012; Tepley *et al*. 2016). Degraded vegetation, including landscape traps are more vulnerable to the pressures of climate change or altered fire regimes, How people manage stressors, like fire, to manage vegetation resilience will affect its vulnerability to change.

Landscape fires are determined by four ‘switches’: biomass (vegetation type and fuel structure), availability to burn (fuel moisture), fire spread (climatic conditions, also called ‘fire weather’, ‘fire climate’ or ‘fire danger’) and ignition (lightning and anthropogenic causes) (Bradstock 2010). Fires are constrained in the landscape by the availability of these pyric resources at a global scale (Krawchuk & Moritz 2011; Pausas & Ribeiro 2013), a continental scale (Bradstock 2010), a regional scale (Williams *et al.* 1996a; Spessa *et al.* 2005) and at a local scale (Unwin 1983, 1989; Ash 1988; Turton & Duff 1992; Turton & Sexton 1996; Little *et al.* 2012). Climate also strongly influences vegetation (fuel) type and fire behaviour in Australia and is demonstrated across the latitudinal gradient of the continent (Bradstock 2010; Murphy *et al.* 2013). However, most fires (79%) occur in northern Australia, as a result of the fine, flammable grassy fuels of savanna woodlands (Thackway *et al.* 2008). More intense fires are associated with forests of southeast and southwest Australia with more complex fuel loads and more extreme fire danger events (Ashton 1981; Ashton & Attiwill 1994; Gill & Catling 2002; Gill 2012). Climate change will directly influence biomass, fuel moisture, fire weather and ignitions. Depending on the regional and local changes in climate, shifts in fire regimes and vegetation distribution are expected at each of the scales.

Fire regimes consist of variants in fire attributes, such as frequency, intensity, interval, ignitions, seasonality, patchiness and spatial heterogeneity of fire (Whelan 1995). Each of these components has the capacity to influence the structure, function and distribution of vegetation types. Conversely, vegetation characteristics or feedbacks may influence aspects of a fire regime, such as by fuel structure (vegetation type and structure), fuel moisture (vegetation type and climate) (Walker 1981; Whelan 1995), or microclimate (Wilson & Agnew 1992)..This study focussed on how climate change might affect one of the four switches of fire regimes, fire danger (Bradstock 2010) and its potential affect on vegetation.

Climate change is predicted to intensify fire regimes in Australia (Beer & Williams 1995; Cary & Banks 1999; Williams *et al.* 2001, 2009; Cary 2002; Hennessy *et al.* 2005; Lucas *et al.* 2007; Pitman *et al.* 2007; Hasson *et al.* 2008; King *et al.* 2011; Cary *et al.* 2012; Clarke 2015; CSIRO & Bureau of Meteorology 2015; Dutta *et al*. 2016), consistent with patterns around the globe (Flannigan *et al.* 2009; Krawchuk *et al.* 2009; Liu *et al.* 2010; Moritz *et al.* 2012). Fire danger has already increased in Australia between 1973 and 2010, including fire danger extremes and the length of the fire season (Clarke *et al.* 2013). There is, of course, regional variation in these trends. In the Wet Tropics over this period, only small increases in fire danger conditions were observed at the Cairns meteorological station (relative to other locations). Predictions of future change in fire weather in the Wet Tropics is variable, but with general consensus of little change or a slight increase in mean and extreme fire danger conditions (Pitman *et al.* 2007; Clarke *et al.* 2011; McInnes *et al.* 2015). However, these projections are of a coarse regional scale (see section 1.5). Closer intra-regional inspection of spatial and temporal patterns in climate and fire danger is required to determine the likely ecological impacts of climate change.

In Australia, fire danger, is typically measured using McArthur's Forest Fire Danger Index (FFDI). FFDI is calculated from meteorological observations, using temperature, relative humidity, wind speed, rainfall and a drought factor (Noble *et al.* 1980; Griffiths 1999; Finkele *et al.* 2006). FFDI is predicted to increase in Australia, based on projections of the underlying meteorological variables. This includes increases in average and extreme temperatures, an increase in extreme events (such as heatwaves and droughts) and a reduction in seasonal rainfall (Beer & Williams 1995; Cary & Banks 1999; Williams *et al.* 2001, 2009; Cary, 2002; Hennessy *et al.* 2005; Lucas *et al.* 2007; Pitman *et al.* 2007; Hasson *et al.* 2008; Low 2011; King *et al.* 2011; Cary *et al.* 2012; Williams *et al.* 2012; CSIRO & Bureau of Meteorology, 2015). How these meteorological variables change in different regions, will ultimately influence how fire climate and fire regimes will shift in those areas (Williams *et al.* 2009, 2012; Low 2011; CSIRO & Bureau of Meteorology 2015). Furthermore, changes in fire regimes will affect particular vegetation types in different regions in potentially variable and unpredictable ways (Williams *et al.* 2009). Indeed, a shift in fire regimes associated with climate change will further add to the ongoing global quest for sustainable fire management (Bowman *et al.* 2013). The Australian Wet Tropics is an ideal area to study the interacting effects of climate change and fire on vegetation, as there is a range of climatic zones, fire regimes and vegetation types of high conservation value within close proximity.

1.3 Study Area

The Wet Tropics region of northeastern Queensland, Australia (Figures 1.1 and 1.2) is a mountainous coastal area with a mosaic of vegetation types associated with elevation gradients and complex terrain (Nix 1991). It is a region of global ecological and evolutionary significance and includes the Wet Tropics of Queensland World Heritage Area. It is also adjacent to a large shallow ocean shelf supporting the Great Barrier Reef World Heritage Area. The Wet Tropics is an ideal region to understand fire-vegetation interactions. The mountainous topography and prevailing southeast trade winds, result in steep moisture gradients that influence vegetation patterns and fire activity.

The region is characterised by north-south orientated steep mountain ranges that stretch along approximately 500 kilometres of coastline from near Townsville in the south to Cooktown in the north and span no more than 75 kilometres inland from the east coast (Figure 1.1). The geology of the ranges and tablelands are predominantly Permo-Carboniferous granite, including rhyolite, with some volcanic basalts occurring on the central Atherton Tablelands (Johnson 2004; Lottermoser *et al.* 2008). The coastal ranges steeply rise to 1622 metres in elevation (Chooreechillum/ Mt Bartle Frere) and attract high orographic rainfall, cloud stripping and precipitation interception (McJannet *et al.* 2007)

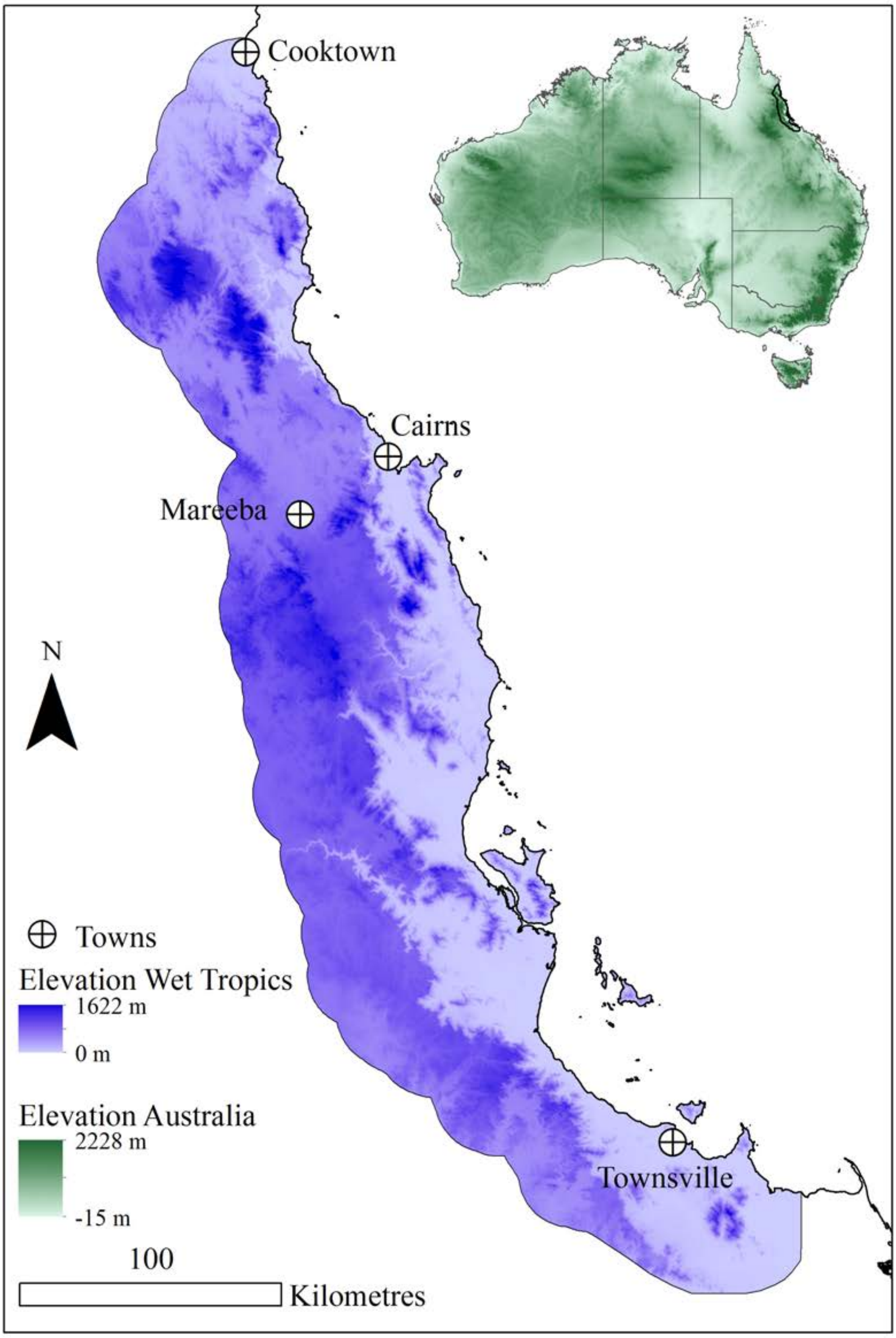

Figure 1.1 Map of the Australian Wet Tropics study area, showing elevation. Locations of relevant towns with official meteorological stations are also shown.

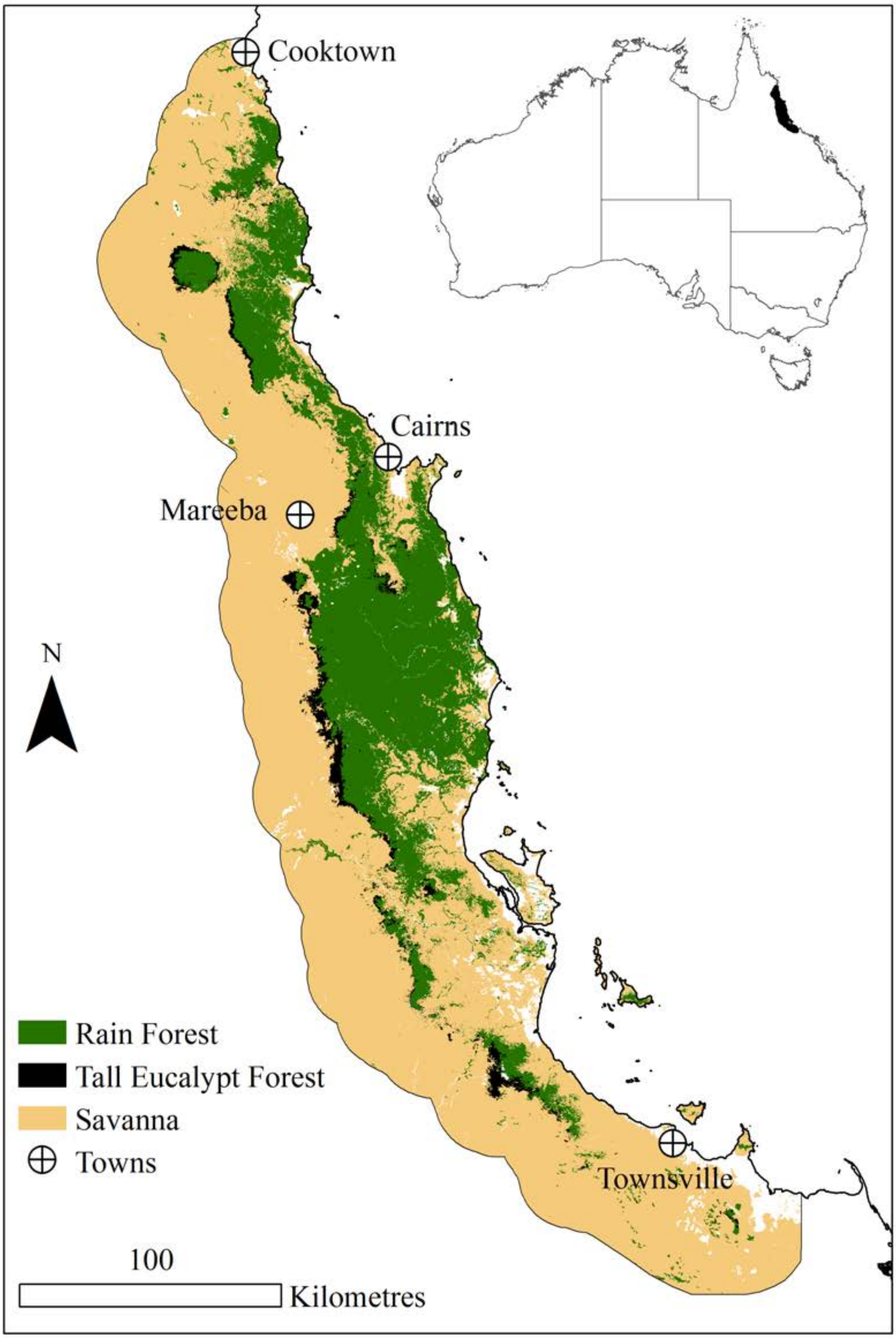

Figure 1.2 Map of the Australian Wet Tropics study area, showing the distribution of broad vegetation types; rain forest, tall eucalypt forest and savanna. Locations of relevant towns with official meteorological stations are also shown.

from prevailing southeasterly on-shore trade winds , seasonal monsoonal troughs and occasional tropical cyclones (Bonell *et al.* 1991). With high rainfall and moisture inputs, brings protection from fire and thus, supports rain forest vegetation over much of the coastal ranges (Figure 1.2) (Winter *et al.* 1991b). The rain forests in this region are among the oldest living forests on the planet and are a source of high biological diversity and significance both nationally and internationally, being listed as a World Heritage Area (Rainforest Conservation Society of Queensland 1986; Nix 1991). Precipitation, however, is highly variable in the landscape, with an average rainfall of 2000 millimetres (mm) and a mean maximum temperature of 29.0°C on the coast at Cairns, 850 mm and 28.7°C inland at Mareeba and 7856 mm at 1588 metres elevation on Wooroonooran (Mt Bellenden Ker; the region's second highest peak) (www.bom.gov.au 2010). Other vegetation types occur where there is less available moisture and higher probability of fire occurrence. A mosaic of rain forest, open forest and woodland occurs on the coastal flats and open grassy savanna woodland dominates the inland western plains, extending across northern Australia. On the leeward side of the mountain ranges, on their western slopes and plains, there is a fairly typical rainshadow effect with a marked climatic gradient associated with elevation. This environmental gradient is associated with strong moisture and temperature gradients (Unwin 1983; Nix 1991; Turton *et al.* 1999; Harrington *et al.* 2000). The probability of fire interacting with the environmental gradient in the rainshadow has a strong influence on the location of natural vegetation boundaries, both in the past and present.

With declining moisture and increased temperatures to the west, is an increased incidence of fire. Consequently more drought- and fire-tolerant vegetation outcompete fire sensitive rain forest in these areas. The boundaries between vegetation types are often abrupt transitions (Unwin 1983; Duff 1987; Unwin 1989; Nix 1991). Consequently, along this gradient there is a range of climatic variability, vegetation types, narrow ecotones and fire regimes in close proximity. Wedged between the pyrophobic rain forests and fire-prone savanna woodlands are a narrow band of tall open and open eucalypt forests, which are generally no more than 4km wide, but extend nearly 400km in a discontinuous length. This vegetation type is more synonymous with temperate and sub-tropical eucalypt forests in southeastern Australia, than the surrounding tropical savanna woodlands.

The study area includes rain forest outliers and other topographically important areas, within a 20km buffer around the Wet Tropics of Queensland World Heritage Area boundary. The Wet Tropics analysis area (3,662,446 ha) is consistent with the analysis area of other research in this region (VanDerWal *et al.* 2009b; Shoo *et al.* 2011; Little *et al.* 2012). This analysis area was much larger than the Australian designated Wet Tropics bioregion and included parts of adjacent bioregions; Cape York Peninsula, Einasleigh Uplands and Brigalow Belt North bioregions (Thackway & Cresswell 1997).

1.4 Vegetation of the Wet Tropics

1.4.1 Vegetation classification

Vegetation in Australia is classified and mapped at different spatial scales and resolutions by various Local, State and Federal Government departments. There is general agreement between them for broad classification groups, however, discrepancies may occur for fine-scale classifications. At a national level, vegetation is classified by Major Vegetation Groups and Subgroups (National Land and Water Resources Audit 2002; Department of the Environment and Water Resources 2007; Thackway *et al.* 2007). These classifications are broadly consistent with the Broad Vegetation Groups (BVG) classified by the Queensland Government (Sattler & Williams 1999; Neldner *et al.* 2012; Accad *et al.* 2013; Neldner *et al.* 2014) and relationships between these are given in Appendix 4 of Neldner *et al.* (2014).

This study utilised the fine-scale mapping of Queensland regional ecosystems (Sattler & Williams 1999; Neldner *et al.* 2012; Accad *et al.* 2013), but adopted vegetation categories that were amalgamated from Queensland BVGs at the 1:5 million scale (Neldner *et al.* 2014). Mapped regional ecosystems sometimes include the presence of dominant and subdominant types co-occurring for the same map unit, however, the dominant types only were used in this study. Vegetation was categorised into three main structural groups represented across the environmental gradient of interest in the region. These were rain forest (RF), tall eucalypt forest dominated by *Eucalyptus grandis* or *E. resinifera*) (TEF) and open savanna woodland (dominated by *Corymbia citriodora*, *E. crebra*, *E. granitica*, *E. shirleyi*, *E. cullenii*, *E. atrata or E. melanophloia)* (SAV). These three structural groups are broadly consistent with nationally mapped Major Vegetation Groups (Department of the Environment and Water Resources 2007). Rain forest was equivalent to 'rain forests and vine thickets'; tall eucalypt forest was equivalent to 'eucalypt tall open forests' and savanna was equivalent to 'eucalypt open forest' and 'eucalypt woodland'. Rain forest (RF) consisted of the Queensland BVGs 'rain forests, scrubs', tall eucalypt forest (TEF) consisted of the broad vegetation group 'wet eucalypt open-forest' and savanna woodland (SAV) consisted of all broad vegetation groups of open-forest or woodland ('coastal eucalypt woodlands to open-forests', 'eucalypt open-forests to woodlands on floodplains', 'eucalypt dry woodlands on inland depositional plains', 'eucalypt low open-woodlands usually with spinifex understorey', '*Callitris* woodland – open-forests', '*Melaleuca* open-woodlands on depositional plains', 'other *Acacia* dominated open-forests, woodlands and shrublands', 'mixed species woodlands – open woodlands (inland bioregions) includes wooded downs', 'other coastal communities or heaths' (excluding heaths) and 'tussock grasslands, forblands') (Accad *et al.* 2013). Together, the three structural groups used here account for 95% of the vegetation in the Wet Tropics study area (Figure 1.2).

Of the vegetation types considered in this study, all of the regional ecosystems within the ‘tall eucalypt forest’ category are legislatively listed as threatened (Accad *et al.* 2013). There are also a number of rain forest and savanna regional ecosystems that are also listed as threatened. The restricted area and long narrow shape of their distribution with high edge to area ratio, contributes to the vulnerability and endangered listing of this vegetation type. Additionally, tall eucalypt forests support important biota and contain high vertebrate species richness and endemism, almost equivalent to the adjacent rain forests, and all within a comparatively small geographic area (Williams *et al.* 1996b). Accordingly, particular attention will be paid to this vegetation type.

Savanna vegetation is a tropical open woodland confined to northern Australia, but with affinities to temperate open woodlands in southern Australia (Groves 1994). Tall eucalypt forests occur in three broad regions of Australia; southeastern Australia and Tasmania, southwestern Australia and east coastal Australia, with their northern most occurrence in the Wet Tropics (Ashton 1981; Ashton & Attiwill 1994; Gill & Catling 2002; Gill 2012). Tall eucalypt forests are commonly found in association with rain forests and open woodlands throughout eastern Australia. Rain forests are found in eastern Australia with small pockets in the monsoonal tropics in northern Australia, within similar floristic regions to that of tall eucalypt forests (Werren & Kershaw 1987; Adam 1992; Groves 1994).

1.4.2 A spectrum of fire tolerance

Rain forests are characterised by fire sensitive species (Bowman 2000; Cochrane 2003), while eucalypt savannas are dominated by fire tolerant species and may be subjected to frequent fire (Williams *et al.* 2003a). Tall eucalypt forests are often associated with rain forest and are also fire sensitive. However, they may be subject to infrequent high intensity fires that kill canopy trees, but also initiate eucalypt seedling recruitment (Unwin 1989). Eucalypt savanna and rain forest vegetation therefore represent opposite ends of the fire tolerance spectrum, with tall eucalypt forests in between. In northern Australia the drivers of these vegetation patterns have been investigated at a regional scale (Williams *et al.* 1996a; Spessa *et al.* 2005) and at various sites in the Wet Tropics (Unwin 1983; Ash 1988; Unwin 1989; Turton & Duff 1992; Turton & Sexton 1996). However, no assessment of fire history information has been undertaken between vegetation types in the Wet Tropics, or in Queensland. This is because fire history records are relatively recent in Queensland (c. 2001, pers. obs.) and current evaluation methods using satellite detection of hot spots and fire scars, generally fail to detect fire incidents beneath tall or closed canopy forests (pers. obs.). The juxtaposition of these vegetation types provides the opportunity to examine relative patterns in microclimate and fire danger between vegetation types (Little *et al.* 2012).

1.4.3 A history of vegetation change

Historic changes in climate (and fire) have influenced vegetation distribution in the Wet Tropics, like other parts of Australia (Hill 1994). Certain vegetation types in the Wet Tropics and elsewhere in Australia have demonstrated fluctuations in their relative distribution, with rain forests having expanded and contracted significantly in the landscape, associated with broad climatic changes and fire activity (Kershaw 1976; Hopkins *et al.* 1990; Kershaw 1994; Hilbert *et al.* 2001a; Hilbert *et al.* 2007; Kershaw *et al.* 2005; Kershaw *et al.* 2007a; Moss 2008; VanDerWal *et al.* 2009b). Rain forests have persisted in the Wet Tropics, whereas they have declined across most of Australia (Hill 1994), primarily due the persistence of a combination of moist meso- and micro-climates associated with the coastal mountain ranges, which afford protection from fire, considered one of the main drivers of rain forest distribution (Bowman 2000). Conditions favourable for the expansion of rain forest are likely to have been accompanied by a decline in fire danger, which is supported by charcoal evidence found in areas now covered by rain forest vegetation (Hopkins *et al.* 1993). Although some pioneer rain forest species resprout following a single low-intensity fire event (Marrinan *et al.* 2005; Williams *et al.* 2012c), repeated burning will kill these species without recruitment. Generally, fires are destructive to rain forest, which can take centuries to recover. Long multi-century, fire-free periods are required for rain forests to persist or expand (Bowman 2000; Jackson & Brown 2005; Haberle *et al.* 2010). Consistent with fire return periods elsewhere in Australia (Jackson 1968; Jackson & Brown 2005), evidence of fire return periods at rain forest boundaries in the Wet Tropics are 230 years in tall eucalypt forests and much longer for rain forest vegetation (Chen 1990). Time periods of this length represent many human generations, well beyond living memory and fire events at this frequency are unlikely to be from anthropogenic burning and more likely associated with extreme climatic events. Current rain forest distribution in Australia largely represents microclimatic and fire refugia. Biodiversity and threatened species rely on these refugia and their persistence under future climate is a critical conservation and management issue (Shoo *et al.* 2011).

Recent changes in the distribution and structure of vegetation have also been recorded in the Wet Tropics using paleontology, palynology and charcoal records (Haberle 2005; Haberle *et al.* 2006; Haberle *et al.* 2010). The most significant has occurred since the 1880s, coinciding with the arrival of Europeans in the region. Changes detected include degradation of rain forest vegetation and increase in fire. Substantial, broad scale European disturbances have impacted the Wet Tropics since the 1880s, including land clearing, timber harvesting, grazing (Birtles 1982, 1988, 1997a, 1997b; Frawley 1988, 1991; Unwin *et al.* 1988; Winter *et al.* 1991a; Crome 1992; Frost 1997; Haberle *et al.* 2006; Turton 2008) and increased fire frequency (Haberle 2005; Haberle *et al.* 2006, 2010). The European impacts, including increase in fire frequency reported for the Wet Tropics, are consistent with European impacts elsewhere in Australia (Enright & Thomas 2008; Bowman & Haberle 2010; Mooney *et al.* 2011).

More recent vegetation change patterns have been detected since the 1940s from aerial and satellite imagery interpretation (Harrington & Sanderson 1994; Johansen & Phinn 2005; Tng *et al.* 2011). These changes have included vegetation thickening (primarily of rain forest species) near rain forest boundaries and within tall eucalypt forests. Controversy persists regarding the cause of these changes since the 1940s (Harrington & Sanderson 1994). Vegetation changes in the Wet Tropics have been widely attributed to a reduction in Indigenous burning practices (Unwin *et al.* 1988; Stocker & Unwin 1989; Unwin 1989; Harrington & Sanderson 1994; Russell-Smith & Stanton 2002; Stanton *et al.* 2014a, b). Yet the attribution of vegetation change to a reduction in burning is presented without evidence and ignores other available evidence (see Appendix 1.1 for further discussion).

Observed understorey thickening patterns are consistent with vegetation recovery from European disturbances elsewhere in Australia (Griffiths 2001; Hateley 2010). The impact of European activities since the 1880s and other available evidence suggests other drivers of these vegetation changes (Chen 1990; Hill *et al.* 2000; Hill *et al.* 2001; Haberle 2005; Brook & Bowman 2006; Haberle *et al.* 2006; Haberle *et al.* 2010; Medlyn *et al.* 2010; Tng *et al.* 2012, 2013). Vegetation changes also correlate with and may result from the atmospheric influence of elevated carbon dioxide (CO_2) associated with climate change (Brook & Bowman 2006; Medlyn *et al.* 2010). In any case, relying on imagery from the 1940s (Harrington & Sanderson 1994) is an unsuitable benchmark for vegetation structure, as it represents a degraded state following 60 years of European disturbance (Turton 2008). Other sources of evidence, such as paleontology, palynology and charcoal records provide the best empirical evidence of the pre-European state of vegetation, which is a more appropriate benchmark.

Regardless of the breadth of available evidence, land management agencies have attempted to apply frequent burning in some tall eucalypt forest areas to arrest vegetation change to maintain vegetation structure and distribution as it was in the 1940s (Department of National Parks Recreation Sport and Racing 2013; Queensland Herbarium 2014; Stanton *et al.* 2014a, b; Tng *et al.* 2014). If the 1940s vegetation structure represents a degraded state, then current management practices may be inhibiting natural regeneration pathways. Fire management practices may contribute to vegetation being in a landscape trap driven by fire (fire trap) and are therefore, vulnerable to switch to an alternative stable state of vegetation. Human colonisation followed by altered fire regimes can tip fire sensitive vegetation to another state, which is then maintained by positive feedbacks and recurring fire (Tepley *et al*. 2016). Such traps have also been detected in the Wet Tropics, where grasses monopolise and persist for long periods preventing rainforest regeneration (Winter *et al.* 1991a) and also in adjacent savannas (Werner 2012). Alternative stable states could be triggered by climate change impacts and their interaction with other stressors such as altered fire regimes (Driscoll *et al.* 2012). How climate change will affect fire regimes across an environmental gradient of multiple vegetation types, fire-sensitive vegetation and high biodiversity has not been empirically evaluated.

1.5 Climate change in the Wet Tropics

Climate change projections for the Wet Tropics region present dire consequences for its communities and its ecosystems (Suppiah *et al.* 2007; Balston 2008; Hilbert 2010; Suppiah *et al.* 2010; Low 2011; Murphy *et al.* 2012; Williams *et al.* 2012b; Hilbert *et al.* 2014; CSIRO & Bureau of Meteorology 2015; McInnes *et al.* 2015). Detailed regional analysis, based on the most recent global climate models and downscaling techniques, have been completed for Australia's bioregions and Natural Resource Management cluster areas (CSIRO & Bureau of Meteorology 2015), including for the Wet Tropics (Hilbert *et al.* 2014; McInnes *et al.* 2015). In this region, temperatures, extreme events and heatwaves, are expected to increase. Rainfall predictions remain variable, but an increase in drought and longer dry seasons are expected. Fire weather conditions are expected to worsen slightly. These predictions are generally consistent with previous reports, albeit with greater certainty. The potential impact of climate change to the region could be catastrophic for ecosystems and biota, including rain forest (Williams *et al.* 2003b; Hilbert 2010; Low 2011; Murphy *et al.* 2012b; Costion *et al.* 2015; McInnes *et al.* 2015), tall eucalypt forest (Hilbert *et al.* 2001; Hilbert 2010) and their associated species.

Shifts in climatic environments are expected to be very rapid and exceed the ability of vegetation types to migrate accordingly (Hilbert 2010; Low 2011; Murphy *et al.* 2012; Hilbert *et al.* 2014; McInnes *et al.* 2015). The greatest risk to vegetation is likely to be at vegetation boundaries and for ecotonal or transitional communities, the tall eucalypt forests, with significant shifts in the spatial distribution, or disappearance, of vegetation types in these areas being likely (Hilbert *et al.* 2001; Hilbert 2010). Some rain forest types, particularly high elevation montane types, are predicted to decline, while others expand, however the projections for tall eucalypt forest are alarming. The climatic environment for tall eucalypt forest is expected to largely disappear by 2050, with no existing refugia remaining for this vegetation type (Hilbert 2010). Although, potential increases in tall eucalypt forest are predicted following this period (Hilbert 2010), the rapid shift in climate will drive changes in vegetation structure and composition, ultimately resulting in potential transition to other vegetation types (Hilbert *et al.* 2014) or collapse (Keith *et al.* 2013). These climate-driven changes are predicted even without the added threat of altered fire regimes. Yet the occurrence and frequency of fire is the mechanism that directly affects the distribution and survival of rain forest (Bowman 2000) and tall eucalypt forests species (Unwin 1989; Campbell & Clarke 2006; Bradstock 2010; Campbell *et al.* 2012; Hoffmann *et al.* 2012a; Lewis *et al.* 2012; Williams *et al.* 2012c). Climate change induced shifts in the fire regime could have a greater impact on vegetation distribution in the Wet Tropics than by the direct influence of climate alone (Hilbert *et al.* 2001; Hilbert 2010).

Predictions of future fire danger in northeastern Australia, however, vary, with some predictions of large increases along the Queensland coast during January (Pitman *et al.* 2007) and others suggesting a decrease in fire danger (Clarke *et al.* 2011). Based on these studies and more recent global climate models, region-wide predictions of climate change impacts on fire weather in the Wet Tropics suggest little change to fire weather, with a tendency towards increasing fire weather (McInnes *et al.* 2015). However, these predictions are at a coarse scale and are not suitable for representing patterns at a fine-scale across the environmental gradients of the Wet Tropics. The finest resolution utilised by Clarke *et al.* (2011) were pixels of approximately 210 km x 210 km (1.9° x 1.9°) and 356 km x 623 km (3.2° x 5.6°) by Pitman *et al.* (2007). The most recent global climate models (CMIP5) involve a spatial resolution of approximately 180 km (CSIRO & Bureau of Meteorology 2015). The finest resolution downscaling technique used on this data, using bilinear interpolation, provided a spatial resolution to 5 km. However, the spatial interpolation algorithms used do not add more information and are therefore no more accurate than the original global climate model (p. 178, CSIRO & Bureau of Meteorology 2015). The ecological implications of climate change and change in fire danger will be experienced at a much smaller spatial scale than represented in current predictions (within 20 km). Understanding local microclimate conditions and intra-regional variation is crucial in interpreting implications of broad-scale predictions of climate change for a region, particularly where complex topography, environmental gradients and multiple vegetation distributions are involved.

1.6 Aims

The overall aim of this thesis was to address the question:

'will climate change interacting with fire affect the distribution of vegetation types?'

To answer this question, a diversity of approaches was explored; fine-resolution vegetation distribution models, evaluation of spatially interpolated climate data, field evaluation of topographic microclimate between vegetation types, evaluation of fire danger between vegetation types, comparisons with official meteorological stations and an assessment of historic climate and fire danger trends at key sites within the region. These methods were relied on, as other more direct approaches were not viable for adoption. These other methods trialled consisted of an assessment of fire history information (spatial records), reconstruction of fire history information from satellite imagery, fire - vegetation simulation models and predictive vegetation distribution models under future climate scenarios. None of these approaches were suitable for answering the research question at an appropriate local scale.

The main motivation for undertaking this applied research was to better understand conservation issues associated with tall eucalypt forests and rain forest boundaries under future climate and their management implications. The specific research approach was to assess potential impacts of fire risk associated with climate change. This involved review and discussion of current literature, including potential ecosystem risk (Keith *et* al. 2013) and resilience of these vegetation types into the future. The thesis contains some discussion which may be indirectly related to data collected, but which is relevant to management considerations associated with fire management and persistence of healthy and resilient vegetation types into the future.

The thesis contains four data chapters, each taking a different approach to garner evidence for the likely impact of climate change on fire danger and vegetation distribution. The specific objectives of the thesis were to:

1. *Determine the relative contribution of topographic, climatic and edaphic factors in explaining current vegetation distributions* (Chapter 2);
2. *Assess the fine-scale variation in climate driven by topography and vegetation along an environmental gradient* (Chapter 3);
3. *Determine the relative performance of spatially interpolated macroclimate, vegetation and topography in explaining in situ topoclimate* (Chapter 3);
4. *Assess the fine-scale variation in fire danger driven by topography and vegetation along an environmental gradient* (Chapter 4)*;*
5. *Identify historic climate and fire danger trends and extremes within the Wet Tropics region* (Chapter 5)*;*
6. *Determine whether observed climate and fire danger trends are consistent with projected future climate trajectories* (Chapter 5)*;*
7. *Identify historic and likely future changes in climate and fire danger relative to vegetation types* (Chapter 5); and
8. *Evaluate likely impacts of climate change interacting with fire and other potential stressors on vegetation types* (Chapter 6).

a.

b.

Plate 2. Tall eucalypt forest/ rain forest boundary on the Carbine Tableland; a remote and undisturbed section of the Wet Tropics. Rain forest vegetation appears in the far right of both images. Savanna vegetation can be observed on the distant, inland, range in the top of Plate 2a.

CHAPTER 2

Vegetation distribution along an environmental gradient in the Wet Tropics of northeastern Australia

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2.1 Abstract

The distribution of biota is often linked to an environmental niche, which can often be explained by climatic, geographic or edaphic variables. However, vegetation can sometimes occur in disequilibrium from such factors and be influenced by stochastic disturbances or vegetation feedbacks, causing alternative stable states of vegetation within a landscape. The aim of this study was assess how well geographic, edaphic and climatic factors alone explain the distribution of vegetation types in the Wet Tropics and how much remains unexplained. Three vegetation types; rain forest, tall eucalypt forest and savanna types, occur along an environmental gradient associated with a montane tropical environment in the Wet Tropics of northeastern Australia. Species distribution models were used to explain environmental suitability of vegetation within this complex topographic landscape. A fine-scale systematic lattice grid at 250 metre resolution was applied to the entire region and analysed with a spatial geostatistical approach. Spatial generalised linear models were implemented with a large dataset using a novel spatial residuals autocovariate technique. This study was the first comprehensive modelling of vegetation in the Australian Wet Tropics region, which employed a fine-resolution, systematic and geospatial approach. All vegetation types were best explained by the same eight variables; easterly distance to the coast, elevation, geology, landform, relief, soil, mean diurnal temperature range and precipitation of driest annual quarter. Even though robust fine-scale models of the full extent of these vegetation types were used, the best model only explained deviance of 59% of rain forest, 41% of tall eucalypt forest and 54% of savanna vegetation. Despite using every data point in region, these models still retain a high level of inaccuracy and it is suggested that there are key missing elements that affect and explain vegetation distribution, such as fire and alternative vegetation states. Modelled distributions were compared with the full known extent of vegetation types to estimate the difference between the potential distribution and the realised distribution of vegetation and identify potential presence and extent of vegetation disequilibrium and alternative stable states. Savannas were found to be the most stable vegetation type, occupying 97% of their predicted distribution, whereas rain forest occupied 89% and tall eucalypt forests only 74%. Savanna occupied 9% of predicted rain forest and 16% of predicted tall eucalypt forest. The prevalence of savanna vegetation occupying suitable areas for the other vegetation types was suggestive of fire-driven alternative stable states. However, rain forests also occupied 10% of predicted tall

eucalypt forest. The curious case of temperate tall eucalypt forests in a tropical montane setting, wedged between short-term frequent fire intolerance and long-term shade intolerance was explored. These findings support the premise that rain forest boundaries and ecotonal tall eucalypt forests are particularly vulnerable to climate change and tipping points associated with fire-driven alternative stable states.

Keywords: vegetation distribution model, climate, topography, environmental gradient, spatial interpolation, spatial autocorrelation, residuals autocovariate regression, alternative stable states

2.2 Introduction

Shifts in vegetation distribution associated with climatic change have occurred throughout the Earth's history (Hill 1994; Cramer *et al.* 2001; Harrison & Prentice 2003; Pickett *et al.* 2004; Kershaw *et al.* 2007b). However, the rapid rate of current climate change is causing observable, often abrupt, shifts in vegetation distribution (Walther *et al.* 2005; Bowman *et al.* 2010; Elliott & Kipfmueller 2011; Tng *et al.* 2011; Bond & Midgley 2012; Corlett & Westcott 2013). Of concern is that some vegetation types are more vulnerable to change (Gonzalez *et al.* 2010) and face tipping points (Laurance *et al.* 2011) that destabilise vegetation (Lloret *et al.* 2012), causing a transition into an alternative stable state (Wilson & Agnew 1992; Scheffer *et al.* 2001; Beisner *et al.* 2003; Scheffer 2003; Higgins & Scheiter 2012), otherwise known as ecosystem collapse (Rodríguez *et al.* 2011; Keith 2013, 2015; Keith *et al.* 2013). The ability to explain the drivers and distribution of vegetation may help to predict or mitigate impacts and to identify important climate change refugia (Ashcroft *et al.* 2009; Ashcroft 2010; Keppel *et al.* 2012; Keppel & Wardell-Johnson 2012; Mackey *et al.* 2012; Reside *et al.* 2013).

Models can be used to explain or predict distributions of species, or communities such as vegetation types (Mac Nally 2000; Ferrier & Guisan 2006; Elith *et al.* 2008; Elith & Leathwick 2009; Franklin 2009; Hijmans 2012; Miller 2012). Models can help identify refugia, conservation priorities, management actions, species or ecosystem resilience and potential threats to long-term persistence or climate change impacts. Myriad distribution model approaches are available to explain or predict vegetation distributions specifically (Peng 2000; Austin 2002; Dirnböck *et al.* 2002; Miller & Franklin 2002; Segurado & Araujo 2004; Elith *et al.* 2006; Ferrier & Guisan 2006; Lawler *et al.* 2006; Austin 2007; Elith & Graham 2009; Elith & Leathwick 2009; Scheiter *et al.* 2013; Franklin 2013). Different modelling techniques can produce a high variation (Araújo & New 2007; Lawler *et al.* 2006) and thus uncertainty (Buisson *et al.* 2010), so it is important that data inputs and models used are robust, appropriate for the task, ecologically meaningful and include a methodological framework (Jiménez-Valverde *et al*. 2008). Distribution model approaches might include a multi-model approach within an ensemble forecasting framework (Thuiller 2003; Araújo & New 2007; Thuiller *et al*. 2009), or a consensus model approach (Marmion *et al.* 2009b).

To help understand potential impacts of climate change on vegetation distribution, it is important that models can accurately explain current vegetation distribution before attempting to predict future distributions. Knowing the relative influence of climate on vegetation distribution will influence predictions based on future climate. Therefore, identifying a robust and accurate model of contemporary vegetation distribution is a necessary precursor to sound predictions of future distribution.

2.2.1 Aims

The aim of this study was to model the distribution of vegetation types in the Wet Tropics and assess model capacity to accurately predict vegetation distribution under future climate.

2.2.2 Wet Tropics vegetation models

The Wet Tropics of northeastern Australia is a mountainous coastal area with a mosaic of vegetation types associated with steep environmental gradients and complex terrain (Nix 1991). Broad vegetation types consist of rain forest, tall eucalypt forest and savanna. It is a region of global ecological and evolutionary significance demonstrated by the listing of the greater part of the region in the Wet Tropics of Queensland World Heritage Area, primarily due to the abundance of rain forest vegetation. Climate change poses a serious threat to vegetation in this region (Hilbert, *et al.* 2001a, b; Hilbert & Ostendorf 2001; Ostendorf *et al.* 2001; Hilbert 2008; VanDerWal *et al.* 2009b; Hilbert 2010) and ecosystem collapse of relevant vegetation types in this region is of legitimate concern (Burns *et al.* 2015; Metcalfe & Lawson 2015). To accurately assess these risks to vegetation, first requires sound explanatory models of the vegetation.

Patterns and processes affecting the distribution of vegetation types in the Wet Tropics region are broadly understood (Nix 1991). However, regional models of vegetation have shown low accuracy explaining the distribution of tall eucalypt forests and boundaries between vegetation types (Hilbert & van den Muyzenberg 1999; Hilbert *et al.* 2001a, b; Hilbert & Ostendorf 2001; Ostendorf *et al.* 2001; Hilbert *et al.* 2007; VanDerWal *et al.* 2009b). Being able to accurately explain and predict vegetation boundaries and distributions of confined communities, such as tall eucalypt forest, is critical for understanding how future climate may affect vegetation distribution.

There have been various approaches to modelling vegetation distribution in the Australian Wet Tropics (Nix 1991; Mackey 1993, 1994; Hilbert & van den Muyzenberg 1999; Hilbert *et al.* 2001a, 2001b, 2007; Hilbert & Ostendorf 2001; Ostendorf *et al.* 2001; Mackey & Su 2005; Accad & Neil 2006; Graham *et al.* 2006, 2010; Hilbert 2008, 2010; VanDerWal *et al.* 2009b). Many of these studies have focussed on rain forest vegetation, due to its conservation significance, but exclude the diversity of the very different vegetation types in the region. Some studies have utilised climatic parameters only and exclude geographic considerations. Historic vegetation distribution and palaeoclimatic evidence (Hill 1994; Kershaw *et al.* 2005; Kershaw *et al.* 2007a) has been used in validating model predictions of past vegetation distribution under palaeoclimatic conditions (Nix 1991; Hilbert *et al.* 2001a, 2007; Hilbert & Ostendorf 2001; Graham *et al.* 2006, 2010; Hilbert 2008; VanDerWal *et al.* 2009b) and projections under future climate scenarios (Hilbert, *et al.* 2001a, b; Hilbert & Ostendorf 2001; Ostendorf *et al.* 2001;

Hilbert 2008, 2010; VanDerWal *et al.* 2009b). Here, current high-resolution spatial data was used to explain the fine-scale distribution of vegetation types in the Australian Wet Tropics

2.2.3 Methodological approach

A component framework analysis was adopted, using ecological knowledge, data measurement and statistical methodology, consistent with Austin (2002). Ecological theory was applied to targeting and testing specific geographic and climatic variables most likely to influence vegetation distribution. Data measurement involved fine-scale spatial analysis of three vegetation types and assessment of geographic and climatic attributes of each vegetation type across the entire study region. Statistical methodology consisted of an iterative process in establishing best practice in distribution modelling and finally resulted in the use of a common and robust statistical technique - generalised linear models (see Appendix 2.1 for details).

2.2.4 Ecological theory

A more thorough and rigorous exploration of likely drivers that explain current vegetation patterns in the Wet Tropics is required to improve fine-scale predications of vegetation distribution. The best available data for a range of geographic, climatic and other, pyric, coupled with ecological knowledge of forces most likely to influence vegetation distribution were tested to explain the current distribution of vegetation types in this study area.

In addition to climatic and geographic variables, one of the primary and acute drivers of rain forest - savanna boundaries is repeated fire, which will suppress rain forest vegetation in favour of more flammable (pyrophytic) vegetation types such as savanna (Bowman 2000). Fire is influenced by weather patterns, vegetation flammability and ignition (Bradstock 2010), as well as grazing regimes and vegetation feedbacks (Wilson & Agnew 1992; Hoffmann *et al.* 2002; Beckage & Ellingwood 2008; Beckage *et al.* 2009; Hoffmann *et al.* 2009; Warman & Moles 2009; Odion *et al.* 2010). The influence of fire has not been previously incorporated into vegetation distribution models of the Australian Wet Tropics. Vegetation - fire models are generally performed at a coarse-scale and are not of fine enough resolution to accurately explain vegetation boundaries and distributions (Keane *et al.* 2004; Keane *et al.* 2013). In the absence of fine-scale vegetation - fire model options, surrogate information must be considered. The probability of fire, which may be used as a fire surrogate, is often measured from climatic information to define a fire danger. In Australia, fire danger, as measured by McArthur’s Forest Fire Danger Index (FFDI) (Noble *et al.* 1980; Griffiths 1999; Finkele *et al.* 2006), is calculated from temperature, relative humidity, wind speed, rainfall and a drought factor. The influence of fire, or its surrogates, that most likely capture fire danger patterns was targeted for their ability to explain vegetation distributions in the region.

In selecting appropriate fire surrogates, specific consideration was given to regional geographic and climatic patterns. There are strong orographic climate gradients in the region influencing local weather patterns (and thus fire danger, flammability and vegetation distribution). These include precipitation interception, exposure to prevailing southeasterly winds (McJannet *et al.* 2007) and an opposing rainshadow in the lee of the mountain ranges (Unwin 1983; Kitzberger *et al*. 1997; Harrington *et al.* 2000; Malhi *et al.* 2010). These strong moisture gradients become more pronounced during the dry (fire) season, when moisture persists in the upper mountain ranges, but dries quickly in the lowlands and inland plains (Nix 1991). Based on these phenomena, spatial data of directional easterly and southeasterly geographic variables were generated using GIS, for testing in spatial analysis. Regional specific variables relating to exposure and prevailing winds have been previously recommended for improvements to model performance (Ashcroft 2006; Ashcroft *et al.* 2008; Ashcroft *et al.* 2009; Ashcroft & Gollan 2012). Similarly, climatic variables were selected that best captured prevailing conditions during the fire season.

2.3 Methods

2.3.1 Study area

The Wet Tropics region of northeastern Australia is characterised by steep coastal mountain ranges to 1622 metres in elevation, stretching approximately 500 kilometres of coastline by 75 kilometres inland (Figures 1.1 and 1.2). The coastal ranges attract high orographic rainfall and precipitation interception from prevailing southeasterly on-shore trade winds and seasonal monsoonal troughs; however, precipitation is highly variable in the landscape, with a strong moisture gradient in the leeward westerly side of the mountain ranges caused by a rainshadow affect (Unwin 1983; Nix 1991; Turton *et al.* 1999; Harrington *et al.* 2000). This environmental gradient is associated with abrupt transition between vegetation types (Unwin 1983, Duff 1987; Unwin 1989, Nix 1991).

Much of the wet mountain ranges are covered by rain forest vegetation (Winter *et al.* 1991b), with variable occurrence of rain forest or savanna woodlands on the coastal flats and savannas dominating the drier western plains (Figure 1.2). On the western slopes of the ranges (in the rainshadow) and on the tablelands in between these two communities, may be found other distinct communities; tall open and open eucalypt forests. The rain forests and tall eucalypt forests associated with the ranges of the Wet Tropics are discontiguous from similar forests found either north or south of the region.

The Wet Tropics analysis area (3,662,446 ha) (Figure 1.1 and 1.2) was consistent with the analysis area of other research in this region (VanDerWal *et al.* 2009b; Shoo *et al.* 2011; Little *et al.* 2012), which encompassed a 20 kilometre buffer zone surrounding rain forest and tall eucalypt forest vegetation. A range of spatial data was obtained for the entire study area, consisting of vegetation, climate, soil, geology, topography and latitude.

2.3.2 Remotely sensed spatial data analysis

All data sources used in this analysis were publicly available from the Australian and Queensland Governments. Vegetation type distribution data in the form of detailed vegetation (regional ecosystem) mapping (Sattler & Williams 1999; Neldner *et al.* 2012; Accad *et al.* 2013), was obtained from the Queensland Government. Using vegetation descriptions associated with broad vegetation groups (BVG; 1:5M scale), which underlie regional ecosystems (Accad *et al.* 2013; Neldner *et al.* 2014), vegetation was categorised into three main structural groups represented across the environmental gradient of interest in the region. These were rain forest (RF), tall eucalypt forest (TEF) and open savanna woodland (SAV). These three structural groups are broadly consistent with nationally mapped major vegetation groups (Department of the Environment and Water Resources 2007) (see section 1.4.1 for more details).

Geographical, geological and soil data were obtained for the Wet Tropics study area. Geographical data were derived from a Digital Elevation Model (DEM) mapped at a scale of approximately 80 metres resolution (GEODATA 9 S DEM Version 2, Geoscience Australia http://www.ga.gov.au/; Rochester 2003). Ten geographic variables were generated from and snapped to the DEM (elevation) raster; aspect, hillshade, latitude, slope, wind shear (southeasterly and northwesterly directions), easterly and southeasterly directional distance to the eastern coastline. Southeasterly is the direction of prevailing trade winds for the region. All but elevation and latitude were calculated from spatial analysis within a geographic information systems platform. Hillshade is a three dimensional shaded relief based on elevation data and an illumination source angle and its shadow. Given the steep mountains of the region, hillshading can be an influence on distribution of biota. Wind shear is similarly represented by ray tracing of elevation data from a defined angle and identified topographic areas that are intercepted by a directional ray (or wind) source, such as southeasterly or northwesterly. Wind shear was hoped to capture orographic rainfall and rain intercept (southeasterly) and its opposite, the rainshadow (northwesterly).

Distance to the nearest stream was calculated as the spatial distance from the nearest Strahler stream order of 3 or greater and was derived from the GeoScience Australia 1:100,000 drainage network. An additional four geographic and edaphic variables were also evaluated; soil, relief, landform and geology. These variables were derived from mapped soil data from the Australian Soil Resource Information System (ASRIS) classification system (McKenzie *et al.* 2012). Soil data was based on 'soil order' of the Atlas of Australian Soils mapped at a scale of approximately 1: 2,000,000 (McKenzie *et al.* 2012). Detailed information on the soils of the

Wet Tropics are described by Lottermoser *et al.* (2008). Relief and landform were derived from the level-5 descriptors of land system, ‘relief/ modal slope’ and ‘landform pattern’ mapped at a scale of approximately 1: 100,000 (McKenzie *et al.* 2012). Geology data was derived from detailed surface geology, using ‘rock name’ mapped at a 1:100,000 scale (Queensland Government Department of Natural Resources and Mines).

Climatic data used here consisted of spatially interpolated (thin plate smoothing spline) climatic data created using ANUCLIM (Hancock *et al*. 2001; Xu & Hutchinson 2011; Xu & Hutchinson 2013) and presented in a distribution model, BIOCLIM (Booth *et al*. 2014). BIOCLIM contained 35 variables, including 11 temperature variables, eight precipitation variables, eight solar radiation variables and eight moisture index variables. Of these, the 19 temperature and precipitation variables are commonly used in national and global climate modelling (Hijmans *et al*. 2005) were used here (Table 2.1).

Table 2.1 Climatic (BIOCLIM) variable codes and descriptions for 11 temperature variables and eight precipitation variables.

Code	Description
bc01	Annual mean temperature
bc02	Mean diurnal range
bc03	Isothermality
bc04	Temperature seasonality
bc05	Max. temperature of warmest period
bc06	Min. temperature of coldest period
bc07	Temperature annual range
bc08	Mean temperature of wettest quarter
bc09	Mean temperature of driest quarter
bc10	Mean temperature of warmest quarter
bc11	Mean temperature of coldest quarter
bc12	Annual precipitation
bc13	Precipitation of wettest period
bc14	Precipitation of driest period
bc15	Precipitation seasonality
bc16	Precipitation of wettest quarter
bc17	Precipitation of driest quarter
bc18	Precipitation of warmest quarter
bc19	Precipitation of coldest quarter

A 250 m by 250 m (6.25 ha) raster geospatial grid was applied to the study area (3,662,446 ha) and all environmental layers (GDA 94) were sampled (spatial-join and point-intersect GIS analysis) from the centre of each of the 586,045 grid cells, evenly stratified. Spatial sampling in a systematic regular design, such as this, is a widely used and convenient approach, that avoids statistical sampling biases and is more efficient in estimating spatial patterns than by a random design (Diggle & Ribeiro 2007).

Each of the 14 geographical and 19 climatic variables were then used as an explanatory variable in distribution models for each vegetation type. Five of the geographical explanatory variables were categorical, rather than continuous data (aspect, soil, relief, landform and geology). Aspect was defined as flat, northeast (0-89.9 °), southeast (90-179.9°), southwest (180-269.9°) and northwest (270-359.9°). Other categorical variables, however, contained a greater number of categories. To prevent unnecessary loss in degrees of freedom and to simplify models with categorical explanatory variables, the numbers of categories in each variable were reduced (Franklin 2009). To do this, the individual percentage contribution within the region for each category, was assessed. Individual categories that contributed less than 5% for that variable were lumped into a generic category (‘other’). All other categories that contributed 5% or greater were retained.

2.3.3 Model analysis

Binomial generalised linear models (logistic regression), were used to model the distribution of each vegetation type. Generalised linear models (GLM) were applied to each vegetation type in a separate analysis. Other model techniques were considered (Appendix 2.1), such as multinomial logistic regression as used elsewhere (Ackerly *et al.* 2015). However, GLMs make use of presence and absence data, allowed each vegetation type to be analysed separately, allowed assessment of variability in the key drivers between vegetation types and would allow assessment of how climate change might affect individual vegetation types. Additionally, GLMs perform well compared to other model techniques (Bedia *et al.* 2011; Khatchikian *et al.* 2011; Clark *et al.* 2012; Royle *et al.* 2012) and have established techniques for direct model comparison and selection (Burnham & Anderson 2002; Burnham & Anderson 2004; Burnham *et al.* 2010). GLMs were generally implemented following the analysis sequence described by Logan (2010), using ‘R’ statistical software (Version 3.0.2; R Development Core Team 2002). Assumptions of linearity, normality and homogeneity of variance were assessed by comparing variable distributions (via a scatterplot matrix with box-plots) for each variable and checking for skewed distributions. Linear correlations between all variables were tested by calculating Pearson’s correlation coefficient (r) for each combination between all explanatory variables. Values between -0.5 and 0.5 were considered not strongly correlated. Multi-collinearity tests (Dormann *et al.* 2013) were also performed on the data, with potential collinearity indicated by a variance inflation factor greater than five (Logan 2010).

Evaluation metric(s) that are appropriate for model evaluation require careful consideration and multiple metrics may be required (Zuur *et al.* 2007; Marmion *et al.* 2009a; Franklin 2009; Mouton *et al.* 2010; Liu *et al.* 2011; Jolliffe & Stephenson 2012; Aguirre-

Gutiérrez *et al.* 2013; Ebert *et al.* 2013; Li & Guo 2013; Pottier *et al.* 2013)., Three evaluation metrics were adopted. GLMs are commonly evaluated by Akaike Information Criteria (AIC and AICc) and can be used in model selection (Burnham & Anderson 2002; Burnham & Anderson 2004; Burnham *et al.* 2010). Secondly, explained deviance (Mittlböck & Schemper 1996) is a useful and widely used measure of goodness of fit for model performance, however is not appropriate for model selection (Burnham & Anderson 2002). Explained deviance (or D^2) is presented as a proportion or percentage of model deviance explained relative to the null model. An adjusted explained deviance was used (Barbosa *et al*. 2014), as this accounts for the number of observations and explanatory variables in each model and adjusts model explained deviance accordingly for a more accurate comparison between models (Guisan & Zimmermann 2000; Weisberg 2014). The third evaluation metric was the true skill statistic (TSS), as this is a superior alternative for presence-absence data (Allouche *et al.* 2006). TSS values range from -1 to 1, with 1 for a perfect model fit and a value of 0 indicating no skill. Threshold selection can be a source of uncertainty within models (Nenzén & Araújo 2011). An optimised threshold analysis was adopted, selecting the threshold that maximised sensitivity plus specificity (via 'SDMTools' in R; Vanderwal *et al*. 2014). Optimised specificity and sensitivity were used to calculate maximum TSS (specificity + sensitivity -1) (Allouche *et al.* 2006).

The purpose of modeling here was for explanation, rather than prediction and thus estimating prediction error is not warranted. However, a 10-fold cross validation evaluation of prediction error was calculated for each of the multi-variables models (Fielding and Bell 1997; Harrell Jr 2001; Hijmans 2012). Although independent evaluation, such as by cross-validation is often recommended (Guisan *et al.* 2002), other methods such as AIC (Hijmans 2012), are shown to outperform evaluation measures (Warren and Seifert 2011). Nonetheless, the prediction error of each final vegetation model was calculated using a 10-fold cross validation implemented via cv.glm in the 'boot' package (Canty & Ripley 2015). The obtained adjusted delta values report the average number of misclassifications (Davison & Hinkley 1997).

The process for model analysis included a number of stages in model development eventuating in a set of model candidates for inclusion in a model selection. Each individual variable was tested separately before being considered in multi-variables models. Model development and selection adopted the approach and recommendations of Beaumont *et al.* (2005). This included a model with the full set of variables, a customised set of models, based on biological knowledge, and a generalised set of models, based on variables that performed well for all vegetation types. It was computationally impossible to test every combination of every variable for model selection. Attention was also given to restricting the number of variables and number of parameters (K) in each model to avoid over-fitting (Beaumont *et al*. 2005). Collinearity issues were detected with the climatic variables and to avoid collinearity, only two climatic variables (one temperature and one precipitation variable) were utilised.

The first stage was to test individual variables separately. Individual models were run for each of the 35 individual explanatory variables (14 geographic and 19 climatic), *i.e.* one explanatory variable per model. All continuous variables were tested using a non-linear quadratic function (that is variable + variable^2), consistent with niche theory (Austin 2002; Franklin 2009). Model performance was evaluated based on AICc and TSS and overall model goodness of fit was determined by the percent of explained deviance.

Fifteen multi-variable models were considered in final model selection, descriptions of which are given in Table 2.2. The first (model M1) was a full model with all climatic, edaphic and topographic variables (33 variables) and a second model (M2) with two climatic variables (one temperature and one rainfall) and all edaphic and topographic variables (16 variables). All other variables were restricted to a maximum of eight variables or less (Beaumont *et al.* 2005). Customised models (M3 - M8) selected combinations of the best performing individual variables for each vegetation type, including variables that were considered particularly ecologically meaningful relative to restricting the distribution of vegetation types, such as climatic, topographic and edaphic dryness. The generalised set of models (M9 - M14) included those individual variables that performed best for all three vegetation types. These started with a maximum number of eight variables (K=36) and variants to a minimum of three variables (K=11). The final model (M15) was a climate-only model used by others and included here for comparative purposes (Hilbert & van den Muyzenberg 1999; Hilbert *et al.* 2001a, b; Hilbert *et al.* 2007; Hilbert 2008; VanDerWal *et al.* 2009b). This model used seven variables (mean annual temperature, minimum temperature of the coldest period, mean temperature of the warmest quarter, mean temperature of the coldest quarter, annual precipitation, precipitation of the wettest quarter and precipitation of the driest quarter). All models were analysed against the null model as spatial GLMs with a residuals autocovariate and all continuous variables included a non-linear quadratic function. A summary of the explanatory variables used in each of the 15 models is given in Table 2.2.

Model selection was based on Akaike Information Criterion (AICc) and Akaike weights (*wi*), which identify the most parsimonious model from all model candidates (Burnham & Anderson 2002; Burnham & Anderson 2004; Burnham *et al.* 2010). The best performing models from the candidate set are generally selected on the lowest AICc and where the delta AICc is less than seven, which indicate that there are no significant improvements between models (Burnham *et al.* 2010). However, models M1 and M2 were excluded from final model selection as they were saturated models with too many variables and were included for comparison purposes only. Models were also evaluated based on the percent of explained deviance, TSS scores and delta values.

Table 2.2 Description of models with combinations of climatic and geographic variables used for predicting the distribution of vegetation types in the Australian Wet Tropics. Variables whose names commence with ‘bc’ are bioclimatic variables, which are described in Table 2.1. K is the number of parameters in each model, including catgories.

Model	Description	Variables	K	No. variables
M1	All climatic and geographic variables		88	33
M2	All geographic variables and best 2 generic climatic variables (bc17, bc05)		54	16
M3	Best 8 (RF, SAV)	Soil, bc19, bc02, Coast distance (SE), Relief, Geology, Landform, Slope	36	8
M4	Best 8 (TEF)	Soil, bc17, bc10, Elevation, Geology, Landform, Coast distance (E)	27	8
M5	Best 5 (RF, SAV)	Soil, bc19, bc02, Coast distance (SE), Relief	22	5
M6	Best 5 (TEF)	Soil, bc17, bc10, Elevation, Geology	20	5
M7	Best 3 (RF, SAV)	Soil, bc19, bc02	11	3
M8	Best 3 (TEF)	bc10, Elevation, Geology	13	3
M9	Generic 8	Soil, bc17, bc05, Relief, Geology, Coast distance (E), Landform, Elevation	36	8
M10	Generic 6	Soil, bc17, bc05, Relief, Geology, Coast distance (E)	29	6
M11	Generic 5	Soil, bc17, bc05, Relief, Geology	27	5
M12	Generic 4a	Soil, bc17, bc05, Relief	20	4
M13	Generic 4b	Soil, bc17, bc05, Geology	18	4
M14	Generic 3	Soil, bc17, bc05	11	3
M15	Climate only	bc01, bc06, bc10, bc11, bc12, bc16, bc17	15	7
Null	Null	NA	2	0

2.3.4 Spatial generalised linear models

Spatial dependence or spatial autocorrelation (SAC) is an important issue with spatially structured data that affects model results and performance. This is problematic, as SAC may breach assumptions of the model and lead to false or inaccurate predictions (Dormann 2007; Miller *et al.* 2007). Geostatistical spatial analysis is rapidly evolving (Diggle & Ribeiro 2007; Fischer & Getis 2010; Franklin 2009; Gelfand *et al*. 2010; Borcard *et al*. 2011; Fischer & Wang 2011; Bivand *et al*. 2013) and a number of methods have been developed for addressing spatial autocorrelation in spatial data analysis (Dormann *et al.* 2007; Miller *et al.* 2007; Fischer & Getis 2010; Gelfand *et al.* 2010; Fischer & Wang 2011; Crase *et al.* 2012; Plant 2012; Bivand *et al.* 2013). Addressing SAC is recommended to improve model robustness and performance (Lennon 2000; Guisan *et al.* 2006; Dormann 2007b; Miller *et al.* 2007; Franklin 2009, 2013).

Assessment of the presence and extent of spatial autocorrelation was performed prior to undertaking spatial model analysis. Generally, correlograms or variograms are used for this purpose (Diggle & Ribeiro 2007; Fischer & Getis 2010; Franklin 2009; Gelfand *et al*. 2010;

Borcard *et al*. 2011; Fischer & Wang 2011; Bivand *et al*. 2013), however, these are computationally demanding and not possible on a standard computer. A simplified method was used, where Moran's index (Moran's I) was calculated for specific distances in separate calculations. The global Moran's I was calculated using the 'R' package 'raster' (Hijmans *et al.* 2014) for a sequence of radial distances from each pixel in a stepwise fashion. Distances used were 250 m, 500 m, 1 km, 2km, 5 km, 10 km, 20 km, 30 km, 50 km and 100 km. Probabilities of significance may be calculated for Moran's I values, however, as previously described, become meaningless for large datasets. A Moran's index value of 0 indicates a random spatial pattern (no spatial autocorrelation), a value of 1 indicates perfect correlation and value of -1 indicates perfect dispersion. Moran's I values below 0.1 were considered acceptable for accounting for SAC within models. Accordingly, the lowest calculated radial distance with a Moran's I lower than 0.1 was used in model development.

A residuals autocovariate (RAC) technique (Crase *et al.* 2012) was used for addressing spatial autocorrelation. This technique has been found to outperform both non-spatial models and standard autocovariate regression models (Crase *et al*. 2014). Techniques for addressing SAC are generally computationally intensive with few options of low intensity (Dormann *et al.* 2007; Miller *et al.* 2007; Franklin 2009). However, the RAC method was found to be a simple, low computational and robust approach with the large datasets in this study (see Appendix 2.1).

2.3.5 Models of vegetation distribution

The final model for each vegetation type was fitted to the full data and spatially presented. Rather than fitting the model for predictive purposes, as the full distribution of each vegetation type was already known, this was done to explore patterns between actual distribution and predicted distributions between vegetation types. Spatial prediction of vegetation was fitted using the 'predict.glm' command in 'R' software, which was configured to generate predicted probabilities for the response type. This was then combined with point data and exported to raster format for spatial presentation.

The potential distribution of each vegetation type (likelihood of occurrence or probability), based on the fitted model was examined for all 586,045 grid cells. Categories of probability examined were very high confidence areas with greater than 90% probability of occurring (p = 0.9 -1), areas of high confidence (p = 0.7 - 1) and moderate confidence areas with greater than a 50% chance of occurring (p = 0.5 - 1). Comparisons of observed data (realised distribution) with probability data (potential distribution) were made for each vegetation type at each point. For each of the cells used in model making, the vegetation type with the highest likelihood of occurring was determined (highest p value). A comparison of the modelled vegetation type and occupant vegetation type was performed.

2.4 Results

2.4.1 Remotely sensed spatial data analysis

Within the Wet Tropics analysis area (586,045 data points or 3,662,446 hectares), 25% (149,423 points, or 933,894 hectares) was covered by rain forest, 2% (12,929 points or 80,806 hectares) by tall eucalypt forest and 67% (392,487 points or 2,453,044 hectares) by savanna, with a remaining 6% (33,799 points or 211,244 hectares) by other vegetation communities or cleared land (Table 2.3). Due to missing data at some points and inability of spatial models to account for data gaps, only 568,800 points were used in the spatial analysis. Averages for geographical, edaphic and climatic variables are given for the region and for each vegetation type in Table 2.3. See Appendices 2.3-2.7 for detailed figures and graphs of these variables. For categorical variables, geology had eight final categories (contributing more than 5% total area), landform had seven, relief had 10 and soil had six categories (see Appendices 2.3-2.7 for details).

Table 2.3 Average values for a range of variables for three broad vegetation types (rain forest, tall eucalypt forest and savanna woodland) the Wet Tropics region.

Variable	Total	Rain Forest	Tall Eucalypt Forest	Savanna
Regional cover of vegetation (%)	100	25.4	2.2	66.6
Easterly distance to coast (km)	41.4	26.6	43.2	48.8
Southeasterly distance to coast (km)	213	81.1	201.9	269.9
Elevation (m)	412.3	470	777.1	402.5
Hillshade	176.5	173	176.1	177.8
Stream distance (m)	2041.8	1954.3	1734.9	1981.4
Latitude (dec. deg.)	-17.8	-17.4	-17.8	-17.9
Slope (°)	6.8	10	9.3	5.8
Northwesterly wind shear	3.1	3.8	4.2	3
Southeasterly wind shear	3.4	4.9	3.9	3
Temperature annual mean (°C)	21.9	21.5	19.9	22
Temperature mean diurnal range (°C)	9.6	9	9.6	9.8
Precipitation annual (mm)	1654.9	2483.6	1830.8	1322.2
Precipitation driest quarter (mm)	96.1	180.3	124.2	63

2.4.2 Spatial generalised linear models

Tests for correlation and multi-collinearity detected no significant issues with geographic variables with few exceptions (Pearson's correlation coefficients were between 0.5 and -0.5 and variance inflation factor values were all less than 5). The only exceptions were for one of the categories in soil (‘tenosols’) and one in landform (‘rises’), where collinearity was detected. As these categories were integral to the categorical variables themselves, collinearity between these categories was ignored. Tests on the BIOCLIM data variables, however, indicated that most of the individual variables did not meet all the assumptions. Variables displayed non-normal (asymmetrical) distributions, non-homogeneity of variance (uneven spread of points around each trend), correlation ($r > 0.5$ or < -0.5) and collinearity (variance inflation factors > 5). Transformations of the data climatic data were applied (square-root and logarithmic), but these were not successful in resolving data profile issues. Due to the extent of assumptions not being met, resolving conflicts with climatic data was ignored. Given the evidence of correlation and collinearity, greater imperative was placed on the careful selection of fewer explanatory variables (Beaumont *et al*. 2005). The numbers of climatic variables included in candidate models, therefore, were intentionally restricted to avoid collinearity issues. Of the 19 climatic variables, only two independent climatic variables are represented; temperature and rainfall. Eleven different temperature variables and eight different rainfall variables are derived from these two datasets (Table 2.1). Due to the tested and inherent collinearity issues with climatic variables, only one temperature and one rainfall variable were used in multi-variable models.

Individual climatic, edaphic and topographic variables gave good models for each vegetation type. Soil type was consistently a good explanatory variable. Rainfall variables were particularly strong performers for both rain forest and savanna (precipitation of the coldest quarter, precipitation of the driest quarter), however, temperature variables performed better for tall eucalypt forests (mean temperature of the warmest quarter). Variables that were consistently good explanatory variables for all vegetation types were soil type, precipitation of the driest quarter, maximum temperature of the driest period, relief, geology, easterly distance to coast, landform and elevation. Details of the relative performance for individual variables for each vegetation type are given in Appendix 2.8.

Fifteen multi-variable candidate models were identified for model comparison and selection (described in Table 2.2). The results of the model comparison are given in Table 2.4. Of the 15 models, two models (M1, M2) contained in excess of eight variables and, although were the best performing models for all vegetation types (AICc, *wi*), were not considered for final model selection. It was determined that a maximum of eight explanatory variables be used in the model, for reasons outlined in Beaumont *et al.* (2005). The next best model was M9, the generic model with the eight best performing variables for all three vegetation types (K=36). The following model M10, another generic model, also performed well for all vegetation types with only six variables (K=29). Even model M14 with only three variables (K=11) performed well against this other models. Model M9 included elevation, which is not suitable for prediction purposes into different climate scenarios, and landform, which had seven factors. The next best model, M10, which performed well for all vegetation types, had suitable variables for explanation and prediction and had a good balance of number of parameters, was selected as the preferred model for further analysis (although other models would also have been suitable). Model M10 explained 59% of the deviance for rain forest (TSS = 0.8; delta = 0.07), 42% for tall eucalypt forest (TSS = 0.75; delta 0.02) and 53% for savanna (TSS = 0.73; delta = 0.09). Details of model M10 are given in Table 2.5. Further consideration of the distribution of vegetation in the Wet Tropics (2.4.3) is based on the performance of the preferred model.

Table 2.4 Relative performance of multi-variable models (Table 2.2) for predicting distribution of three vegetation types (a. rain forest, b. tall eucalypt forest and c. savanna). Models were non-linear logistic regressions and included a residuals autocovariate based on spatial autocorrelation analysis. Model selection is based on AICc values, Akaike weights (*wi*) and percentage explained deviance (D^2). True Skill Statistic (TSS) also indicate model performance and delta indicates predictive performance from a 10-fold cross validation. Columns are ranked by AICc values.

a. rain forest

Rain Forest	**K**	**AICc**	**Delta AICc**	***wi***	**D^2**	**TSS**	**delta**
M1	88	226902.8	0	1	65.3	0.81	0.06
M2	54	229019.3	2116.4	0	64.9	0.81	0.06
M9	36	234835.8	7933	0	64	0.81	0.06
M3	36	265095.4	38192.5	0	59.4	0.79	0.07
M10	29	267715.5	40812.6	0	59	0.8	0.07
M11	27	272846.3	45943.5	0	58.2	0.79	0.07
M4	27	274232.7	47329.8	0	58	0.78	0.07
M5	22	274490.7	47587.9	0	58	0.79	0.07
M12	20	275911.8	49009	0	57.7	0.79	0.07
M6	20	282093	55190.1	0	56.8	0.77	0.08
M13	18	284739	57836.1	0	56.4	0.77	0.08
M14	11	288640.5	61737.7	0	55.8	0.76	0.08
M15	15	301380.9	74478.1	0	53.8	0.75	0.08
M7	11	289483.2	62580.4	0	55.7	0.77	0.08
M8	13	381408	154505.2	0	41.6	0.65	0.1
null	2	570416.5	343513.7	0	12.6	0.36	0.17

b. tall eucalypt forest

Tall Eucalypt Forest	**K**	**AICc**	**Delta AICc**	***wi***	**D^2**	**TSS**	**delta**
M1	88	58596.9	0	1	52.6	0.82	0.01
M2	54	69301.6	10704.7	0	43.8	0.77	0.02
M9	36	70264.5	11667.6	0	43	0.76	0.02
M10	29	71016	12419.2	0	42.4	0.75	0.02
M4	27	71341.5	12744.6	0	42.1	0.76	0.02
M11	27	71894.5	13297.6	0	41.7	0.73	0.02
M12	20	71944.7	13347.9	0	41.6	0.73	0.02
M3	36	72183.7	13586.8	0	41.5	0.73	0.02
M6	20	73244	14647.2	0	40.6	0.75	0.02
M5	22	73365.5	14768.7	0	40.5	0.72	0.02
M13	18	73418.7	14821.9	0	40.4	0.75	0.02

M14	11	73769.6	15172.8	0	40.1	0.75	0.02
M15	15	75854.4	17257.5	0	38.5	0.76	0.02
M7	11	76304.8	17707.9	0	38.1	0.73	0.02
M8	13	94655.7	36058.9	0	23.2	0.64	0.02
null	2	100535.9	41939	0	18.4	0.54	0.02

c. savanna

Savanna	**K**	**AICc**	**Delta AICc**	***wi***	**D^2**	**TSS**	**delta**
M1	88	288226.5	0	1	59.5	0.76	0.08
M2	54	290933.8	2707.4	0	59.1	0.76	0.08
M9	36	328224.6	39998.2	0	53.9	0.73	0.09
M10	29	331940.5	43714	0	53.4	0.73	0.09
M3	36	331944.9	43718.4	0	53.4	0.74	0.09
M4	27	334462.1	46235.6	0	53	0.73	0.09
M11	27	335915.3	47688.9	0	52.8	0.73	0.09
M13	18	340635.2	52408.7	0	52.1	0.72	0.09
M6	20	340785.7	52559.3	0	52.1	0.72	0.09
M12	20	343016.7	54790.3	0	51.8	0.72	0.09
M5	22	345055.9	56829.4	0	51.5	0.72	0.09
M14	11	347377.7	59151.2	0	51.2	0.72	0.09
M7	11	351217.3	62990.9	0	50.7	0.71	0.09
M15	15	361555.5	73329	0	49.2	0.7	0.1
M8	13	451042.1	162815.7	0	36.6	0.59	0.13
null	2	646411.4	358184.9	0	9.2	0.32	0.19

Model M15 (K = 15), which has been used elsewhere (Hilbert & van den Muyzenberg 1999; Hilbert *et al.* 2001b; Hilbert *et al.* 2007; Hilbert 2008; VanDerWal *et al.* 2009b), explained 54% of the model deviance for rain forest (TSS = 0.75; delta = 0.08), 39% of tall eucalypt forest (TSS = 0.76; delta = 0.02) and 49% for savanna vegetation (TSS = 0.7; delta = 0.1) (Table 2.4). This model did not perform well compared to other models, even against models with much fewer explanatory variables and parameters (M14,) (Table 2.4). Model M14, which contained only two climatic and one edaphic variable (K = 11), soil type, precipitation of driest quarter and maximum temperature of the warmest period, yet explained 56% of the distribution of rain forest, 40% of tall eucalypt forest and 51% of tall eucalypt forest (Table 2.4).

Table 2.5 Details of a preferred model (M10) explaining the distribution of three vegetation types (a. rain forest, b. tall eucalypt forest and c. savanna) in the Australian Wet Tropics. These results are for a non-linear spatial logistic regression model with six explanatory variables (Table 2.2) and a residuals autocovariate (RAC) (K = 29). Model details list AICc values, percentage explained deviance (D^2) and True Skill Statistic (TSS), which indicate overall model performance, while the adjusted delta is the prediction error from a 10-fold cross validation and indicates the average number of misclassifications.

a. rain forest

Rain Forest	**Estimate**	***p***	**AICc**	**D^2**	**TSS**	**delta**
(Intercept)	-54.85	0	267715.5	59	0.8	0.07
Soil Ferrosol	0.23	0				
Soil Kandosol	-1.06	0				
Soil Other	-1.31	0				
Soil Sodosol	-2.21	0				
Soil Tenosol	-3.11	0				
bc17	0.01	0				
bc17^2	0	0				
bc05	3.88	0				
bc05^2	-0.07	0				
Relief GR	0.39	0				
Relief LP	0.17	0				
Relief Other	1.18	0				
Relief RL	0.98	0				
Relief RR	1.79	0				
Relief SH	0.86	0				
Relief SL	0.32	0				
Relief UL	-0.9	0				
Relief VH	0.66	0				
Geology Basalt	1.34	0				
Geology Colluvium	-1.03	0				
Geology Felsites	0.53	0				
Geology Granitoid	0.4	0				
Geology Mudrock	-0.15	0				
Geology Other	0.1	0				
Geology Rudite	0.02	0.58				
Coast distance (E)	0	0				
Coast distance (E)^2	0	0				
RAC	100300	0				

b. tall eucalypt forest

Tall Eucalypt Forest	**Estimate**	***p***	**AICc**	**D^2**	**TSS**	**delta**
(Intercept)	29.25	0	71016	42.4	0.75	0.02
Soil Ferrosol	-1.01	0				
Soil Kandosol	-0.54	0				
Soil Other	-1.74	0				
Soil Sodosol	-1.49	0				
Soil Tenosol	-1.37	0				
bc17	0.08	0				
bc17^2	0	0				
bc05	-2.35	0				
bc05^2	0.03	0				
Relief GR	-12.79	0.8				
Relief LP	-0.82	0				
Relief Other	-1.5	0.01				
Relief RL	0.7	0				
Relief RR	0.33	0.05				

Relief SH	0.79	0
Relief SL	0.43	0.03
Relief UL	2.18	0
Relief VH	1.1	0
Geology Basalt	-0.63	0
Geology Colluvium	0.21	0.15
Geology Felsites	0.88	0
Geology Granitoid	0.83	0
Geology Mudrock	0.9	0
Geology Other	0.09	0.54
Geology Rudite	-0.62	0
Coast distance (E)	0	0
Coast distance (E)^2	0	0
RAC	43980	0

c. savanna

Savanna	**Estimate**	***p***	**AICc**	**D^2**	**TSS**	**delta**
(Intercept)	-51.19	0	331940.5	53.4	0.73	0.09
Soil Ferrosol	0.47	0				
Soil Kandosol	1.12	0				
Soil Other	0.86	0				
Soil Sodosol	1.61	0				
Soil Tenosol	2.38	0				
bc17	-0.01	0				
bc17^2	0	0				
bc05	3.01	0				
bc05^2	-0.04	0				
Relief GR	-0.45	0				
Relief LP	-0.65	0				
Relief Other	-0.98	0				
Relief RL	-0.98	0				
Relief RR	-1.26	0				
Relief SH	-0.75	0				
Relief SL	-0.46	0				
Relief UL	0.06	0.05				
Relief VH	-0.48	0				
Geology Basalt	-1.37	0				
Geology Colluvium	1.33	0				
Geology Felsites	-0.83	0				
Geology Granitoid	-0.41	0				
Geology Mudrock	0.35	0				
Geology Other	-0.7	0				
Geology Rudite	0.38	0				
Coast distance (E)	0	0				
Coast distance (E)^2	0	0				
RAC	104300	0				

2.4.3 Models of vegetation distribution

The potential (modelled) distribution for each vegetation type, based on predictions from model M10, is spatially presented for rain forest (Figure 2.1), tall eucalypt forest (Figure 2.2), savanna (Figure 2.3) and a composite image (Figure 2.4). Likelihood of occurrence is indicated by a probability between 1 (absolute likelihood) and 0 (no likelihood). In Figures 2.1 - 2.3 are two maps, the first with the potential distribution (model output) and the second with potential distribution overlayed by the actual distribution. Likelihood of occurrence is discussed as probability categories; very high (0.9 or greater), high (0.7 or greater), moderate (0.5 or greater) and low (0.2 or greater). Very high and high confidence areas are likely to represent core habitat (environmental space) areas, whereas low confidence areas are likely to represent marginal or sub-optimal habitat.

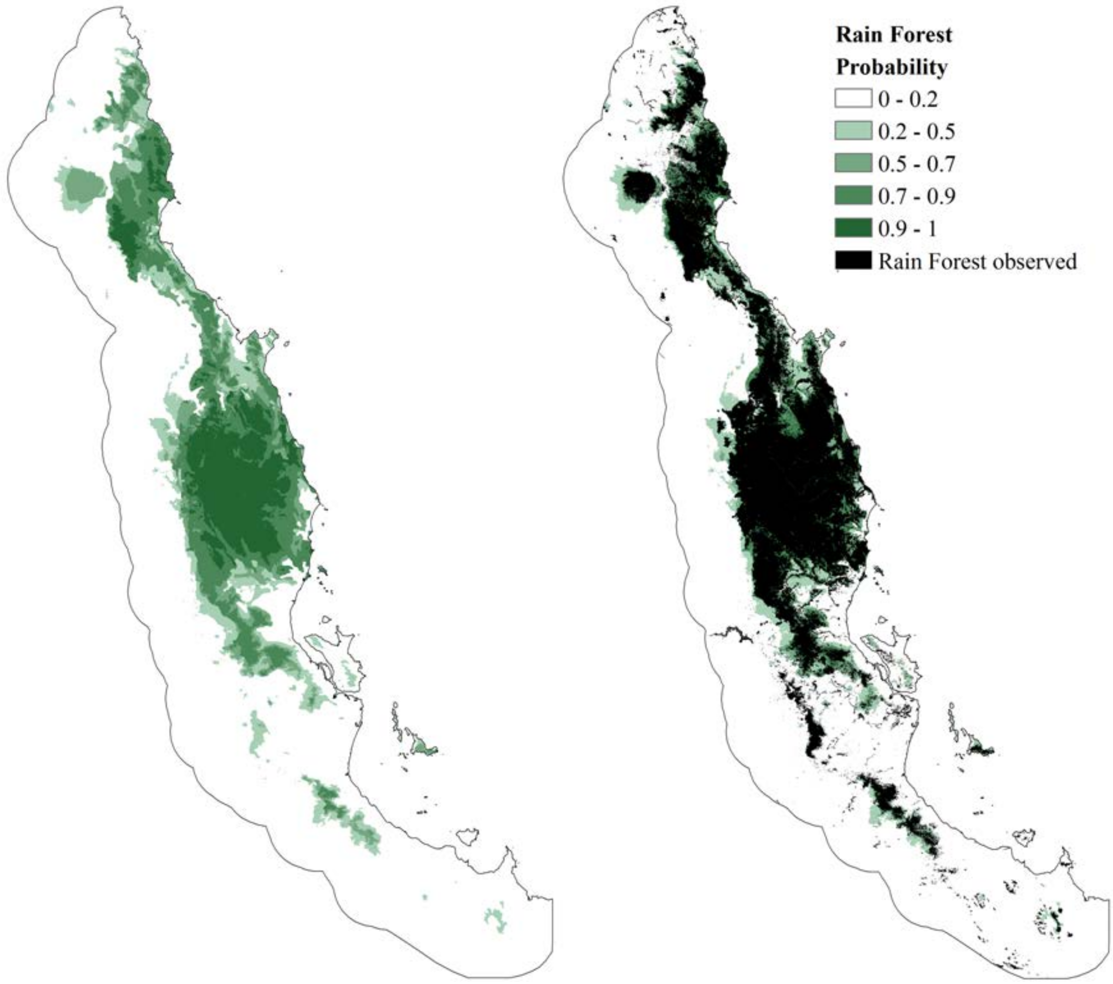

Figure 2.1 Predicted distribution of rain forest (left) and overlayed with observed distribution (right). Highest probability is indicated by values closer to 1 and least probability by values closer to 0. Probabilities determined by fitted values for GLMs of rain forest distribution.

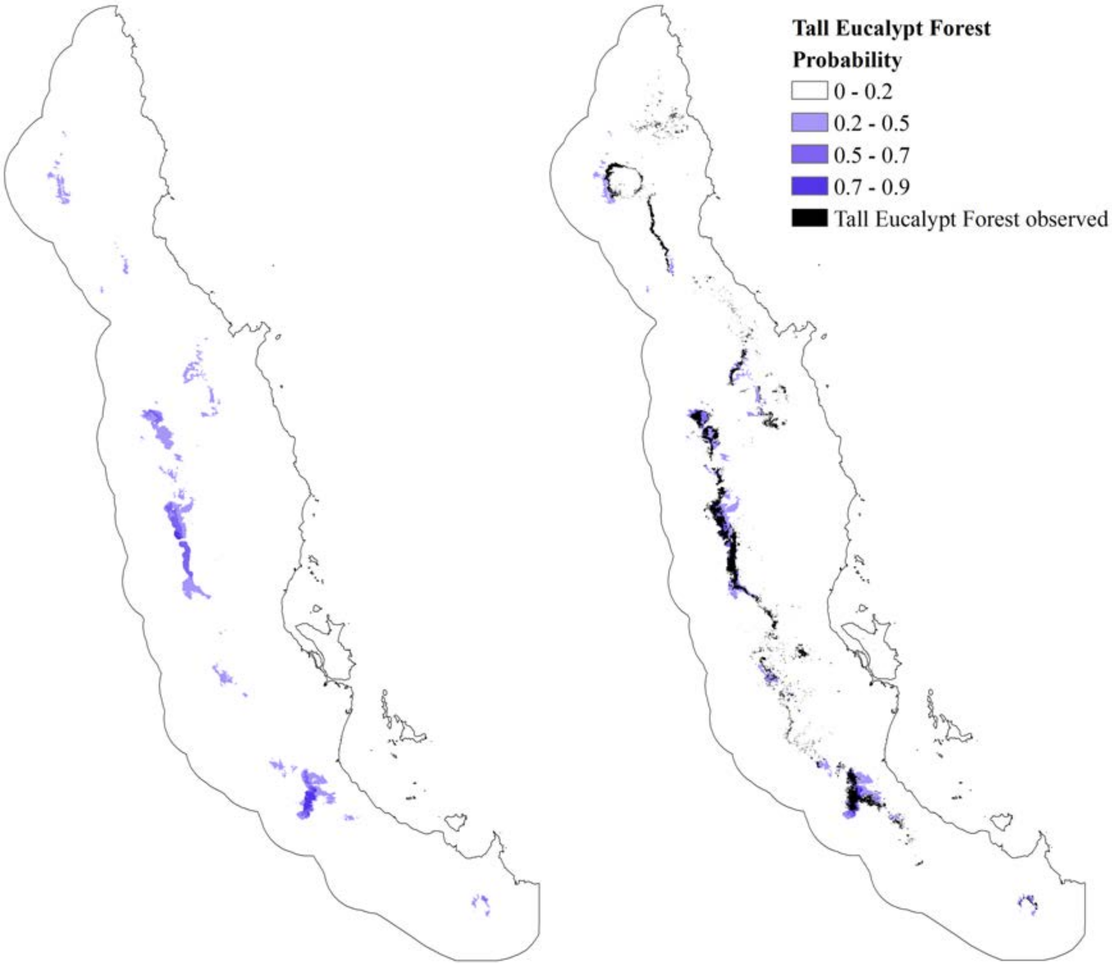

Figure 2.2 Predicted distribution of tall eucalypt forest (left) and overlayed with actual distribution (right). Highest probability is indicated by values closer to 1 and least probability by values closer to 0. Probabilities determined by fitted values for GLMs of tall eucalypt forest distribution.

Models performed quite well (spatially) in predicting the distribution of rain forest (Figure 2.1) and savanna (Figure 2.3) across their range with at least moderate confidence. The model for tall eucalypt forest did not spatially predict as well. Even at low probability of occurrence, the model did not predict large areas of its observed (realised) distribution (Figure 2.2) and predicted large areas where tall eucalypt forests do not occur.

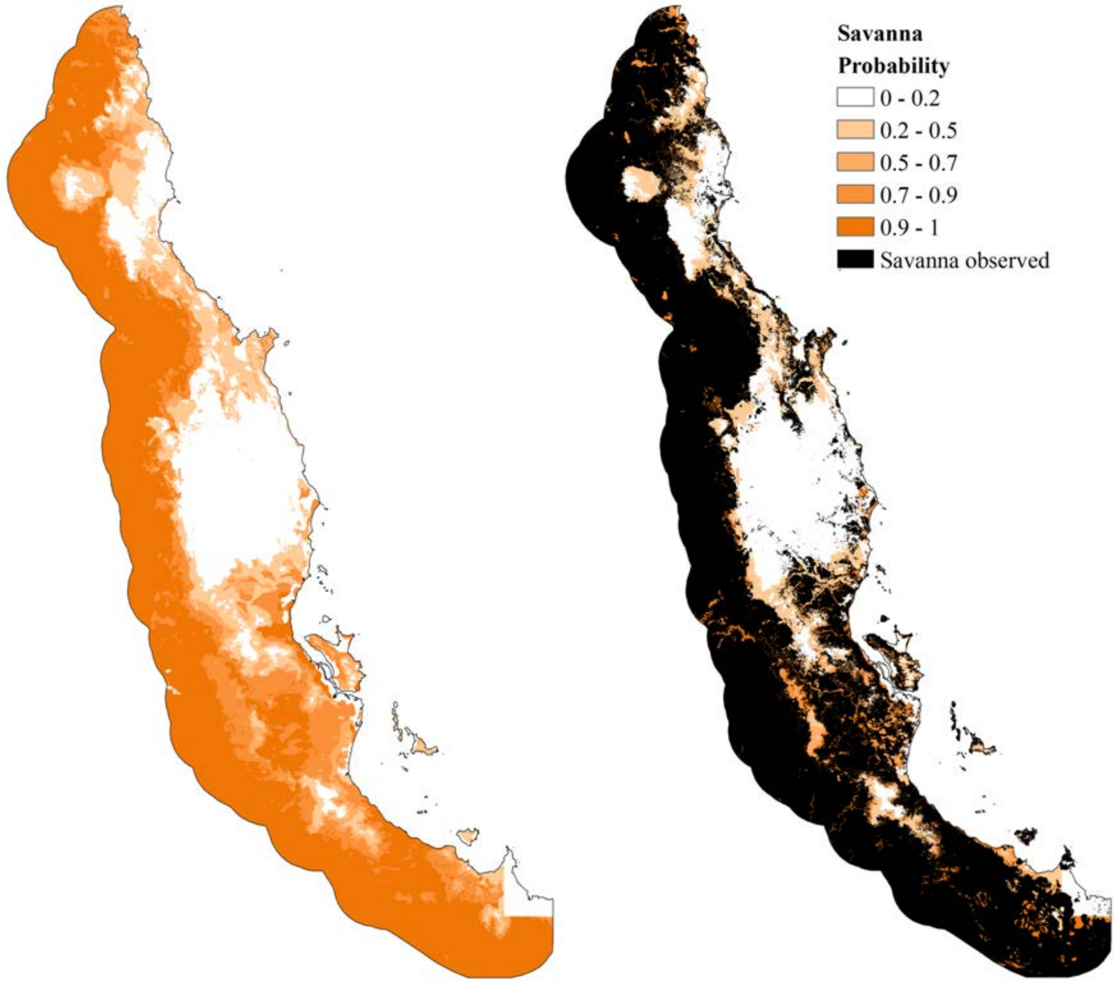

Figure 2.3 Predicted distribution of savanna (left) and overlayed with actual distribution (right). Highest probability is indicated by values closer to 1 and least probability by values closer to 0. Probabilities determined by fitted values for GLMs of savanna distribution.

Table 2.6 compares the modelled distribution of each vegetation type with the actual vegetation type observed for areas of very high, high, moderate and low probability. Rain forest occupied 97% of its predicted core area (greater than 0.9), tall eucalypt forest occupied 69% and savanna 97%. In its core area, 15% of the potential tall eucalypt forest habitat was occupied by rain forest, 15% by other vegetation and 1% by savanna. In core and marginal areas (areas with a greater than 70% chance of occurring), rain forest occupied 88% of its potential distribution, tall eucalypt forest 70% and savanna 94%. For rain forest, 9% of its potential distribution was occupied by savanna, whereas, rain forest only occupied 3% of predicted savanna. For tall eucalypt forest, 12% of the high potential area was occupied by rain forest and 13% by savanna. At a moderate predicted probability (greater than 50% chance of occurring), rain forest occupied 82% of its predicted area, tall eucalypt forest occupied 64% and savanna occupied 91%. For rain forest, 14% of its potential distribution was occupied by savanna, whereas for savanna, only 5% was occupied by rain forest. For tall eucalypt forest, rain forest occupied 20%

and savanna occupied 14% respectively). Areas of low probability were also important for tall eucalypt forest, as only at this threshold was an equivalent area predicted, to that of its actual distribution. In these marginal areas, tall eucalypt occupied 42% of its modelled area with both rain forest and savanna occupying about 30%.

Table 2.6 Comparison of the area of observed and modelled vegetation for 568,800 points (3,555,000 ha). Total area (hectares) and percentage of area (%) of observed vegetation type within modelled areas are given for rain forest (RF), tall eucalypt forest (TEF) and savanna (SAV) at various likelihood of occurrence: $p \geq 0.9$, $p \geq 0.7$ and $p \geq 0.5$.

Rain Forest model	$p \geq 0.9$	$p \geq 0.7$	$p \geq 0.5$	$p \geq 0.2$	Observed area of rain forest
Total modelled area ha (%)	312619 (100)	717581 (100)	947063 (100)	1223563 (100)	927056 (26.1)
Area occupied by:					
RF	301906 (96.6)	629694 (87.8)	773925 (81.7)	852819 (69.7)	
TEF	3025 (1)	14744 (2.1)	27125 (2.9)	56831 (4.6)	
SAV	5281 (1.7)	61925 (8.6)	128200 (13.5)	287556 (23.5)	
Other	2406 (0.8)	11219 (1.6)	17813 (1.9)	26356 (2.2)	

Tall Eucalypt Forest model	$p \geq 0.9$	$p \geq 0.7$	$p \geq 0.5$	$p \geq 0.2$	Observed area of tall eucalypt forest
Total modelled area ha (%)	2575 (100)	12394 (100)	29356 (100)	83431 (100)	80638 (2.3)
Area occupied by:					
RF	394 (15.3)	1525 (12.3)	5769 (19.7)	24200 (29)	
TEF	1775 (68.9)	8669 (69.9)	18656 (63.6)	35225 (42.2)	
SAV	13 (0.5)	1594 (12.9)	4194 (14.3)	22769 (27.3)	
Other	394 (15.3)	606 (4.9)	738 (2.5)	1238 (1.5)	

Savanna model	$p \geq 0.9$	$p \geq 0.7$	$p \geq 0.5$	$p \geq 0.2$	Observed area of savanna
Total modelled area ha (%)	1694263 (100)	2214231 (100)	2456281 (100)	2894375 (100)	2422869 (68.2)
Area occupied by:					
RF	20613 (1.2)	63775 (2.9)	117475 (4.8)	353244 (12.2)	
TEF	2456 (0.1)	13256 (0.6)	23294 (0.9)	58513 (2)	
SAV	1639413 (96.8)	2069306 (93.5)	2228725 (90.7)	2373550 (82)	
Other	31781 (1.9)	67894 (3.1)	86788 (3.5)	109069 (3.8)	

A similar analysis of the spatial patterns of vegetation in the region was achieved by comparing the most likely (highest probability) vegetation type at each point with the actual occupant vegetation type (Table 2.7). Rain forest occupied an area equivalent to 95% of its modelled most likely area, however, not the same locations; savanna occupied 152,600 ha of that area. Savanna, on the other hand, occupied an area equivalent to 100% of its modelled most likely area, but again not the same locations, as rain forest occupied 131,969 ha most likely to be savanna. Tall eucalypt forest, as seen in the previous analysis (Table 2.6) had a very small area of high probability of occurrence. Not surprisingly, the area of tall eucalypt forest most likely to occur was significantly underestimated, with its actual distribution 262% larger than its modelled most likely area. Also, tall eucalypt forest only occupied 68% of those areas modelled most likely to be tall eucalypt forest, with 15% occupied by rain forest and 17% occupied by savanna.

Combined, these results indicate some interesting patterns in the vegetation dynamics of the region, with tall eucalypt forest seemingly competing less well in the shared environmental space with rain forest and savanna. Accordingly, special consideration was given to the curious case of tall eucalypt forests.

Table 2.7 Comparison of the area (hectares and percentage) of observed and modelled vegetation for 568,800 points (3,555,000 ha), excluding other vegetation types. Modelled area shows the vegetation type with the highest probability of occurrence at each point. Proportion of modelled areas occupied by other vegetation types is shown.

	Area ha. (%)	Modelled area ha. (%)	Percent of modelled area (total/ modelled)	Model occupied by RF	Model occupied by TEF	Model occupied by SAV
RF	**927056 (27)**	972925 (28.4)	95.3	790519 (81.3)	29806 (3.1)	152600 (15.7)
TEF	**80638 (2.4)**	30825 (0.9)	261.6	4569 (14.8)	21006 (68.1)	5250 (17)
SAV	**2422869 (70.6)**	2426813 (70.7)	99.8	131969 (5.4)	29825 (1.2)	2265019 (93.3)
Total	3430563 (100)	3430563 (100)	NA	**927056 (27)**	**80638 (2.4)**	**2422869 (70.6)**

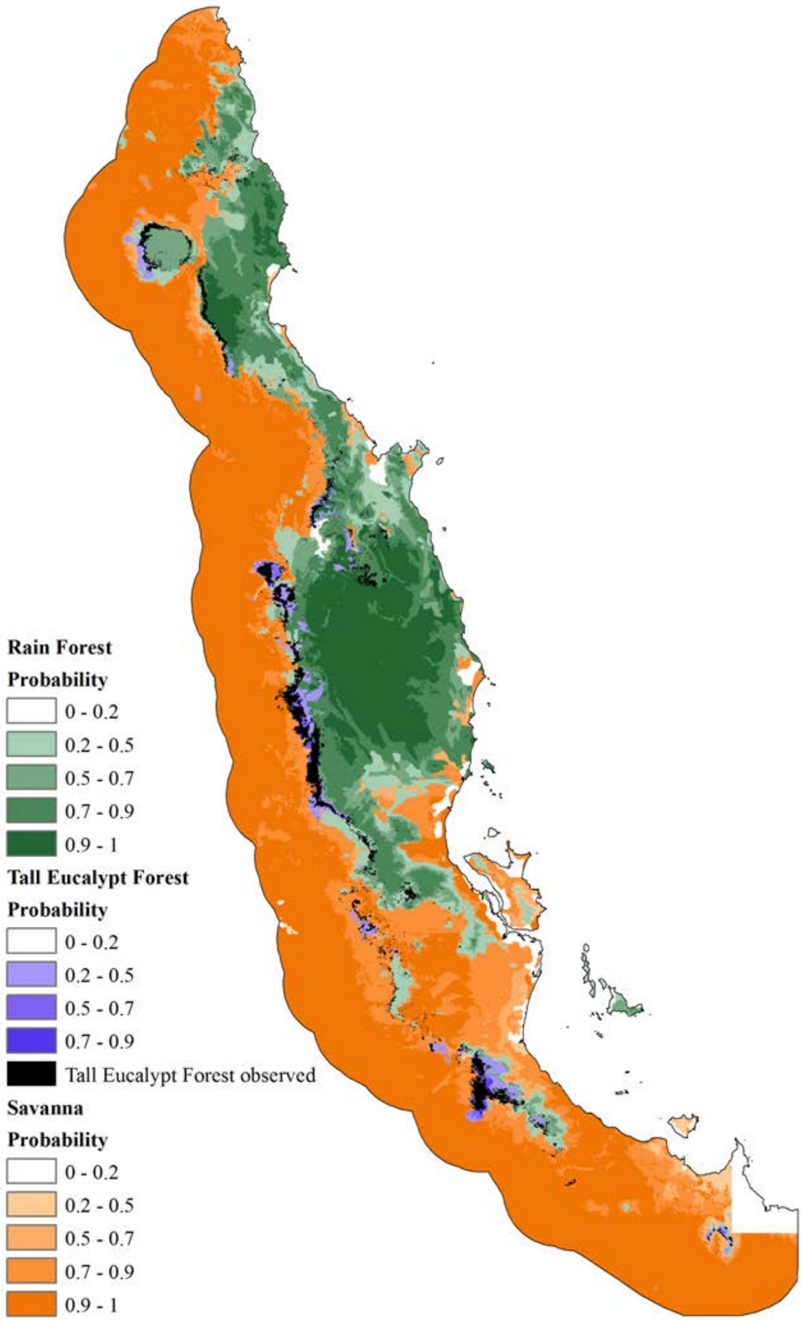

Figure 2.4. Predicted distribution of rain forest, tall eucalypt forest and savanna overlayed with actual distribution of tall eucalypt forest. Highest probability is indicated by values closer to 1 and least probability by values closer to 0. Probabilities determined by fitted values for GLMs of vegetation distribution.

2.4.4 Tall eucalypt forests

Special consideration was given to tall eucalypt forests for a number of reasons; their performance in a competitive environmental space, their endangered status (Accad *et al.* 2013; Department of National Parks Recreation Sport and Racing 2013; Queensland Herbarium 2014), restricted distribution and the difference in explanatory variables from other vegetation types. Both previous analyses (Tables 2.6 and 2.7) show that tall eucalypt forests did not occupy more than 70% of its modelled distribution. Of the three vegetation types, tall eucalypt forest occupied the least area of its core predicted distribution and occurred in sub-optimal areas of low suitability ($p \geq 0.2$). At very high probability of occurring (0.9 or greater), 15% of this area was occupied by rain forest and at high probability of occurring (0.7 or greater), 13% of this area was occupied by savanna and 12% by rain forest. Similarly for the modelled most likely distribution of tall eucalypt forest, which is likely to represent those very and high probability areas, rain forest occupied 15% and savanna 17%. In general, it appears that both rain forest and savanna occupy similar significant areas (roughly 15% each) of the preferred tall eucalypt forest environmental space, leaving about 70% available for tall eucalypt forests. Given the restricted distribution of tall eucalypt forests and their juxtaposition between rain forest and savanna, additional analyses were undertaken.

The nearest distance of tall eucalypt forest to rain forest vegetation was computed (by path distance analysis in ArcGIS), as was the nearest distance to savanna vegetation. Tall eucalypt forest does not occur any further than 5.5km from either rain forest or savanna vegetation (see Appendix 2.3). Spatial GLMs of the ‘distance to rain forest’ and ‘distance to savanna’ were computed. Distance to rain forest was a better model (AICc = 93608.32; D^2 = 24.63%; TSS = 0.64) compared with distance to savanna (AICc = 100817.4; D^2 = 18.83%; TSS = 0.56). These models indicate tall eucalypt forest had a strong relationship with juxtaposition to adjacent vegetation types. An evaluation was done of some of the landscape patterns for tall eucalypt forest in areas with very high (0.9 or greater), high (0.7 or greater) and moderate (0.5 or greater) predicted habitat (see Appendix 2.3 for details).

2.5 Discussion

High-resolution distribution models of vegetation performed well, particularly for rain forest and for savanna; the more restricted tall eucalypt forest to a lesser extent. Models were not perfect, despite fine-scale data inputs, robust techniques and the inclusion of all available data in the models. Models were based on systematic regional sampling using a full data set (no data were retained for model training and testing) and should present near perfect models.

How a model is evaluated to be a ‘good’ is often subjective and arbitrary. Performance categories have been used for AUC (Swets 1988) and for kappa (Landis & Koch 1977), but not for AIC, D^2 or TSS. Others have rejected any models where TSS <0.3 (Araújo *et al.* 2011) or

<0.4 (Engler *et al.* 2011; Hodd *et al.* 2014) and suggested D^2 >50% is well modelled and <25% is poorly modelled (Fleishman *et al.* 2001). Kappa is a comparable metric to TSS and by applying the divisions suggested by Landis and Koch (1977), would imply that the preferred model (M10) was substantial for rain forest (TSS= 0.8), tall eucalypt forest (0.75) and savanna (0.73). The D^2 values for these models are greater than 50% for rain forest (59%) and savanna (53%), but only 42% for tall eucalypt forest. Overall this suggests that the preferred model had good performance for all vegetation types and was substantial for rain forest and savanna. This finding is consistent with difficulty in modelling tall eucalypt forest in the Wet Tropics previously (Hilbert & van den Muyzenberg 1999; Hilbert *et al.* 2001a, b; Hilbert & Ostendorf 2001; Ostendorf *et al.* 2001; Hilbert *et al.* 2007; Hilbert 2008; Hilbert 2010).

There are a number of potential explanations why models did not perform better. Firstly, the accuracy of input variables may be too coarse or inaccurate to be reliable at the local scale relative to mapped vegetation. Input variables were each spatial interpolations and not necessarily accurate at a 250 metre scale. Vegetation data was likely to be the most accurate data set, as unlike the explanatory variables, can be systematically sampled from air photo interpretation. Consideration is given to spatially interpolated climate data (2.5.1), due to its importance in modelling the potential impacts of future climate on biota. Secondly, there are likely to be environmental factors other than those included in the models that are influencing vegetation distribution. These might include the influences of disturbance regimes, such as fire, and the influence of vegetation feedbacks, which can result in distributions not in equilibrium with climate or geographic features (2.5.2).

2.5.1 Spatially interpolated data

Climatic and edaphic data used as explanatory or predictor variables are spatial interpolations derived from sparse point data. The algorithms used in building spatial interpolations are a likely source of error that can lead to inaccurate results in models using this data. This has implications for model predictions, such as for distributions under future climates. Spatially interpolated climate data for Australia via BIOCLIM (Booth *et al.* 2014), is based on meteorological data from sparse measurement stations (Kesteven & Hutchinson 1996). These are spatially interpolated by a thin plate smoothing spline (Hancock *et al.* 2001; Hutchinson & Xu 2013) using latitude, longitude and elevation (Hutchinson & Xu 2013). However, this interpolation does not capture important topoclimatic factors, such as strong climatic gradients, rainshadows, rain intercept associated with elevational topography and coastal influences (Daly 2006; McKenney *et al.* 2011). Climatic conditions associated with mountainous terrain are complex and often unpredictable (Barry 2008). Patchy localised conditions may create a mosaic of microclimates that affect the distribution of vegetation types and fire in otherwise unpredictable ways (Sharples 2009). Spatially interpolated climate data is unlikely to capture these complex conditions (Guisan & Zimmermann 2000; Lookingbill & Urban 2003; Daly 2006; Scherrer & Körner 2011; Scherrer *et al.* 2011; Suggitt *et al.* 2011; Franklin *et al.* 2013). Current interpolated climatic data, therefore, may not reflect actual conditions, or the drivers affecting species or ecosystem distributions.

Localised topographic phenomena are a strong influence on meteorology in the Wet Tropics, such as orographic and coastal orientation, precipitation intercept from prevailing southeasterly winds (McJannet *et al.* 2007) and a pronounced rainshadow (Unwin 1983; Nix 1991; Turton *et al.* 1999; Harrington *et al.* 2000). These localised conditions affect the distribution of vegetation and are critical for making accurate model predictions of biota (Ashcroft *et al.* 2009). Inaccuracies in model inputs are problematic for predicting vegetation that occurs under such conditions, such as the tall eucalypt forests of the Wet Tropics are almost entirely within the rainshadow of the region. This may explain the moderate model performance for this vegetation type compared with the others. How BIOCLIM data is calculated will have significant effects on species distribution models that use it and may provide misleading model results in the absence of topographic, edaphic or other factors (Slavich *et al*. 2014). BIOCLIM consists of up to 35 individual variables (Booth *et al.* 2014), but correspond to only four meteorological variables and inherent correlations are therefore inevitable (Ashcroft *et al.* 2009). This data was also heavily affected by non-normal distributions, non-homogeneity of variance, correlation and collinearity.

Geographic factors are regularly used as a surrogate for climatic conditions (Ashcroft *et al.* 2008) to capture complex weather patterns (for example, raytrace analysis was used as a surrogate for southeasterly wind-shear and southeasterly distance to coast was used as a surrogate for a moisture gradient and possible rain intercept). This study and others (Ashcroft *et al.* 2009) have shown that these surrogate geographical variables perform better than many interpolated climate explanatory variables. Model M15, a climate only model with seven variables as used by others (Hilbert & van den Muyzenberg 1999; Hilbert *et al.* 2001a, b; Hilbert *et al.* 2007; Hilbert 2008; VanDerWal *et al.* 2009b), did not perform as well as models with fewer variables that incorporated topographic and edaphic variables.

Including regional-scale meteorology or topoclimate data can improve distribution models that use interpolated climate data (Ashcroft 2006; Ashcroft *et al.* 2008; Ashcroft *et al.* 2009; Ashcroft & Gollan 2012) and outperform spatially interpolated macroclimate in predicted species distributions (Ashcroft *et al.* 2012; Ashcroft & Gollan 2012, 2013a, 2013b, Gollan *et al.* 2013, 2015; Letten *et al.* 2013; Slavich *et al.* 2014). Although spatially interpolated meteorological data was available for the Wet Tropics (Jones *et al*. 2009), data inputs (5 km grid) were too coarse relative to local scale distribution of vegetation types and showed considerable discrepancies compared with statistically downscaled empirical meteorology data (Storlie *et al*. 2013). Although, some microclimatic conditions across this gradient have been studied at a local scale (Unwin 1983; Ash 1988; Unwin 1989; Turton and Duff 1992; Turton and Sexton 1996), there are no regional-scale studies involving multiple topographic settings and vegetation types. This is the subject of analysis in Chapter 3.

2.5.2 Vegetation feedbacks, competition and fire

Other factors influencing vegetation in this region are likely to include disturbance regimes, the influence of vegetation feedbacks and competition resulting in alternative stable states in disequilibrium from climate or geographic features (Low 2011; Svenning & Sandel 2013). These can be a major barrier to effective modelling and understanding future conditions under climate change (Good *et al*. 2016; Harris *et al*. 2016). The modelled distribution of vegetation types compared with their actual distribution showed patterns that suggest alternative stable states of vegetation. By comparing models of different vegetation, it was evident that some were more dominant or competitive for overlapping environmental space than others.

Tall eucalypt forests appear to be the least competitive of the three vegetation types. It occupied less than 70% of its preferred environmental space, with rain forest and savanna occupying the remaining 30%. The area of tall eucalypt forest occupying predicted savanna (<1%) and rain forest (<3%) was negligible (<1%). Areas of low probability for tall eucalypt forest remain important where the bulk of tall eucalypt forests actually occur. This suggests that tall eucalypt forest largely occurs, perhaps opportunistically, in areas that appear less suitable to adjacent competing vegetation types (Figure 2.4). Tall eucalypt forest occurs between two opposing forces; short-term frequent fire intolerance on one side (occupied by savanna) and long-term shade intolerance on the other (occupied by rain forest). These opposing conditions between pyrophobic and pyrophytic vegetation are well documented (Kitzberger *et al*. 2016). These dual pressures are the most likely reason tall eucalypt forest does not occupy much of its core niche or preferred environmental space and persists in large areas that are not its preferred habitat. This may suggest that tall eucalypt forests are already unstable and vulnerable to shifts and tipping points.

Rain forests and savanna both occupy most of their environmental space. Rain forest occupied 97% of its modelled core environmental space, with declining to 82% for areas of moderate probability (Table 2.6). The bulk of this displacement was by savanna vegetation, which occupied 2-14% ($p \geq 0.9$ to ≥ 0.5); an area of 61,925 - 128,200 hectares of potential rain forest. The extent of this incursion of savanna into rain forests is most likely caused by the prevalence of fire in savanna vegetation encroaching into adjacent fire sensitive rain forests. suggesting savanna and, presumably, its associated fire regime is responsible for restricting rain forest and maintaining an alternative vegetation state. This finding is consistent with research showing that rain forest distribution is restricted by the repeated occurrence of fire (Furley *et al*. 1992; Bowman 2000; Bond *et al.* 2005).

Savanna appeared to be stable and occupied 97% of its core environmental space down to 91% of its moderate probability environmental space (Table 2.6). This observation is reliable, given the large area of savanna predicted with high probability (1,694,263 hectares). Although rain forest occupied areas of modelled environmental space for savanna (20,613 - 117,475), this range was small compared to the opposite trend with savanna having a net gain of 40,000 hectares of potential rain forest. The relative stability of savanna vegetation and its capacity to occupy large areas of fire sensitive vegetation types suggest that fire could be a strong driving force influencing the distribution of vegetation and alternative stable states in the region. Fire-vegetation feedbacks are exacerbated under climate change and associated increased fire risk, which will further increase the risk to fire sensitive vegetation (Kitzberger *et al*. 2016).

These observations are consistent with national findings, showing that rain forests and tall eucalypt forests do not fill their predicted distribution and that savanna exceeds its predicted distribution (Hilbert & Fletcher 2012). Rain forest nationally only occupied 65% of its predicted distribution and tall eucalypt forest only 56%, whereas savanna (eucalypt woodlands, eucalypt open woodlands, tropical eucalypt woodlands/ grasslands) occupied 319% of its predicted range. These results suggest that rain forest and tall eucalypt forest are restricted in their distribution by savanna and associated frequent fire and that tall eucalypt forests are equally restricted by the long-term shade intolerance of rain forests.

A methodological consideration is that the size and area studied will affect the relative results for savanna vegetation, but not the others. The study area contained the full extent of both rain forest and tall eucalypt forest, but not for savanna, which surrounds the other vegetation types. None-the-less, all overlapping environmental space has been captured within the boundary of the study area, as demonstrated by the results of the rain forest model (Figure 2.1). Thus absolute values of areas of occupancy are accurate and should be considered, rather than percentages for savanna only. Arguably, the larger study area, as used here, is important, as it gives more weight to savanna vegetation, reflecting the predominance of savanna vegetation across northern Australia compared with the rarity of rain forest vegetation. Savannas (eucalypt woodlands, eucalypt open woodlands, tropical eucalypt woodlands/ grasslands) occupy 26% of the Australian continent (approximately 179366800 hectares), compared with only 0.65% (4491200 hectares) by rain forest (Hilbert & Fletcher 2012). Accordingly, incursions of rain forest into adjacent savanna boundaries are negligible, when considering the vast extent of savannas to that of rain forest. Concerns regarding a loss of savanna to rain forest are, therefore, unwarranted, however, a loss of rain forest, or tall eucalypt forest to savanna are quantifiable and ecologically legitimate.

2.5.3 Implications

The evidence that some vegetation types do not fill their potential range, but are occupied by alternative vegetation types, is consistent with alternative stable state theory and vegetation feedbacks in the region (Wilson & Agnew 1992; Hoffmann *et al.* 2002; Beckage & Ellingwood 2008; Beckage *et al.* 2009; Hoffmann *et al.* 2009; Warman & Moles 2009; Odion *et al.* 2010; Tng *et al.* 2013, 2014). Results indicated that substantial areas of potential tall eucalypt forest exist in alternative stable states of rain forest and savanna. Both rain forest and savanna otherwise appear relatively stable and although exist in alternative states within each other's environmental space, savanna appears to occupy substantially more area of rain forest than the reverse (Table 2.6). It is argued that they are maintained in this alternative state by vegetation - fire feedbacks (Wilson & Agnew 1992), whereby savanna promotes frequent (but low intensity) fires associated with its grassy, highly flammable understorey and rain forest suppresses fire with a cool and moist, shaded microclimate. Each vegetation type displays its own feedback mechanisms (Wilson & Agnew 1992; Warman & Moles 2009), whether by soil (Warman *et al*. 2013), fuels (Hoffmann *et al.* 2012b) or microclimate (see Chapter 3). For example, the observed distribution of tall eucalypt forest was far greater than predicted ($p \geq 0.5$), suggesting self-reinforcing feedback mechanisms to persist in sub-optimal situations. However, the tendency for tall eucalypt forest to occur in areas outside its preferred habitat suggests that this vegetation type may already be unstable and thus vulnerable to tipping points.

Vegetation feedbacks and the potential presence of alternative stable states make modelling and predicting vegetation distributions more complicated. It is also an indication that there is potential for tipping points between stable states in areas of overlapping or migrating environmental space. Vegetation types already vulnerable to tipping points may be at increased risk due to climate change (Gonzalez *et al.* 2010; Laurance *et al.* 2011a; Higgins & Scheiter 2012; Lloret *et al.* 2012). Changes from one 'state' to another, in this case, are likely to be mediated by events such as fire, which is expected to increase in frequency and intensity with climate change (Cary & Banks 2000; Cary 2002; Hennessy *et al.* 2005; Lucas *et al.* 2007; Pitman *et al.* 2007; Hasson *et al.* 2008; Hasson *et al.* 2009; Krawchuk *et al.* 2009; Williams *et al.* 2009; Liu *et al.* 2010; Clarke *et al.* 2011; Cary *et al.* 2012; Moritz *et al.* 2012; CSIRO & Bureau of Meteorology 2015). Climate change, interacting with fire has the potential to impact vegetation, which is vulnerable to tipping points, particularly areas where there is already evidence of alternative stable states of vegetation. Climate change presents implications for vegetation in the Wet Tropics, with predictions of significant shifts in vegetation distribution, mostly in the ecotonal zone between rain forest and savanna and particularly for tall eucalypt forest, which is wholly found within the ecotonal zone (Hilbert *et al.* 2001b). This is supported by the results suggesting extent of alternative stable states in the region and relative instability of tall eucalypt forests.

Other evidence suggests tall eucalypt forests are particularly vulnerable to tipping points and are at risk from climate change. Temperate eucalypt forests and elevationally restricted mountain ecosystems are identified as two of the most vulnerable Australian ecosystems to tipping points (Laurance *et al.* 2011a). Tall eucalypt forests of the Wet Tropics fit both these criteria, as they are a temperate outlier in the tropics (Ashton 1981; Ash 1988; Ashton & Attiwill 1994). and are restricted to elevated mountain areas, with an average elevation of near 800m (Table 2.3). The conservation status of tall eucalypt forests in the Wet Tropics is already listed as endangered, partly due to the perceived threat from rain forest invasion (Department of National Parks Recreation Sport and Racing 2013; Queensland Herbarium 2014; Tng *et al.* 2014). However, evidence about their preferred environmental space and occupancy suggests they may be more at risk by rapid invasion of fire, than the slow invasion by rain forest (Tng *et al.* 2011). Other vegetation types occupied large areas of identified high probability for tall eucalypt forest and tall eucalypt forest instead occupied sub-optimal environmental conditions. This suggests that tall eucalypt forests are closer to the edge of their environmental niche than the other communities and are likely to be less resilient to additional threats, such as from climate change. Combined these threats suggest that tall eucalypt forests could be at risk of ecosystem collapse and, without formal assessment, appear to meet many of the criteria for an ecosystem at risk (Rodríguez *et al.* 2011; Keith 2013, 2015; Keith *et al.* 2013).

2.5.4 Wet Tropics vegetation models

There have been many previous approaches to modelling vegetation distribution in the Wet Tropics (Nix 1991; Mackey 1993, 1994; Hilbert & van den Muyzenberg 1999; Hilbert *et al.* 2001a, 2001b, 2007; Hilbert & Ostendorf 2001; Ostendorf *et al.* 2001; Mackey & Su 2005; Accad & Neil 2006; Graham *et al.* 2006, 2010; Hilbert 2008, 2010; VanDerWal *et al.* 2009b). This study was the first to adopt a geospatial approach that appropriately addresses spatial autocorrelation. It was also the first to evaluate relative performance of a variety of explanatory variables, include multiple candidate models and utilise full presence and absence data for the range of dominant vegetation types. Many of the previous regional studies have only considered rain forest vegetation and only the works by Hilbert and others (Hilbert & van den Muyzenberg 1999; Hilbert *et al.* 2001a, b; Hilbert & Ostendorf 2001; Ostendorf *et al.* 2001; Hilbert *et al.* 2007; Hilbert 2008; Hilbert 2010) have considered the spectrum of vegetation types represented in this region. Considering the spatial co-occurrence of these vegetation types and presence of vegetation feedbacks, it is erroneous to consider the distribution and drivers of one vegetation type only without also considering the distribution of adjacent vegetation types.

Compared with previous approaches to modelling vegetation distribution in the Wet Tropics, this study uses higher resolution vegetation mapping and explanatory variable inputs.

The scale of analysis is based on a 250m (6.25 hectare) grid, compared with a 80-100 metre (1 hectare) grid (Hilbert & van den Muyzenberg 1999; Hilbert *et al.* 2001a, b; Hilbert & Ostendorf 2001; Accad & Neil 2006; Hilbert *et al.* 2007; Hilbert 2008; Graham *et al.* 2010) and a 1,000 metre (100 hectare) grid (VanDerWal *et al.* 2009b; Graham *et al.* 2010). A 1,000 metre grid is too coarse to capture the distribution of highly restricted tall eucalypt forests, or the accurate location of rain forest-savanna boundaries. This has been demonstrated herewith by the preference for tall eucalypt forest to exist within only 500 metres of rain forest. A resolution of at least 250 m is required to adequately capture vegetation boundaries and transitions in the landscape, based on ecological knowledge and *in situ* conditions (see Chapter 3). However, fine-scale improvements to topographic inputs would not necessarily improve model predictions (Pradervand *et al.* 2013).

Climatic inputs used in modelling were more carefully selected than in previous studies. Nineteen climate variables were individually evaluated and directly compared before being considered for inclusion in complex models. Only one of each climate type (temperature and precipitation) were used to avoid model bias associated with identified collinearity between climate variables (Dormann *et al.* 2013), which have been ignored in previous studies. Other studies adopted seven particular climate variables (Hilbert & van den Muyzenberg 1999; Hilbert *et al.* 2001a, b; Hilbert & Ostendorf 2001; Accad & Neil 2006; Hilbert *et al.* 2007; Hilbert 2008; VanDerWal *et al.* 2009b) or fewer (Graham *et al.* 2010; Graham *et al.* 2006) without justification or comparison. It was tested and shown here that alternative climate variables perform better than those selected in previous models.

Geographic inputs used in other vegetation models of the Wet Tropics, largely ignore ecological knowledge of the region and the influence of topographic parameters such as relief or landform, prevailing (southeasterly) trade winds, rain intercept, rainshadow and proximity to the coastline, which are considered important for many regions (Ashcroft *et al.* 2008). The inclusion of ecologically meaningful geographic variables substantially improved model performance compared to climate only models.

2.5.5 Conclusions

The aim of this study was to model the distribution of vegetation types in the Wet Tropics and assess model capacity and appropriate explanatory variables to accurately predict vegetation distribution under future climate. Topographic, edaphic and climatic factors explained the distribution of vegetation types with good performance. However, climate variables alone, performed less well and contain inherent errors of correlation. The occurrence of vegetation feedbacks and competition between vegetation types within overlapping environmental space, complicate models and their accuracy. These complicating factors require consideration in modelling as they affected the distribution of all vegetation types, particularly tall eucalypt forests. Alternative stables states of vegetation and stochastic disturbances by fire are other mechanisms potentially contributing to vegetation distribution and affecting model performance. The relative performance of models between vegetation types and occupancy of potential distributions by other vegetation types indicate that savanna is the most stable vegetation type and tall eucalypt forests the least. Tall eucalypt forests appeared to occupy sub-optimal environmental space, indicative of a high degree of vulnerability to landscape change., They are wedged between long-term shade intolerance associated with rain forest and short-term frequent fire intolerance associated with savanna. Issues relating to the accuracy of explanatory variables, particularly climate, and complicating factors associated with vegetation feedbacks and alternative stable states require further investigation to improve model performance. These would be important if trying to accurately predict vegetation distribution under future climate.

Plate 3. Rain forest vegetation of the Wet Tropics.

Plate 4. Tall eucalypt forest vegetation of the Wet Tropics.

Plate 5. Savanna vegetation of the Wet Tropics.

CHAPTER 3

The microclimate of vegetation types along an environmental gradient: implications for bioclimatic models

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3.1 Abstract

Predictions of climate change in topographically complex regions may be problematic due to undersampling of official meteorological locations in various topographic settings and across environmental gradients. Spatial climate data used in climate change predictions is often based on algorithms which over-simplify meteorological patterns between official meteorological stations. Understanding these patterns between sparse meteorological stations in complex terrain and across environmental gradients is important for understanding how climate change may impact biota at a scale relevant to their local distribution. Predictions of climate change impacts on vegetation distribution, such as shifting vegetation boundaries along environmental gradients, require this detailed understanding. However, the climate data used in model predictions have seldom been assessed against actual *in situ* conditions, nor the microclimates which biota actually experience. Also bioclimatic models impute linkage between climate and vegetation under the assumption of equilibrium. Yet vegetation is often in disequilibrium with climate and may exist in alternative stable states influenced by vegetation feedbacks or periodic disturbances such as fire. Not accounting for these influences can be a major problem in trying to make predictions of vegetation distribution under future climates (Harris *et al*. 2016). The aims of this study were to assess the microclimate of vegetation types along an environmental gradient and determine whether climate data models could meaningfully predict vegetation distributions under future climate scenarios.

Here is presented the first assessment of (fine-resolution) microclimate conditions measured *in situ* between vegetation types along an environmental gradient. Three years of micrometeorological measurements (temperature, humidity, wind speed, soil moisture, solar exposure and rainfall) were made at multiple locations along eight transects, each positioned to include three vegetation types (rain forest, tall eucalypt forest and savanna) that occur along an environmental gradient in the Australian Wet Tropics. Generalised linear models and linear-mixed effects models are used to establish the relative influence of vegetation and topographic position (transect and elevation) on microclimate patterns and to establish correlations with measurements at a nearby official (long-term) meteorological station at Mareeba.

Pairwise comparisons showed that micrometeorology was significantly different between vegetation types, with adjacent vegetation having the greatest similarity. Each micrometeorological variable displayed an increasing or decreasing trend along the

environmental gradient, between rain forest and savanna, with tall eucalypt forest consistently represented in between. Meteorological data at the nearby official meteorological station and vegetation type explained only 1-30% of the deviance in site microclimate. Despite low model performance, correlations between official meteorological stations and vegetation or site are useful in identifying *in situ* conditions.

Vegetation, transect and elevation explained up to 39% of site-based microclimate patterns. Vegetation was demonstrated to be an important, if not better predictor of *in situ* microclimate, than the topographically driven predictors (transect and elevation) and contributed up to 99% of the overall model performance. This result suggests a significant and important effect of vegetation feedbacks on microclimate conditions. The influence of vegetation-mediated microclimate feedbacks on vegetation distribution, disequilibrium and alternative stable states is discussed.

In situ micrometeorological data were compared with spatially interpolated climate for the area and showed that while some modelled climate variables are reasonable predictors of *in situ* microclimate conditions (32-63% for temperature, 16-24% for humidity), others show very weak relationships (2-17% for wind and 3-5% for solar exposure), or no relationship (less than 1% for rainfall). The low performance of this data in reflecting field microclimatic conditions indicates that spatially interpolated climate data cannot reliably predict vegetation distributions under present, let alone future, climate scenarios. It was also demonstrated that vegetation was an important, if not better, predictor of microclimatic conditions than modelled climate, with vegetation only models generally outperforming climate-only models and contributing up to 90% of overall model performance. These results demonstrated that current spatially interpolated climate data models would not accurately predict vegetation distributions under future climate scenarios. The implications of these results for bioclimatic distribution models is that incorporating vegetation type and microclimate will improve the ability of a model to predict actual physical conditions more realistically.

Key words: micrometeorology, interpolated climate, forest boundaries, environmental gradients, feedbacks, bioclimatic models

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Some of the data collected in this chapter was used in the following publication (Appendix 3.1):

Shoo, L. P., Storlie, C., Vanderwal, J., Little, J. & Williams, S. E. (2011) Targeted protection and restoration to conserve tropical biodiversity in a warming world. *Global Change Biology* **17**, 186–193.

Associated with the above publication identifying cool climate refugia and areas requiring targeted protection in the Australian Wet Tropics, the author managed a successful conservation campaign to have priority climate refuge areas protected, which have now become National Parks (Appendices 3.2 - 3.4).

3.2 Introduction

The distribution of vegetation types within a landscape is affected by climatic conditions, geography, edaphic features, topography, disturbance regimes and ecological interactions (Specht & Specht 1999). Changes in any of these conditions can influence a shift in the spatial distribution of vegetation. Spatial models of vegetation based on these factors are useful tools in helping to understand and explain current distributions and how their distribution might change with a change in controlling factors (Peng 2000; Austin 2002; Dirnböck *et al.* 2002; Miller & Franklin 2002; Segurado & Araujo 2004; Elith *et al.* 2006; Ferrier & Guisan 2006; Lawler *et al.* 2006; Austin 2007; Elith & Graham 2009; Elith & Leathwick 2009; Scheiter *et al.* 2013; Franklin 2013). Distribution models can be used to predict potential shifts in distributions of species or vegetation, or identify important refugial areas with a change in climate (Pearson & Dawson 2003). However, distribution models have limitations, because they rely on assumptions that are oversimplifications of true ecosystem processes (Heikkinen *et al.* 2006). For example, some climatic distribution models of vegetation (Beaumont *et al.* 2005; Elith *et al.* 2006; Perry & Enright 2006; VanDerWal *et al.* 2009b; Roberts & Hamann 2011), have assumed that vegetation is primarily determined by climatic variables and that vegetation is in equilibrium with climate (Austin 2002). Vegetation is sometimes found in disequilibrium with its potential climatic or geographic distribution (Chapter 2; Low 2011; Svenning & Sandel 2013) or in alternative stable states (Beisner *et al.* 2003), which may be driven by other factors, such as vegetation feedbacks or disturbance regimes such as from fire or tropical cyclones. For example, the global distribution of rain forests are limited to half their potential distribution because of fire (Bowman 2000; Bond *et al.* 2005; Bowman *et al.* 2009). Frequent fire can maintain vegetation in a stable state, preventing succession or transition to an alternative vegetation state. The multiple, complex and interactive factors affecting vegetation types make accurate explanation or prediction of their distributions difficult (Chapter 2).

Problems also arise when attempting to model the climatic or geographic distributions of vegetation with coarse scale or inaccurate data. For example, temporal mismatch between climate data and period of species occurrence may not reflect preferred climate regimes, nor limiting conditions for species or vegetation and, therefore, significantly reduce model performance (Roubicek *et al.* 2010). Climatic data used in modelling provides attributes for above canopy macroclimatic conditions, but not for actual on ground microclimatic conditions that species naturally experience. Climate data is also typically based on average conditions and does not portray anomalies, extremes or variability, which may be associated with longer term patterns or cycles (Power *et al.* 1999). Comparisons of daily climate model data against daily microclimate observations have demonstrated that while climate model data may be a useful representation of mean microclimate values, they do not reliably predict extreme conditions (Pitman & Perkins 2008). Species and vegetation distributions, however, have been increasingly shown to be limited by specific microclimate conditions, extreme events and related disturbance events, rather than by average climatic conditions (Power *et al.* 1999; Parmesan *et al.* 2000; Ashcroft *et al.* 2009; Reside *et al.* 2010; Bateman *et al.* 2012; Wallisdevries *et al.* 2011; O'Donnell *et al.* 2011). These conditions are often not reflected in average climate data. Accordingly, incorporating microclimate data and climate extremes into bioclimatic models may improve their performance.

Spatial interpolations of climatic or geographic data are generated to represent conditions throughout a landscape. These interpolated data are commonly used as explanatory factors in distribution models (Meynecke 2004; Beaumont *et al.* 2005; VanDerWal *et al.* 2009a; Xu & Hutchinson 2013). Spatially interpolated climate data, for example, is based on records from official meteorological stations, usually located near populated, or rural areas, but seldom in remote locations. Official meteorological stations are often sparsely located, avoid areas associated with mountainous, complex terrain and rarely, if ever, are located along environmental gradients. Therefore, spatial interpolations of climate are often used to fill in gaps between meteorological station locations (Jeffrey *et al*. 2001; Frost *et al.* 2011). Spatially interpolated climate data has performed well for some distribution models (Khalili *et al*. 2013), but may be problematic in mountainous areas, where complex mosaics of microclimatic conditions prevail (Barry 2008; Sharples 2009). Interpolation algorithms based on latitude, longitude and elevation in generating spatial climate data (Hutchinson & Xu 2013) fail to capture on ground topographic and orographic conditions including rain intercept and rainshadows (Daly 2006; McKenney *et al.* 2011). In these situations, interpolated climate data calculated from remote meteorological stations often does not reflect actual conditions in complex topography (Scherrer *et al.* 2011). Accordingly, spatially interpolated climate data is unlikely to represent the microclimatic conditions that are actual drivers of local vegetation and plant species distribution in complex topography (Scherrer & Körner 2011).

Predictions of future species or vegetation distribution with climate change are based upon spatially interpolated climate data (Jeffrey *et al.* 2001; Booth *et al.* 2014). However, interpolated climate has showed low performance in explaining or predicting present vegetation distribution in the Australian Wet Tropics, let alone the reliability to explain future distributions (Chapter 2). This may be due to any combination of coarse scale of the data, poor interpolation algorithms, vegetation in disequilibrium with climate, influence of disturbance regimes, vegetation feedbacks or alternative stable states. Spatially interpolated climate has seldom been assessed against actual *in situ* conditions to determine its accuracy, particularly in complex terrain. More recently, spatial models of macroclimate have been compared with fine-scale near-surface topoclimate data from below canopy (Ashcroft *et al.* 2012; Ashcroft & Gollan 2012, 2013a, 2013b, Gollan *et al.* 2013, 2015; Letten *et al.* 2013; Slavich *et al.* 2014) and have shown that near-surface topoclimate data outperforms spatial models of macroclimate in distribution models (Ashcroft *et al.* 2008, 2014, Gollan *et al.* 2013, 2015; Letten *et al.* 2013; Slavich *et al.* 2014). Their conclusions suggest that widespread adoption of spatial models of macroclimate without quantifying their inaccuracies has implications for species (Stoklosa *et al.* 2015). The intention of this study, was to quantify some of these inaccuracies. To better understand vegetation or species distributions in topographically complex landscapes, robust microclimate data across environmental gradients in a variety of topographic positions and vegetation types are required (Suggitt *et al.* 2011).

Environmental gradients associated with mountain ranges have been identified as being of particular ecological interest (Peterson *et al.* 1997), particularly in the tropics (Malhi *et al.* 2010), given the close proximity of multiple vegetation boundaries, narrow ecotones and bioclimatic variability. Species and vegetation in these regions are also considered to be sensitive to climate change (Williams *et al.* 2003b; Walther *et al.* 2005; Löffler *et al.* 2011), particularly in the tropics (Laurance *et al.* 2011b). However, studies of microclimatic conditions for multiple vegetation types along any environmental gradients are lacking. Only one approach has attempted to measure fine resolution microclimatic conditions for different vegetation types in a complex topographic landscape (Ashcroft *et al*. 2012; Ashcroft & Gollan 2012). This work demonstrated that temperature and humidity were predominantly determined by elevation, vegetation type (canopy cover), distance to coast and topography and that averaged climate data concealed important trends and extremes.

Vegetation sometimes produce positive feedbacks on its environment, such as influencing microclimatic conditions (Wilson & Agnew 1992). Feedbacks can modify fine-scale variation in microclimate conditions and act as a buffer against macroclimate or extreme meteorological events (Lloret *et al.* 2011; Shoo *et al.* 2011; Suggitt *et al.* 2011). The degree to which different vegetation types modify microclimate, however, remains largely unknown. Some studies have measured microclimatic differences across a single vegetation boundary (Williams-Linera 1990; Young & Mitchell 1994; Freifelder *et al.* 1998; Morecroft *et al.* 1998; Davies-Colley *et al.* 2000; Gehlhausen *et al.* 2000; Scherrer & Körner 2011; Hoffmann *et al.* 2012b) or vegetation treatments (Heithecker & Halpern 2007; Ma *et al.* 2010), showing varying degrees of difference for different microclimate variables, but very few studies have compared multiple vegetation types (Uhl & Kauffman 1990).

The Wet Tropics of northeastern Australia is an ideal place to study vegetation, climatic and geographic interactions, as it is a mountainous tropical region with steep elevation and environmental gradients supporting multiple vegetation types in close proximity (Nix 1991). The region is characterised by rain forest associated with orographic rainfall of the coastal ranges, but is surrounded by seasonally dry flammable eucalypt savanna woodlands and a narrow band of tall eucalypt forest in between. Microclimatic conditions have been measured within rain forest (Shoo *et al.* 2011), across the rain forest – open forest boundary (Unwin 1983;

Duff 1987; Turton & Duff 1992; Turton & Sexton 1996) and across disturbance boundaries (Pohlman *et al.* 2007; Pohlman *et al.* 2009), however, multiple vegetation types across environmental gradients have not previously been studied. The aims of this study were to:

(1) assess the fine-scale variation in climate driven by topography and vegetation along an environmental gradient; and

(2) determine the relative performance of spatially interpolated macroclimate, vegetation and topography in explaining in situ topoclimate.

3.3 Methods

3.3.1 Study design

Eight transects were established along the environmental gradient on the leeward side of the mountain ranges in the Wet Tropics region of northeastern Queensland, Australia. Transects followed an east-west direction and incorporated a range of different elevations and latitudes (Table 3.1; Figure 3.1). Transects incorporated rain forest vegetation on the upper eastern elevations, savanna woodlands on the lower western elevations and plains, with tall eucalypt forests in between. Transect length varied between 2.3 and 9.9 kilometres, depending on the slope and spatial scale of vegetation transitions (Table 3.1). Each transect was located on similar (granitic or rhyolitic) geologies (Bain & Draper 1997; Johnson 2004; Lottermoser *et al.* 2008) to avoid confusing vegetation boundaries associated with lithographic or edaphic boundaries. Along each transect, four sites were established, one within rain forest vegetation, two within tall eucalypt forest and one within savanna. Sites were arranged so that there was one site either side of the rain forest - tall eucalypt forest boundary and one site either side of the tall eucalypt forest - savanna boundary. This meant that there were two sites within tall eucalypt forest. For the purposes of analysis, results for the two tall eucalypt forest sites were averaged. Details for each site are given in Table 3.2 and are depicted in Figure 3.2.

Table 3.1 Details of transects shown in Figure 3.1, incorporating rain forest, tall eucalypt forest and savanna vegetation. Details of sites for each transect are given in Table 3.2.

Transect	Lat. (°S)	Long. (°E)	Geology	Elevation Range (m)	Length (km)	Slope (°)
1 Mt Windsor	-16.21	144.98	Granite	1040-1285	7.15	6
2. Mt Spurgeon	-16.44	145.19	Granite	840-1180	3.47	2
3. Mt Lewis	-16.6	145.26	Granite	643-1015	2.44	18
4. Davies Creek	-17.03	145.61	Granite	623-737	3.67	11
5. Tinnaroo Creek	-17.11	145.56	Granite	878-1200	2.36	7
6. Mt Baldy	-17.27	145.41	Granite/ Rhyolite	1020-1203	7.5	11
7. Koombooloomba	-17.83	145.57	Granite	760-797	7.61	3
8. Paluma	-19.02	146.15	Granite/ Rhyolite	809-963	9.91	6

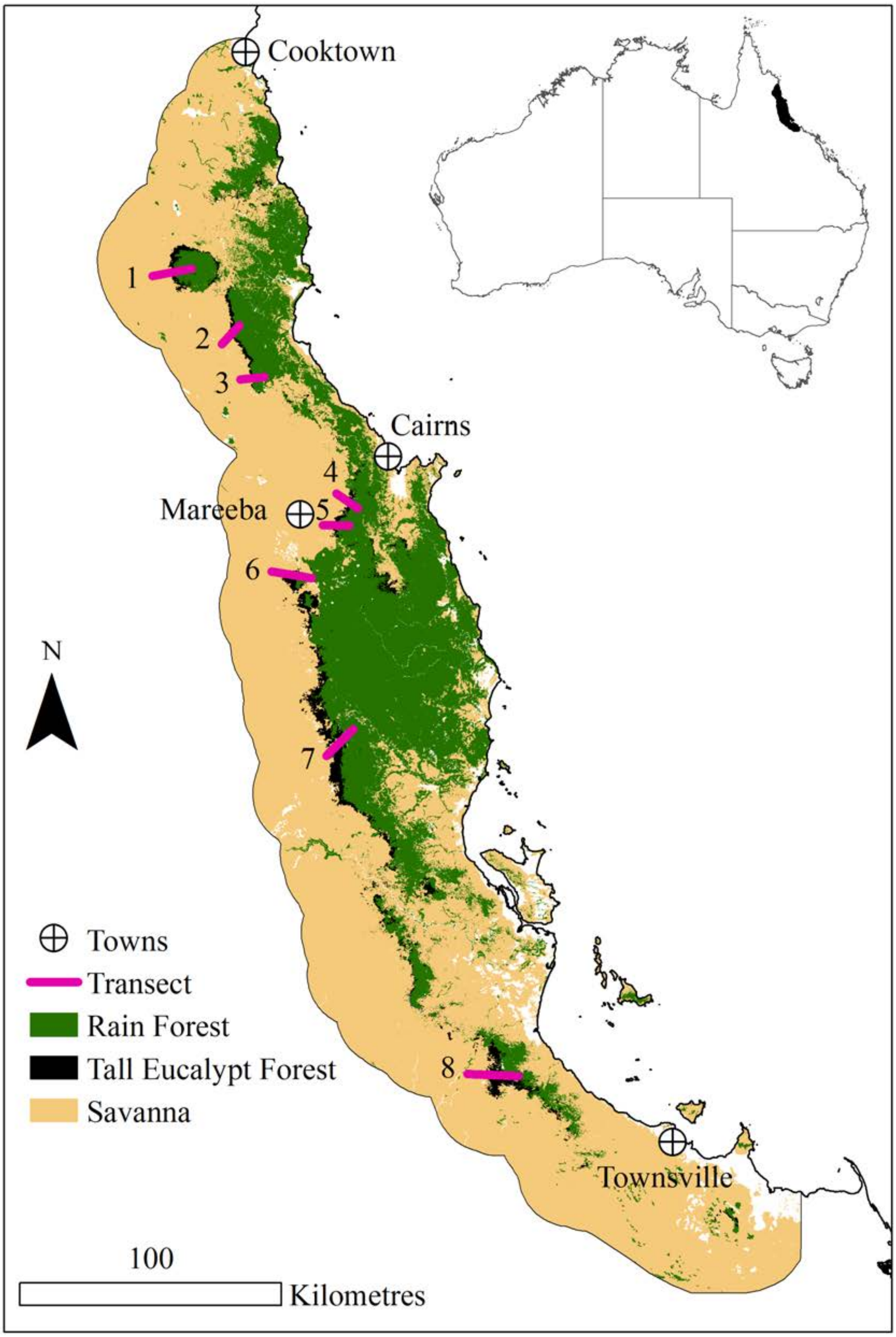

Figure 3.1 Map of the Australian Wet Tropics region showing distribution of three broad vegetation types rain forest, tall eucalypt forest and savanna. Location of study transects and major towns are also shown. Descriptions of the numbered transects are listed in Table 3.1.

Table 3.2 Details of field sites along 8 transects with one site in rain forest (RF), two sites in tall eucalypt forest (TEF) and one site in savanna (SAV) for each transect.

Transect	Site No.	Vegetation Type	Lat. (°S)	Long. (°E)	Elevation
1. Mt Windsor	1.1	RF	-16.23	145.01	1290
1. Mt Windsor	1.2	TEF	-16.21	144.98	1189
1. Mt Windsor	1.3	TEF	-16.23	144.98	1136
1. Mt Windsor	1.4	SAV	-16.24	144.94	1045
2. Mt Spurgeon	2.2	RF	-16.44	145.2	1218
2. Mt Spurgeon	2.2	TEF	-16.44	145.19	1132
2. Mt Spurgeon	2.3	TEF	-16.45	145.19	1125
2. Mt Spurgeon	2.4	SAV	-16.46	145.17	854
3. Mt Lewis	3.1	RF	-16.6	145.27	991
3. Mt Lewis	3.2	TEF	-16.6	145.26	954
3. Mt Lewis	3.3	TEF	-16.6	145.26	843
3. Mt Lewis	3.4	SAV	-16.6	145.25	649
4. Davies Creek	4.1	RF	-17.03	145.61	756
4. Davies Creek	4.2	TEF	-17.03	145.61	750
4. Davies Creek	4.3	TEF	-17.03	145.61	706
4. Davies Creek	4.4	SAV	-17.02	145.58	651
5. Tinnaroo Creek	5.1	RF	-17.11	145.57	1201
5. Tinnaroo Creek	5.2	TEF	-17.11	145.56	1168
5. Tinnaroo Creek	5.3	TEF	-17.11	145.55	981
5. Tinnaroo Creek	5.4	SAV	-17.11	145.55	878
6. Mt Baldy	6.1	RF	-17.28	145.43	1218
6. Mt Baldy	6.2	TEF	-17.27	145.41	1151
6. Mt Baldy	6.3	TEF	-17.28	145.38	1103
6. Mt Baldy	6.4	SAV	-17.27	145.36	1039
7. Koombooloomba	7.1	RF	-17.84	145.59	750
7. Koombooloomba	7.2	TEF	-17.84	145.58	763
7. Koombooloomba	7.3	TEF	-17.87	145.57	739
7. Koombooloomba	7.4	SAV	-17.89	145.54	782
8. Paluma	8.1	RF	-19.02	146.16	968
8. Paluma	8.2	TEF	-19.02	146.15	920
8. Paluma	8.3	TEF	-19.01	146.12	905
8. Paluma	8.4	SAV	-19.01	146.06	831

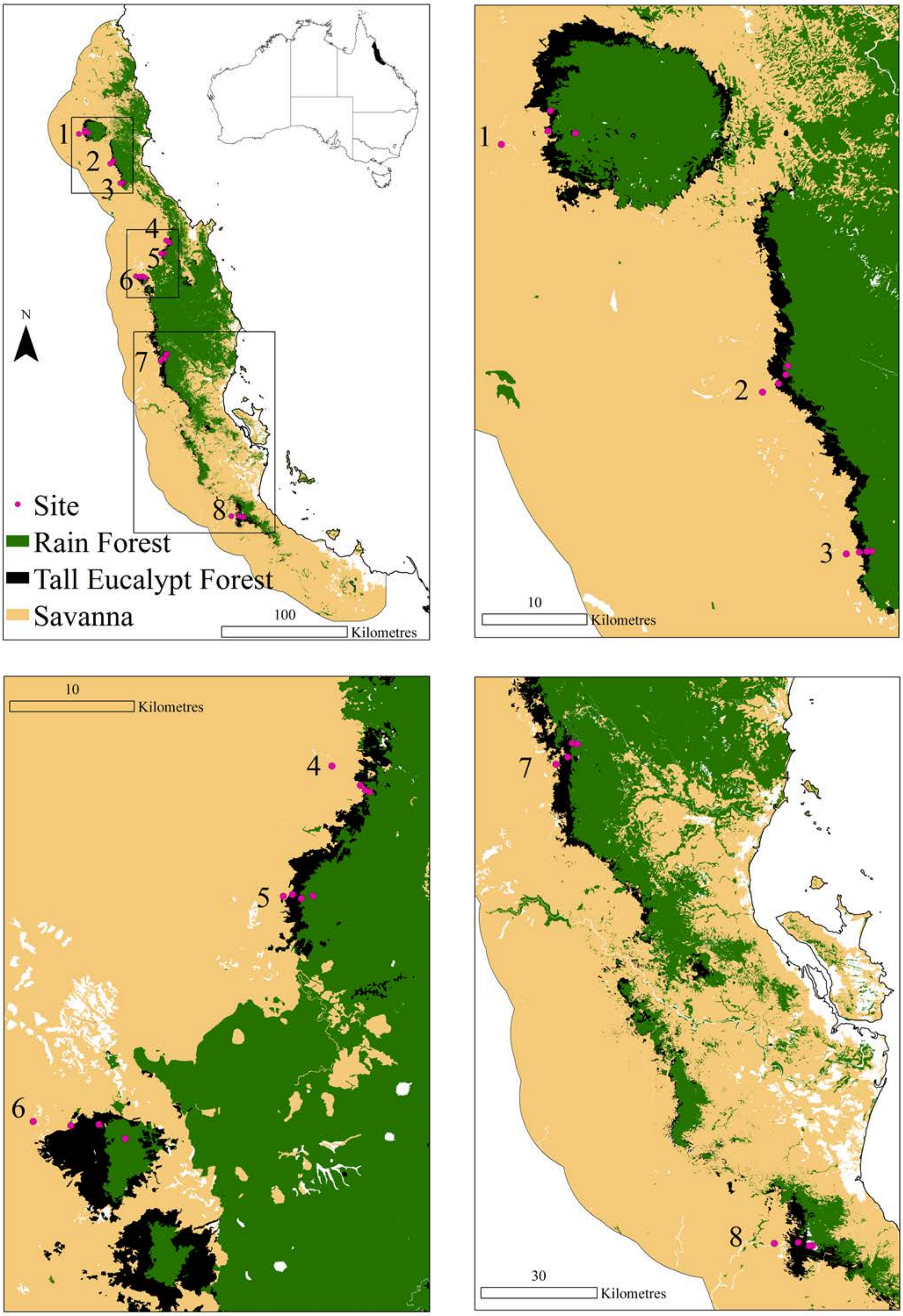

Figure 3.2 Map of the Australian Wet Tropics region showing the location of study transects within three broad vegetation types. Descriptions of the numbered transects are listed in Table 3.1 and site descriptions are listed in Table 3.2.

3.3.2 Micrometeorological measurements within vegetation types

Micrometeorological variables were measured daily at each site over a three year period (April 2007 to April 2010). Not all sites were able to be sampled for the full period, but were sampled for a minimum of at least one full year. Air temperature, relative humidity, wind speed, soil moisture and solar radiation (photosynthetically active radiation; PAR) were measured at a rate of between 15 and 60 minute intervals throughout the day. Rainfall was also measured, but at savanna sites only. Daily maxima, minima and mean (and rainfall totals) were derived from these microclimate data.

Maxim data loggers (DS1923 Hygrochron iButton; www.maxim-ic.com/datasheet/index.mvp/id/4379) were used to record air temperature and relative humidity. Onset HOBO Micro Station data loggers (H21-002; www.onsetcomp.com) were used for all other meteorological variables. Meteorological sensors were placed 1.2 m above ground level, consistent with Australian Bureau of Meteorology standards (Canterford 1997). The only exceptions were for soil moisture sensors, which were buried 10 cm below ground level and an anemometer, which was exposed at 2 m above ground level. Australian standards specify anemometers to be exposed at 10 m above the ground, however, this was not possible for this study. Sensors were installed at fixed points within each vegetation type using PVC plumbing pipe mounted on a metal picket (Plate 6). Australian standards for the siting of meteorological instruments specify in the middle of a 30 by 30 m square buffer zone (Canterford 1997). Such areas do not exist for the variety of topographic and vegetation situations required for this study. Instead, instruments were placed in an area free of vegetation within a two metre radius, but not within unnaturally cleared or open situations. Temperature and relative humidity sensors were installed within customised shelters, which mimicked approved meteorological sensor shelters. This rudimentary design consisted of the sensor placed within a tea-strainer suspended within a 250 mm length of 50 mm plumbing pipe (DWV 50 PVCU) capped on the upper end. The pipe was perforated with a 20 eight mm drill holes above and below, but not adjacent to the sensor (to facilitate air flow), but prevent direct sunlight and rainfall from affecting the sensor. Temperature measurements are affected by sensor housing and accordingly, all micrometeorological measurements were calibrated with data collected using an approved Stevenson's sensor shelter (Canterford 1997). For calibrations, official Skye Stevenson’s Screens were fitted with matching temperature sensors and placed adjacent random micrometeorological stations at various sites within each vegetation type over a minimum period of three months. As direct sunlight proved to influence deviation in measurements, solar radiation was incorporated as an additional term in calibration equations (Appendix 3.5). R^2 for the relationships between temperature in the PVC housing and Stevenson Screen temperature ranged from 0.89 to 0.99 (Appendix 3.5). Temperature measurements taken in the PVC housing were then adjusted to official Stevenson Screen measurements using the calibration equation for the corresponding level of canopy cover (vegetation type).

PAR was measured at each site with a HOBO Smart Sensor (S-LIA-M003), fitted to each micrometeorology station at two metres above ground level. PAR values were converted to solar exposure ($MJ.m^{-2}$) to be compatible with standard spatial climatic variables. No adjustments were made to correct for differences in canopy cover.

Soil moisture was measured using HOBO compatible ECH_2O Dielectric Aquameter probe (S-SMA-M005 or S-SMC-M005; www.onsetcomp.com). Probes were pierced into undisturbed soil at a 45-degree angle, 5-10 cm below the soil surface. Soil moisture data was calibrated for each following laboratory techniques described by Campbell (www.microdaq.com/occ/hws/soil_moisture_smart_sensor.php). Calibrated data was then used to generate a daily Soil Moisture Deficit index (SMD) as used in the formulations for drought factor and Forest Fire Danger Index in Australian environments (Griffiths 1999; Finkele *et al.* 2006). Official SMD calculation assumes a field capacity of 200 mm of available water, however, laboratory calibrations indicate this assumption is false. Nonetheless, data were adjusted to match a 200 mm field capacity, for consistency with national standards.

A rain gauge (Davis Instruments Rain Collector; www.davisnet.com) was wired up to the Onset data logging system at each of the savanna sites. Rainfall was only measured at open canopy savanna sites, as canopy intercept and stemflow strongly affect water inputs beneath dense canopies (Ashton & Attiwill, 1994; McJannet *et al.* 2007). Although rain intercept may occur in other vegetation types also, only in savanna vegetation were there sufficiently sized canopy gaps to install a rain gauge without overhead or nearby canopy coverage to interfere with actual unimpeded rainfall. Accordingly, rain gauges were not located beneath rain forest or tall eucalypt forest canopies.

Wind and gust speed was measured with the HOBO Wind Speed Smart Sensor (S-WSA-M003), erected on each meteorology station at two metres above the ground level. These data were then corrected for standard wind measurements (at 10 metres above ground level), by multiplying wind data by 1.25 (http://www.firebreak.com.au/bkdi_df.html).

All micrometeorological data were summarised to daily data for the three year study period (April 2007 to April 2010). This included daily means, maxima and minima. Daily data were then used for the first three analyses (n=1095) and averaged monthly means, maxima and minima used in the fourth analysis comparing modelled macroclimate (n=36).

3.3.3 Official meteorological station measurements

Meteorological data from official sites in the Australian Wet Tropics were obtained from the Australian Government's Bureau of Meteorology (BOM). One official meteorological site (Mareeba) was selected as the most central and representative of the 32 micrometeorological sites and for which long-term meteorological data were also available (1957-present; chapter 5). Preliminary analysis demonstrated that data from Mareeba correlated more strongly with field sites than other official meteorological sites, such as at Cairns on the coastal lowlands (Figure 3.1). Relationships in micrometeorological data were compared among study sites, vegetation types and Mareeba station data during the study period. Mareeba meteorological station does not contain data for solar exposure or soil moisture against which measurements could be compared. A surrogate soil moisture index, however, was calculated from available Mareeba data, using the Keetch-Byram Drought Index (KBDI) (Finkele *et al.* 2006).

3.3.4 Spatially interpolated climate data

Australian spatially interpolated climate data were obtained for the region from continental scale modelled information, via ANUCLIM software (Xu & Hutchinson 2011; Xu & Hutchinson 2013) and an 80 metre grid regional Digital Elevation Model (DEM) (Rochester 2003). These ANUCLIM climate models were based on meteorological data collected at official meteorological stations between January 1952 and December 1990 (Kesteven & Hutchinson 1996). Monthly (ESOCLIM) and annual (BIOCLIM) climate data were extracted for each of the study sites from ANUCLIM models. Site data were extracted using point intersect (Hawth's Tools; www.spatialecology.com/htools) and spatial join techniques in a Geographic Information Systems (GIS) platform.

3.3.5 Statistical modelling

To address the research questions, four different analyses were performed:

- pairwise comparisons of the daily microclimate data for each of three vegetation types;
- analysis of the relationship of meteorological variables between the Mareeba meteorological station and vegetation type;
- analysis of the relationship between vegetation type and topographic position, and
- comparison of below canopy microclimate data and modelled climate for each site.

Generalised linear models (GLM) and linear mixed effects (LME) models were used to analyse daily meteorological data with multi-model inference and model selection based on Akaike's Information Criterion (AICc) (Burnham & Anderson 2002). Candidate models included a full model of all explanatory variables and their interaction, with other models consisting of all possible derivative combinations of the explanatory variables. Models were compared and evaluated using Akaike weights (*wi*) and explained deviance (D^2) as an estimator of model performance. Statistical analyses were run from the statistical software "R" (Version 2.11.1 R Development Core Team 2002, using the 'lme4' package (Bates *et al.* 2011; http://lme4.r-forge.r-project.org).

The first analysis was to test for significance of micrometeorological differences among vegetation types (rain forest, tall eucalypt forest and savanna). GLMs were used in pairwise comparisons of the daily site-based data between vegetation types for each of ten different microclimate variables; temperature (maximum, minimum and average), relative humidity (maximum, minimum and average), wind speed (average), soil moisture deficit (maximum and mean) and solar exposure (total). In each of these three sets of analyses (rain forest *vs* savanna, rain forest *vs* tall eucalypt forest and tall eucalypt forest *vs* savanna), microclimate of one vegetation type was used as the response variable and microclimate of another vegetation type with transect, and their interaction, were the explanatory variables.

The second analysis was to test the ability of official meteorological data from Mareeba to predict micrometeorological conditions at field sites. LME models were used with meteorological data at Mareeba and vegetation type as predictor variables for site-based microclimate data. This was repeated for each of ten variables; temperature (mean, maximum and minimum), relative humidity (mean, maximum and minimum), SMD (mean and maximum) mean wind speed and rainfall. ‘Transect’ was incorporated as a random effect in all models. Model selection, based on AICc, was performed on five model candidates, consisting of the full model and models using all possible derivatives of predictor variables.

The third analysis, using LME models, was to investigate the relative influence of vegetation type and topographic position (transect and elevation) on each micrometeorological variable. An interaction between vegetation type and topographic position (transect and elevation in alternate analyses) was included in the global model and ‘Date’ was included as a random factor in all models. Model selection, based AICc, was performed on five model candidates, including the full model and all possible model derivatives. This was repeated with transect and elevation in separate analyses.

The final analysis was to examine the relationship between spatially interpolated climate and *in situ* below canopy microclimate. Spatially interpolated climate models were designed for above canopy or open space situations and are not equivalent to below canopy conditions. However, the intent here was not to ‘test’ climate models, but to compare and examine their relationship with on ground conditions experienced by biota. Interpretation of these results should be considered with caution. LME models were used to predict *in situ* below canopy micrometeorology from spatially interpolated climate. Vegetation type was included as an additional predictor term, to test for improvements in model fit. Monthly ESOCLIM spatially interpolated climate data (Xu & Hutchinson 2011; Xu & Hutchinson 2013) and vegetation type, including their interaction were used as predictor variables. The response microclimate variables were derived from daily site-based micrometeorological data. Daily site-based data were averaged by month, so that there were values at each site, for each month (average data per calendar month from three years of data; April 2007 to April 2010). The microclimate values tested included only those variables that were also produced from ESOCLIM models and used ten micrometeorological variables in separate analyses: temperature (mean, maximum and minimum), relative humidity (mean), rain days, rainfall, wind speed (mean), wind run and solar exposure (independent, rainfall dependent). Each analysis was repeated alternately using ‘Month’, ‘Transect’ and ‘Elevation’ as a random effect, to test the influence of each.

Incomplete or missing microclimate data resulted from equipment failure and duration of operation. Relevant data was omitted from analysis where it was significantly incomplete; that is 5% or more missing data for that period. Only days with >95% complete data was obtained were used in deriving daily data. Only months with >95% available daily data were used to derive monthly data. Only seasons with >95% available daily data were used to derive seasonal data.

3.4 Results

Daily meteorological patterns at Mareeba and micrometeorological patterns for sites within rain forest, tall eucalypt forest and savanna showed differences between each vegetation type and with Mareeba for all variables (Figures 3.3-3.5). In almost all cases, patterns were ordered progressively in relation to canopy cover (or vegetation complexity) from cleared land (Mareeba), through savanna, tall eucalypt forest and with rain forest (most complex and closed vegetation cover). Temperatures (mean, maximum and minimum), wind speed, SMD and solar exposure generally decreased with increasing vegetation complexity (with the exception of mean temperatures in savanna), while relative humidity (mean, maximum and minimum) increased with increasing vegetation complexity (Figures 3.3-3.5). The only exception was that there was less rainfall at savanna sites than at Mareeba, when the presumed pattern was an increase in rainfall from Mareeba through to rain forest (Figure 3.5).

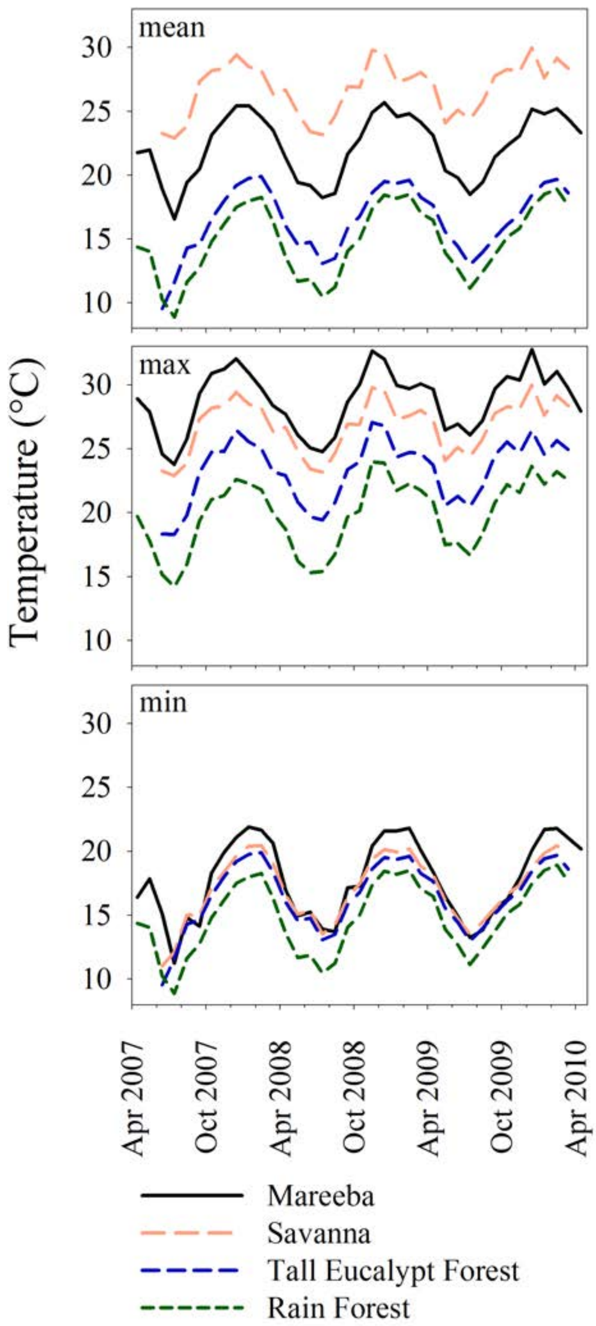

Figure 3.3 Average monthly temperature at the Mareeba meteorological station and within three broad vegetation types (savanna, tall eucalypt forest and rain forest) in the Australian Wet Tropics region over a three-year study period.

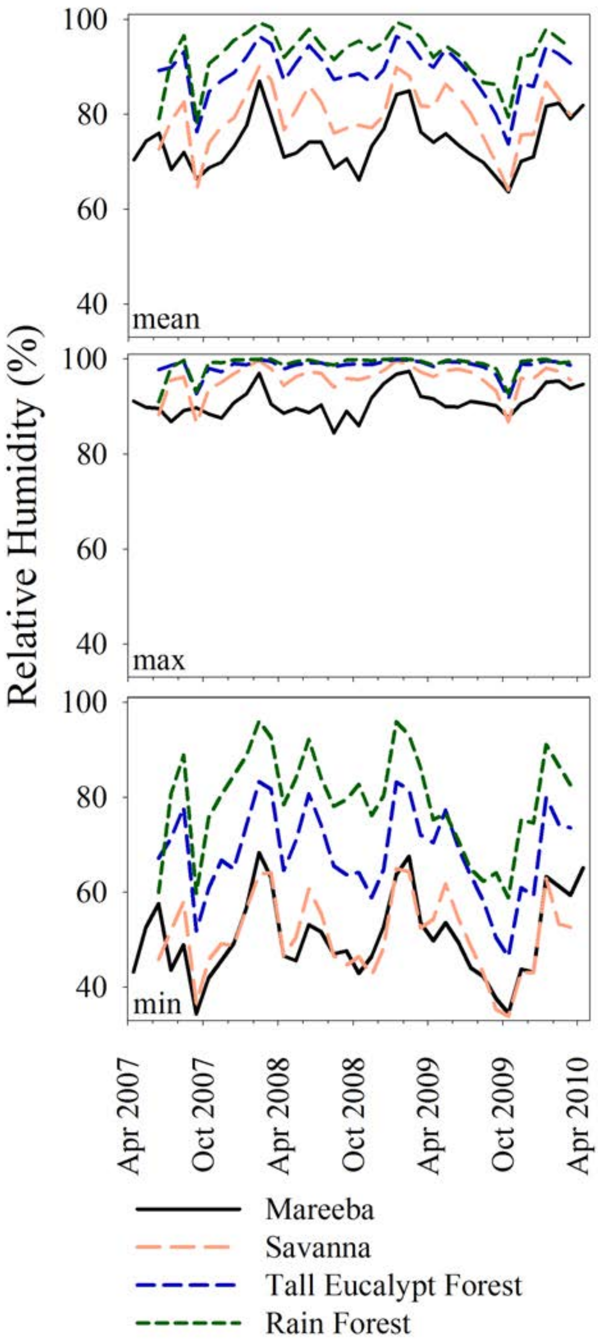

Figure 3.4 Average monthly relative humidity at the Mareeba meteorological station and within three broad vegetation types (savanna, tall eucalypt forest and rain forest) in the Australian Wet Tropics region over a three-year study period.

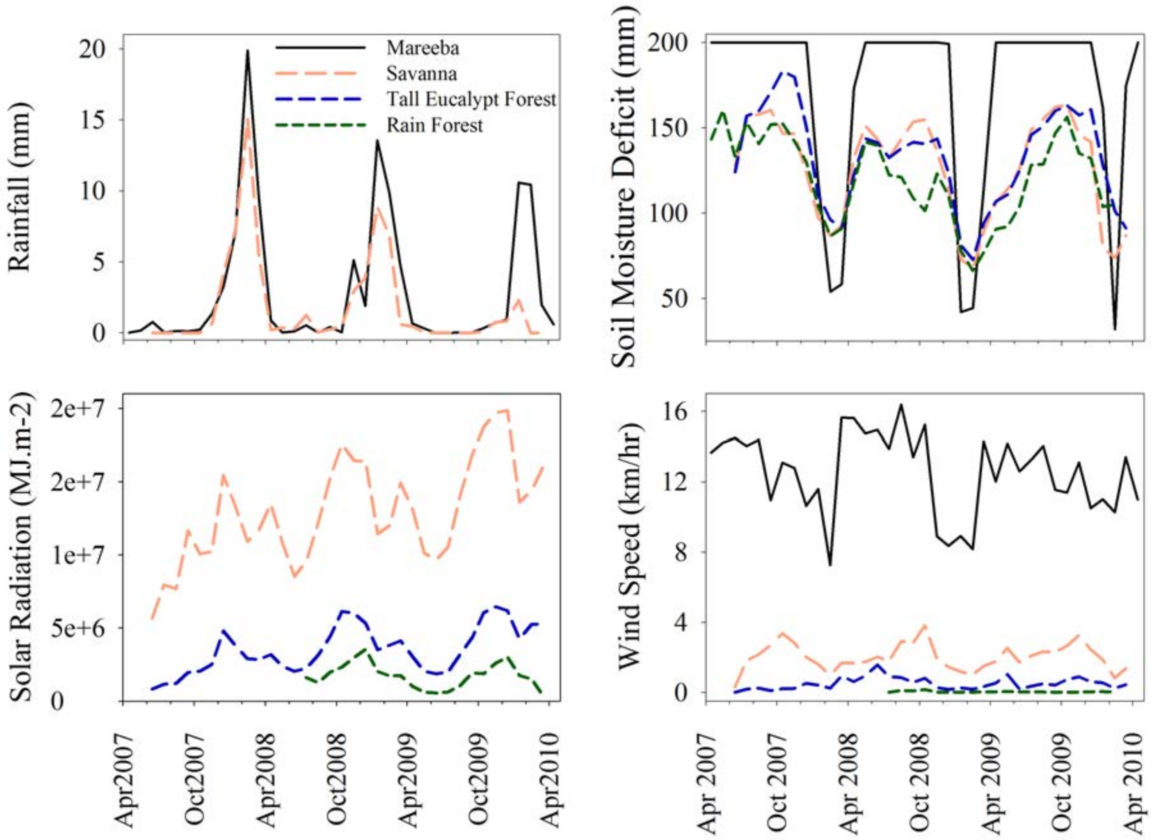

Figure 3.5 Average monthly meteorological measurements at the Mareeba meteorological station and averaged conditions within three broad vegetation types (savanna, tall eucalypt forest and rain forest). Soil moisture deficit was calculated by the Keetch-Byram Drought Index at the meteorological station at Mareeba.

Pairwise comparisons of observed microclimate for vegetation type demonstrated that micrometeorological patterns were distinctly different between vegetation types (Appendix 3.6). In all cases, model selection showed the full model, with vegetation and transect, to have the strongest statistical support (Appendix 3.7) and were able to reliably predict microclimate patterns in other vegetation types (Table 3.3). Although the full model received the strongest support, vegetation alone was consistently a stronger explanatory variable than transect. That is, model 2 from the candidate models (Appendix 3.7), which included vegetation, but not transect, in most cases contributed the most to model performance (see explained deviance). Vegetation type alone accounted for 53-89 % of the explained deviation for temperature, 45-80% for relative humidity, 6-20% for wind, 34-56% for solar exposure and 10-61% for SMD. The inclusion of transect (i.e. the full model) improved upon model 2 by 5-24% explained deviance for temperature, 3-12% for relative humidity, 4-21% for wind, 23-31% for solar exposure and 16-72% for SMD. In all cases and for each micrometeorological variable, the strongest

Table 3.3 Differences in microclimate by vegetation type and landscape position. Model performance (explained deviance) for generalised linear models comparing microclimate variables among vegetation types and landscape position (transect). Three vegetation types, rain forest (RF), tall eucalypt forest (TEF) and savanna (SAV) were compared in a pairwise analysis. The response variable was micrometeorological variable of vegetation type 1 and the explanatory variables in the global model were micrometeorological patterns of vegetation type 2, transect, and their interaction. See Appendix 3.6 for full details of these results.

Micrometeorological Variable	Explained Deviance (%)		
	RF:TEF	RF:SAV	TEF:SAV
temperature maximum	87.73	77.12	83.69
temperature mean	93.94	90.60	95.49
temperature minimum	91.16	87.39	94.36
relative humidity maximum	79.18	61.66	64.51
relative humidity mean	85.01	72.34	86.00
relative humidity minimum	74.68	57.11	82.84
wind speed mean	22.20	11.60	41.03
soil moisture deficit maximum	84.72	76.17	76.43
soil moisture deficit mean	84.32	75.91	76.55
solar exposure	64.74	60.74	82.21

relationships were among adjacent vegetation types (i.e. between rain forest and tall eucalypt forest and between tall eucalypt forest and savanna) and weakest for comparisons among communities that were most different (rain forest and savanna).

The second analysis, showed that the capacity to predict site-based micrometeorology from daily baseline Mareeba meteorological data and vegetation type varied among meteorological variables (Table 3.4). Temperature variables (mean, maximum and minimum) were the most reliably predicted (22-30% explained deviance), with mean wind speed and minimum relative humidity (both 8%) being the next best explained variables, while all other variables demonstrated low predictive power (1-5% explained deviance) (Table 3.4). The statistical analysis for predicting local microclimate variables in all cases was improved by the inclusion of both vegetation type and input from the closest (Mareeba) meteorological station (Appendix 3.9). Generally, Mareeba climate data (Model 2, Appendix 3.9) was a better predictor than vegetation (Model 3) in all cases except for maximum and mean relative humidity and for wind speed. Micrometeorological variables for each vegetation type varied differently relative to baseline Mareeba meteorological patterns (Figures 3.6-3.8). Temperature and relative humidity showed the best relationship in slope with Mareeba, but with less well-defined relationships for SMD (no doubt reflecting the differing calculation of SMD and KBDI as a SMD surrogate), wind speed and rainfall.

Table 3.4 Summary results of individual linear mixed effects models, each testing the capacity for daily Mareeba meteorological data and vegetation type to predict daily observed microclimate at 32 field study sites with ‘Transect’ as a random effect (climate_variable ~ Mareeba * VegType). The explained deviance is reported. See Appendix 3.8 for details of these results.

Meteorological variable	Explained Deviance (%)
Temperature maximum	21.73
Temperature mean	30.11
Temperature minimum	21.56
Relative Humidity maximum	0.79
Relative Humidity mean	5.28
Relative Humidity minimum	7.75
Wind Speed mean	7.82
Soil Moisture Deficit maximum	3.21
Soil Moisture Deficit mean	4.59
Rainfall	3.00

The third analysis investigated the relative influence of vegetation type and topographic position (transect and elevation) on each micrometeorological variable. For all micrometeorological variables, the full model (Table 3.5; Appendices 3.10 and 3.12) showed the greatest statistical support (Appendices 3.11 and 3.13). However, vegetation type had a greater influence on microclimate than transect or elevation (Appendices 3.11 and 3.13). Models with transect as an explanatory variable consistently outperformed equivalent models with elevation as an explanatory variable (Table 3.5). Some microclimate variables performed better than others (Table 3.5). Temperature variables were the best performing models (ranging between 15 and 39% explained deviance), with all other variables with 10% or lower explained deviance. Models for wind speed, however, were not able to be fitted and gave negative explained deviance results. Models for rainfall were particularly poor and explained less than 0.3% of the model deviance, presumably in part because data was only available for savanna sites. Vegetation type generally had a greater influence on microclimate than either transect or elevation. That is, models with only vegetation (model 2, Appendices 3.11 and 3.13), performed better than models with only transect or elevation (model 3, Appendices 3.11 and 3.13). The only exceptions were for minimum temperature and SMD variables (transect only). Compared with the full model, vegetation (model 2) contributed 69% (transect) and 79% (elevation) of the overall model performance for maximum temperature, 52% and 57% for mean temperature, 33% and 47% for minimum temperature, 46% and 99% for maximum humidity, 81% and 99% for mean humidity, 79% and 99% for minimum humidity, 7% and 40% for maximum SMD, 6% and 41% for mean SMD and 65% and 99% for solar exposure.

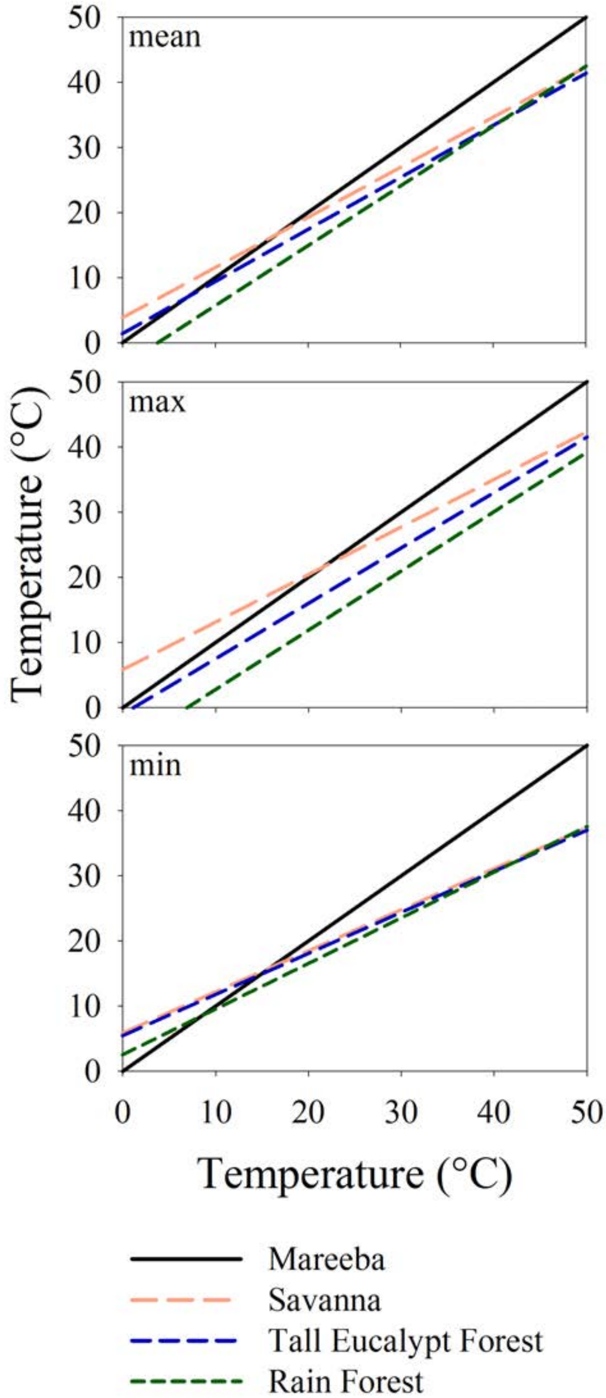

Figure 3.6 The predicted relationships of daily temperature in three broad vegetation types (savanna, tall eucalypt forest and rain forest) compared with Mareeba meteorological station.

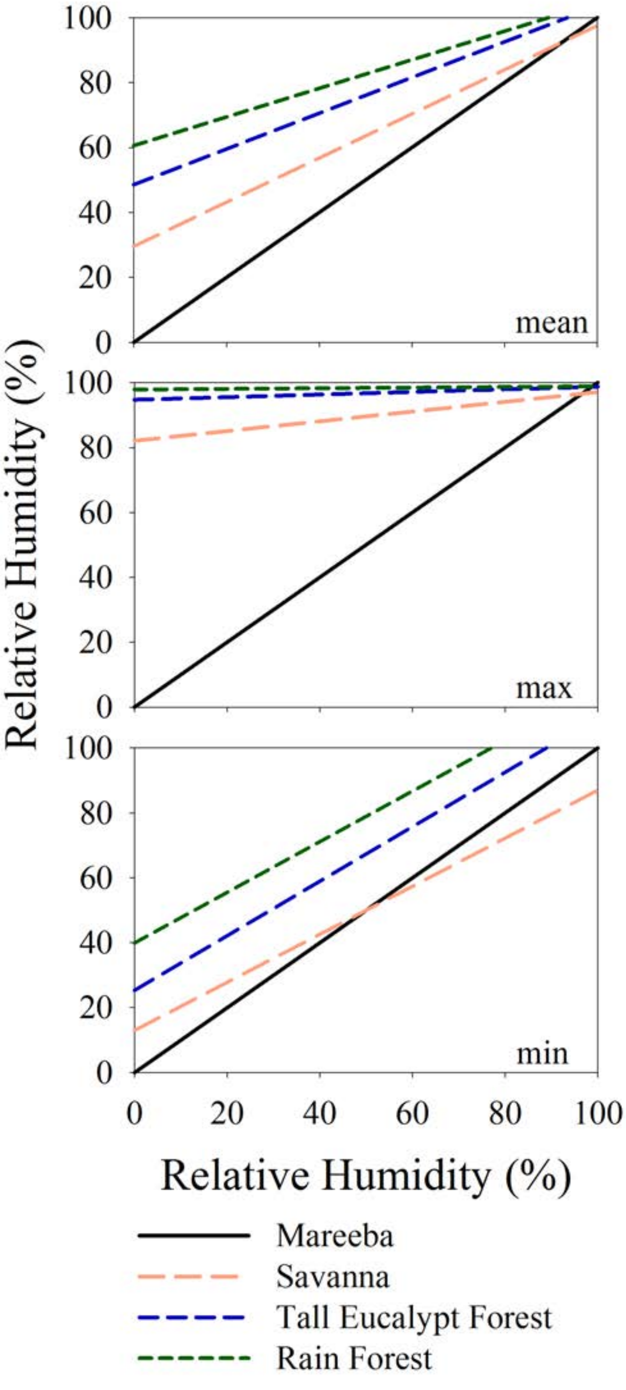

Figure 3.7 The predicted relationships of daily relative humidity (RH) in the three broad vegetation types (savanna, tall eucalypt forest and rain forest) compared with Mareeba meteorological station.

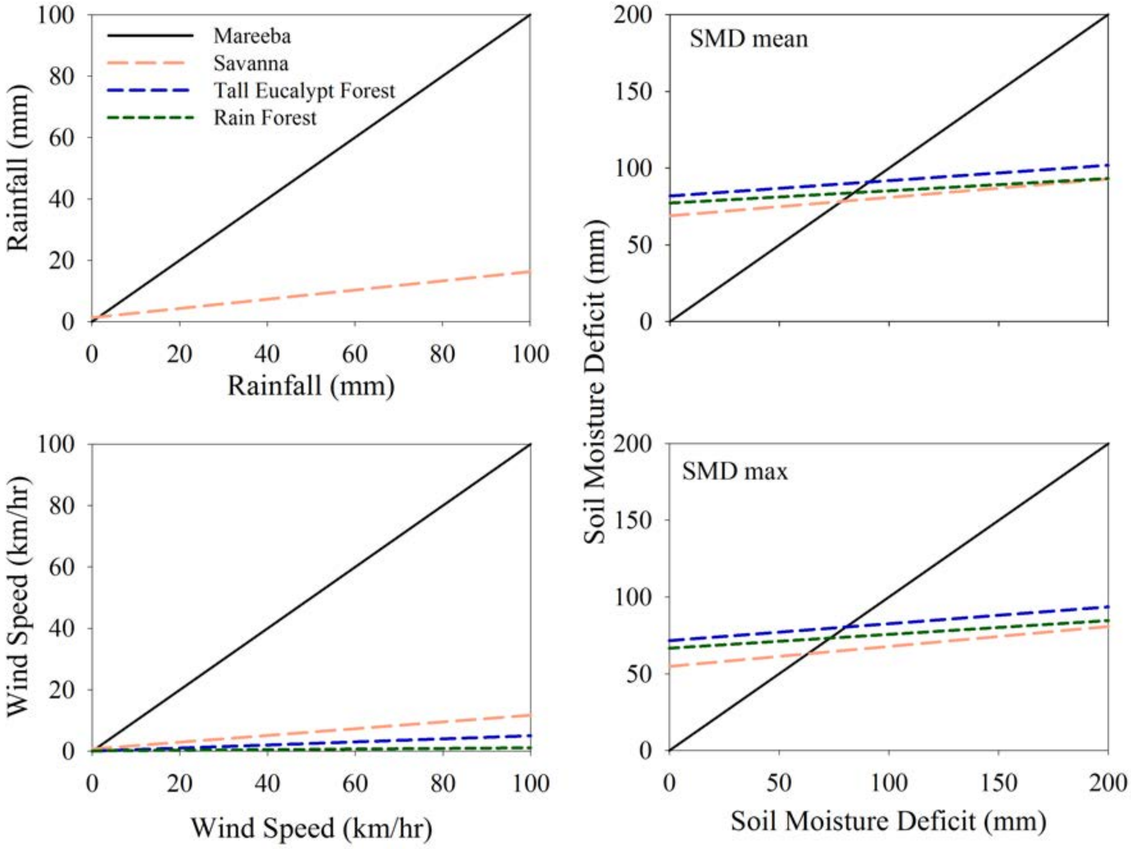

Figure 3.8 The relationships of four meteorological variables (rainfall, wind speed, mean soil moisture deficit and maximum soil moisture deficit) between Mareeba meteorological station and three broad vegetation types (savanna, tall eucalypt forest and rain forest).

Table 3.5 Summary of individual linear mixed effects models testing the relationship among vegetation type, transect and elevation with daily observed micrometeorological data at 32 field study sites (recorded daily over a three-year period). Vegetation types were rain forest (RF), tall eucalypt forest (TEF) and savanna (SAV). See Appendices 3.6-3.9 for full model details.

Micrometeorological Variable	Explained Deviance (%)	
	Vegetation: Transect	Vegetation: Elevation
temperature maximum	24.77	21.62
temperature mean	38.85	35.10
temperature minimum	21.53	15.42
relative humidity maximum	2.80	1.33
relative humidity mean	10.15	8.23
relative humidity minimum	10.21	8.17
wind speed mean	-61.21	-36.39
soil moisture deficit maximum	2.94	0.50
soil moisture deficit mean	5.42	0.84
rainfall	0.23	0.01
solar exposure	4.50	2.97

The final analysis, examined the relationship among microclimate, spatially interpolated climate and vegetation. This showed that both vegetation type and modelled climate were important in model performance and explained 0.5-63% of model deviance (Table 3.6). In most cases, the full model (Table 3.6; Appendix 3.14) had the greatest statistical support from model selection (Appendix 3.15). The only exceptions were for rainfall (rain days and total rainfall), which performed so poorly that no models explained more than 0.5% of the model deviance (Appendix 3.15.g, h). Models for temperature performed the best (27-62%), followed by relative humidity (7-24%) and wind speed (5-15%). All other variables generally showed low statistical support (1- 6% explained deviance) (Table 3.6). For the rain analyses, there appears to be no relationship between modelled rain and *in situ* rain.

Of the candidate models, vegetation type (model 3 of the candidate models, Appendix 3.15) was in most cases a better predictor of micrometeorological patterns, than modelled climate (model 2). This was consistent for fifteen of the total twenty-seven model selection processes undertaken (nine variables repeated with three different random effects). These cases consisted of both mean and maximum temperatures (both with month as a random effect), mean humidity (with month and transect as a random effect), wind run and wind speed (both with month and transect as random effects), solar exposure (with month and transect as random effects), rain days (with month and transect) and all rainfall models (Appendix 3.15). Compared with the full model, vegetation (model 3) contributed 68% (with month as random effect), 28%

(with transect as the random effect) and 5% (with elevation as the random effect) of the overall model performance for maximum temperature (Appendix 3.15). Respectively, vegetation explained 44%, 9% and 3% of overall model performance for mean temperature, 28%, 3% and 1% for minimum temperature, 81%, 47% and 15% for mean humidity, 79%, 83% and 19% for wind run, 79%, 80% and 17% for wind speed, 54%, 65% and 15% for rain days, 65%, 61% and 53% for rainfall and 90%, 76% and 12% for solar exposure. In other situations, however, modelled climate (model 2) performed better than vegetation (e.g. up to 56% better in explained deviance), for monthly average of mean temperature with elevation as the random factor (Appendix 3.15).

Table 3.6 Assessing the ability of interpolated climate data in predicting on ground microclimate conditions. Summary of linear mixed-effects models examining the relationship between monthly micrometeorological variables (as recorded over a three year period) and monthly interpolated climate (ESOCLIM) for each of 32 study sites within three vegetation types (rain forest, tall eucalypt forest, savanna). The response variable was one of nine micrometeorological variables and the explanatory variables were modelled climate of the corresponding month, vegetation type, and their interaction. Models were repeated using different random effects, with ‘month’, ‘transect’ and ‘elevation’ used alternately in separate models. The percent explained deviance (relative to the null model) for the full model is reported. For full model details, see Appendix 3.14. For model selection from candidate models, see Appendix 3.15.

Monthly meteorology	Explained Deviance (%)		
	Month	Transect	Elevation
temperature maximum	34.94	39.63	40.96
temperature mean	52.96	57.29	63.42
temperature minimum	31.81	50.57	57.64
relative humidity	24.17	20.78	15.78
wind run	4.98	5.57	2.45
wind speed	14.22	16.94	9.67
rain days	0.52	0.52	0.33
rainfall	0.37	0.41	0.34
solar exposure	3.88	5.16	2.91

3.5 Discussion

Microclimatic conditions were significantly different between vegetation types. Each microclimatic variable showed a trend between vegetation types, with savanna and rain forest at either extreme and with tall eucalypt forest in between. These trends were consistent with the physical distribution of vegetation types along the environmental gradient. Differences in vegetation microclimate were consistent with previous studies in the region (Unwin 1983; Duff 1987; Turton & Duff 1992; Turton & Sexton 1996) and elsewhere (Hoffmann *et al.* 2012b), which also showed sharp gradients between vegetation types. Although it was not possible to directly measure rainfall in all vegetation types, a three-year study of rainfall patterns on the Herberton Range in the Wet Tropics (Unwin 1983), clearly showed rainfall (measured in the open) to be highest within rain forest vegetation, followed by tall eucalypt forest and lowest in savanna. Contrary to studies that suggest that microclimate gradients across vegetation boundaries are inconstant (Newmark 2001), this study showed a consistent pattern across eight transects and with other studies.

Vegetation type had a stronger influence on microclimate than topographic factors. The consistency of this result for all transects and regardless of elevation suggests a positive feedback from vegetation on microclimate (Wilson & Agnew 1992). This feedback could be buffering sites against broader macroclimatic conditions in the landscape. Broader macroclimatic conditions in the landscape, independent of vegetation, however, could not be sampled. So the relative influence of different vegetation types on microclimate, compared to exogenous macroclimate is not known. This would require *in situ* microclimatic comparisons between above and below canopy conditions, or between below canopy and adjacent cleared area conditions where standard meteorological measurements could be made, including a 30 by 30 m clearing and 200 - 600 m buffer from vegetation that is 20 m tall (Canterford 1997). Physical sites where this could occur across an environmental gradient are extremely limited, if non-existent (see for example Pohlman *et al.* 2007, 2009).

Spatially interpolated climate data (ANUCLIM) gave a reasonable indication (up to 63%) of *in situ* below canopy microclimate conditions for some climate variables (temperature and relative humidity), but other variables (wind, solar exposure) were poorly correlated, or showed no correlation at all (rainfall, rain days). It was also demonstrated that vegetation is an important, if not better predictor of below canopy microclimate conditions than spatially interpolated climate designed for open space conditions, with vegetation outperforming modelled climate in most cases (Table 3.6; Appendix 3.15). Spatially interpolated climate data did not accurately represent the in situ conditions experienced by biota beneath a canopy..

It could be argued that interpolated climate does in fact reflect *in situ* above canopy conditions and that poor performance in predicting *in situ* microclimatic conditions is more the result of microclimatic buffering from vegetation. However, whether interpolated climate data accurately reflects *in situ* macroclimate (exogenous above canopy) conditions in complex topography is questionable (Daly 2006; McKenney *et al.* 2011). Spatially interpolated climate data based only on latitude, longitude and elevation, as with ANUCLIM (Hutchinson & Xu 2013), exclude regionally meaningful topographic and orographic factors such as rainshadows, prevailing wind direction and cloud interception (which have a strong influence in the Wet Tropics) and thus fail to represent *in situ* microclimate conditions (Daly 2006; McKenney *et al.* 2011). While others have assumed that interpolated climate data produce reliable results for above canopy climatic conditions in the Wet Tropics (Nix 1991; Mackey 1993, 1994; Hilbert & van den Muyzenberg 1999; Hilbert *et al.* 2001a, 2001b, 2007; Hilbert & Ostendorf 2001; Ostendorf *et al.* 2001; Mackey & Su 2005; Accad & Neil 2006; Graham *et al.* 2006, 2010; Hilbert 2008, 2010; VanDerWal *et al.* 2009b), this has never been tested. Quantitative experiments comparing microclimatic gradients in cleared areas and in adjacent vegetated areas are required to accurately determine exogenous and endogenous effects on micro- and macro-climates.

Spatially interpolated climate (above canopy macroclimate) data are frequently used in species or vegetation distribution modelling. If spatially interpolated climate data does not accurately reflect *in situ* macroclimate (exogenous above canopy) conditions, nor microclimate (endogenous below canopy) conditions, particularly in complex terrain, then the use of this data in species distribution modelling and for producing meaningful, spatially accurate predictions is questionable. The strong influence of vegetation on *in situ* microclimatic conditions requires consideration, as it these conditions that species experience (Storlie *et al.* 2014). These results indicate that bioclimatic models may be substantially improved by incorporating vegetation type and microclimate information.

The strong influence of vegetation on *in situ* microclimate is consistent with a vegetation feedback, which is one factor used to explain the presence of alternative stable states of vegetation (Wilson & Agnew 1992). Where alternative stable states occur, vegetation types may exist in disequilibrium with their potential climatic distribution (Beisner *et al.* 2003). Accordingly, bioclimatic models of vegetation distribution (Hilbert *et al.* 2001a, 2001b, 2007; Ostendorf *et al.* 2001; VanDerWal *et al.* 2009b) might be unable to accurately predict vegetation distributions. It might not be climate, *per se*, driving vegetation patterns, but vegetation interacting with other factors. Vegetation feedbacks on microclimate can affect other factors, such as the likelihood of fire. Fire-mediated vegetation feedbacks can influence fuel (moisture, flammability and structure) or microclimate (Wilson & Agnew 1992; Hoffmann *et al.* 2012b). Vegetation feedbacks associated with the forest – savanna boundary are documented in the Wet Tropics region (Wilson & Agnew 1992; Warman & Moles 2009; Little *et al.* 2012) and elsewhere (Beckage *et al.* 2009). Specific consideration of fire weather patterns between vegetation types across the gradients in the Wet Tropics are the subject of enquiry in Chapter 4 (Little *et al.* 2012).

Vegetation feedbacks, stochastic effects and the accuracy of spatially interpolated climate are important considerations for distribution models (Ashcroft 2010). Thus, in the quest for predicting potential future distributions, or refugia of vegetation or biota, the inclusion of disturbance events such as fire, vegetation and topography are critical (Harris *et al*. 2016). At present, however, spatially interpolated climate data does not accurately reflect *in situ* topoclimatic conditions or disturbances that affect the distribution of biotas (Pitman & Perkins 2008).

This study was the first assessment of a range of microclimatic conditions between multiple vegetation types at a landscape scale in the Australian Wet Tropics. Using this microclimate data, important knowledge gaps were addressed; the relative influences of vegetation and topography on microclimate, the correlation of *in situ* results with data from official meteorological stations (used in building climate data for bioclimatic models) and the performance of bioclimatic models in predicting local micrometeorological conditions. The results of this microclimate data have important implications for the use and interpretation of distribution models using spatially interpolated climate data.

3.5.1 Conclusions

These results demonstrate that vegetation has a significant and important effect on microclimate conditions, moreso than topographic factors, and that microclimate conditions were distinct between vegetation types. Vegetation was in many cases a better predictor of microclimate than spatially interpolated climate. Both observations were suggestive of a vegetation feedback on microclimate.

Spatially interpolated climate data displayed inherent collinearity and low performance in explaining or predicting vegetation types (Chapter 2). Tests to evaluate the reliability of interpolated data in reflecting field microclimatic conditions also demonstrated low performance. The conclusion is that spatially interpolated climate data can not reliably predict vegetation distributions relevant to biota under present, let alone future, climate scenarios. These results have significant implications for the use and interpretation of bioclimatic models and spatially interpolated climate. Spatially interpolated climate, as commonly used in distribution models, may not accurately predict actual microclimate conditions, which are the conditions experienced by biota. Furthermore, interpolated climatic data in topographically complex landscapes may oversimplify the landscape and not reflect above canopy macroclimate conditions. Consideration needs be given to the influence of vegetation microclimate feedbacks, complex topographic variations in microclimate (orographic influences and variation along environmental gradients) and extreme climatic events, rather than climate averages alone. The incorporation of vegetation and microclimate may help improve accuracy of species distribution and bioclimatic models.

Spatially interpolated climate data did not provide accurate indications of *in situ* microclimate. Accordingly, distribution models using future climate data cannot accurately predict the distribution of vegetation types at a meaningful local scale. Other methods of enquiry may be required.

a.

b.

Plate 6. Micrometeorological stations *in situ.* a. in savanna vegetation with rainfall gauge; b. depicting data retrieval.

CHAPTER 4

Fire weather risk differs across rain forest - savanna boundaries in the Wet Tropics of northeastern Australia

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4.1 Abstract

Alternative stable state theory has been applied to understanding the control by landscape fire activity of pyrophobic tropical rain forest and pyrophytic eucalypt savanna boundaries, which are often separated by tall eucalypt forests. The microclimate and relative fire risk, as measured by McArthur's Forest Fire Danger Index (FFDI), were evaluated for three vegetation types across an environmental gradient. Microclimatic data were collected from rain forest, tall eucalypt forest and savanna sites on eight vegetation boundaries throughout the Wet Tropics in north Queensland over a three year period and were compared to data from a nearby meteorological station. There was a clear annual pattern in daily FFDI with highest values in the June - July - August dry season and lowest values in the December - January - February wet season. There was a strong association of the meteorological station FFDI values with those from the three vegetation types, albeit they were substantially lower. The rank order of FFDI values amongst the vegetation types decreased from savanna, tall eucalypt forest, then rain forest, a pattern that was consistent across each transect. Only very rarely would rain forest be flammable, despite being adjacent to highly flammable savannas. These results demonstrate the very strong effect of vegetation type on microclimate and fire risk, compared to the weak effect of elevation, consistent with a fire – vegetation feedback. This study is the first demonstration of how vegetation type influences microclimate and fire risk across a topographically complex tropical forest – savanna gradient.

Key words: Alternative state stable theory, forest boundaries, feedbacks, fire ecology, fire weather danger rating

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This chapter is published (Appendix 4.1) as:

Little, J. K., Prior, L. D., Williamson, G. J., Williams, S. E., & Bowman, D. M. J. S. (2012) Fire weather differs across rain forest-savanna boundaries in the humid tropics of north-eastern Australia. *Austral Ecology* **37**, 915-925.

4.2 Introduction

The distribution of vegetation types can be predicted reliably by models using climatic, geographic and/ or edaphic variables (Chapter 2; Pearson & Dawson 2003). However, some vegetation types, such as rain forest, do not occupy their full potential ranges, apparently because of the influence of fire (Furley *et al.* 1992; Bowman 2000). Fire is an integral part of many terrestrial ecosystems globally, influencing ecosystem processes, structure and composition (Bowman 2005; Bowman *et al.* 2009). Modelling suggests that in the absence of fire, the global extent of forests would be double that of their current distribution, at the expense of more fire tolerant vegetation types such as grasslands and savanna (Bond *et al.* 2005), indicating that fire can maintain forests and savannas in alternative stable states (Hirota *et al.* 2011; Hoffmann *et al.* 2012b; Staver *et al.* 2011). Understanding how fire and vegetation patterns are interrelated demands consideration of many vegetation feedbacks. Indeed, application of alternative stable state theory to explain fire-driven biome switching from grassland to forest cover is based on the idea that fire feedbacks control landscape vegetation dynamics (Warman & Moles 2009). Nonetheless, there exist only rudimentary assessments of how interactions amongst climate and vegetation type influence landscape fire activity (Ray *et al.* 2010; Wood *et al.* 2011; Hoffmann *et al.* 2012b; Harris *et al*. 2016). Consideration was given to how vegetation type (rain forest, tall eucalypt forest and savanna) influences fire risk in the Australian Wet Tropics, as measured by McArthur's Forest Fire Danger Index (FFDI).

The Wet Tropics region is an ideal model system to understand fire-vegetation interactions. The mountainous topography (with elevations of up to 1622m) causes steep rainfall gradients that influence vegetation patterns and fire activity. Rain forests are characterised by fire sensitive species (Bowman 2000; Cochrane 2003), while eucalypt savanna are dominated by highly fire tolerant species and may burn frequently (Williams *et al.* 2003a). Tall eucalypt forests, which are often sandwiched between rain forest and savanna, experience periodic high intensity fire that kills trees, but also initiates eucalypt seedling regeneration (Unwin 1989). Eucalypt savanna and rain forest vegetation therefore represent opposite ends of the fire tolerance spectrum, with tall eucalypt forests in between. In northern Australia the drivers of these vegetation patterns have been investigated at a regional scale (Williams *et al.* 1996; Spessa *et al.* 2005) and at various sites in the Wet Tropics (Unwin 1983; Ash 1988; Unwin 1989; Turton & Duff 1992; Turton & Sexton 1996) although no landscape assessment of fire activity has been undertaken.

Landscape assessment of fire activity has relied on fire spread models that are difficult to parameterise (Cary *et al.* 2006; Schumacher *et al.* 2006) and while remote sensing analyses can yield long-term fire records, this approach is unable to detect reliably surface fires beneath dense canopies (Gillieson *et al.* 2006).The representativeness of fire indices in complex terrain or across steep gradients when calculated from remote official meteorological sites is a recognised limitation (Sharples 2009), particularly where official meteorological sites are sparsely located (Blanchi *et al.* 2010). Higher resolution, or more localised weather information is required to calibrate for regional or local conditions in these situations. New techniques are being sought to provide greater resolution to regional variation in fire risk, such as refined spatial information (Carvalho *et al.* 2011). However, quantifying fire risk based on microclimatic data from a range of locations in the landscape may provide the most useful insights into patterns of fire activity where other methods cannot be practically used (see Freifelder *et al.*1998; Drobyshev *et al.* 2010). Site-based weather information is readily used for determining fire behaviour, fire spread or fire risk (Cheney *et al.* 1993; Ray *et al.* 2005; Leonard 2009), but has rarely been used to refine or calibrate regional fire indices to local conditions. Where this has been done, local conditions show good correlation with centralised fire weather indices (Beverly & Wotton 2007; Carvalho *et al.* 2008). Fire risk was assessed across environmental gradients in the Wet Tropics of northeastern Australia using McArthur's Forest Fire Danger Index (FFDI). FFDI is the standard measure of fire danger rating in Australia most suitable for all the vegetation types in this study. Reviews of the relative performance of different fire danger rating systems have shown that this index is one of the best performing in Australian ecosystems, including those in this study (Xiao-rui *et al.* 2006; Dowdy *et al.* 2009; Matthews 2009; Sharples *et al.* 2009; Dowdy *et al.* 2010).

The aims of this research are to (1) Assess differences in fire danger between vegetation types and topographic locations along a regional environmental gradient and (2) Assess the capacity for fire danger conditions in the field to be inferred from official meteorological stations. This approach provides an alternative pathway to understand patterns of landscape fire activity in regions for which detailed meteorological or fire history information are lacking.

4.3 Methods

4.3.1 Study design

The methodologies described here build on those described in Chapter 3 (3.3). Eight transects were established on the leeward side of the mountain ranges within the Queensland Wet Tropics region, to capture the geographic variation (latitudinal, elevation and moisture) of the rain forest – tall eucalypt forest – savanna boundary (see Figures 3.1 and 3.2; Tables 3.1 and 3.2). The geology of each transect was restricted to infertile soils of granite and rhyolite (Bain & Draper 1997; Johnson 2004; Lottermoser *et al.* 2008) and basalt soils were avoided because of the limited occurrence of uncleared vegetation transitions on this parent material. Transects were orientated in an east-west axis and their length was variable, depending on the spatial scale of the vegetation transition. On each transect, at least one micrometeorological data logging station was established at a representative site within each vegetation type (there were two sites within tall eucalypt forests) and data were collected for at least one year over the three year study period (April 2007 to April 2010). The following data were collected to enable calculation of the McArthur's Forest Fire Danger Index (FFDI): air temperature, relative humidity, wind speed, soil moisture and rainfall (Noble *et al.* 1980; Sirakoff 1985; Griffiths 1999; Finkele *et al.* 2006).

4.3.2 Microclimatic measurements

Maxim data loggers (DS1923 Hygrochron iButton; www.maxim-ic.com/datasheet/index.mvp/id/4379) were used to record temperature and relative humidity and Onset HOBO Micro Station data loggers (H21-002; www.onsetcomp.com) were used for all other weather variables. Meteorological sensors were installed at1.2 m above ground level and at 10cm below the soil surface for soil moisture sensors; consistent with Australian standards (Canterford 1997). An anemometer was installed at 2 m above the ground. The minimum sampling rate was hourly. Field instruments were housed in a construction of PVC plumbing pipe.

4.3.2.1 Temperature and humidity

The temperature and relative humidity data loggers were placed inside a metal tea strainer, which was suspended within a 250 mm length of 50 mm PVC plumbing pipe (DWV 50 PVCU), capped on the upper end. Either end of the housing was perforated with approximately forty 8 mm breather holes to allow ample air circulation, with a non-perforated centre to prevent direct sunlight on the sensor. These data were calibrated against data from an approved meteorological housing (Skye Stevenson's Screens) (Canterford 1997) fitted with multiple matching iButton sensors and placed next to micrometeorological data logging stations. Readings were collected under different levels of canopy cover (0-25%, 26-75%, 76-100%) over a minimum period of 3 months at various sites. Photosynthetically Active Radiation (PAR) was also measured at these sites using a HOBO Smart Sensor (S-LIA-M003) and used as a term in the calibration equations (Appendix 3.5). R^2 for the relationships between temperature in the PVC housing and Stevenson Screen temperature ranged from 0.89 to 0.99 (Appendix 3.5). Temperature measurements taken in the PVC housing were then adjusted to Stevenson Screen measurements using the calibration equation for the corresponding level of canopy cover. The adjusted data were used to calculate FFDI.

4.3.2.2 Soil moisture

Soil moisture was measured at each site using a HOBO compatible ECH_2O Dielectric Aquameter probe (S-SMA-M005 or S-SMC-M005; www.onsetcomp.com). Probes were placed into naturally compacted soil at a 45-degree angle between 10 cm below the soil surface. Soil moisture data for each site was calibrated in the laboratory following recommended techniques described by Campbell (www.microdaq.com/occ/documents/calibrating_echo_soil_moisture_probes.pdf). These data were used to generate a daily Soil Moisture Deficit index (SMD) as used in FFDI calculation (Griffiths 1999), which assumes a maximum SMD factor of 200 mm (Finkele *et al.* 2006). Soil moisture values were then converted to SMD values, where maximum field soil dryness was equivalent to a SMD value of 200 mm and maximum soil saturation given a SMD value of 0 mm.

4.3.2.3 Rainfall

A rain gauge (Davis Instruments Rain Collector; www.davisnet.com) connected to the Onset data logging system was installed for every transect at each savanna site where there was an open canopy and rainfall interception was not likely to influence records. Rain gauges were not located beneath rain forest and tall eucalypt forest canopies because interception and stem flow make it difficult to directly measure inputs of water in these environments (Ashton & Attiwill 1994; McJannet *et al.* 2007). Rainfall in these vegetation types was predicted from soil moisture measurements, based upon the following empirical relationship between rainfall and soil moisture recorded at the savanna sites:

Rainfall (mm)= -0.1 + 510* (increase in soil moisture) (mm), R^2 = 0.992.

This equation was also used to estimate rainfall in the savanna sites during periods when no rainfall data were collected due to instrument malfunction. Only daily rainfall greater than 2 mm was used in the calculation of the FFDI.

4.3.2.4 Wind

Wind and gust speed were measured with the HOBO Wind Speed Smart Sensor (S-WSA-M003). Australian standards specify anemometers to be exposed at 10 m above the ground, however, this was not possible for this study and were instead exposed at 2 m.

4.3.3 Forest Fire Danger Index (FFDI)

McArthur's Forest Fire Danger Index (FFDI) was selected as the most widespread measure of fire risk in Australia most suitable for each of the vegetation types. To provide a longer-term context for this study, FFDI was calculated using data from a nearby official meteorological station site at Mareeba, from October 1991 to April 2010, the period for which appropriate data were available. Input data were daily measures of maximum temperature, mean wind speed, minimum relative humidity, total rainfall and mean soil moisture (Noble *et al.* 1980; Sirakoff 1985; Griffiths 1999; Finkele *et al.* 2006). FFDI at Mareeba Meteorological Station was calculated using the Keetch-Byram Drought Index (KBDI) to estimate Drought Factor and Soil Moisture Deficit. KBDI is a surrogate measure used for estimating SMD in FFDI calculations with inputs of rainfall and maximum temperature (Finkele *et al.* 2006).

Forest Fire Danger Index (FFDI) was calculated daily for the three-year (1096 day) study period for all sites using measured microclimatological data. Where there were gaps in the data due to equipment failure, information from adjacent sites was used to calculate FFDI on those days. In contrast to Mareeba meteorological data, the Soil Moisture Deficit (SMD) on the transects was calculated from direct measures of soil moisture calibrated to the standard 0-200 mm soil water capacity (Finkele *et al.* 2006) and Drought Factor was estimated using predicted rainfall and SMD.

4.3.4 Statistical modelling

Linear mixed effects modelling, multi-model inference and model selection based on Akaike's Information Criterion (AIC) (Burnham & Anderson 2002) were used to determine the relative influences of vegetation type and location on FFDI. To examine relationships among the vegetation types across the full range of temporal variability in FFDI, pairwise comparisons were made of the daily FFDI of the three major vegetation types in all eight transects (rain forest (RF), tall eucalypt forest (TEF) and savanna (SAV)). For each of these three sets of analyses (RF *versus* SAV, TEF *versus* SAV and RF *versus* TEF), linear models were used with response variable FFDI of vegetation type 1, and the explanatory variables FFDI of vegetation type 2, transect, and their interactions. Candidate model sets containing all combinations of the explanatory variables and their interaction were evaluated.

Linear mixed-effects models were used to investigate the relationship between vegetation type (rain forest, tall open forest and savanna) and elevation. The response variable was FFDI and the explanatory variables were vegetation type, elevation and their interaction, with 'day' as a random factor.

Linear mixed-effects models were also used to examine the relationship between FFDI calculated for Mareeba meteorological station and the FFDI for each of the three vegetation types. The response variable was FFDI for each site, and the explanatory variables were FFDI at Mareeba, vegetation type, and their interaction. For this analysis, 'Transect' was used as a random effect, because its effect was shown to be minor relative to the vegetation effect. Statistical analyses were run using the statistical package "R" (Version 2.11.1; R Development Core Team 2002) and S-PLUS software (Version 8.0; Insightful Corporation, Seattle, USA).

4.4 Results

The meteorological variables measured in each of the three vegetation types closely tracked the measurements at the Mareeba meteorological station, albeit at different levels. Maximum temperature (Figure 4.1) and minimum relative humidity (Figure 4.2) in the savanna were closest to Mareeba, followed by tall eucalypt forest and then rain forest. Wind speed (Figure 4.3) was substantially higher at Mareeba than in any of the transects, but shows the same pattern with savanna most closely related, then tall eucalypt forest, then rain forest. Soil moisture deficit (Figure 4.4) was well correlated among vegetation types, with a general trend for rain forest soils to be the wettest, followed by tall eucalypt forest and savanna. The surrogate KBDI measure at Mareeba, while picking up seasonal extremes of field SMD measures such as peak soil saturation during the month of February, does not show a strong correlation with *in situ* soil moisture patterns. Rainfall in the savanna was reasonably well correlated with Mareeba, although generally lower (Figure 4.5).

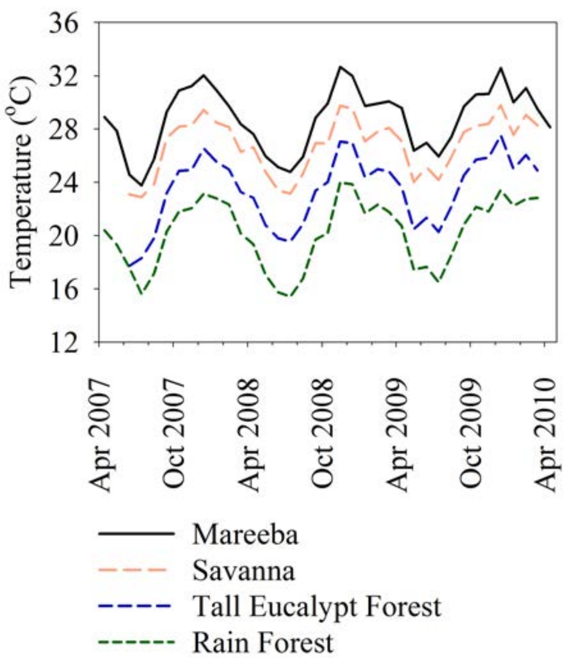

Figure 4.1 Average monthly maximum temperature at the meteorological station at Mareeba and within three broad vegetation types (savanna, tall eucalypt forest and rain forest) in the Australian Wet Tropics region over a three-year study period (see also Figure 3.3).

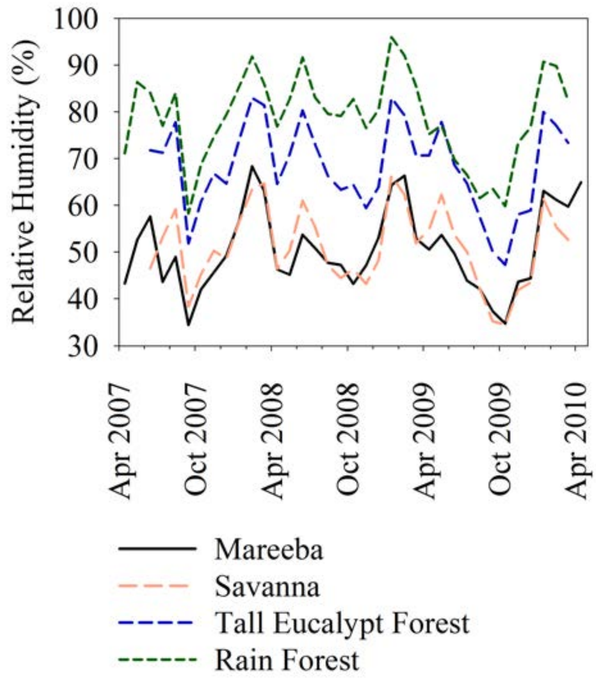

Figure 4.2 Average monthly minimum relative humidity at the meteorological station at Mareeba and within three broad vegetation types (savanna, tall eucalypt forest and rain forest) in the Australian Wet Tropics region over a three-year study period (see also Fig 3.4).

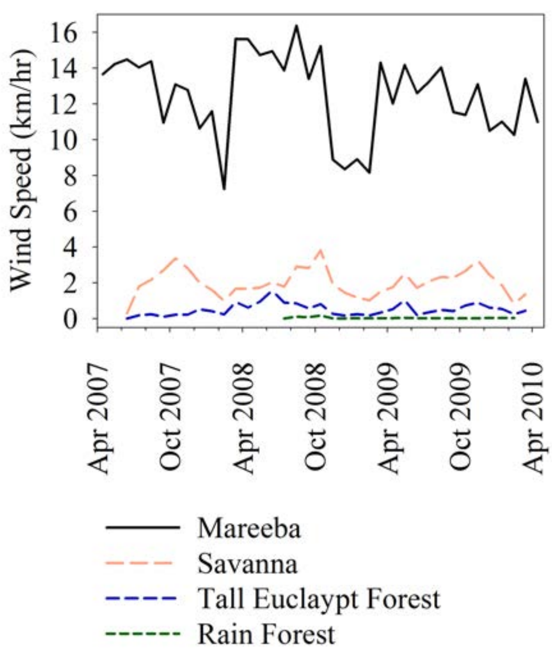

Figure 4.3 Average monthly wind speed at the Mareeba meteorological station and within three broad vegetation types (savanna, tall eucalypt forest and rain forest) in the Australian Wet Tropics region over a three-year study period (see also Fig 3.5).

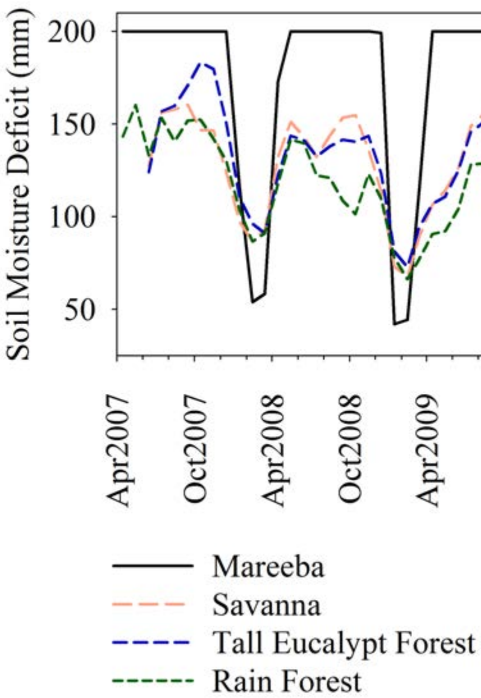

Figure 4.4 Average monthly Soil Moisture Deficit (SMD) within three broad vegetation types (savanna, tall eucalypt forest and rain forest), plotted against the Keetch-Byram Drought Index (surrogate SMD measure) at the Mareeba meteorological station in the Australian Wet Tropics region over a three-year study period (see also Fig 3.5).

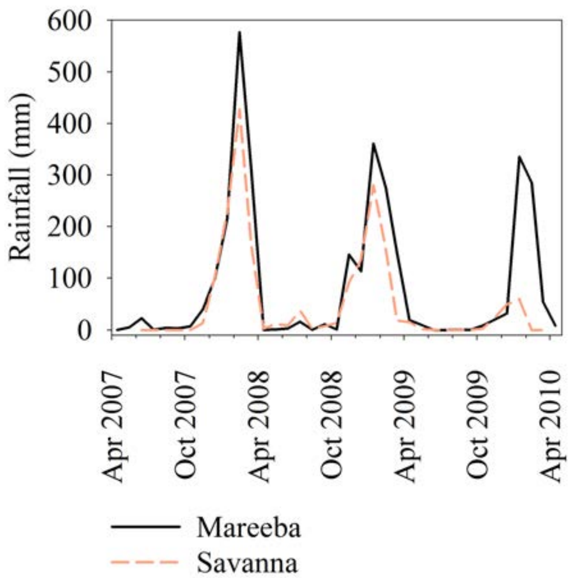

Figure 4.5 Total monthly rainfall recorded at the meteorological station at Mareeba and averaged across 8 sites in savanna vegetation in the Australian Wet Tropics region over a three-year study period (see also Fig 3.5).

The Forest Fire Danger Index at Mareeba during the three-year study period (Figure 4.6) was representative of that recorded at Mareeba since earliest available records (Figure 4.7). The FFDI values calculated from Mareeba data were higher than, but strongly correlated with those values calculated for transects. The statistical analysis showed the best-supported model

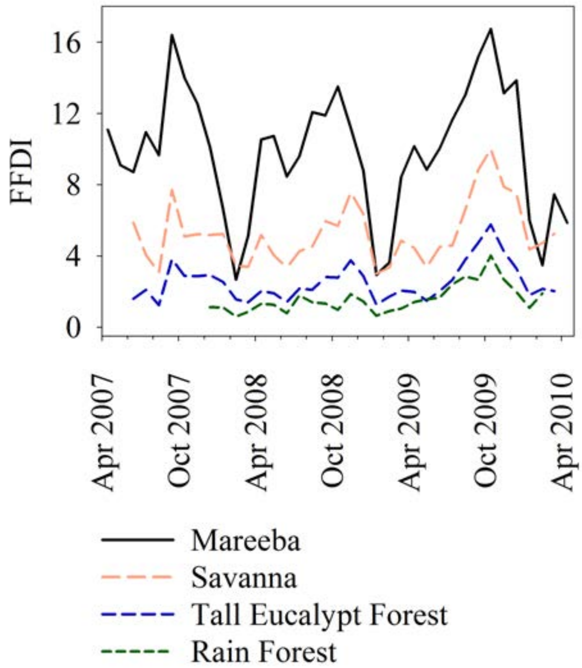

Figure 4.6 Average monthly Forest Fire Danger Index (FFDI) at the meteorological station at Mareeba and within three broad vegetation types (savanna, tall eucalypt forest and rain forest) in the Australian Wet Tropics region over a three-year study period.

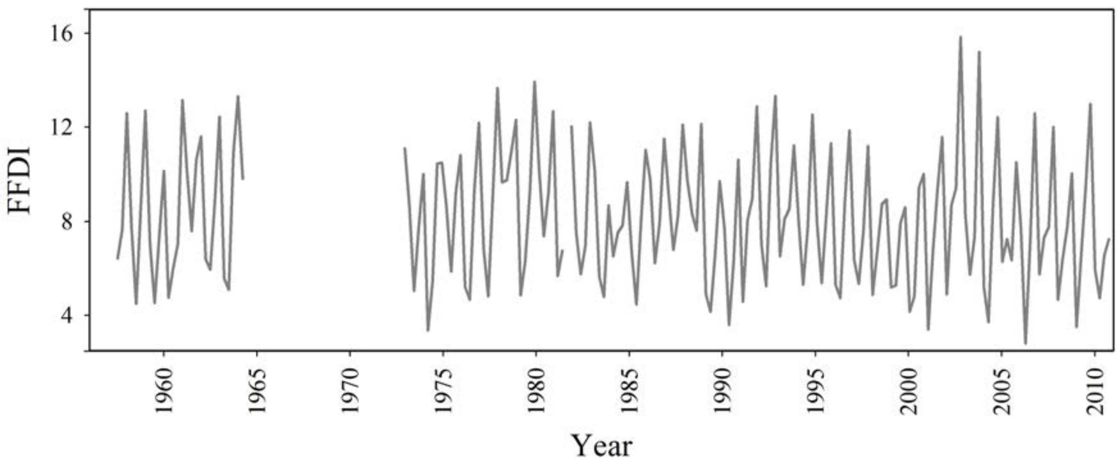

Figure 4.7 Average monthly Forest Fire Danger Index (FFDI) at Mareeba between 1957 and 2010. The study period from April 2007 to April 2010 was typical of the entire period.

Mareeba FFDI (Table 4.1). This result indicates that the slope of the relationship with Mareeba FFDI differed among vegetation types, and was largest for savanna (23.7), intermediate for tall eucalypt forest (15.2), and lowest for rain forest (10.9), which showed the largest departure from the Mareeba values (Figure 4.8).

Amongst the three vegetation types there was a decline in median FFDI from savanna (4.2) to tall eucalypt forest (1.9) and rain forest (1.1). This rank order of FFDI values amongst the vegetation types was consistent across each transect. There was a clear seasonal pattern in FFDI with highest values during the late dry season from August to November and lowest during the wet season from January to April. For example, 75-85% of the FFDI values above the 95^{th} percentile occurred between August and November for each vegetation type, as did 87-96% of the values above the 98^{th} percentile. A feature of these data are the long tails of outliers above the 90th percentile (Figure 4.9) which have the same rank order among vegetation types as the median values.

The most extreme FFDI recorded in savanna was 33.9 compared with 29.6 in tall eucalypt forest and 21.3 in the rain forest. Pairwise comparison of the daily FFDI values amongst the three vegetation types revealed that there was a strong correlation amongst these variables, with the global model receiving all the statistical support in all cases (Table 4.2). In keeping with the results above, the strength of the association was greatest for vegetation types that are typically adjacent and ecologically similar, namely savanna *versus* tall eucalypt forest (45% deviance explained) and tall eucalypt forest *versus* rain forest (49% deviance explained) and lowest for rain forest *versus* savanna (32% deviance explained). Although the variable ‘transect’ was included in all of the pairwise models, the contribution this variable made to the models was low (between 2 and 5% deviance explained), signalling the limited effect of location relative to vegetation type on FFDI patterns.

Investigation of the relationship between vegetation type and elevation showed that both vegetation type and elevation influenced FFDI, with an interaction between the two. The global model showed the greatest statistical support (wi = 1.0) and explained 6.1% of the deviance in the data relative to the null model (Table 4.3). Vegetation type alone showed the greatest individual influence on FFDI and explained 6.0% of the deviation compared with elevation (1.0%).

Table 4.1 Linear mixed effects models comparing Forest Fire Danger Index (FFDI) of the three vegetation types with those of the meteorological station at Mareeba (first model set). The response variable was FFDI for the vegetation type, and the explanatory variables were FFDI at Mareeba on the corresponding day, vegetation type, and their interaction (i.e. the multiplicative effects of the two predictive variables). 'Transect' was a random effect in all models. *wi* is the Akaike weight, and 'D^2' is % explained deviance relative to the null model. This model set shows that all of fire risk at Mareeba, vegetation type, and their interaction were useful predictors of fire risk.

Model	Formula	*wi*	D^2
Global	FFDI ~ Mareeba * VegType	1.00	10.3
Model 1	FFDI ~ Mareeba + VegType	0.00	9.7
Model 2	FFDI ~ Mareeba	0.00	4.9
Model 3	FFDI ~ VegType	0.00	3.5
Null Model	FFDI ~ 1	0.00	NA

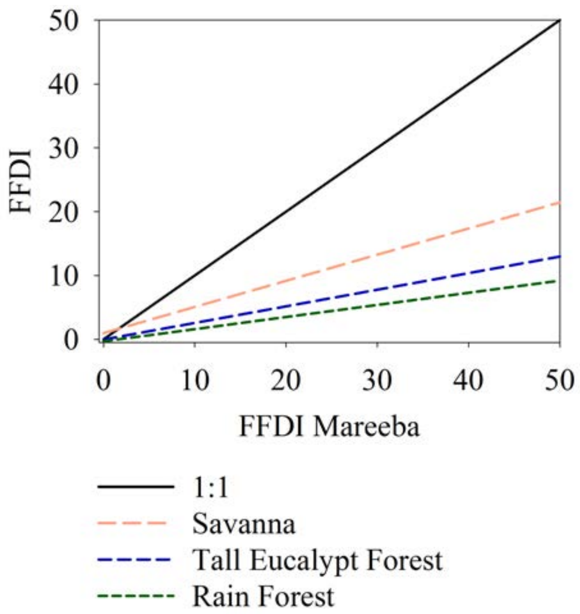

Figure 4.8 The predicted relationships of daily Forest Fire Danger Index (FFDI) in the three broad vegetation types (savanna, tall eucalypt forest and rain forest) compared with Mareeba meteorological site.

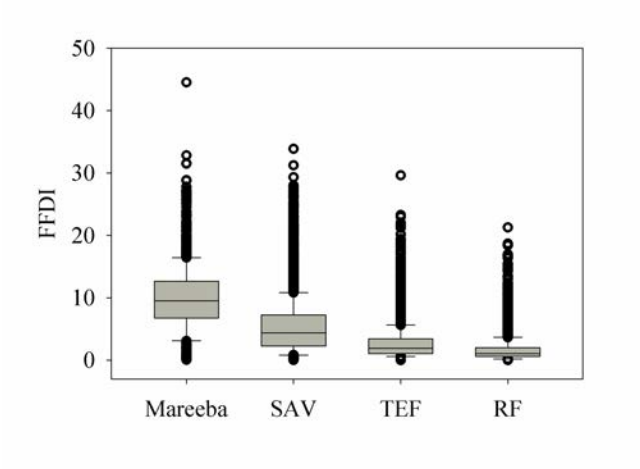

Figure 4.9 Daily Forest Fire Danger Index (FFDI) at the meteorological station at Mareeba and within three broad vegetation types (savanna (SAV), tall eucalypt forest (TEF) and rain forest (RF) in the Australian Wet Tropics region over a three year study period. Boxes indicate medians (lines) and upper and lower quartiles, bars show 10^{th} and 90^{th} percentiles and circles, outliers.

Table 4.2 Linear models comparing Forest Fire Danger Index (FFDI) among vegetation types and landscape positions (transect). The three vegetation types, rain forest (RF), tall eucalypt forest (TEF) and savanna (SAV) were compared in a pairwise fashion in the three models shown below. The response variable was FFDI of vegetation type 1, and the explanatory variables in the global model were FFDI of vegetation type 2, transect, and their interaction (i.e. the multiplicative effects of the two predictive variables). The candidate model sets shown compared all combinations of these explanatory variables. Akaike weights (*wi*) indicate the preferred model and overall model performance is indicated by percent of the deviance explained (D^2).

Model	Formula	*wi*	D^2
Global	FFDI_RF ~ FFDI_SAV * Transect	1.0	32.3
Model 1	FFDI_RF ~ FFDI_SAV + Transect	0.0	31.4
Model 2	FFDI_RF ~ FFDI_SAV	0.0	26.9
Model 3	FFDI_RF ~ Transect	0.0	2.7
Null Model	FFDI_RF ~ 1	0.0	0
Global	FFDI_TEF ~ FFDI_SAV * Transect	1.0	44.9
Model 1	FFDI_TEF ~ FFDI_SAV + Transect	0.0	42.1
Model 2	FFDI_TEF ~ FFDI_SAV	0.0	37.1
Model 3	FFDI_TEF ~ Transect	0.0	4.5
Null Model	FFDI_TEF ~ 1	0.0	0
Global	FFDI_RF ~ FFDI_TEF * Transect	1.0	49.4
Model 1	FFDI_RF ~ FFDI_TEF + Transect	0.0	47.5
Model 2	FFDI_RF ~ FFDI_TEF	0.0	44.4
Model 3	FFDI_RF ~ Transect	0.0	2.7
Null Model	FFDI_RF ~ 1	0.0	0

Table 4.3 Comparison of linear mixed-effects models investigating the relationship between fire and vegetation type (savanna, tall eucalypt forest and rain forest) with elevation. The response variable was Forest Fire Danger Index (FFDI) and the explanatory variables were vegetation type (VegType), elevation, their interaction and with 'day' as a random factor. The model with most support (global model) has the highest Akaike weight (*wi*) and highest percent explained deviance (D^2).

Model	Model Formula	*wi*	D^2
Global	FFDI ~ VegType * Elevation + (1 | Day)	1.0	6.11
Model 1	FFDI ~ VegType + Elevation + (1 | Day)	0.0	6.03
Model 2	FFDI ~ VegType + (1 | Day)	0.0	6.02
Model 3	FFDI ~ Elevation + (1 | Day)	0.0	1.07
Null Model	FFDI ~ 1 + (1 | Day)	0.0	NA

4.5 Discussion

Weather variations at different positions in a topographically complex landscape strongly affect fire risk, but have rarely been studied in detail (Bradstock *et al.* 2010; Holden & Jolly 2011). Fire risk across climatic gradients, however, have demonstrated the influence of climatic variables (Barton 1994; Kitzberger *et al.* 1997; Haire & McGarigal 2009; Krawchuk *et al.* 2009; Krawchuk & Moritz 2011), elevation (Caprio & Swetnam 1995) and combinations of elevation and climate (Barton 1994). Likewise, fire risk has been demonstrated to be influenced by fuel characteristics across vegetation gradients (Kauffman *et al.* 1994; Biddulph & Kellman 1998; Hoffmann *et al.* 2012b). Here is presented the first field study of fire risk across an environmental gradient in complex terrain. It was demonstrated that vegetation influences microclimatic characteristics of fire risk to a greater extent than elevation or transect location. This study showed that vegetation type has a pronounced influence on microclimate (see also Chapter 3) and fire risk across rain forest boundaries, with rain forest having the lowest levels of FFDI and savanna the highest. These patterns were consistent across eight rain forest boundaries in representing steep climatic gradients regardless of transect location or elevation in the north Queensland Wet Tropics.

These results harmonise with previous microclimatic studies in the Wet Tropics, which also showed steep gradients of light and humidity across rain forest boundaries (Turton & Duff 1992; Turton & Sexton 1996). Such microclimatic patterns reinforce other factors that increase the likelihood of fire outside rain forest boundaries (Cochrane 2003; Hoffmann *et al.* 2009). Of prime importance is the change from dense leaf litter layers characteristic of rain forests to the aerated grass fuels in the savannas (Unwin *et al.* 1985; Bowman & Wilson 1988; Banfai & Bowman 2007). However, whether the microclimatic gradient reflects the climate of the region (i.e. exogenous effect) or is a consequence of the vegetation gradient (i.e. an endogenous effect) remains uncertain. To resolve this requires controlled experiments (e.g. comparing microclimate gradients along cleared areas, such as powerline easements, that cut across rainforest boundaries with adjacent uncleared areas) with siting of meteorological instruments that meet Australian standards (Canterford 1997). A network of such sites does not exist in this region.

FFDI values in tall eucalypt forest were intermediate between those in rain forest and savanna, reflecting the open crowns of the eucalypts and the variable understorey stratum, which can range from grass to closed shrub and tree layer. These forests produce high volumes of leaf litter and have higher and more flammable fuels than the rain forests they adjoin (Parsons & Congdon 2008). These factors may allow infrequent fires to burn into tall eucalypt forests, which trigger the regeneration of eucalypt species that may otherwise be inhibited by the shading of rain forest understories in long unburnt stands (Stocker & Unwin 1986; Duff 1987). Intense fires are important in opening up rain forest understories beneath tall eucalypt forests, and under extreme fire weather conditions fires in these forests can also spread into adjacent rain forest. Nonetheless, some rain forest species that are burnt by fire can recover from fire damage albeit at a slower rate than eucalypts (Stocker & Unwin 1986; Adam 1992; Marrinan *et al.* 2005; Edwards & Krockenberger 2006; Williams *et al.* 2011).

The contrasts in fuel type and FFDI between rain forest and savanna result in higher levels of fire activity in the savanna and therefore provide a fire-vegetation feedback. Vegetation feedbacks in relation to fire and forest – savanna boundaries have been demonstrated in Australia and elsewhere (Wilson & Agnew 1992; Hoffmann *et al.* 2002; Beckage & Ellingwood 2008; Beckage *et al.* 2009; Hoffmann *et al.* 2009; Warman & Moles 2009; Odion *et al.* 2010). Indeed, Wilson and Agnew (1992) described fire-mediated vegetation feedback switches using the specific example of rain forest boundaries in the Australian Wet Tropics. Warman and Moles (2009) applied alternative stable state theory to rain forest boundaries in the Wet Tropics. They suggested that although rain forest and savanna occupy sites with contrasting moisture and soil availability, fire can cause changes from one state to another. They considered tall eucalypt forest as an intermediate and geographically mobile community that is sandwiched between pyrophobic rain forest and pyrophytic savanna. The biological diversity of tall eucalypt forests and the dependence on fire for regeneration suggest they are a specialised ecotonal habitat.

Although fire weather (such as measured by FFDI) influences fire activity, so too does biomass, fuel availability and ignitions (Bradstock 2010). The Wet Tropics are a highly productive environment, so biomass availability is only ever limiting during a short period after a fire. Flammability of fuels, however, is clearly constrained by the seasonal moisture cycle (Figure 4.5). These results demonstrate that FFDI varies markedly across rain forest boundaries. Yet even under extreme fire weather conditions when rain forest would burn, ignitions are often limiting. The two sources of fire ignitions in the Wet Tropics are lightning and anthropogenic ignitions, with anthropogenic ignitions being the greatest contemporary cause of fire (Ash 1988;

Fensham 1997; Preece 2007), consistent with other regions in Australia (Davies 1997). Indigenous Australians have used fire since their arrival on the continent (Bowman 1998), although there is debate as to how much they increased fire activity above background levels (Enright & Thomas 2008; Mooney *et al.* 2011). In the Australian Wet Tropics, palynological evidence points to increased burning at the time of Aboriginal colonisation in the late-Pleistocene, although this fire activity was unable to limit the Holocene expansion of rain forest (Kershaw 1986; Hopkins *et al.* 1990, 1993; Kershaw 1994; Haberle 2005). The palynological records suggests that subsequent European land management also shows an increase in forest disturbance and fire activity (Haberle *et al.* 2006; Mooney *et al.* 2011), in contrast to ecological evidence of recent expansion of rain forests into tall eucalypt forests, which has been raised as a potential conservation issue (Harrington & Sanderson 1994).

The FFDI values computed for Mareeba are low compared with elsewhere in Australia (Finkele *et al.* 2006), with fewer than 5% of values exceeding an FFDI of 20, which is regarded as high fire risk (Figure 4.6). Even fewer days (0.03 %) exceeded this value in rain forest, which highlights the importance of rare extreme events in causing fires in rain forest. The statistical relationships between FFDI values calculated from the Mareeba meteorological station and those measured in each vegetation type, should be considered with caution. The comparison of above canopy FFDI with below canopy (microclimate) FFDI are not equivalent measures. The accuracy of microclimate FFDI has not been tested for accurately reflecting actual fire hazard. None-the-less, microclimate FFDI does allow assessment of relative fire danger between vegetation types and may be a useful surrogate measure for other influencing factors such as fuel moisture. The statistical relationships with official meteorological stations could be used by land managers to predict periods of extreme fire danger in each vegetation type. They can also be used to reconstruct past fire danger patterns (Lucas 2010) using historical data from other meteorological stations and thus identify return times of extreme fire weather events for each vegetation type. This is the subject of enquiry in Chapter 5. Likewise, these relationships can be used to predict changes in fire risk under future climate scenarios (Hennessy *et al.* 2005; Lucas *et al.* 2007; Hasson *et al.* 2008; Clarke *et al.* 2011) and to quantify the likely climate change impacts on vegetation types (Williams *et al.* 2009). Further research is required to relate FFDI to actual landscape fire in order to identify thresholds when savanna, tall eucalypt forest and rain forest will burn.

4.5.1 Conclusions

The Australian Wet Tropics have a strongly seasonal climate, with peak FFDI values in the June - July - August dry season. However, these peak FFDI values are low relative to those overall in the rest of Australia. These results demonstrate a very strong gradient in FFDI values across rain forest – savanna boundaries in the Australian Wet Tropics and highlight the importance of rare extreme FFDI values in providing conditions conducive for fire spread in rain forest or tall eucalypt forests. A vegetation – fire risk feedback helps explain the juxtaposition of pyrophobic rain forest and pyrophytic savanna, and also the existence of tall eucalypt forests, which require periodic severe fires to regenerate and resist engulfment by rain forest.

Plate 7. Prescribed fire in tall eucalypt forest above 1000 metres elevation in the Lamb Range (Davies Creek National Park), Australian Wet Tropics. The vegetation gradient can be seen, with savanna in the foreground (light green), tall eucalypt forest on the midslopes (tall white tree trunks) and rain forest vegetation (dark green with closed canopy) on the mountain summit (Kahlpahlim, 1306 m asl).

CHAPTER 5

Historic trends in climate and fire danger: evidence of climate change trajectories and implications for vegetation

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5.1 Abstract

How vegetation might be affected by different stressors is usually assessed by different types of models. The impact of climate change on vegetation is often examined with distribution models, whereas the impact of changing fire conditions is usually assessed with a perturbation models, but rarely are multiple stressors assessed together. In any case, model projections of future climate and fire danger may be too coarse to accurately reflect local scale conditions relevant to vegetation and biota. Spatial climate data is often based on over-simplified interpolation algorithms, which do not capture important local scale conditions, such as the microclimatic conditions experienced by biota. Using coarse scale models is unlikely to yield accurate spatial predictions on how vegetation might be affected by future climate or fire danger.

Climate data, as used in models, generally represent average conditions, not extremes or variability. Yet extreme climatic or fire danger events are possibly the most acute impact of climate change on biota or vegetation. Understanding the intensity and frequency of such extreme events requires knowledge of long-term climatic patterns, rather than generalised climate averages.

Rather than relying on dubious, coarse-scale models of future climate and fire danger to predict future distributions of vegetation, this study took a quantifiable data approach to assess how climate change and fire might affect vegetation. This was done by examining climate and fire danger patterns and trends at a local scale relevant to vegetation types and biota. Specific objectives were to: (1) identifying historic climate and fire danger trends and extremes within the Wet Tropics region; (2) determine whether observed climate and fire danger trends were consistent with projected future climate trajectories; and (3) identify historic and likely future changes in climate and fire danger relative to vegetation types.

Historic trends in climate and fire danger were analysed from two official meteorological sites in the Australian Wet Tropics. Observed daily climate data at Cairns (1890-2010) and Mareeba (1957-2010) were analysed with dynamic time series regressions for trends and extremes. Fire danger, as represented by the Forest Fire Danger Index (FFDI) was reconstructed at these sites for the time series and was also analysed for trends and extremes. Relationships between daily conditions at Mareeba and conditions within three

different vegetation types (rain forest, tall eucalypt forest and savanna) was known from a previous study. Quantified relationships between climate and fire danger trends at Mareeba with those of three vegetation types were used to reconstruct historic trends and extremes for each vegetation type. This allowed evaluation of actual recurrence and magnitude of extreme events experienced by biota and vegetation and potential insight into future conditions.

Means, maxima and minima for a suite of historic climate and fire danger variables were assessed for trends. The trajectories for each trend were compared with documented future climate projections. Cairns and Mareeba displayed similar trends for some variables, but opposing trends for others. This indicated substantial intra-regional climatic variability over even a short distance (40 km). Average and extreme fire danger increased significantly (p<0.05) at Cairns between 1890 and 2010, however, fewer significant results were observed between 1957 and 2010. Similarly, fire danger trends at Mareeba were not significant between 1957 and 2010 (p<0.05), but some trends were near significance including a decrease in average fire danger (p=0.06) and an increase in extreme fire danger (p=0.13). The climatic variables underlying fire danger contributed to these results in different ways. For example, temperature significantly increased at both sites and rainfall also increased at Mareeba only. Fire danger levels were lower in each vegetation type than at Mareeba and, consistent with trends at Mareeba, showed an increasing trend in extreme fire danger conditions.

The trajectories of observed climatic and fire danger trends were generally consistent with future climate projections. However, future projections are not available at an intra-regional scale and downscaled projections remain inaccurate. Results here indicate significant variation at the intra-regional scale and provide greater regional detail for future climate and fire danger trajectories. With this detailed information, accurate predictions of climate change impacts on vegetation types and fire regimes may be more robust. It is likely that the patterns and trends described here hold greater certainty as climate change trajectories than projections based on global climate models that do not evaluate local-scale climate conditions. Increases in extreme fire danger pose a threat to fire sensitive tall eucalypt forests and rain forests, with immediate implications for fire management practices in these communities.

Key words: fire, climate, fire danger rating, environmental gradient, rain forest, tall eucalypt forest, savanna, historic, alternative stable states

5.2 Introduction

Meteorological observations are commonly summarised to understand climatic trends, cycles, spatial and temporal variability and to make predictions about future climate (Sturman & Tapper 2006; Mudelsee 2010; Rao *et al.* 2012). Meteorological data are also used to evaluate fire danger, drought conditions or other extreme weather events (Griffiths 1999; Finkele *et al.* 2006; Nicholls 2008). Recent and historic observed climate trends have been used to make projections for climate change in the 21st century. The influence of anthropogenic enhanced global climate change has already been observed in the climate record, with future projections indicating accelerating changes and substantial environmental, social and economic impacts, both globally and locally (IPCC 2013; Allen *et al.* 2014).

For Australia, observable changes in climate have occurred over the last century, partly attributable to anthropogenic enhanced climate change (Hughes 2003; Nicholls 2006; Steffen *et al.* 2009; CSIRO & Bureau of Meteorology 2014, 2015). Recent analysis of climate trends in Australia (CSIRO & Bureau of Meteorology 2014, 2015) indicate an accelerating rate of change and substantial increases in environmental impacts. Temperatures have increased, heatwaves have increased, rainfall has changed in pattern, average fire danger and extreme fire danger conditions have both increased and fire seasons have become longer. These ongoing and worsening conditions will have profound impacts on society and the environment, including vulnerable ecosystems and species. Impacts of climate change have already manifest in biological and ecological systems and are predicted to accelerate with future climate change projections (Hughes 2003; Steffen *et al.* 2009; CSIRO & Bureau of Meteorology 2014, 2015).

The identification of key vulnerable regions and ecosystems to climate change (Hughes 2011) provides the opportunity to focus attention on likely impacts of climate change in priority areas and to devise adaptation, mitigation and conservation strategies (Lindenmayer *et al.* 2010). For example, the Wet Tropics region of northeastern Australia, which is a biologically, geographically and climatically complex region of outstanding ecological and evolutionary significance, is identified as a key vulnerable region (Hughes 2011). This region is expected to experience potentially catastrophic climate change impacts (Hilbert *et al.* 2001b; Williams *et al.* 2003b; Williams & Hilbert 2006; Williams *et al.* 2008; Hilbert *et al.* 2014; Costion *et al*. 2015; McInnes *et al.* 2015).

Projections of future climate are frequently used to predict impacts of climate change on species or ecosystems. Predicted impacts may indicate whether species or vegetation types, may expand, contract or shift in their distribution based on bioclimatic niches (Beaumont *et al.* 2005; Beaumont *et al.* 2007; Franklin 2009). These predictions may assist in the identification of climate refugia for threatened biota (Ashcroft *et al.* 2009; Ashcroft 2010; Shoo *et al.* 2011; Keppel & Wardell-Johnson 2012; Keppel *et al.* 2012; Mackey *et al.* 2012; Reside *et al.* 2013, 2014) and prioritisation of conservation issues to develop mitigation or adaptation strategies

(Lindenmayer *et al.* 2010). Bioclimatic niche, or simply distribution models are generally based on spatially interpolated climate information (Jeffrey *et al.* 2001; Booth *et al.* 2014) and presence records of species or communities, which may then be extrapolated to different climate in the past or future. Spatially interpolated climate information used in such models, however, has its limitations.

Spatially interpolated climate information may be a useful representation of mean climate values for that period of time upon which it summarises, however, such summaries do not portray anomalies, extremes or variability in meteorological conditions during that time period, nor any representation of longer time periods (Power *et al.* 1999; Pitman & Perkins 2008). Rare events (such as a one in one hundred year event) may be of significant biological importance or a critical limiting factor for some biota are simply not represented. Species and vegetation distributions are often influenced by these factors, rather than mean conditions (Power *et al.* 1999; Parmesan *et al.* 2000; Ashcroft *et al.* 2009; Reside *et al.* 2010; Bateman *et al.* 2012; Wallisdevries *et al.* 2011; O'Donnell *et al.* 2011).

Another issue, with spatially interpolated climate is that its scale is often very coarse (continental or sub-continental), being interpolated from sparse meteorological sites. Official meteorological sites often avoid mountainous terrain, rarely occur along elevational gradients and fail to capture fine, intra-regional variation in climate. Intra-regional climate variability is of immense importance in places of high topographic complexity (Barry 2008) and key to the physical distributions of biota in such places. Climate data interpolated between meteorological sites create spatial models of climate across a landscape (Jeffrey *et al.* 2001; Booth *et al.* 2014). Interpolations may be accurate in flat terrain between nearby meteorological stations, however, sparse meteorological sites may have difficulty representing conditions in complex or mountainous terrain (Daly 2006). Both meso- and micro-climatic conditions in mountainous terrain may be difficult to predict, due to complex interactions with biogeographic variation in slope, aspect, elevation, hillshading, solar exposure, as well as other geographic factors such as orographic rainfall and rainshadow impacts. Biogeographic characteristics may buffer, enhance or even create their own local-scale meteorological conditions. Vegetation can also create feedback mechanisms, such as microclimatic influences (Wilson & Agnew 1992). Unfortunately, validation of conditions across environmental gradients or mountain ranges is often lacking in the published literature (see Chapter 3). Accordingly, spatially interpolated climate may be a source of inaccuracy in bioclimatic distribution models (see Chapters 2 and 3) and may not detect the critical thresholds influencing species or vegetation distributions at finer spatial scales.

Attempts have been made to refine spatial climate information to address intra-regional climate variability. These include techniques of downscaling spatially interpolated macroclimatic data (Thatcher *et al.* 2007; Frost *et al.* 2011; Storlie *et al.* 2013) and supplementing daily meteorological data with additional sample points at a fine-scale in the landscape (Chapter 3; Ashcroft 2006; Ashcroft *et al.* 2009; Ashcroft & Gollan 2012; Ashcroft *et al.* 2012; Storlie *et al.* 2013). In any case, intra-regional climate, particularly in mountainous terrain, is can be empirically and systematically examined by physical meteorological measurements within the landscape. This information is invaluable for interpreting and improving coarse scale climate models.

Biota are not just influenced by climate, they are also influenced by other factors such as resource availability, soils, habitat, competition and stochastic disturbance events such as from fire or cyclones. In this study, the focus is on the interaction among vegetation, climate and fire. Each are strongly linked and both are influenced by climate and meteorological extremes. Fire influences the distribution, structure and composition of vegetation types globally (Goldammer 1993; Bond *et al.* 2005; Bowman 2005; Bowman *et al.* 2009). For example, the global distribution of rain forests are limited to half their potential distribution because of fire (Bowman 2000; Bond *et al.* 2005; Bowman *et al.* 2009)., Vegetation may also persist in an area, as an alternative stable state (Beisner *et al.* 2003), due to the mechanism of fire (Grady & Hoffmann 2012; Werner 2012). Changes in climate or fire regime have the capacity to interrupt stable states and induce a tipping point that causes a switch in vegetation to an alternative, perhaps irreversible state (Gonzalez *et al.* 2010; Laurance *et al.* 2011a; Higgins & Scheiter 2012; Lloret *et al.* 2012). This can occur in the short-term as a result of a single fire event (Kitzberger *et al*. 2016). Fire is strongly related to climatic events or extremes rather than climate averages (Boer *et al.* 2008). The threat of vegetation tipping points are likely to be more immediate and catastrophic from a fire event or change in fire regime, than from a gradual change in climate.

There is extreme variation in fire regimes in Australia. These vary based on geographic location, vegetation type, climatic influences and ignitions (Bradstock 2010; Murphy *et al.* 2013). For example, there is a strong latitudinal influence on fire regimes, based on austral summer (December - January - February) monsoonal activity (Murphy *et al.* 2013).
The frequency and intensity of a fire regime have the capacity to influence the survivability and distribution of vegetation types, some of which are highly fire-sensitive. The fire regimes associated with vegetation types vary also, based on their fuel type, fuel structure and moisture, as well as on micrometeorological conditions (Chapters 3 and 4; Little *et al.* 2012) and on their macroclimate. Changes in climatic trends or extremes may abruptly affect the frequency or intensity of fire regimes, thereby influencing the survivability and distribution of vegetation types. Changes in the fire regime have the potential to alter vegetation distribution, structure and health and be a bigger impact on ecosystems than climate change directly (Flannigan *et al.* 2000, 2005). Indeed, climate change interacting with other stressors will have the most profound impacts on species and ecosystems (Driscoll *et al.* 2012; Staudt *et al.* 2013).

Fire danger (as measured by meteorological variables) is predicted to intensify with climate change around the globe (Flannigan *et al.* 2009; Krawchuk *et al.* 2009; Liu *et al.* 2010) and in Australia (Beer & Williams 1995; Cary & Banks 1999; Williams *et al.* 2001; Cary 2002; Hennessy *et al.* 2005; Lucas *et al.* 2007; Pitman *et al.* 2007; Hasson *et al.* 2008; Williams *et al.* 2009; King *et al.* 2011; Cary *et al.* 2012; CSIRO & Bureau of Meteorology 2015), including regions such as southeastern Australia, among others (Hennessy *et al.* 2005; Lucas *et al.* 2007; Hasson *et al.* 2008; Clarke *et al.* 2011; King *et al.* 2011; CSIRO & Bureau of Meteorology 2015). The impact of climate change induced shifts in fire danger on different vegetation types will vary with the local and regional specific changes in climate. The relationship among vegetation type, climate and fire danger is theoretically understood, however, there is little quantitative evidence to demonstrate how these differ among vegetation types. What evidence that does exist, demonstrates strong climatic and fire danger differences among adjacent vegetation types within even one region (Chapter 3, 4; Little *et al.* 2012). There is a risk that climate change could decouple the existing relationship between vegetation distribution and fire danger and induce 'tipping points' to alternative vegetation stable states. To understand and evaluate this risk requires knowledge of the return time (frequency) of extreme climatic and fire danger events, which are the particular conditions under which vegetation (particularly fire-sensitive communities) will be affected. Using historical meteorological data, it is possible to reconstruct past fire danger (Lucas 2010; Clarke *et al.* 2013) and, like climate, understand historic trends and extremes in fire danger. Historic trends add value to future fire danger predictions and evaluating the risk of future fire danger on vegetation types (Clarke *et al.* 2013).

Projections of future fire danger for all of north Queensland broadly, indicate little change with perhaps a slight decrease in fire danger (Pitman *et al.* 2007; Clarke *et al.* 2011). No fine resolution predictions of fire danger specifically for the Australian Wet Tropics region, let alone intra-regional projections, have yet been made. However, high resolution projections of future climate for the Wet Tropics indicate increasing temperatures, more heatwaves, increased rainfall variability and more extreme climatic events (Suppiah *et al.* 2007, 2010; Hilbert *et al.* 2014; McInnes *et al.* 2015). There are also indications of regional variability in observed climatic trends that are not necessarily represented in future climate trajectories (Suppiah *et al.* 2010; McInnes *et al.* 2015). However, it is important to understand fine-scale, intra-regional spatial and temporal climatic variability to understand how projections of future climate and fire danger will impact biota at the local scale. Rather than attempting to make new predictions or models of future climate and vegetation distributions, this study aims to better understand intra-regional climate variability and the frequency of extreme meteorological and fire danger from past events to better inform interpretation of regional climate predictions.

5.2.1 Objectives

So far in this thesis it has been shown that fine-scale distribution models of vegetation retain a high level of inaccuracy (Chapter 2); spatially interpolated data used in such models does not accurately reflect *in situ* conditions (Chapter 3); vegetation feedbacks and alternative stable states complicate distribution patterns (Chapter 2 and 3), and that interactions with fire are likely to further complicate the relation between vegetation distribution, climate and geography. For these reasons, simply applying future climate data to distribution models of vegetation, as is commonly done, to assess potential distributions of species under future climate scenarios, will not yield an accurate result at a local scale meaningful to vegetation distributions. This study aimed to understand how climate change might affect local scale conditions relevant to vegetation by assessing historic climatic and fire danger trends within one region to determine likely trajectories under changing climate. The specific aims of this chapter were to:

1. Identify historic climate and fire danger trends and extremes within the Wet Tropics region;
2. Determine whether observed climate and fire danger trends are consistent with projected future climate trajectories; and
3. Identify historic and likely future changes in climate and fire danger relative to vegetation types.

5.3 Methods

5.3.1 Study area

The study area was the Wet Tropics of northeastern Australia, a complex mountainous region identified as a key vulnerable region to climate change (Hughes 2011) and with a diversity of vegetation types and fire regimes in close proximity. The juxtaposition of these vegetation types provided the opportunity to examine relative patterns in microclimate and fire danger between vegetation types (Chapter 3 and 4; Little *et al.* 2012) and which have direct implications for other regions of Australia.

The Wet Tropics is characterised by mountainous coastal terrain (to 1622 metres elevation), with high annual rainfall, coastal windward orographic rainfall, significant occult rainfall interception on windward slopes (McJannet *et al.* 2007) and rainshadow effects (strong rainfall gradient) in the lee of the mountain ranges (Nix 1991; Turton *et al.* 1999). Rain forest vegetation is generally associated with areas of high rainfall and/ or protection from fire. However, alternative vegetation types occur where there is less available moisture and probability of fire occurrence. Associated with the leeward rainshadow is a strong environmental gradient often displaying abrupt boundaries among vegetation types. Rain forests generally occur on the summits and upper slopes, transitioning to tall eucalypt forests on mid to upper slopes, which are then replaced by fire-prone grassy savanna woodlands on lower slopes and plains (Figure 5.1). The probability of fire interacting with the moisture gradient in the rainshadow no doubt has a strong influence on the location of these vegetation boundaries.

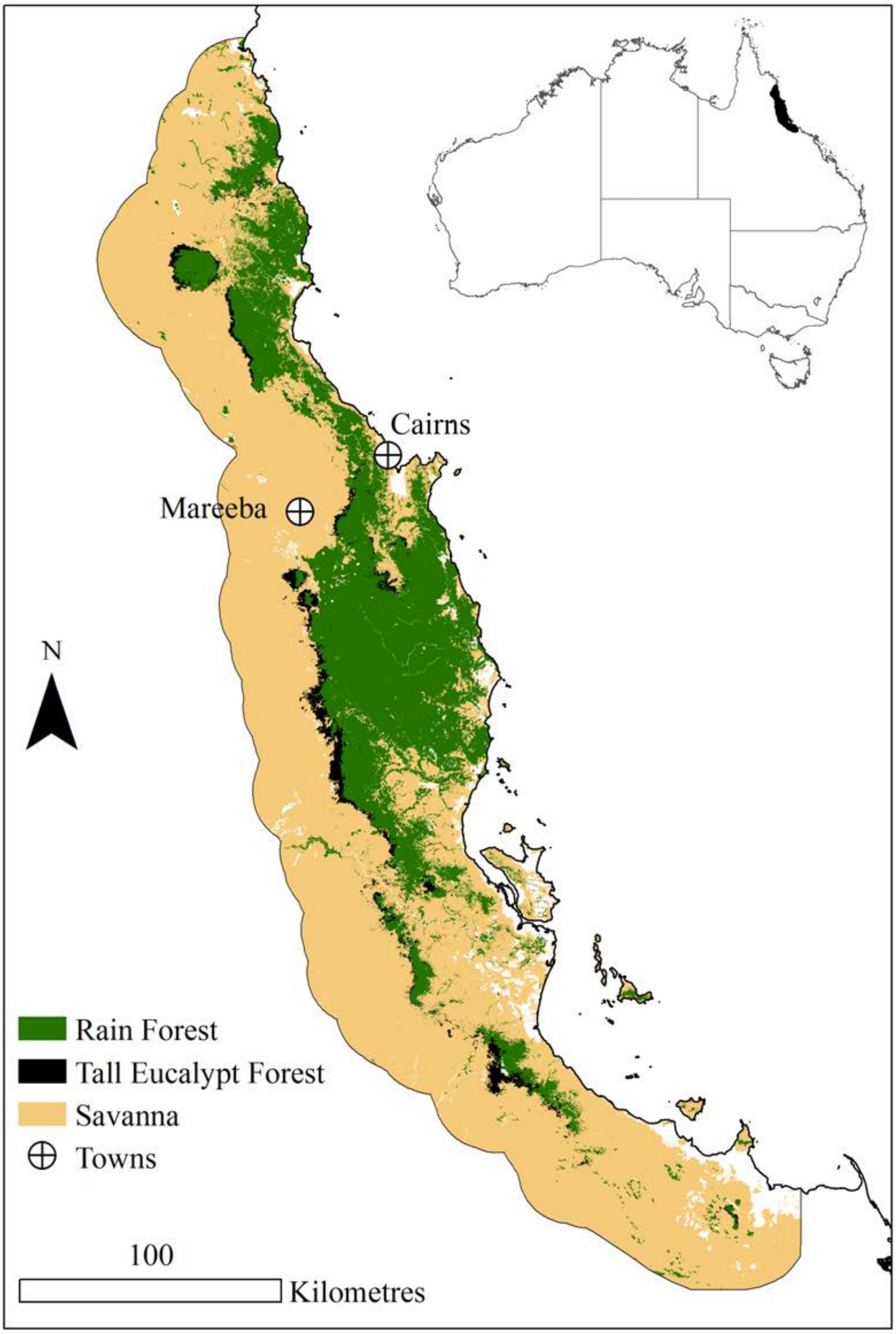

Figure 5.1 The location of two official meteorological stations, Cairns and Mareeba, relative to the distribution of three broad vegetation types in the Wet Tropics of northeastern Australia.

5.3.2 Historic climate and data homogenisation

Historic daily meteorological observations for the region were obtained from the Australian Government Bureau of Meteorology (BoM). Two official meteorological stations, Cairns and Mareeba, were selected from the region for their proximity to the environmental gradient on either side of the main coastal range and for the duration of their climate records (Figure 5.1). Cairns is found on the coastal lowlands on the windward side of the coastal ranges, whereas Mareeba is 40 kilometres inland on the plains in the lee of the coastal ranges. These stations are ideally located either side of the main coast range, however, do not capture the extreme climatic and microclimatic variation that is experienced in the complex mountainous terrain (to 1622 metres) in between (Turton *et al.* 1999; Barry 2008).

Cairns and Mareeba meteorological stations were among the few in the region that had an ongoing long-term record, which included all the climate variables necessary for calculating fire danger (5.3.3). Climate records at Cairns were analysed from 1890 and at Mareeba from 1957. The Cairns station occupied two physical sites between 1882 and the present day, which were overlapping in their records for the period between 1942 and 1957. Mareeba occupied three sites, which had overlapping data between 1991 and 1992, then between 2000 and 2002.

To maximise the length of this available time series data, it was essential to account for multiple official meteorological site 'sites' at each location. Time series data homogenisation methods (Easterling & Peterson 1995, 1996; Aguilar *et al*. 2003; Lucas 2010) were used to account for non-climatic patterns, such as shifts in the location of an official meteorological site, change in equipment or technology. Data homogenisation was applied to daily data at Cairns and Mareeba for each of the following climate variables: temperature (mean, daily maximum and minimum), rainfall, relative humidity (mean, maximum and minimum) and mean wind speed. This process involved three steps (Easterling & Peterson 1995, 1996; Aguilar *et al.* 2003), data stitching, data calibration and data homogenisation, which are described below. Data gaps are commonplace in meteorological time series. To avoid inaccurate results, data scrutiny and cleaning was done to remove data, which were substantially incomplete (more than 10% missing) for the time period being analysed (season and year).

5.3.2.1 Data stitching

This process involved bringing data from multiple sites into one continuous time series each for Cairns and Mareeba. In all cases, the more recent site data were used over the older site data. Mareeba data used in analysis consisted of data from site #031066 (1.1.1957 - 3.10.1991), site #031190 (4.10.1991 - 16.6.2000) and site #031210 (17.6.2000 - 30.4.2010). Cairns data used in analysis consisted of data from site #031010 (1.1.1890 - 30.9.1953) and site #031011 (1.10.1953 - 30.4.2010).

5.3.2.2 Data calibration

Where reference time series data is available, a data calibration can be applied (Aguilar et al. 2003). In this case, reference data refers to overlapping time series data records between meteorological sites for one location. For Cairns, the two sites had overlapping records between 1942 and 1957. For Mareeba, the more recent sites had overlapping records between 2000 and 2002 and the older sites between 1991 and 1992, as quoted above. The only exception was for the rainfall variable, which directly overlapped between the most recent site (31210) and the oldest site (31066) between 17/6/2000 and 28/2/2008. A calibration was made directly between these two sites.

Simple linear regressions were derived from the time period of overlapping records, for each climatic variable for Cairns and Mareeba. These equations were then applied to the older data to calibrate it to the newer site data.

5.3.2.3 Data homogenisation

Data homogenisation was then applied to the calibrated time series data for Cairns and Mareeba. A break-point analysis identified anomaly shifts in the calibrated data (such as by change of equipment or site change) and then an offset correction was automatically applied to homogenise the data. Break-point analysis and offset correction were implemented using the statistical package "RHtests" (http://cccma.seos.uvic.ca/ETCCDMI/software.shtml; Wang *et al.* 2007; Wang 2008a, 2008b) using "R" statistical software (Version 3.0.2; R Development Core Team 2002).

5.3.3 Forest Fire Danger Index (FFDI)

The meteorological conditions in which fires may spread are termed fire weather or fire danger. Fire danger, is generally measured in Australia by McArthur's Forest Fire Danger Index (FFDI). The FFDI was also the most suitable single measure of fire danger for all vegetation types represented in this study. FFDI is calculated from a combination of standard daily meteorological observations, using temperature, relative humidity, wind speed, rainfall and a drought factor (Noble *et al.* 1980; Griffiths 1999; Finkele *et al.* 2006). Drought Factor is an estimate of the soil dryness index or soil moisture deficit (SMD) (Griffiths 1999). SMD was directly measured at microclimate monitoring sites, but was not available for official meteorological stations as it is not an official measurement. The Keetch-Byram Drought Index (KBDI) (Keetch & Byram 1968) is a surrogate measure used for estimating SMD in FFDI calculations with inputs of rainfall and maximum temperature (Finkele *et al.* 2006) and can thus be calculated for official meteorological stations. SMD data were formatted to a KBDI equivalent for comparative purposes (Griffiths 1999). Fire danger values are categorised into 'Low-Moderate' (0-11), 'High' (12-24), 'Very High' (25-

49), 'Severe' (50-74), 'Extreme' (75-99) and 'Catastrophic' (100+). The peak fire season and the period when highest FFDI values are observed, occurs during September-October-November (SON) in northeastern Australia (Clarke *et al.* 2011).

Historic daily FFDI was calculated for both Cairns (1890-2010) and Mareeba (1957-2010) from homogenised climate data. FFDI calculations at Cairns and Mareeba used the Keetch-Byram Drought Index (KBDI) to estimate Drought Factor and Soil Moisture Deficit (SMD). Daily FFDI was calculated (Noble *et al.* 1980; Griffiths 1999; Finkele *et al.* 2006) for the Mareeba meteorological station and for each of the micrometeorology sites (5.3.4) for the duration of the study period (April 2007 to April 2010) and the relationships between each site and Mareeba were determined (Chapter 4; Little *et al.* 2012). It was established that Mareeba was a better predictor of climate and FFDI conditions at these sites than was Cairns.

5.3.4 Microclimate measurements

Eight transects were established along the environmental gradient on the leeward side of the mountain ranges through a latitudinal span of the Wet Tropics region (s3.3, Chapter 3). Each transect was arranged to incorporate three different vegetation types; rain forest, tall eucalypt forest and savanna. Sites were located along each transect with at least one site located within each vegetation type (there were two sites located within tall eucalypt forests on each transect and their site data was averaged for each transect). At each site, daily micro-meteorological data were collected (for a minimum of one year) over the three-year study period from April 2007 to April 2010 (s3.3, Chapter 3). Five climate variables were measured at each site; air temperature, relative humidity, wind speed, soil moisture, solar radiation and an additional variable (rainfall) at savanna sites only. Rainfall was not collected at other sites, as canopy interception of rain was determined to seriously bias sampling, at all sites but the open savanna woodlands. For sites where rainfall was not measured, rain days and rainfall were estimated from soil moisture and adjacent savanna rain days (4.3, Chapter 4; Little *et al.* 2012). For details of these transects and sampling methodologies, refer to section 3.3 (Chapter 3).

Daily weather observations for Cairns and Mareeba official meteorological stations were also obtained for the same study period. Relationships between daily site-based microclimate and fire danger observations with those recorded at Cairns and Mareeba meteorological stations were investigated. Of the two sites, Mareeba was determined to be a better predictor of microclimate and FFDI conditions with sites in the network of micro-meteorological stations. Mareeba data was then used in determining relationships with the field study sites and vegetation types (Chapters 3 and 4).

5.3.5 Historic climate for vegetation types

Relationships between daily microclimate observations at each of the study sites with those recorded at the Mareeba meteorological station were identified (s3.4 Chapter 3), as were FFDI and SMD observations (s4.4 Chapter 4; Little *et al.* 2012). Vegetation type was consistently found to be the strongest predictor of site-based microclimate from Mareeba weather observations. Thus, the identified relationship between Mareeba observations and microclimate of each vegetation type (rather than site) over the 3-year study period, were used to predict historic climate conditions for each vegetation type. This was done using linear regressions (Chapters 3 and 4) for each vegetation type, applied to historic daily Mareeba climate and FFDI.

5.3.6 Trend Analysis

There are many approaches to statistical analysis of climate data and time series analysis (von Storch & Zwiers 1999; Mudelsee 2010; McLeod *et al.* 2012; Rao *et al.* 2012), however for consistency and comparative purposes, the general approach of Clarke *et al.* (2013) was adopted. A series of trend analyses were undertaken for the span of data for Cairns, Mareeba and for the recreated historic data for each vegetation type, to determine the significance of temporal patterns in the time series. Dynamic linear models (DLM) were fitted via ordinary least squares, to test for significance and were implemented via the 'dynlm' function in the "R" software package 'dynlm' (Zeileis 2014). Clarke *et al.* (2013) used ordinary least squares linear regression, however, while a DLM is similar to standard linear models, it is a specific time series regression that has the added advantage of being able to retain time series properties, including trends and cyclical patterns (McLeod *et al.* 2012; Zeileis 2014). Models were evaluated by F -statistic and overall model performance by adjusted R^2 value. Model significance was determined via p-values ($p < 0.1$).

DLMs were implemented following an analysis sequence described by Logan (2010), using "R" statistical software (Version 3.0.2, R Development Core Team 2002). Assumptions of linearity, normality and homogeneity of variance were assessed by comparing variable distributions (via a scatterplot matrix with box-plots) for each variable and checking for skewed distributions. Linear correlations between all variables were tested by calculating Pearson's correlation coefficient (r) for each combination between all predictor variables. Values between -0.5 and 0.5 were considered not strongly correlated. Multi-collinearity tests were also performed on the data, where potential collinearity would be detected by a variance inflation factor greater than 5 (Logan 2010). Tests for correlation and multi-collinearity detected no significant issues with the data.

Annual and seasonal time series linear regressions were performed on a number of climatic and FFDI variables. The aspect of most interest regarding FFDI was the maxima. Accordingly a number of percentile bands as well as the maxima were examined. Some FFDI variables were examined for direct comparison with Clarke *et al*. (2013). FFDI analyses were based on those by Clarke *et al.* (2013) and a number of FFDI variables were tested: mean, average daily maximum, annual (extreme) maximum (highest record during the annual or seasonal period), annual minimum and average daily minimum, 99th percentile, 95th percentile, 90th percentile, 50th percentile (median), cumulative FFDI (Σ FFDI), number of days of 'High' FFDI (12 or greater) and number of days of 'Very High' FFDI (25 or greater). The latter count variables (number of days) could only be calculated for Cairns due to missing days of data at Mareeba. Cumulative data for Mareeba were deducted from average data multiplied by the number of days in that period.

Temperature (°C) analyses consisted of the following variables: mean, annual (extreme) maximum (hottest temperature record during period), average daily maximum (for that period), annual (extreme) minimum (coldest temperature record during period), average minimum and the number of days with a temperature greater than or equal to 35°C (heatwave event). Rainfall (mm) variables consisted of total rainfall and the number of days with rainfall less than 50 mm. Relative humidity (%) variables consisted of mean, minimum (lowest humidity record during period) and average minimum. Wind analyses consisted of average and average maximum (not gust speed) variables. KBDI (mm) variables consisted of average, maximum and the number of dry days (KBDI greater than 150 mm). For comparative purposes with other variables, a Southern Oscillation Index (SOI) analysis was included using average SOI, SOI greater than eight (La Niña) and SOI less than negative eight (El Niño). When the SOI is strongly negative (less than negative eight), Australia is considered to experience an El Niño phase of the SOI, or El Niño Southern Oscillation (ENSO) event (Sturman & Tapper 2006).

For all analyses addressing season, standard austral southern hemisphere meteorological seasons were used; December–January–February (DJF), March–April–May (MAM), June-July-August (JJA) and September-October-November (SON). To accurately include each 'season' as it chronologically occurred (specifically the DJF season, which occurs across calendar years), 'year' was adjusted to occur from December of the previous year to November (rather than January to December), which was consistent with Clarke *et al.* (2013). Specific attention was given to analyses of fire danger during the peak fire season, which occurs during the SON months in the region (Clarke *et al.* 2011).

5.4 Results

For details of linear regressions used to calibrate time series data see Appendix 5.1. For details of raw (stitched), calibrated and homogenised (cleaned) time series for Cairns and Mareeba, see Appendix 5.2.

5.4.1 Forest Fire Danger Index

Average fire danger conditions at Cairns were consistently lower than at Mareeba and both sites displayed inter-annual variability that appeared to correlate with the SOI (Figure 5.2). High FFDI values generally co-occurred with ENSO events (low SOI values) and low FFDI values with high SOI.

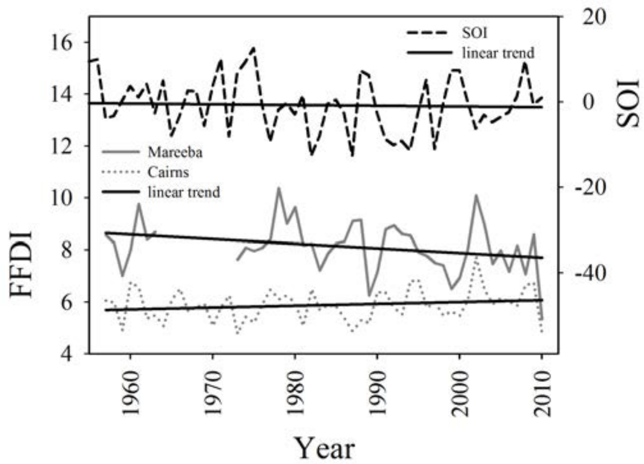

Figure 5.2 Historic annual mean Forest Fire Danger Index (FFDI) at Cairns and Mareeba, with the global mean Southern Oscillation Index (SOI). SOI and FFDI display an inverse relationship, with high FFDI values occurring when SOI is strongly negative (El Niño conditions).

The highest FFDI record at Cairns between 1890 and 2010 was 42, recorded in 1965 and the highest at Mareeba was 44, recorded in 2009. Cairns recorded 35 days of ‘Very High’ fire danger since 1890, 34 of which occurred after 1957.

All annual FFDI trends increased significantly at Cairns between 1890 and 2010 (Figure 5.3, Table 5.1). Extreme annual maximum fire danger increased linearly by 17 over this period. However only two trends were significant for the period from 1957 to 2010 (Table 5.2); the number of days of ‘High’ fire danger (which increased by 34 days between 1890 and 2010 and by 23 days since 1957), and the 90th percentile. There was also a near significant increase in the 95th percentile during the latter period (*p*=0.12, Appendix 5.4).

Mareeba displayed no significant trends in FFDI between 1957 and 2010 (Table 5.2), although some near significant trends are noteworthy. Mean FFDI and cumulative FFDI both decreased at Mareeba (*p*=0.06), while the maximum annual FFDI increased (*p*=0.13).

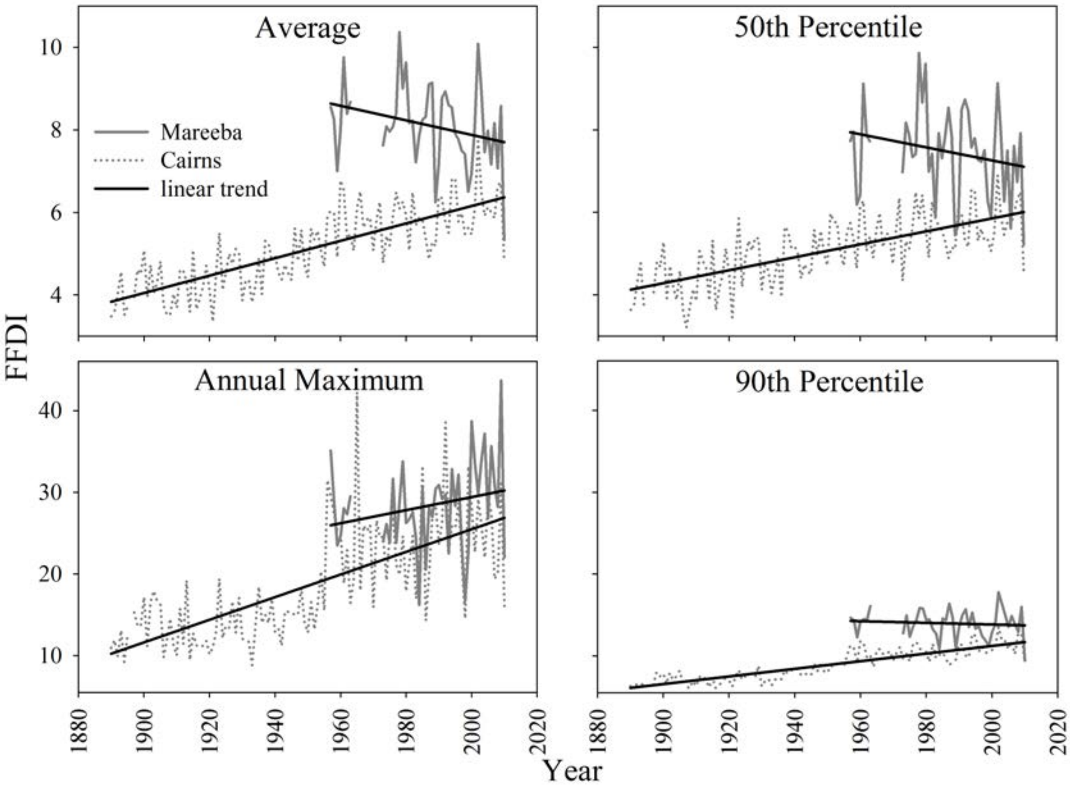

Figure 5.3 Historic annual Forest Fire Danger Index (FFDI) at Cairns and Mareeba. All trends were significant for Cairns for the period from 1890 to 2010, but only the 90th percentile trend was significant from 1957 to 2010. None of these trends were significant for Mareeba.

Table 5.1 Linear trends in FFDI values for Cairns, from 1890 to 2010. Values represent the linear annual or seasonal change per year (slope coefficient). Shading indicates trends that were significant at the 95% level. Model details are provided in Appendix 5.3 for annual outputs and Appendices 5.5-5.8 for seasonal outputs.

Location	**Variable**	**Annual**	**Seasonal**			
			DJF	**MAM**	**JJA**	**SON**
Cairns	FFDI mean	0.02	0.01	0.02	0.03	0.02
Cairns	Σ FFDI	7.7	0.63	1.84	2.96	2.25
Cairns	FFDI max.	0.14	0.07	0.08	0.1	0.13
Cairns	FFDI 99%	0.09	0.05	0.06	0.08	0.1
Cairns	FFDI 95%	0.06	0.04	0.05	0.06	0.07
Cairns	FFDI 90%	0.05	0.02	0.04	0.06	0.05
Cairns	FFDI 50%	0.02	0	0.02	0.03	0.02
Cairns	FFDI days ≥25	0.01	0	0	0	0.01
Cairns	FFDI days ≥12	0.28	0.04	0.03	0.09	0.13

Table 5.2 Linear trends in FFDI values for Cairns and Mareeba, from 1957 to 2010. Values represent the linear annual or seasonal change per year (slope coefficient). Shading indicates trends that were significant at the 95% level. Model details are provided in Appendix 5.4 for annual outputs and Appendices 5.5-5.8 for seasonal outputs.

Location	**Variable**	**Annual**	**Seasonal**			
			DJF	**MAM**	**JJA**	**SON**
Cairns	FFDI mean	0.01	-0.01	0.02	0.02	0
Cairns	Σ FFDI	2.61	-0.72	2.02	1.49	0.16
Cairns	FFDI max.	0.02	0.03	0.07	0.04	0.01
Cairns	FFDI 99%	0.01	0.02	0.05	0.01	0
Cairns	FFDI 95%	0.02	0	0.04	0.02	0.01
Cairns	FFDI 90%	0.02	0	0.04	0.02	0.01
Cairns	FFDI 50%	0.01	-0.01	0.03	0.02	0
Cairns	FFDI days ≥25	0	0	0	0	0
Cairns	FFDI days ≥12	0.19	0	0.05	0.07	0.07
Mareeba	FFDI mean	-0.02	-0.04	0	-0.02	-0.01
Mareeba	Σ FFDI	-6.44	-3.9	0.02	-1.65	-1.33
Mareeba	FFDI max.	0.08	0.04	0.03	0	0.04
Mareeba	FFDI 99%	-0.01	-0.03	0.01	-0.01	0.04
Mareeba	FFDI 95%	0	-0.01	0.02	-0.01	0.01
Mareeba	FFDI 90%	-0.01	-0.03	0.01	-0.02	0.01
Mareeba	FFDI 50%	-0.02	-0.04	0	-0.02	-0.02

Seasonal fire danger trends, differed from annual trends and among meteorology sites (Figure 5.4 and 5.5). Average and maximum fire danger increased significantly in all seasons at Cairns from 1890 to 2010 (Table 5.1; Figure 5.4 and 5.5), but was only significant during MAM and JJA from 1957 to 2010 (Table 5.2). Seasonal fire danger trends at Mareeba showed both increasing and decreasing trends, however, only some decreasing trends during DJF were significant (Table 5.2). While average fire danger conditions (average, cumulative and 50th percentile) declined at Mareeba, annual maxima increased throughout the year (although not significantly).

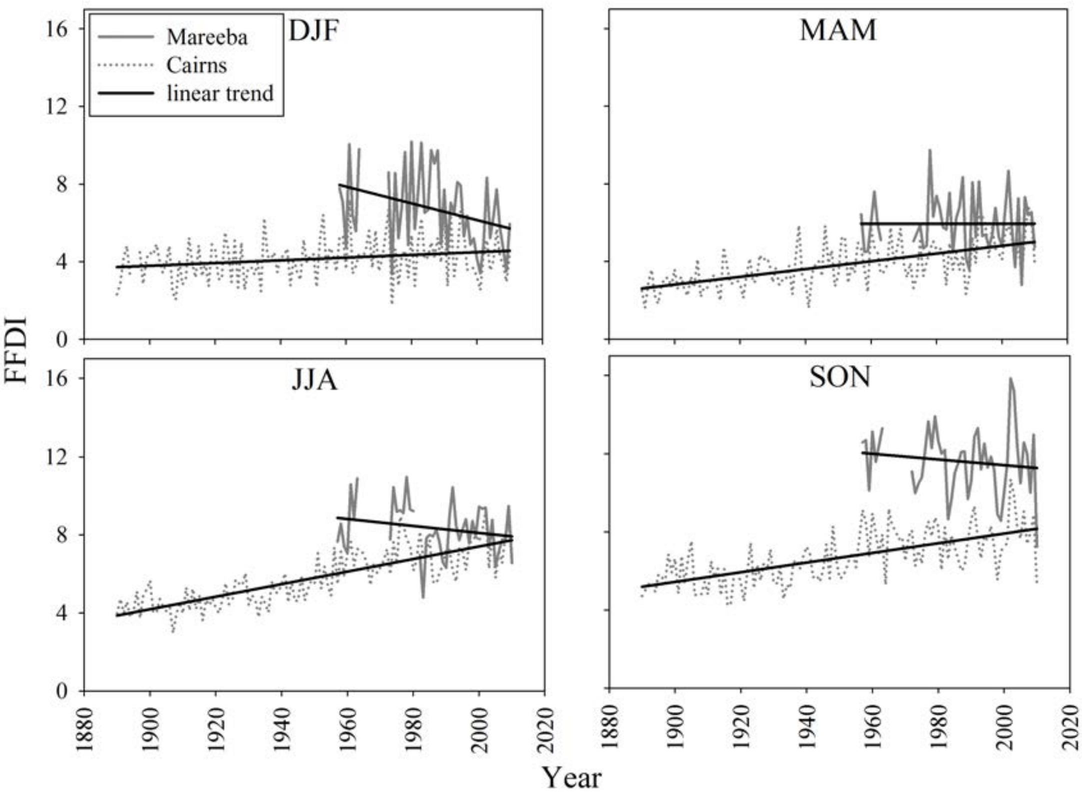

Figure 5.4 Historic seasonal average Forest Fire Danger Index (FFDI) at Cairns and Mareeba for the period December-January-February (DJF), March-April-May (MAM), June-July-August (JJA) and September-October-November (SON).

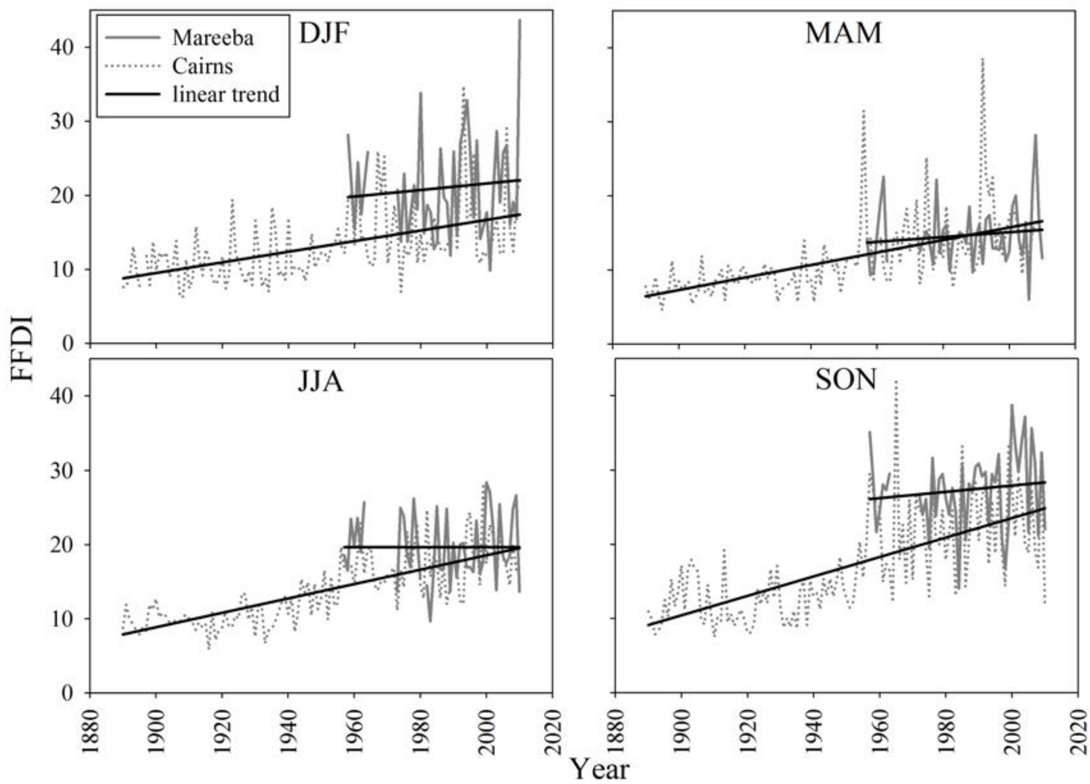

Figure 5.5 Historic seasonal maximum Forest Fire Danger Index (FFDI) at Cairns and Mareeba for the period December-January-February (DJF), March-April-May (MAM), June-July-August (JJA) and September-October-November (SON).

A focus on the peak fire season in the region (SON) (Clarke *et al.* 2011) was warranted, as this is the period of highest fire activity and maximum fire danger (Figures 5.4-5.6). During this season, all fire danger variables increased significantly at Cairns from 1890 to 2010 (Table 5.1), but none from 1957 to 2010 (Table 5.2). Likewise, no fire danger trends were significant at Mareeba (Table 5.2).

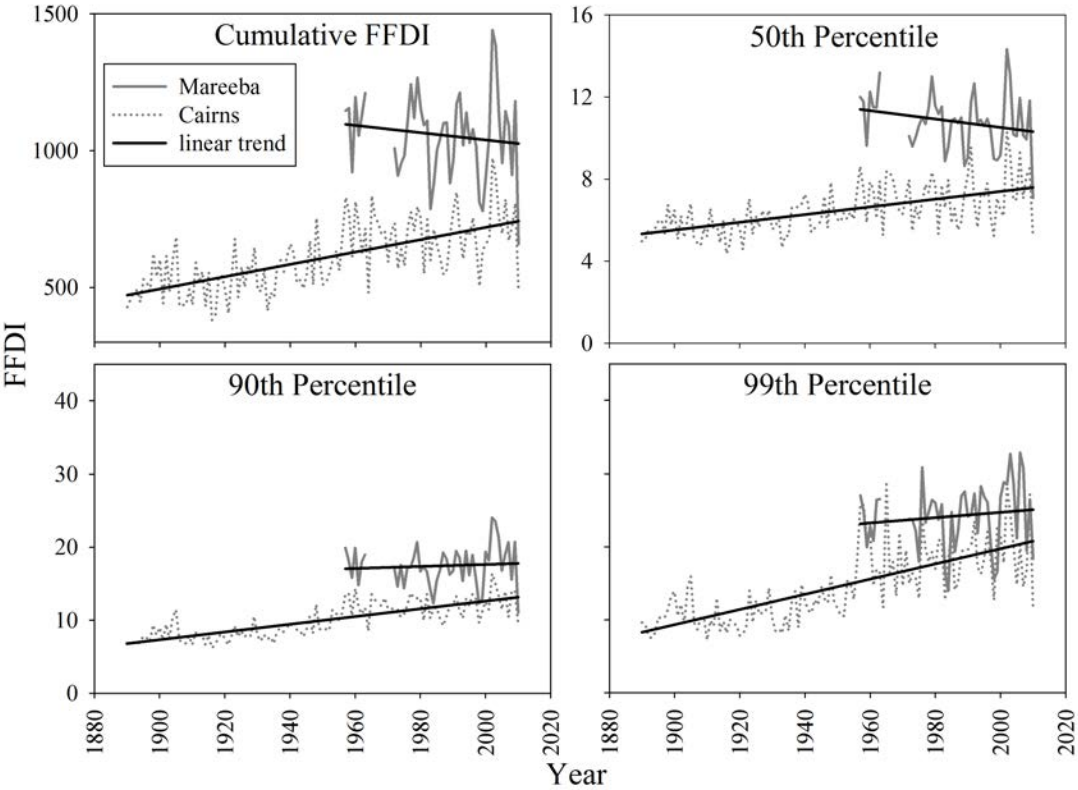

Figure 5.6 Historic Forest Fire Danger Index (FFDI) at Cairns and Mareeba for the annual fire season during September-October-November (SON). Average (Figure 5.4) and annual maximum (Figure 5.5) for the fire season are depicted elsewhere.

Fire danger trends for each vegetation type naturally demonstrated the same patterns as at Mareeba, but with different absolute values (Table 5.3; Figure 5.7). Rain forest experienced a maximum FFDI of eight and tall eucalypt forest a maximum FFDI of 11.9, neither exceeding a ‘Low-Moderate’ FFDI rating (Figure 5.7). Savanna, on the other hand, experienced ‘High’ fire danger conditions, with a maximum FFDI of 20. The same trends were observed during the fire season, with none of these being significant declines (Figure 5.8.).

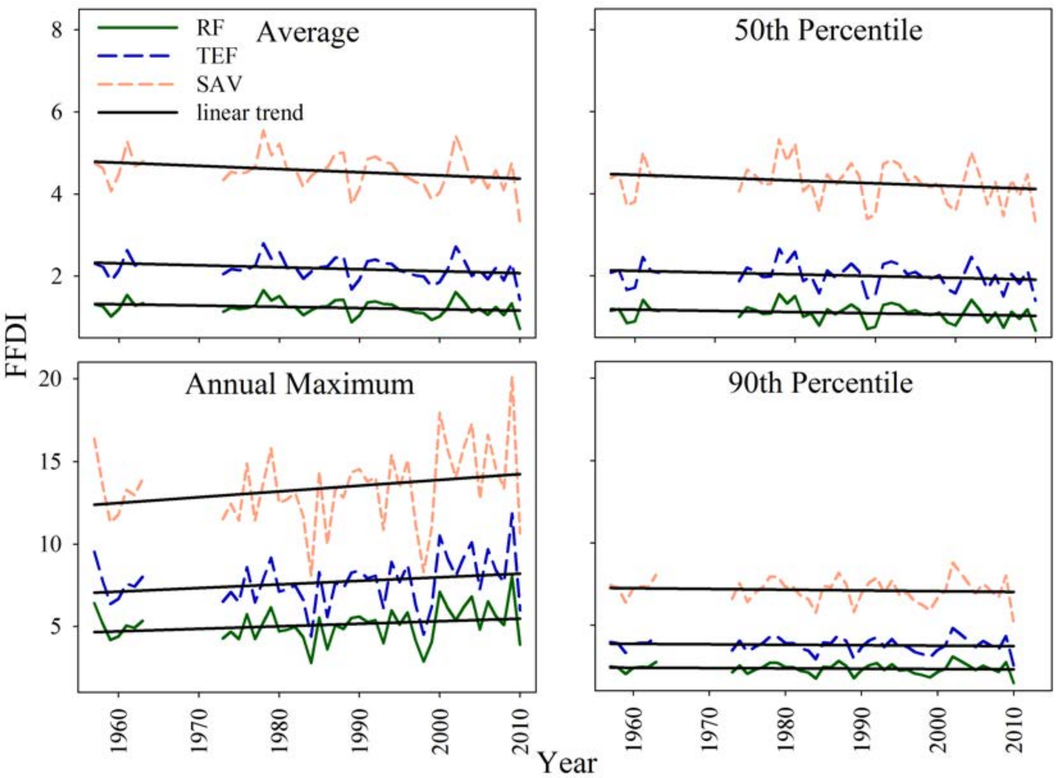

Figure 5.7 Historic annual Forest Fire Danger Index (FFDI) for three vegetation types, rain forest (RF), tall eucalypt forest (TEF) and savanna (SAV). These trends were not statistically significant (Table 5.3).

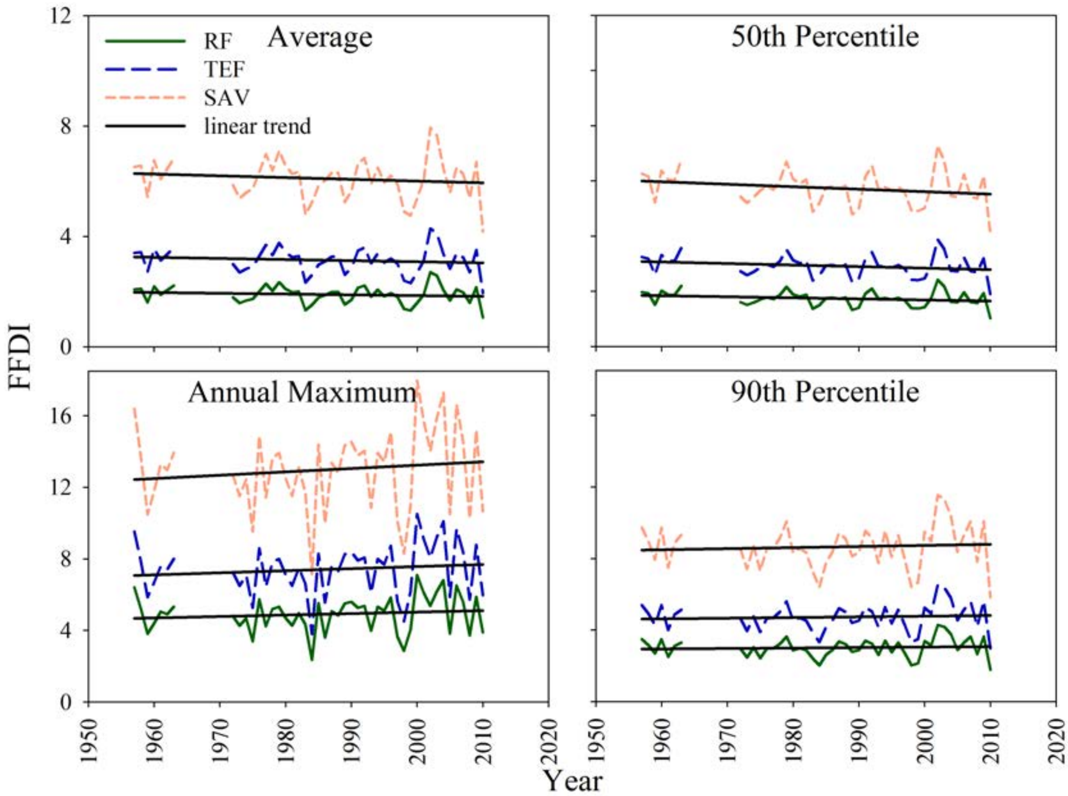

Figure 5.8 Historic Forest Fire Danger Index (FFDI) for the annual fire season during September-October-November (SON), for three vegetation types, rain forest (RF), tall eucalypt forest (TEF) and savanna (SAV). These trends were not statistically significant (Table 5.3).

Table 5.3 Linear trends in FFDI values (reconstructed from Mareeba data) for rain forest, tall eucalypt forest and savanna, from 1957 to 2010. Values represent the linear annual or seasonal change per year (slope coefficient). Shading indicates trends that were significant at the 95% level. Model details are provided in Appendix 5.4 for annual outputs and Appendices 5.5-5.8 for seasonal outputs.

Location	Variable	Annual	Seasonal			
			DJF	MAM	JJA	SON
Rain Forest	FFDI mean	0	-0.01	0	0	0
Rain Forest	Σ FFDI	-1.13	-0.67	0.02	-0.31	-0.25
Rain Forest	FFDI max.	0.02	0.01	0.01	0	0.01
Rain Forest	FFDI 99%	0	-0.01	0	0	0.01
Rain Forest	FFDI 95%	0	0	0	0	0
Rain Forest	FFDI 90%	0	-0.01	0	0	0
Rain Forest	FFDI 50%	0	-0.01	0	0	0
Tall Eucalypt Forest	FFDI mean	0	-0.01	0	0	0
Tall Eucalypt Forest	Σ FFDI	-1.75	-1.06	0	-0.45	-0.36
Tall Eucalypt Forest	FFDI max.	0.02	0.01	0.01	0	0.01
Tall Eucalypt Forest	FFDI 99%	0	-0.01	0	0	0.01
Tall Eucalypt Forest	FFDI 95%	0	0	0	0	0
Tall Eucalypt Forest	FFDI 90%	0	-0.01	0	0	0
Tall Eucalypt Forest	FFDI 50%	0	-0.01	0	-0.01	-0.01
Savanna	FFDI mean	-0.01	-0.02	0	-0.01	-0.01
Savanna	Σ FFDI	-2.82	-1.71	0.01	-0.72	-0.58
Savanna	FFDI max.	0.04	0.02	0.01	0	0.02
Savanna	FFDI 99%	0	-0.01	0.01	0	0.02
Savanna	FFDI 95%	0	-0.01	0.01	-0.01	0
Savanna	FFDI 90%	0	-0.01	0	-0.01	0.01
Savanna	FFDI 50%	-0.01	-0.02	0	-0.01	-0.01

5.4.2 Climate

Some of the trends for climatic variables underlying fire danger differed between Cairns and Mareeba, both in direction and magnitude (Tables 5.4 and 5.5). Annual trends for all temperature variables increased significantly (except for annual minima) at Cairns from 1890 to 2010 (Table 5.4; Figure 5.9). However, only increases in mean and average daily minima were significant from 1957 to 2010 (Table 5.5). For this latter period, temperature maxima showed a declining trend, with declines in 95th and 90th percentiles being significant (Table 5.5). Annual trends for temperature generally increased significantly at Mareeba, except for average daily maximum and for annual minimum (Figure 5.9, Table 5.5).

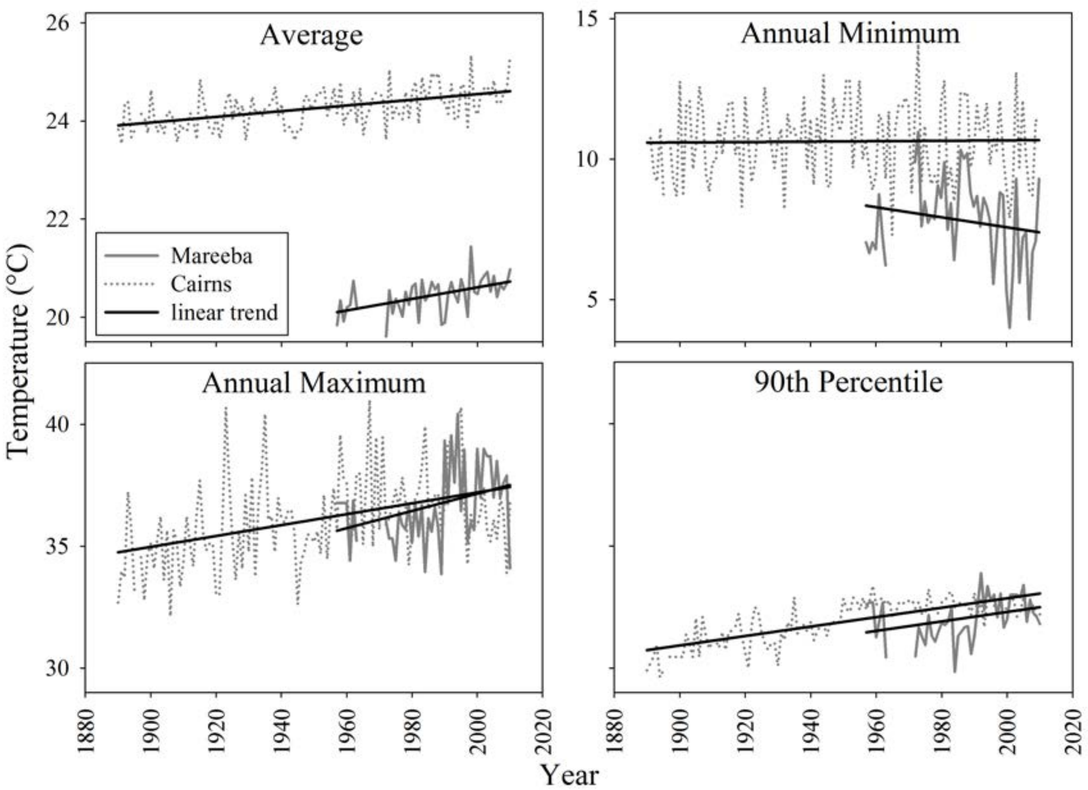

Figure 5.9 Historic annual temperature values at Cairns and Mareeba were average, annual extreme minimum (coldest record), annual extreme maximum (hottest record) and the 90th percentile. All trends were significant for Cairns between 1890 and 2010, except for annual minimum (Table 5.4), but only average and 90th percentile trends (decreasing) were significant from 1957 to 2010 (Table 5.5). All trends for Mareeba were significant except for annual minimum temperature (Table 5.5).

Annual rainfall trends at Cairns were not significant from 1890 to 2010, nor from 1957 to 2010 (Figure 5.10, Table 5.4 and 5.5). However, rainfall significantly increased at Mareeba (Figure 5.10), which was most strongly detected during the wet (DJF) season (Table 5.5). Seasonal rainfall trends show increasing rainfall at both Cairns and Mareeba for all seasons, with the exception of a decrease in Cairns rainfall during MAM and JJA months (Tables 5.4 and 5.5). The increasing rainfall trend at Mareeba was significant for all seasons, except MAM and SON (Table 5.5)

Relative humidity significantly decreased at Cairns both between 1890 and 2010 and between 1957 and 2010. However, humidity increased at Mareeba significantly between 1957 and 2010. Drought conditions (KBDI) also increased significantly at Cairns between 1890 and 2010. For Figures of other climatic variables refer to Appendix 5.9.

Comparisons of these trends in relation to other examinations of historic climate and fire danger are discussed in the following section. Likewise, a comparison of these trends with future climate projections is also discussed.

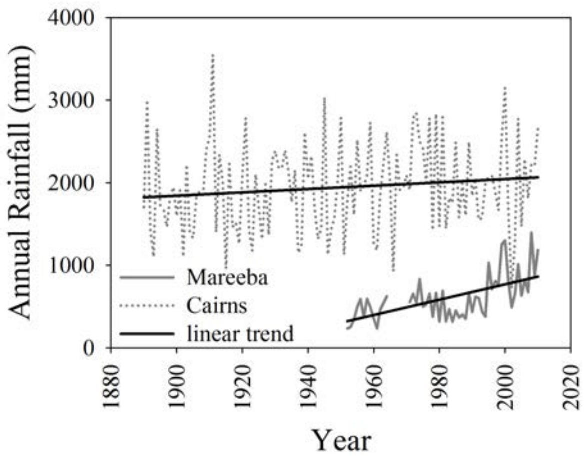

Figure 5.10 Historic annual total rainfall (mm) at Cairns and Mareeba. The trend for Cairns was not significant (Table 5.4 and 5.5), but was significant for Mareeba (Table 5.5).

Table 5.4 Linear climatic trends for Cairns, from 1890 to 2010. Values represent the linear annual or seasonal change per year (slope coefficient). Shading indicates trends that were significant at the 95% level. Model details are provided in Appendix 5.3 for annual outputs and Appendices 5.5-5.8 for seasonal outputs. Climate variables were the Southern Oscillation Index (SOI), temperature (Temp.), relative humidity (R. Hum.), rainfall, wind speed and drought factor (KBDI).

Location	Variable	Annual	Seasonal			
			DJF	MAM	JJA	SON
Global	SOI mean	-0.02	-0.03	-0.03	-0.02	0
Global	SOI max.	-0.01	-0.01	-0.01	-0.02	0.01
Global	SOI min.	-0.04	-0.04	-0.04	-0.03	0
Cairns	Rain total	2.01	1.99	-0.52	-0.18	0.56
Cairns	Rain days ≥5 mm	-0.03	0.03	-0.04	-0.02	0
Cairns	Wind mean	-0.08	-0.1	-0.06	-0.05	-0.08
Cairns	Wind max.	-0.01	-0.04	-0.01	0.01	-0.01
Cairns	Temp. mean	0.01	0.01	0.01	0	0
Cairns	Temp. max. annual	0.02	0.02	0.02	0.02	0.02
Cairns	Temp. max. mean daily	0.02	0.02	0.02	0.02	0.02
Cairns	Temp. max. 99%	0.02	0.02	0.02	0.02	0.02
Cairns	Temp. max. 95%	0.02	0.02	0.02	0.02	0.02
Cairns	Temp. max. 90%	0.02	0.02	0.02	0.02	0.02
Cairns	Temp. max. days ≥35 °C	0.03	0.02	0	NA	0
Cairns	Temp. min. annual	0	0.02	0.01	0	0
Cairns	Temp. min. mean daily	0.01	0.01	0.01	0.01	0.01
Cairns	R.Hum. mean	-0.09	-0.07	-0.08	-0.12	-0.1
Cairns	R.Hum. min. annual	-0.25	-0.17	-0.2	-0.23	-0.25
Cairns	R.Hum. min. mean daily	-0.11	-0.07	-0.1	-0.15	-0.12
Cairns	R.Hum. min. 1%	-0.22	-0.15	-0.17	-0.22	-0.24
Cairns	R.Hum. min. 5%	-0.18	-0.14	-0.15	-0.2	-0.19
Cairns	R.Hum. min. 10%	-0.16	-0.12	-0.14	-0.19	-0.17
Cairns	KBDI mean	0.12	-0.05	0.17	0.29	0.06
Cairns	KBDI max.	0.06	-0.02	0.24	0.19	0.07
Cairns	KBDI 99%	0.07	-0.02	0.25	0.2	0.07
Cairns	KBDI 95%	0.09	-0.03	0.23	0.2	0.07
Cairns	KBDI 90%	0.11	-0.05	0.21	0.21	0.08

Table 5.5 Linear climatic trends for Cairns and Mareeba from 1957 to 2010. Values represent the linear annual or seasonal change per year (slope coefficient). Shading indicates trends that were significant at the 95% level. Model details are provided in Appendix 5.4 for annual outputs and Appendices 5.5-5.8 for seasonal outputs. Climate variables were the Southern Oscillation Index (SOI), temperature (Temp.), relative humidity (R. Hum.), rainfall, wind speed and drought factor (KBDI).

Location	**Variable**	**Annual**	**Seasonal**			
			DJF	**MAM**	**JJA**	**SON**
Global	SOI mean	-0.04	0	-0.07	-0.06	-0.02
Global	SOI max.	0.03	0	-0.03	-0.03	-0.01
Global	SOI min.	-0.07	0	-0.13	-0.08	-0.02
Cairns	Rain total	-0.62	0.25	-3	-0.07	1.53
Cairns	Rain days ≥5 mm	0.09	0.06	-0.07	0.01	0.06
Cairns	Wind mean	-0.08	-0.07	-0.08	-0.09	-0.09
Cairns	Wind max.	-0.1	-0.11	-0.08	-0.15	-0.12
Cairns	Temp. mean	0.01	0.01	0.01	0.01	0.01
Cairns	Temp. max. annual	-0.02	-0.03	0	0.01	0
Cairns	Temp. max. mean daily	0	-0.01	0	0	0
Cairns	Temp. max. 99%	-0.01	-0.03	0	0.01	0
Cairns	Temp. max. 95%	-0.01	-0.01	0	0	0
Cairns	Temp. max. 90%	-0.01	-0.01	-0.01	0	0
Cairns	Temp. max. days ≥35 °C	-0.02	-0.03	0	NA	0
Cairns	Temp. min. annual	0	0.01	0.02	0	-0.01
Cairns	Temp. min. mean daily	0.01	0.01	0.01	0.01	0.01
Cairns	R.Hum. mean	-0.07	-0.05	-0.11	-0.1	-0.04
Cairns	R.Hum. min. annual	-0.15	-0.08	-0.12	-0.16	-0.12
Cairns	R.Hum. min. mean daily	-0.08	-0.03	-0.12	-0.11	-0.07
Cairns	R.Hum. min. 1%	-0.09	-0.03	-0.1	-0.12	-0.11
Cairns	R.Hum. min. 5%	-0.1	-0.07	-0.12	-0.11	-0.09
Cairns	R.Hum. min. 10%	-0.1	-0.05	-0.13	-0.12	-0.09
Cairns	KBDI mean	0	-0.27	0.32	0.25	-0.14
Cairns	KBDI max.	-0.07	-0.23	0.55	-0.02	-0.22
Cairns	KBDI 99%	-0.08	-0.24	0.56	-0.01	-0.15
Cairns	KBDI 95%	-0.09	-0.28	0.55	0	-0.16
Cairns	KBDI 90%	-0.08	-0.32	0.55	0.01	-0.16
Mareeba	Rain total	9.82	6.86	1.3	0.31	0.83
Mareeba	Wind mean	0.07	0.02	0.09	0.11	0.06
Mareeba	Wind max.	0.36	0.26	0.31	0.34	0.26
Mareeba	Temp. mean	0.01	0.04	0.02	-0.01	0
Mareeba	Temp. max. annual	0.04	0.03	0.01	0	0.04
Mareeba	Temp. max. mean daily	0.01	0.01	0	-0.01	0.01
Mareeba	Temp. max. 99%	0.03	0.03	0.01	0.01	0.03
Mareeba	Temp. max. 95%	0.02	0.02	0.01	0.01	0.03
Mareeba	Temp. max. 90%	0.02	0.02	0.01	0	0.02
Mareeba	Temp. min. annual	-0.02	0.03	0.02	-0.02	0.01
Mareeba	Temp. min. mean daily	0.04	0.06	0.04	0.03	0.04
Mareeba	R.Hum. mean	0.06	0.11	0.05	0.04	0.04
Mareeba	R.Hum. min. annual	-0.01	-0.01	0.06	0.05	0.01
Mareeba	R.Hum. min. mean daily	0.14	0.18	0.12	0.15	0.1
Mareeba	KBDI mean	0.02	-0.71	0.14	0.37	0.1
Mareeba	KBDI max.	0.12	-0.28	0.41	0.36	0.22
Mareeba	KBDI 99%	0.23	-0.34	0.41	0.36	0.22
Mareeba	KBDI 95%	0.21	-0.35	0.44	0.35	0.22
Mareeba	KBDI 90%	0.24	-0.43	0.41	0.35	0.21

5.5 Discussion

This study aimed to understand how climate change might affect conditions relevant to vegetation by assessing historic climatic and fire danger trends within one region. Climate and fire danger trends for representative sites at Cairns and Mareeba can be used to represent conditions experienced by vegetation types and biota at different points within a complex topographic region. Conditions at Mareeba were used to deduce the conditions experienced by vegetation types (rain forest, tall eucalypt forest and savannas) along a gradient associated with an inland leeward rainshadow (Chapters 3 and 4). Similarly, conditions at Cairns could be used to surmise conditions for coastal windward vegetation. Historic climate and fire danger displayed some similar, as well as different trends between these two sites. This variation is important for deciphering and understanding differences in local environmental conditions and intra-regional patterns, such as between coastal windward and inland rainshadow areas, not captured in coarse scale climate models. Yet it is these local environmental conditions that are experienced by vegetation and biota and have been shown to better predict species distributions than macroclimate (Ashcroft *et al.* 2012; Ashcroft & Gollan 2012, 2013a, 2013b, Gollan *et al.* 2013, 2015; Letten *et al.* 2013; Slavich *et al.* 2014). It is likely that the observed trends in climate and fire danger are indicative of future trajectories under climate change. These local scale intra-regional trends may provide critical missing information from coarse climate models for a topographically complex region.

5.5.1 Forest Fire Danger Index

Significant increases in fire danger conditions were detected in the Australian Wet Tropics over the 120 years from 1890 to 2010. However, little change was detected during the 54 years from 1957 to 2010. The number of significant trends relative to the time period (120 years compared to 54 years), suggest that longer time periods may be required for the linear models to detect significance (p <0.05). Longer time-series tend to have more statistical power and ability to detect significant changes (von Storch and Zwiers 1999; Mudelsee 2010; McLeod *et al.* 2012; Rao *et al.* 2012). This may be why no trends were significant for Mareeba, with data only for the latter time period. Were data available for the same period as Cairns (1890 to 2010), it is suspected that some of the trends at Mareeba would also have been significant. Accordingly, some near significance trends in fire danger since 1957 were considered, with caution.

Extreme fire danger conditions increased at both Cairns (1890-2010, but not in the later period 1957-2010) and at Mareeba (with near significance). Average fire danger trends differed within the region. Average fire danger increased at Cairns (1890-2010, but not in the later period 1957-2010), but there was a decrease in average conditions at Mareeba (with near-significance).

Changes in average fire danger conditions, will result in different effects on vegetation than changes in extreme fire danger conditions (assuming fire danger is representative of actual fire occurrence). Savanna woodlands are able to burn under most conditions, such as average fire danger conditions, due to their fine flammable fuels, however, tall eucalypt forest and rain forests are generally only able to burn under extreme fire danger conditions, such as fire danger maxima, due to more complex fuel structures and microclimatic feedbacks (Chapters 3 and 4; Walker 1981; Unwin *et al.* 1985; Bowman & Wilson 1988; Whelan 1995; Banfai & Bowman 2007). Changes in average fire danger conditions are unlikely to influence tall eucalypt forests or rain forests, but a change in extreme fire danger conditions will. Changes in extreme fire danger has the potential to alter vegetation distribution, whereas changes in average fire danger conditions are unlikely to result in distributional changes.

Increasing extreme fire danger conditions have the potential to adversely impact fire sensitive tall eucalypt forests and rain forests, if this is an increase in fire frequency, intensity or area burnt in those vegetation types (Williams *et al.* 2009). An established relationship in fire danger patterns between Mareeba and each vegetation type (Figure 4.9), provided evidence that extreme fire danger is increasing for each vegetation type (consistent with Mareeba). Although vegetation types experience lower FFDI values than at Mareeba, any increase in extreme fire danger patterns represents an increase in the likelihood of fire. Should extreme fire danger increase more substantially under future climatic change, this could threaten rain forests and tall eucalypt forests, despite other declining trends in fire danger. For rain forests and tall eucalypt forests, the trend of increasing fire danger extremes is of concern and could result in an increase in fire frequency (decrease in fire interval) or intensity. These changes could have a significant effect on these fire sensitive communities and, depending on the severity of change, could cause vegetation to shift or collapse.

Although vegetation feedbacks may act as a buffer against periodic changes in climate, an ongoing change may drive a shift in vegetation distributions. This can happen dramatically through fire, which is one of the most pervasive forces in driving vegetation distribution (Bond *et al.* 2005). An increase in fire risk could result in a higher fire frequency, encouraging the spread of fire tolerant savanna vegetation, whereas a decrease in fire risk and frequency may permit the expansion of rain forest vegetation. For example, a major drought was recorded in the region in 1915, following which large areas of rain forest were reportedly burnt (Stocker & Unwin 1986).

There is little indication of any threat from climate change or fire to savanna vegetation. Historic fire danger trends (this chapter) and savanna vegetation stability (Chapter 2) indicate that this vegetation type is stable and has the capacity to expand into overlapping environmental niches of other vegetation types. Savannas are able to burn under even low fire danger conditions and a decline in average fire danger is unlikely to result in a reduction in conditions for savanna fires, nor to an extent that could affect its persistence. Substantial and sustained declines in average fire danger conditions, coinciding with an ongoing increase in rainfall over a long period of time would be required to adversely affect savanna vegetation, via transition to less flammable vegetation. Declines in average fire danger conditions at Mareeba and each vegetation type, could represent a decline in actual fire frequency (increased fire interval) were it not for the prevalence of non-natural, anthropogenic ignitions which are the primary cause of fires in this region (Ash 1988; Fensham 1997; Preece 2007) and elsewhere.

Rain forest, tall eucalypt forest and savanna have different sensitivities and tolerances that will affect their responses to shifts in fire danger. Rain forest, tall eucalypt forest and savanna each display different fire sensitivity, regenerative capacity and shade tolerance. Rain forests are shade tolerant and species can regenerate beneath the closed canopy of a rain forest. However, rain forests are intolerant of frequent fire, despite some plant species ability to resprout following an individual fire (Marrinan *et al.* 2005; Williams *et al.* 2012c). Eucalypt species typical of tall eucalypt forests and savannas are typically shade intolerant and are unable to establish beneath a closed rain forest canopy (or sub-canopy in tall eucalypt forests) (Ashton 1981; Duff 1987; Ashton & Attiwill 1994; Gill & Catling 2002). Tall eucalypt forests may be considered long-term shade intolerant, based on the longevity of dominant eucalypt species, time to reach maturity and slow rate of rain forest encroachment (Tng *et al*. 2011). Savanna, on the other hand, might be more medium-term shade intolerant and tend to be highly fire tolerant and withstand frequent fire. Tall eucalypt forests are less fire tolerant than savanna, but generally rely on an infrequent fire event for dominant eucalypt species to recruit (Unwin 1989; Campbell & Clarke 2006; Bradstock 2010; Hoffmann *et al.* 2012a; Lewis *et al.* 2012; Campbell *et al.* 2012; Williams *et al.* 2012c). Thus, tall eucalypt forests are sensitive to both frequent fire and shade intolerances and are more vulnerable to shifts in fire danger and shifting vegetation than either rain forest or savanna.

5.5.2 Climate

Climatic trends underlying the fire danger conditions differed in many cases between coastal windward and inland rainshadow areas of the Wet Tropics. Mareeba demonstrated more significant and greater increases in temperature than at Cairns, with maximum temperatures increasing substantially both annually and during the fire season. Based on this variable alone, a greater increase in fire danger might be expected for Mareeba than was detected. However, Mareeba also displayed an increase in rainfall and relative humidity, which presumably counter-balanced increased temperature rises (and wind speed) in the fire danger calculations. Cairns on the other hand displayed no increase in rainfall and decreases in relative humidity and wind speed. These divergent climatic trends may differences in fire danger trends between the two sites.

Climatic differences between these two sites indicate intra-regional variation in climatic trends, according to geographic position. Caution should therefore be used when interpreting studies that adopt averaged site trends to represent a region, such as spatially interpolated climate. Variation in trends between Cairns and Mareeba is an indication that inland leeward areas of the Wet Tropics may experience different climatic changes than coastal windward areas.

During the period from 1957 to 2010, Cairns showed less significant climatic trends than for the longer time period from 1890 to 2010. This either indicates that longer time periods are required to detect statistical significance, or that the rate of change was less during the latter period. Longer time-series tend to have more statistical power and ability to detect changes (von Storch & Zwiers 1999; Mudelsee 2010; McLeod *et al.* 2012; Rao *et al.* 2012). Near significance trends and statistical power in relation to short time-series are discussed in the literature and in application (see for example Wilby 2006; McLeod & Vingilis 2008). One cannot be certain that near significant trends are the result of statistical power (because of the need for a longer time-series) or because there is no change. Given this has been observed with the data presented here, consideration of near significant trends, as discussed here, therefore, seems warranted. Accordingly, three near significance fire danger trends at Mareeba should be considered, with caution.

5.5.3 Historic trends and climate change projections

Were historic climate and fire danger trends consistent with other historic analyses?

Historic climate and fire danger trends were broadly consistent with regional evaluations by others. This was not unexpected as all studies were based on the same original Bureau of Meteorology data, but analysed and presented in different ways. Comparisons were made with regional assessments of historic fire danger (Clarke *et al.* 2013) and climate (Turton *et al.* 1999; Suppiah *et al.* 2007, 2010; Heinrich *et al.* 2008; Hilbert *et al.* 2014; McInnes *et al.* 2015). Previous evaluations were available for the broader region and for the Cairns, however, Mareeba had not been previously evaluated.

The general trends for fire danger at Cairns were largely consistent with Clarke *et al.* (2013), with small increases in cumulative and 90th percentile fire danger conditions. However, some fire danger trends for Cairns differed from those for the period from 1973 to 2010 (Clarke *et al.* 2013), which may be associated with differing time scales and start point of the analyses. Clarke *et al.* (2013) detected a greater increase in annual 90th percentile FFDI (0.077 per year), than detected for the period 1890 to 2010 (0.05) or from 1957 to 2010 (0.02). The annual cumulative FFDI significantly increased by 7.63 per year for the period 1890 to 2010, but not significantly from 1957 to 2010, nor for the period 1973 to 2010 (Clarke *et al.* 2013). Seasonal 50th percentile FFDI trends increased significantly for all seasons except DJF from 1890 to 2010, for MAM and JJA between 1957 and 2010 and for MAM only between 1973 and 2010 (Clarke *et al.* 2013). Seasonal 90th percentile FFDI significantly increased in all season from 1890 to 2010, but only in MAM from 1957 to 2010 and in MAM and JJA from 1973 to 2010 (Clarke *et al.* 2013). These results support the finding from Clarke *et al.* (2013) that time series analysis is sensitive to the choice of start point. It is likely that trends and their significance may have been consistent with Clarke *et al.* (2013), had the same time period been used. However, it is preferable to adopt longer time periods (where appropriate) in time series analysis, particularly when linear models are being used (von Storch & Zwiers 1999; Mudelsee 2010; McLeod *et al.* 2012; Rao *et al.* 2012). Clarke *et al.* (2013) discuss their selection of start point during a particularly wet period, whereas here, the earliest available records were used as the start point.

Historic climate trends were broadly consistent with other evaluations of present climate variability for the broader region. Suppiah *et al.* (2010) described average regional trends in temperature between 1950 and 2009. They found average temperature increased by 0.01 °C per year, maximum temperature increased by 0.01 °C (presumably average daily maxima) and minimum temperature increased by 0.01 °C per decade. Here, average temperature (average of Cairns and Mareeba between 1957 and 2010) increased by 0.01 °C per year, average daily maximum temperature (not annual maximum) increased by 0.01 °C and minimum daily temperature increased by 0.03 °C per decade. McInnes *et al.* (2015) identified increases in temperature from 1910-2013; for mean (1.1 °C), maximum (1.0 °C) and minimum (1.2 °C) temperatures. Here, temperatures increased between 1890 and 2010 at Cairns, for mean (1.2 °C), annual maximum (2.4 °C), average daily maximum (2.4 °C) and average daily minimum (1.2 °C). While other studies (Suppiah *et al.* 2010; McInnes *et al.* 2015) have provided average change data for a region or for multiple sites, data for two specific sites are used here. This may explain observed differences in results.

Suppiah *et al.* (2010) and McInnes *et al.* (2015) both detected no clear long-term trend in annual rainfall over the last century, but did show strong inter-decadal and inter-annual variability associated with the Southern Oscillation Index (SOI). Suppiah *et al.* (2010) noted a decline in rainfall in recent years and McInnes *et al.* (2015) slightly stronger trends in recent years (1960-2013). Again, these results were averaged trends for the region, however, significant intra-regional variation was demonstrated here between two representative sites. Here, no significant trends in rainfall were detected at Cairns between 1890 and 2010, nor from 1957 to 2010. Suppiah *et al.* (2007) demonstrated a decline in rainfall at Cairns from 1940 to 2006, with a stronger decrease at Townsville (to the south of the Wet Tropics region). However, Mareeba had a significant increase in rainfall between 1957 and 2010 (530 mm) (see caveat in 5.5.4). Together, these sites demonstrate complex spatial variability in rainfall patterns in the region. Patterns of inter-decadal and inter-annual rainfall variability were consistent with other long-term rainfall studies (Turton *et al.* 1999; Heinrich *et al.* 2008). Observed differences between other observations (Suppiah *et al.* 2007, 2010; Hilbert *et al.* 2014; McInnes *et al.* 2015) with data presented here are inevitable, due to differences in the number of official meteorological sites sampled (only Cairns and Mareeba in the present study) and the process of averaging results across the region. It is not clear how many sites were used by Suppiah *et al.* (2010), however Turton *et al.* (1999) accessed rainfall data from 264 recording sites throughout the region.

At the fine-scale, Cairns and Mareeba each represent opposite ends of a spectrum with sharp climatic contrasts between coastal windward lowlands and inland leeward tablelands. The differences between these two sites are of particular regional importance and have implications for climate variability in other similar regions with complex coastal topography. Averaging their results is nonsensical. An analysis of climate data from an official meteorological station in a montane area between Cairns and Mareeba (if one existed) would be meritorious (see Chapter 3). In its absence, however, the described relationships between Mareeba data and vegetation site data provides meaningful detailed insight into fine-scale landscape climatic patterns. Rainfall patterns between meteorological stations is likely to display far greater variability than for temperature, as it is much more likely to be affected by local topographic features, including elevation, distance from the coast and intercept inputs (Turton *et al.* 1999; McJannet *et al.* 2007; Wallace & McJannet 2008).

Were historic climate and fire danger trends consistent with future climate projections?

Historic climate and fire danger trends were broadly consistent with future climate projections for the Wet Tropics. However, intra-regional trend variability detected from historic data provides valuable insight to localised conditions and patterns, not reflected in broad-scale future climate models. This detail is critical because local environmental conditions are what are experienced by vegetation and biota. Intra-regional trends were not all consistent throughout the region and by ‘averaging’ conditions for the entire region, as is done with global climate models, the detail, variability, complexity, accuracy and certainty of some trends will be weakened. Accordingly, these local intra-regional trends could provide more meaningful information about climate change trajectories than projections based on average coarse scale global climate models (Hilbert *et al.* 2014; McInnes *et al.* 2015).

Historic fire danger trends were broadly consistent with future fire danger projections for the region (Pitman *et al.* 2007; Clarke *et al.* 2011; McInnes *et al.* 2015), but demonstrated intra-regional differences. Projections of future fire danger for northeastern

Australia vary among studies, but generally indicate little change with a likely increasing tendency (Pitman *et al.* 2007; Clarke *et al.* 2011; McInnes *et al.* 2015). Pitman *et al.* (2007) predicted an increasing trend in FFDI to 2050 and to 2100 along the Queensland coast, perhaps to a lesser extent in the Wet Tropics area. However, their study was confined to the month of January only, which is the monsoon period and not representative of the peak fire season in the Wet Tropics or northern Australia. Averaging results for the season including January (DJF) from Cairns and Mareeba presented here would result in a declining trend in average fire danger. This result is not characteristic of broader annual and seasonal trends, particularly the fire season (SON), nor is this consistent with the trend predicted by (Pitman *et al.* 2007). Clarke *et al.* (2011) predicted little change, with a decrease mean and extreme FFDI to 2050, returning to 20th century levels by 2100. Although an average of Cairns and Mareeba results presented here (which would equate to not much change) are in likely agreement with their projections for average fire danger, they are not in agreement regarding extreme fire danger, which has increased in the inland leeward area of the region.

More recent projections, based on advanced global climate models (CMIP5), indicated little change with an increasing trend in fire weather conditions in the Wet Tropics (Cairns and Mackay meteorological stations only; McInnes *et al.* 2015). They predicted a 5-13% increase in cumulative FFDI by 2090 and that fire behaviour would become more extreme. However, details on these conditions were not provided. McInnes *et al.* (2015) did not evaluate extreme FFDI conditions relative to the region, but instead relative to the rest of Australia. They used ‘Severe’ fire weather days (FFDI ≥50), consistent with a benchmark evaluation of fire danger extremes used for all the regions in Australia (CSIRO & Bureau of Meteorology 2015). Conditions of that extreme have not existed in the Wet Tropics since meteorological measurements began. The maximum FFDI recorded at Cairns (1890-2010) was 42 and the maximum FFDI recorded at Mareeba (1957-2010) was 44 and thus a more appropriate measure of extreme fire danger in this region would be ‘Very High’ (FFDI ≥25) or ‘High’ fire weather days (FFDI ≥12). Even though no data was provided regarding fire danger extremes for the Wet Tropics, an increase in extreme fire danger was predicted with medium to high confidence (McInnes *et al.* 2015).

There is considerable difference in scale between fire predictions of others with the analysis presented here. Cairns and Mareeba are only 40 km apart, with significant topographic variability between them, most of which occurs within only 20 km. In comparison, future fire danger models involved much larger analysis areas: 356 km x 623 km (Pitman *et al.* 2007); 210 km^2 (Clarke *et al.* 2011) and approximately 180 km^2 (CSIRO & Bureau of Meteorology 2015; McInnes *et al.* 2015). Even with fine resolution downscaling techniques, no additional information is added to this data (p. 178, CSIRO & Bureau of Meteorology 2015). Thus, results provided for Cairns (McInnes *et al.* 2015), for example, remain an approximation (bilinear interpolation) of average conditions within a 180 km^2 pixel, which would include both Cairns and Mareeba). Using approximations at this scale require averaging variable and divergent local conditions, between even closely located sites. The historic trends detected here include an increase in average fire danger conditions at Cairns (1890-2010) and a decrease at Mareeba (with near significance). Averaging these patterns out to represent trends in the region could easily result in the 'little change' predicted in future fire danger by others. Averaging trends and trajectories for large spatial areas is likely to mask patterns at individual sites. There is demonstrable evidence that there are varying intra-regional fire danger patterns indicated at the site level, which are not reflected in average regional patterns (Pitman *et al.* 2007; Clarke *et al.* 2011; CSIRO & Bureau of Meteorology 2015; McInnes *et al.* 2015). Without explicit site-based models, there is little evidence to suggest that observed historic fire danger trends at Cairns and Mareeba will or will not continue on their current trajectories with ongoing climatic change.

Observed historic climatic trends were consistent with regional climate change projections for temperature (Suppiah *et al.* 2007, 2010; Hilbert *et al.* 2014; McInnes *et al.* 2015). Recent projections estimated an increase between 2.3 and 3.9°C by 2090 (RCP8.5), relative to the 1950-2005 mean (McInnes *et al.* 2015). Increases in temperature extremes were also predicted with the number of heatwaves (days over 35°C) to increase at Cairns by 1600% by 2090 (RCP8.5). Projections of annual average temperature increase for all emission scenarios, with inland areas (such as Mareeba) warming faster than coastal areas (such as Cairns) (Suppiah *et al.* 2010). These projections are consistent with the historic trends presented here.

Regional climate change projections for rainfall were variable with uncertainty regarding the direction of change (Suppiah *et al.* 2007, 2010; Hilbert *et al.* 2014; McInnes *et al.* 2015). Predicted changes are small compared to observed historic rainfall variability. Naturally high variability in rainfall masks detectable long-term trends. Some predictions include a decrease in the 50th percentile of annual and dry season (JJA, SON) rainfall (Suppiah *et al.* 2010). Other projections suggest a mild increase in drought (Kirono *et al.* 2011), although more advanced models show low confidence in drought predictions (Hilbert *et al.* 2014; McInnes *et al.* 2015). No change in rainfall was detected at Cairns, but there was a significant increase in rainfall at Mareeba. It is pattern is not consistent with climate predictions. The scale of analysis for projected rainfall has been much broader than for temperature (Suppiah *et al.* 2010), possibly contributing to the observed spatial variation in model outputs. Another source of error, is that rainfall models do not capture topoclimatic patterns, such as the coastal orographic influence on rainfall (McInnes *et al.* 2015). However, given that Cairns specific projections (Appendix 18, Suppiah *et al.* 2010) were consistent with the lack of change observed at Cairns since 1890, it is likely that observed trends at Mareeba since 1957 also demonstrate future trajectory. Fine-scale or site-specific projections may be more useful for understanding intra-regional patterns than relying on larger macro-scaled projections using regional averages.

There was low confidence in projections of increasing trends for wind speed and decreasing trends for relative humidity in the long-term (Hilbert *et al.* 2014; McInnes *et al.* 2015). These predicted trajectories were consistent with observed trends for Mareeba, however, Cairns displayed a trend towards decreasing wind speed.

5.5.4 Methodology implications

The time series analysis utilised here was a ‘linear’ regression approach. There is no reason to expect climatic change trends to be linear and in fact, they are more likely to be non-linear. Complicating this further, trends show natural variability, including cyclic patterns, which may be high for some variables such as rainfall (Suppiah *et al.* 2007, 2010; Hilbert *et al.* 2014; McInnes *et al.* 2015). Nevertheless, linear trends are an easily digestible indication of change from a start point to the present point. However, due to underlying non-linear trends in climate, the choice of start point and end point will influence the slope and significance of applied linear trends. Tests may be required to assess the level of influence of start and end points (see Clarke *et al.* 2013). Also, more complex trend analysis could be performed to assess the significance of non-linear trends or cycles (Suppiah *et al.* 2010; McInnes *et al.* 2015). The choice of start and end point in the time series may explain inconsistencies in slope and significance of fire danger trends observed for Cairns from 1890 and 1957 (this study) and from 1973 (Clarke *et al.* 2013). Shorter time series are more sensitive to start and end points, thus maximising the length of the time series will provide a more reliable indicator of the slope and significance of change. Although there may be uncertainties regarding the accuracy of early records, data provided by the Bureau of Meteorology included a quality flag description for each site and variable of the highest rating: "quality controlled and acceptable". Including the maximum time series within a strict homogenisation framework provided the best option.

Given the significance of change for (almost) all variables at Cairns from 1890 to 2010, but less so for 1957 to 2010, this could suggest that change trends for Mareeba that were not significant from 1957 to 2010 may have been significant for the period from 1890 to 2010 (if this data were available). Longer time-series tend to have more statistical power and ability to detect changes than shorter ones (von Storch & Zwiers 1999; Mudelsee 2010; McLeod *et al*. 2012; Rao *et al*. 2012). Perhaps longer time series or different analysis techniques (such as non-linear trends) are needed to better assess the meteorological data presented here.

Data homogenisation of time series data produced some unusual results (Appendix 5.2). Rainfall data at Mareeba showed a significant shift from the linear calibration, affecting annual rainfall trends. There may be more appropriate calibration equations than the linear regressions used, but would involve more complex modelling. Two results, annual mean temperature and annual mean relative humidity at Mareeba, both show an unexplained offset correction from the homogenisation step (Appendix 5.2). Homogenised data theoretically should be aligned with the calibrated data towards the end of the time series. Although these offsets do not impact the overall trends, they do affect the absolute values (1.52°C for temperature and -2.03% for humidity). However, validation of the analysis resulted in the same outputs.

5.5.5 Conclusions

Historic climate and fire danger trends demonstrated intra-regional variation within the Wet Tropics. Some patterns varied between coastal windward lowlands and inland leeward tablelands. These intra-regional variations provide invaluable insight into local conditions and potential impacts otherwise masked in coarse regional climate change projections. Historic trends were broadly consistent with other studies and with future climate projections, giving confidence that current trajectories are a reliable indication of future trajectories for those sites. Increasing extreme fire danger trajectories pose a potential threat to fire-sensitive rain forests and tall eucalypt forests.

Plate 8. Tall eucalypt forest that has been logged, grazed and burnt, with signs of frequent fire that has damaged (right) or killed (left) mature *Eucalyptus grandis* trees. The understorey following such intensive disturbances if often grassy with species such as *Imperata cylindrica*. Mt Windsor.

Plate 9. Logged tall eucalypt forest being burnt to maintain the grassy understorey.

Plate 10. Prescribed burning in tall eucalypt forest that does not have a grassy understorey. The lower left image (Paluma) depicts a higher intensity burn with complete understorey and sub-canopy scorch than the other images with low intensity burns (Lamb Range). However, mature *Eucalyptus grandis* are readily killed by repeated low intensity fires (lower right image).

CHAPTER 6

General Discussion

6.1 Introduction

Impacts of climate change on vegetation in Australia suggest the potential for substantial declines in rain forest (-56.5%) and tall eucalypt forest (-41.0%) distribution and a substantial increase in the distribution of savanna (+160.7%) (Hilbert & Fletcher 2012). Within the Wet Tropics, climate change has significant implications for the biodiversity of the rain forests, largely due to the high sensitivity of cool-adapted taxa in the uplands (Williams *et al.* 2003b). However, climate change projections indicate that the greatest risk to vegetation is at rain forest boundaries and specifically tall eucalypt forests with significant shifts in the distribution of vegetation types likely in these areas (Hilbert *et al.* 2001b; Hilbert 2010). While there are predicted increases and decreases in different forest types, climatic refugia for tall eucalypt forests are predicted to "largely disappear by 2050" (p.7, Hilbert 2010), placing this vegetation type at risk of collapse (Keith *et al*. 2013; Rodríguez *et al*. 2015). However, these projections do not take into account the potential impact of fire. Projections for vegetation types are based on change in temperature and rainfall only, yet fire is a primary mechanism affecting rain forest boundaries (Bowman 2000) and tall eucalypt forests in the short-term (Unwin 1989; Campbell & Clarke 2006; Bradstock 2010; Hoffmann *et al.* 2012a; Lewis *et al.* 2012; Campbell *et al.* 2012; Williams *et al.* 2012c). Thus, climate-induced shifts in fire danger are likely to be a significant driver of vegetation change.

Large areas of rain forest and tall eucalypt forest are displaced by savanna in parts of their core niche in the Wet Tropics (Chapter 2; Wilson & Agnew 1992; Hoffmann *et al.* 2002; Beckage & Ellingwood 2008; Beckage *et al.* 2009; Hoffmann *et al.* 2009; Warman & Moles 2009; Odion *et al.* 2010; Tng *et al.* 2013, 2014), which is consistent with patterns throughout Australia (Hilbert & Fletcher 2012). Many studies suggest that frequent fire is the main driver of these alternative vegetation states, caused by vegetation-fire feedbacks (Wilson & Agnew 1992; Clarke & Lawes 2013; Pausas 2015). Changes to the frequency and/or intensity of fire, have the capacity to affect this dynamic and push vegetation towards tipping points which cause a switch into alternative stable states (Warman & Moles 2009; Gonzalez *et al.* 2010; Laurance *et al.* 2011a; Higgins & Scheiter 2012; Lloret *et al.* 2012). Savanna vegetation is already highly fire tolerant, however, rain forest and tall eucalypt forests are not and are vulnerable to an increase in fire frequency or intensity.

Climate change is predicted to result in a widespread increase in fire danger in Australia (Beer & Williams 1995; Cary & Banks 1999; Williams *et al.* 2001; Cary 2002; Hennessy *et al.* 2005; Lucas *et al.* 2007; Pitman *et al.* 2007; Hasson *et al.* 2008; Williams *et al.* 2009; King *et al.* 2011; Cary *et al.* 2012; CSIRO & Bureau of Meteorology 2015). Predictions of future fire danger for the Wet Tropics vary, with some predictions of large increases along the Queensland coast during January (Pitman *et al.* 2007), other predictions of a decrease in fire danger (Clarke *et al.* 2011) and more recently, predictions of little change tending towards a slight increase (McInnes *et al.* 2015). Evidence presented here suggests fire danger has increased in the Wet Tropics, but with some variability within the region (Chapter 5).

The preceding chapters have presented a range of results indicating the complexity of vegetation, topographic, climatic and pyric interactions. How climate change interacting with fire might impact vegetation of the Wet Tropics requires consideration of these complexities. The relative influence of climate, topography and soil on the distributional patterns of vegetation was determined (Chapters 2 and 3) and the potential presence of alternative vegetation states was quantified (Chapter 2). Vegetation feedbacks on microclimate and fire danger were detected (Chapter 3 and 4). Accounting for these complexities in vegetation models is currently a major barrier to making effective predictions of future distributions or refugia under climate change (Harris *et al*. 2016). Spatial macroclimate models alone have poor relationship with *in situ* topoclimate conditions without considering vegetation and topography (Chapter 2 and 3). Their use in distribution modelling should be considered with caution. In the absence of reliable spatial models of future climate, the use of historic climate and fire danger trends were useful to identify trends and potential trajectories under climate change, as well as intra-regional variability not captured by macroclimate models (Chapter 5). Existing regional climate change projections for the Wet Tropics (McInnes *et al*. 2015) do not necessarily reflect detailed local or intra-regional patterns. Fine-resolution intra-regional studies are required to provide greater detail of local climate patterns and potential climate change impacts.

Changes in climate and fire danger alone will not necessarily result in a change to the fire regime. However, an increased likelihood of fire interacting with anthropogenic ignitions could result in an increase fire frequency. Fire frequency is perhaps more strongly linked to anthropogenic ignitions than to climate itself (Collins *et al*. 2016; Mann *et al*. 2016). Ignitions in the Wet Tropics, are primarily of anthropogenic causes (Ash 1988; Fensham 1997; Preece 2007), as with elsewhere in Australia (Willis 2004; Thackway *et al.* 2008; Beale & Jones 2011; Collins *et al*. 2016; Mann *et al*. 2016). No evidence of changes in natural ignitions was found in the literature other than an indication that background or natural fire activity in tall eucalypt forests and rain forests is considerably rare. However, substantial evidence of changes in anthropogenic ignitions was evident (Birtles 1982, 1988, 1997a, 1997b; Frawley 1988, 1991; Unwin *et al.* 1988; Winter *et al.* 1991a; Crome 1992; Frost 1997; Haberle *et al.* 2006; Turton 2008). A review of the literature provided insights into historic practices and vegetation change associated with European activity (see Appendix 1.1 for full discussion). The culmination of this activity suggest tall eucalypt forest have been degraded and may therefore lack resilience to increased disturbance or climatic changes. The risk to vegetation from climate change relates to an increase in fire danger conditions interacting with anthropogenic ignitions. Appropriate management and fire regimes in these forests can build or diminish resilience to future risks. Anthropogenic ignitions are strongly linked to fire frequency suggesting that strict management of ignitions is a priority action to mitigate increasing fire danger conditions.

Evidence presented indicated particular vulnerability of tall eucalypt forests and upland leeward rain forests to potential shifts in distribution, which could result from changes in climate and fire danger. Tall eucalypt forests may be particularly at risk, because they currently occupy sub-optimal areas of their environmental niche and because of historic disturbance regimes. For these reasons, a review of available information regarding tall eucalypt forests, their history, ecology, vulnerability, management and future are provided in Appendix 1.1.

6.2 Synthesis of key findings

The aim of this thesis was to assess whether climate change interacting with fire might affect vegetation distribution along an environmental gradient in the Australian Wet Tropics (1.6). Popular methods for making such predictions rely on distribution models using spatially interpolated climate. However, assessment of vegetation distribution models using present climate conditions, gave cause to question complicating factors in model development. These included potential presence of vegetation feedbacks, alternative stable states of vegetation and accuracy of spatially interpolated climate data inputs. Using distribution models to predict how climate change and fire might affect vegetation was considered too inaccurate without first quantifying complicating factors and thus, other methods were used. This was done by a. quantitative assessment of *in situ* meteorological and fire danger conditions, b. correlating *in situ* conditions with official meteorology, c. assessing historic trends and likely trajectories of change in climate and fire danger and d. relating trends and trajectories to *in situ* conditions.

Recent changes in climate have resulted in changes to fire danger within the Wet Tropics. There was evidence of increasing fire danger at Cairns since 1890 and a near significance trend of declining fire danger at Mareeba since 1957. A near significance increase in extreme fire danger at Mareeba, if it is real, may be a threat to fire sensitive tall eucalypt forests and rain forests (Chapter 5). This is not evidence of an increase in fire frequency or intensity, but of likelihood. The extent to which climate change will continue to influence fire danger conditions is not clear, as future climate projections for the region were not at a meaningful scale relevant to the environmental gradient and vegetation boundaries of the area. There was some evidence that there are variable intra-regional fire danger patterns at a fine spatial scale, which are masked by coarse scale, average regional climate patterns (Pitman *et al.* 2007; Clarke *et al.* 2011; McInnes *et al.* 2015).

Historic trends in climate and fire danger were generally consistent with future climate projections for the region, suggesting that this trajectory accurately reflects the direction of future change. It is also likely that the observed intra-regional variation in trends will also exist under future climate and may provide an indication of the sort of variability to be expected from coarse-scale regional projections.

Evidence was presented demonstrating the influence of vegetation feedbacks and potential extent of alternative stable states between vegetation types in the Wet Tropics (Chapter 2). The most significant trend was for savanna vegetation to dominate over other vegetation types. It exceeded its predicted distribution (presumably because of fire) at the cost of both rain forest and tall eucalypt forests, neither of which filled their potential distribution, suggesting alternative stable states of vegetation. Vegetation had a strong influence on both microclimate (Chapter 3) and fire danger (Chapter 4), suggesting potential vegetation feedback mechanisms that might contribute to alternative vegetation stable states. The presence of alternative stable states may represent the relative vulnerability of each vegetation type to change (Chapter 2), with tall eucalypt forests the most vulnerable.

Tall eucalypt forests are particularly vulnerable to climate change, fire frequency and degradation, as well as interactions between these stressors. They are vulnerable to climate change throughout their distribution, as suitable climatic areas are predicted to disappear by 2050 (Hilbert 2010). This risk may be exacerbated by either degradation or by increased fire frequency. Climate change itself is unlikely to drive rapid change in vegetation, given that vegetation can exist in alternative stable states and in disequilibrium with climate. However, fire is one of the most pervasive drivers of environmental change and does have the capacity to drive rapid change in vegetation (Williams *et al.* 2009; Murphy *et al.* 2012; CSIRO & Bureau of Meteorology 2015). Climate-induced changes in the fire regime, therefore, have the potential to cause abrupt large-scale changes and bring about tipping points in vegetation. Hilbert (2010) did not take into account the impact of fire and his predictions may be exacerbated by other stressors including fire.

A discussion of tall eucalypt forests, their historic disturbance and management is provided in Appendix 1.1. A review of the available literature suggests that the tall eucalypt forests of the Wet Tropics, like elsewhere in Australia, have been degraded by European disturbances and may be managed with fire regimes that are too frequent to sustain pre-European structure and composition. Degraded tall eucalypt forests managed with inappropriate fire regimes may constitute a landscape trap and could further jeopardise some areas of tall eucalypt forests. Impacts may be exacerbated, or mitigated by the frequency and intensity of fires that occur today and the near future. Tall eucalypt forests in this predicament elsewhere in Australia have been identified as critically endangered, vulnerable to climate change and at risk of ecosystem collapse (Burns *et al*. 2015). This is also possible for the tall eucalypt forests in the Wet Tropics. A near significant trend of increasing extreme fire danger , if it is real, could threaten fire sensitive tall eucalypt forests and rain forests by increasing conditions within which they could burn. Although this trend was not significant (p<0.05), the potential it is real is high and should be considered cautiously.

Robust spatial distribution models of vegetation were achieved using a novel technique with a large, fine-scale dataset (Chapter 2). Strong climatic, geographic, edaphic and lithographic influences on vegetation distribution were detected. However, model performance was not perfect, considering all data was used and the full distributions already known, suggesting other factors, perhaps fire or vegetation feedbacks, were also important in determining vegetation distribution (Harris *et al*. 2016). Also, spatially interpolated climate data as used in the models, poorly represented microclimatic conditions along the environmental gradient (Chapter 3), suggesting potential inaccuracies for modelling purposes. Relationships between modelled macroclimate and *in situ* microclimate were generally poor. Using a network of micrometeorological stations, microclimatic and fire danger patterns between vegetation types were established (Chapters 3 and 4 respectively), as were their relationship with a nearby long-term meteorological station. These relationships may be used when future climate projections at a suitably fine resolution become available or in the development of topoclimate grids (Ashcroft & Gollan 2012).

Vegetation demonstrated microclimatic feedbacks (Chapter 3), which in turn influence the likelihood of fire (Chapter 4). Rain forest and tall eucalypt forests demonstrated lower fire danger than savanna, over a three-year period, regardless of their topographic position (Chapter 4). Some evidence of historic change in fire danger conditions suggested increasing extreme fire danger conditions, which may accelerate under future climate. These conditions increase the chance of fires encroaching into rain forests and tall eucalypt forests, despite other decreasing patterns in average fire danger conditions (Chapter 5). Frequent fire affects fire sensitive vegetation by preventing recruitment and persistence of long-lived fire sensitive biota and truncating long-term, postfire successional pathways. Savanna woodlands, on the other hand, are fire tolerant and do not appear to be at risk of tipping points or alternative stable states. They occupy almost all of their modelled distribution as well as substantial areas more suitable for rain forest and tall eucalypt forest, presumably facilitated by repeated fires (Chapter 2). These findings are consistent with Australian continental-scale evaluations, where savannas are predicted to expand by 160.67% (Hilbert & Fletcher 2012) and in the Americas, where savannas are predicted to increase at the expense of forests and other vegetation (Anadón *et al.* 2014).

Climate change induced shifts in fire regimes have the capacity to drive changes to vegetation distribution, structure and function globally, regionally and locally. Some vegetation is more vulnerable to change, including fire sensitive vegetation types, degraded vegetation with reduced resilience, vegetation susceptible to tipping points and vegetation associated with alternative stable states or landscape/ fire traps. Changes in the fire regime can occur in the very short-term and have the potential to tip vulnerable vegetation abruptly into an alternative stable state. For these reasons, fire managers and agencies should consider the impact of fire management practices to improve vegetation resilience to increased fire risk and climate change. Predicted increases in average and extreme fire danger may be offset and vegetation resilience enhanced by reducing stress from fire (Gill *et al.* 2014; Scheffer *et al*. 2015).

This is the first comprehensive, whole-of-ecosystem, regional study to evaluate potential impacts of climate change on fire danger and vegetation along an environmental gradient. The research has been a data-rich, novel approach utilising multiple strategies to address a difficult and complex system, further complicated by interacting stressors of changing climate and fire, as well as the presence of vegetation feedbacks, alternative stable states and potential landscape traps.

6.3 Aims and objectives

In section 1.6, the aims and objectives of this study were introduced. The overall aim was to assess whether climate change interacting with fire will affect vegetation types and their distribution along an environmental gradient in the Wet Tropics of northeastern Australia. Each of four data chapters (Chapters 2-5) addressed a number of objectives (1.6.1) to address this aim, which are repeated here and discussed below.

1. *Determine the relative contribution of topographic, climatic and edaphic factors in explaining current vegetation distributions* (Chapter 2);
2. *Assess the fine-scale variation in climate driven by topography and vegetation along an environmental gradient* (Chapter 3);
3. *Determine the relative performance of spatially interpolated macroclimate, vegetation and topography in explaining in situ topoclimate* (Chapter 3);
4. *Assess the fine-scale variation in fire danger driven by topography and vegetation along an environmental gradient* (Chapter 4)*;*
5. *Identify historic climate and fire danger trends and extremes within the Wet Tropics region* (Chapter 5)*;*

6. *Determine whether observed climate and fire danger trends are consistent with projected future climate trajectories* (Chapter 5)*;*
7. *Identify historic and likely future changes in climate and fire danger relative to vegetation types* (Chapter 5); and
8. *Evaluate likely impacts of climate change interacting with fire and other potential stressors on vegetation types* (Chapter 6).

6.3.1 Determine the relative contribution of topographic, climatic and edaphic factors in explaining current vegetation distributions (Chapter 2)

Topographic, climatic and edaphic factors explained the distribution of vegetation types with moderate performance. Models explained the distribution of 59% of rain forest, 42% of tall eucalypt forest and 53% of savannas. Spatially interpolated climate data displayed moderate performance in explaining vegetation distribution, but there was high correlation between available variables. Accordingly, the number of variables that could be included in models was necessarily restricted. Rainfall and soil type were the strongest explanatory variables for rain forest and savanna, whereas temperature, elevation and geology were for tall eucalypt forest. Climatic variables that performed well for all vegetation types were precipitation of the driest quarter and maximum temperature of the warmest period. Topographic and edaphic variables performed well for all vegetation types were soil type, relief, geology and distance to the coast.

Although model performance was good to substantial, models were expected to be near perfect, as they included all available data points and full distributions were already known. It is most likely that there were other important variables influencing vegetation distribution not captured by these variables. Comparisons of observed and potential vegetation distributions provided insight into landscape patterns and suggested competition and feedbacks between vegetation types. It is likely that alternative stables states of vegetation and stochastic disturbances by fire are mechanisms also contributing to vegetation distribution and thus affecting model performance. The relative performance of models between vegetation types and occupancy of potential distributions by other vegetation types indicate that savanna is the most stable vegetation type and tall eucalypt forests the least; indicative of vulnerability to landscape change. Tall eucalypt forests appeared to occupy sub-optimal environmental space and are wedged between long-term shade intolerance associated with rain forest (Tng *et al.* 2011) and short-term frequent fire intolerance associated with savanna (Kitzberger *et al.* 2016). Given model performance and evidence of other factors influencing vegetation distribution it is unlikely that these models would accurately predict vegetation distribution under future climate.

6.3.2 Assess the fine-scale variation in climate driven by topography and vegetation along an environmental gradient (Chapter 3)

Three years of microclimate measurements (temperature, humidity, wind speed, soil moisture, solar exposure and rainfall) were collected within a network of 32 micrometeorological sites, along eight transects. Each transect consisted of sites within each of three vegetation types (rain forest, tall eucalypt forest and savanna) at various topographic settings along an environmental gradient. For each microclimatic variable measured, there was a consistent climatic trend, among vegetation types along the environmental gradient. From savanna to rain forest, temperatures and wind speed decreased, while humidity, rainfall and soil moisture increased. Microclimatic conditions were statistically different among vegetation types, with measurements from adjacent vegetation explaining between 12-95% of the deviance for different variables.

Site based data within three different vegetation types displayed similar climatic trends, to varying extends, to that at the Mareeba meteorological station over a three-year period. Rain forest vegetation was most dissimilar to Mareeba, followed by tall eucalypt forest, with savanna being most similar. However, vegetation type, daily meteorological data from Mareeba and transect location only explained 1-30% of deviance for site microclimate. Vegetation and Mareeba variables were better predictors than transect location. Despite low model performance, such correlations are useful in calibrating fine-scale landscape variation in microclimate conditions within complex terrain and the influence of vegetation.

Vegetation had a greater influence on microclimate conditions than topographic factors and was significantly distinct between vegetation types. Vegetation and topographic position explained up to 39% of the deviance for site-based microclimate patterns. Vegetation was consistently a better predictor of site based microclimate than topographic position and contributed up to 99% of the overall model performance. This demonstrated a significant and important effect of vegetation feedbacks on microclimate conditions, regardless of topography. These observations are consistent with a vegetation feedback on microclimate and alternative stable state theory.

6.3.3 Determine the relative performance of spatially interpolated macroclimate, vegetation and topography in explaining *in situ* topoclimate (Chapter 3)

The relative performance of spatially interpolated macroclimate, vegetation and topography in explaining *in situ* topoclimate demonstrated high variability. Vegetation was in most cases a better predictor of topoclimate than spatially interpolated macroclimate. Site based microclimatic data were compared with spatially interpolated climate data and showed that while some interpolated climate variables are relatively reasonable predictors of *in situ* topoclimate conditions (32-63% explained deviance for temperature), most showed very weak relationships (16-24% explained deviance for humidity; 2-17% for wind and 3-5% for solar exposure), or no relationship (less than 1% for rainfall). Vegetation was consistently a better predictor of topoclimate conditions than modelled macroclimate, contributing up to 90% of overall model performance. Spatially interpolated climate did not accurately reflect the *in situ* conditions experienced by biota, nor did it express important extreme events, which can limit the distributions of biota. A better understanding of topoclimate conditions in the landscape is required to improve species distribution and bioclimatic models.

Spatially interpolated climate data displayed inherent collinearity and moderate performance in explaining or predicting vegetation types (Chapter 2). Tests to evaluate the relationship of interpolated climate data with *in situ* microclimatic conditions also demonstrated low performance (Chapter 3). It was concluded that spatially interpolated climate data was not likely to reliably predict vegetation distributions under present, let alone future, climate scenarios. Predictive distribution models using spatially interpolated climate data for biota in similar conditions are likely to result in inaccurate predictions. These results have significant implications for the use and interpretation of spatially interpolated climate in distribution models, as this data had a low relationship with the local scale conditions experienced by biota. Consideration needs be given to the influence of vegetation microclimate feedbacks, complex topographic variations in microclimate (including orographic influences and variation along environmental gradients) and extreme climatic events, rather than climate averages alone. The incorporation of vegetation, topographic, edaphic and microclimate factors will help improve accuracy of distribution models under present and future climates.

6.3.4 Assess the fine-scale variation in fire danger driven by topography and vegetation along an environmental gradient (Chapter 4)

Fire danger, as measured by McArthur’s Forest Fire Danger Index (FFDI), was evaluated for rain forest, tall eucalypt forest and savanna at each of 32 sites within a network of micrometeorological sites along an environmental gradient. FFDI values decreased from savanna, tall eucalypt forest, then rain forest; a pattern that was consistent across each of eight transects. Average FFDI conditions were very low and in savanna were generally less than ten, in tall eucalypt forest were less than six and in rain forest less than four. The structure of fuels among vegetation types influence vegetation flammability, with savannas being highly flammable, due to fine aerated grassy fuels, and rain forests highly non-flammable. Thus, high fire danger conditions are generally required to infiltrate rain forest vegetation. Due to observed FFDI patterns coupled with fuel flammability between vegetation types, only very rarely would rain forest be flammable, despite being adjacent to highly flammable savannas. This highlights the importance of extreme FFDI values in providing conditions conducive for fire spread in rain forest.

Daily fire danger conditions were, not surprisingly, poorly predicted from site based vegetation and elevation alone. However, the relative influence of these variables demonstrated that vegetation type had a greater influence than did topographic position. The stronger influence of vegetation type on fire risk, compared with topography, was consistent with a fire – vegetation feedback. This study is the first demonstration of the influence of multiple vegetation types on microclimate and fire risk along an environmental gradient. These results are important considering the potential impact of global climate change on fire regimes and vegetation distribution.

Daily fire danger from the 32 micrometeorological sites were compared with fire danger from a nearby meteorological station at Mareeba. There was a clear annual pattern in daily FFDI with highest values in the austral winter dry season (between August and November) and lowest values in the austral summer wet season (between December and April). Site-based fire danger was poorly predicted from models using Mareeba meteorological data, vegetation type and site location. However, there was a clear sequential trend in degree of similarity between Mareeba FFDI with average FFDI for each vegetation type, with savanna sites slightly lower than Mareeba, then tall eucalypt forest and rain forest being most dissimilar. Vegetation type substantially improved (doubled) site predictions of fire danger from Mareeba meteorological conditions. These results demonstrate a very strong gradient in FFDI values across rain forest – savanna boundaries in the Australian Wet Tropics and highlight the importance of rare extreme FFDI values in providing conditions conducive for fire spread in rain forest or tall eucalypt forests. A vegetation – fire risk feedback helps explain the juxtaposition of pyrophobic rain forest and pyrophytic savanna, and also the existence of tall eucalypt forests, which require periodic severe fires to regenerate and resist engulfment by rain forest.

6.3.5 Identify historic climate and fire danger trends and extremes within the Wet Tropics region (Chapter 5)

Observed daily meteorological data at Cairns (1890-2010) and Mareeba (1957-2010) in the Wet Tropics of northeastern Australia were analysed with dynamic time series regressions for linear trends. Cairns and Mareeba displayed consistent trends for some variables, but opposing trends for others. Temperatures increased at both sites, however, rainfall showed no trend at Cairns, but an increasing trend at Mareeba. Relative humidity and wind speed decreased at Cairns, but increased at Mareeba. These trends were consistent with other climate trend analysis in the Wet Tropics, albeit for shorter time spans. Historic climate trends demonstrated site variation in regional climatic patterns. The variability between these two sites, only 40 km apart, are striking and have implications for the use of coarse-scaled spatially interpolated climate data based on short time spans. Coarse-scaled climate data and climate projections may be highly spatially inaccurate within topographically complex regions and therefore not meaningful for local or regional planning and management purposes.

Fire danger (FFDI) was reconstructed at Cairns (1890-2010) and Mareeba (1957-2010) meteorological stations for the duration of their climate records. Significant increases in average and extreme FFDI were observed at Cairns (1890-2010), with fewer significant trends during the latter time period (1957-2010). No significant increases were detected at Mareeba (1957-2010), however, two near-significance trends were noteworthy. There was a near significance increase in extreme FFDI and conversely a near-significance decrease in average FFDI. Climatic variables underlying FFDI calculation contributed in varying ways to these results. Fire danger trends observed within the region were generally consistent with future fire danger projections. However, with vastly differing fire danger trends observed between only two representative sites, the spatial variation of intra-regional fire danger requires greater spatial accuracy than the current coarse-scale of future projections. Observed trends perhaps provide a greater level of accuracy of future fire danger trajectories.

6.3.6 Determine whether observed climate and fire danger trends are consistent with projected future climate trajectories (Chapter 5)

Observed climate and fire danger trends for two meteorological stations, 40 kilometres apart, were generally consistent with other historic meteorological and fire danger studies of the region, but provided a longer time period and indicate a high degree of intra-regional variability. An increase in average and extreme fire danger conditions at Cairns was consistent with other studies, however, observations at Mareeba have not been previously explored. For Cairns, an increase in temperature and lack of a clear trend in rainfall, are consistent with other studies. However, a significant increase in rainfall was detected at Mareeba, as well as increasing temperature. These observed trends were also broadly consistent with future climate projections. The scale of future projections, however, were too coarse to indicate the spatial variability observed within the region. The accuracy of spatially interpolated climate models has also been questioned (6.3.3). Coarse-scale (c. 200km resolution) future climate and fire danger projections were considered too broad to provide an accurate or meaningful indication of potential ecological impacts at a local scale. Analysis from two key sites within close proximity, demonstrated significant variation in their trends and potential trajectories. Further drilling into climate models would be required to differentiate projections for these two sites. Projections specifically for these two sites may be more valuable than coarse regional projections, given the extent of intra-regional climate variability. Site trends are likely to represent their trajectory under climate change.

6.3.7 Identify historic and likely future changes in climate and fire danger relative to vegetation types (Chapter 5)

Established relationships with Mareeba climate data and fire danger were used to reconstruct historic climate and fire danger for each vegetation type. Accordingly, vegetation types displayed trends consistent with those at Mareeba (1957-2010). No trends in fire danger were significant, although as with Mareeba, two near-significance trends were noteworthy, including a potential decrease in average FFDI and a potential increase in annual extreme fire danger. If the latter increasing trend were real, these conditions are generally the circumstances under which fire sensitive rain forest or tall eucalypt forests are most likely to burn. Although fire danger conditions were generally quite low for these vegetation types, a potential increase in extreme fire danger still represents an increased risk to being burnt. Under extreme conditions, rain forests and particularly tall eucalypt forests, which are suspected to exist in alternative stable states, are exposed to increased risk of fire-driven tipping points which could result in an abrupt shift to an alternative vegetation state. Climatic trends showed an increase in temperatures and rainfall for all vegetation types. Trends for each vegetation type are likely to represent their trajectory under climate change.

6.3.8 Evaluate likely impacts of climate change interacting with fire and other potential stressors on vegetation types (Chapter 6)

Evaluation of historic trends provided insight regarding the potential impacts of climate change for vegetation type, associated with vulnerability from other stressors. An increase in extreme fire danger conditions associated with climate change is a potential threat to fire sensitive tall eucalypt forests and rain forests, with immediate implications for fire management practices in these ecosystems. Their vulnerability is exacerbated by interactions with other stressors, particularly their current condition following European disturbance regimes. Fire management practitioners need to be cognisant of the potential for transitions to alternative stable states and landscape traps, which may be mitigated or exacerbated by current fire management practices.

6.3.9 *Will climate change interacting with fire affect the distribution of vegetation types*?

In summary, the combined evidence presented here, including the relative vulnerability of vegetation types, presence of alternative vegetation stable states and likely increasing fire danger extremes, suggest that changes in vegetation distributions, mediated by fire, could occur under climate change. The tendency would appear to be for expansion of savanna, at the expense of a contraction of rain forest and significant contraction of tall eucalypt forests. However, an increase in fire danger alone is not enough and anthropogenic ignitions are required for changes in fire potential to be realised. Fire frequency, timing and location may be a key stressor to exacerbating risk to vulnerable vegetation. Appropriate fire and ignition management could be used to mitigate this risk. Fire management practices play a more important role in the resilience, distribution and persistence of vulnerable vegetation than directly from climate change. This has substantial conservation and management implications.

6.4 Conservation and management implications

Motivation for undertaking this research was to assess the risk to forest ecosystems from climate change and bushfires and to identify likely management implications. However, fire management practices themselves may have a greater influence on the health and resilience of forests than directly from climate change (Williams *et al.* 2009). Evidence presented here indicated variability in climatic changes and how this has affected fire danger. There have been significant increases in fire danger since 1890, but less evidence of change since 1957. There is potential that the length of time, as well as the rate and magnitude of change since 1957 were insufficient for statistical detection of significance. Some near significance trends were considered noteworthy. These included an increase in extreme fire danger conditions in the west of the region. Under these extreme conditions, fire sensitive rain forests and tall eucalypt forests, which occur in this part of the region, are more likely to burn. If this trend is real, fire managers and land management agencies may need to review their fire management strategies to prevent fire-driven transitions of vegetation. Anthropogenic ignitions interacting with increased fire danger are a potential threat to vegetation dynamics under future climate. Fire management practices, therefore, warrant review to minimise the risk of ecosystem collapse or vegetation change.

Predicted climate-induced shifts in fire regimes have implications for fire sensitive vegetation of the Wet Tropics. However, humans can ameliorate climate-induced shifts in the fire regime by adapting management practices. Of all the elements influencing the distribution of vegetation types, fire is one of the most readily manipulated by humans (Bowman & Haberle 2010; Bowman *et al.* 2011; Hantson *et al.* 2014) and is widely used as a land management tool (Goudie 2013). Regardless of climate change and its influence on fire regimes, managing anthropogenic ignitions is one way to mitigate increasing fire danger conditions. This may avert increased risk to fire-induced tipping points that may cause abrupt changes in vegetation stable states (Clarke & Lawes 2013; Pausas 2015).

Anthropogenic ignitions are the primary cause of fire in Australia (Willis 2004; Beale & Jones 2011; Collins *et al.* 2016; Mann *et al.* 2016). Of these, 81% are unplanned (Thackway *et al.* 2008), the majority of which are a result of arson (Willis 2004; Beale & Jones 2011). Managing arson is likely to be an ongoing issue for managing unplanned fires and inappropriate fire regimes. A similar regional study, in a biodiversity hotspot elsewhere in Australia, made similar recommendations (Gill *et al.* 2014). They recognised that predicted increases in fire danger may be offset by increased fire protection (Gill *et al.* 2014). This can be applied to other regions. It is important that fire practitioners apply fire management based on the best science and evidence, in consideration of changing climatic conditions and the health of their country.

Recommended fire guidelines for vegetation types in Queensland (Queensland Herbarium 2014) and its regions, such as the Wet Tropics (Department of National Parks Recreation Sport and Racing 2013), appear to lack evidence and scientific justification. This is partially due to a lack of evidence synthesis and evidence-based decision-making regarding ecologically appropriate fire regimes for vegetation types. Current recommended fire guidelines are likely to be inaccurate and could be increasing ecosystem risk. The recommended frequency and rationale for prescribed fire in tall eucalypt forests is currently inappropriate and requires revision (Appendix 1.1). Much work needs to be done in Queensland and elsewhere in Australia to effectively integrate current scientific evidence into on ground fire management, planning and implementation. A strategic approach to evidence-based and ecologically sustainable fire management is called for to mitigate climate change implications for vegetation types and the bushfire threat (Hughes & Steffen 2013).

The use of prescribed fire by land managers and agencies requires careful consideration (Zylstra *et al*. 2016). Prescribed fire is increasingly recognised for its adverse affects on biodiversity (Haslem *et al.* 2011; Pastro *et al.* 2011; Penman *et al.* 2011; Andersen *et al.* 2012) and its ineffectiveness in reducing bushfire risk or hazard reduction (Zylstra *et al*. 2016), particularly in relation to climate change (Bradstock *et al.* 2012a; Enright & Fontaine 2014). Climate change interacting with other stressors is likely to have a compounding impact on species and ecosystems (Driscoll *et al.* 2012; Staudt *et al.* 2013). Hence, fire as an environmental stressor can exacerbate climate change impacts, reduce ecosystem health or resilience and could drive vegetation change or collapse. Perverse fire regimes have the potential to tip the balance and drive vegetation change. It is recommended that fire managers and key agencies review current strategies and recommended fire guidelines with an aim to improve forest and boundary resilience to future conditions. This may require a reduction in the frequency of fire in tall eucalypt forests and in savanna woodlands adjacent to tall eucalypt forests and rain forest.

Tall eucalypt forests and ecotonal rain forests are likely to experience an increase in fire risk in the Wet Tropics and are even more likely elsewhere in Australia where they occur, including forested areas of eastern Australia (Dowdy *et al.* 2015; Low 2011; McInnes *et al.* 2015) and areas with similar values, such as the ‘Gondwana Rainforests of Australia’ and ‘Tasmanian Wilderness’ world heritage areas. Predicted increases in fire frequency in and adjacent to these communities could cause them to switch to an alternative stable state and, if widespread, would result in collapse, species extinctions and biodiversity loss.

Identification and protection of climate and pyric refugia for at risk species and communities will help protect against biodiversity loss (Murphy *et al.* 2012; Reside *et al.* 2014; Robinson *et al.* 2013), including for vegetation that is climate- and fire-sensitive; tall eucalypt forests and rain forests (particularly upland, cool-climate adapted and leeward rain forest). Refugial areas for biota are critical for long-term conservation under climate change (Ashcroft *et al.* 2009; Ashcroft 2010; Low 2011; Shoo *et al.* 2011; Keppel *et al.* 2012; Keppel & Wardell-Johnson 2012; Mackey *et al.* 2012; Murphy *et al.* 2012; Reside *et al.* 2013, 2014; Robinson *et al.* 2013). An example the sorts of actions required are given in Appendices 3.1-3.4, which describe a means to protect identified climate and pyric refugia for rain forest and tall eucalypt forest in the Wet Tropics (Shoo *et al.* 2011). Cool climate refugia are typically associated with high elevation locations. Similar action needs to be taken to protect climate and pyric refugia for fire-sensitive vegetation in other situations of high elevation, particularly eastern Australia (Figure 6.1) where rain forests and tall eucalypt forests occur. An evaluation of land tenure, vegetation type and high elevation can be easily achieved to identify priority areas for conservation of climate refugia elsewhere in Australia.

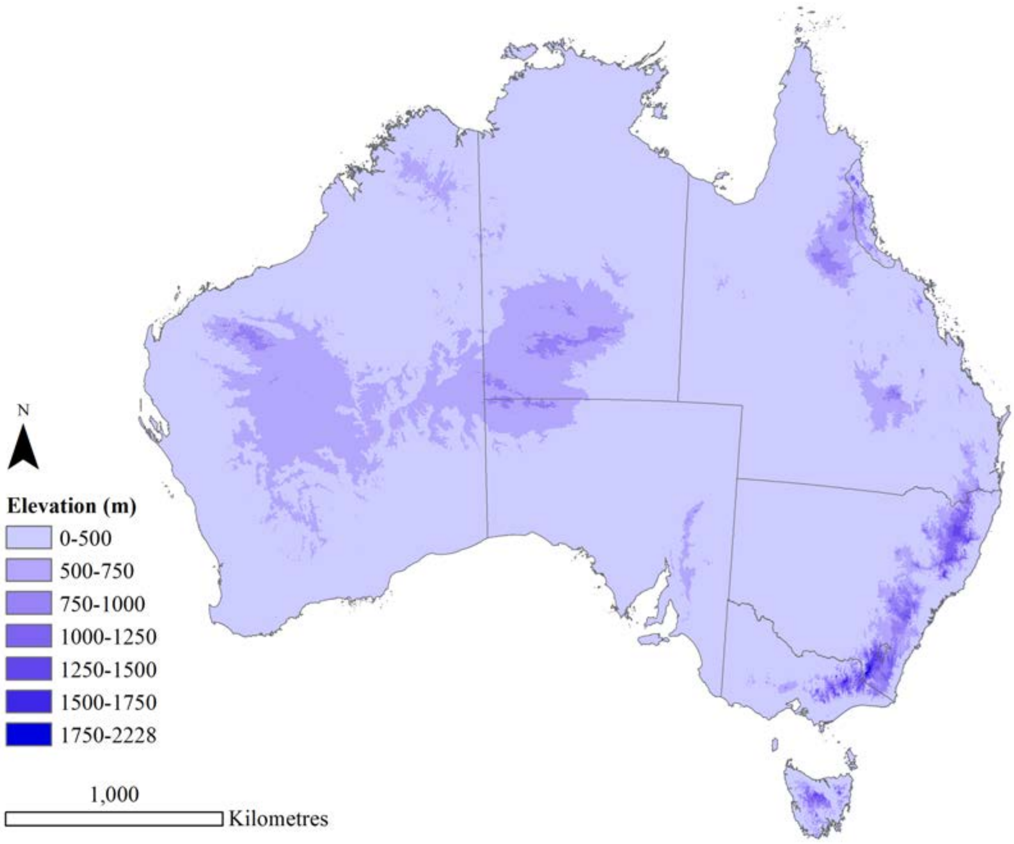

Figure 6.1 High elevation areas of Australia.

The identification and protection of healthy, resilient, undisturbed and long-unburnt tall eucalypt forests should be seen as a high priority. It is recommended that remaining areas of unburnt and unlogged tall eucalypt forests be afforded greater protection. These may be the best climate change and pyric refugia for tall eucalypt forests which in more degraded condition may be on the verge of ecosystem collapse (Keith *et al.* 2013; Burns *et al.* 2015). This protection should also be afforded to other areas of tall eucalypt forest and rain forest boundaries of special interest, such as the subpopulation of Bunya Pine and key habitat of other listed species.

The northern population of bunya pine *Araucaria bidwilli* on the Carbine tableland should receive greater protection from fire, as there is an immediate risk of its extinction. This genetically distinct subpopulation is internationally recognised (International Union for Conservation of Nature) as being highly susceptible and threatened (Thomas 2011). Bunya pine is very restricted and found in one small catchment within only 500 metres of the rain forest - tall eucalypt forest boundary. Analysis of bunya pine recruitment and age class dynamics indicate that this species is killed by fire and requires long fire-free periods for survival, particularly in tall eucalypt forest (Picone 2015).

Queensland state and regional fire management planning and strategy should incorporate the breadth of scientific evidence on regional changes to climate and fire danger. These should also consider ecosystem health and resilience in consideration of recent anthropogenic disturbance history (Appendix 1.1). An audit of ecosystem health, integrity and resilience would help in the identification and protection of healthy, resilient and undisturbed refugia.

The quest for ecologically sustainable fire regimes for vegetation types is relevant globally (Bowman *et al.* 2013), nationally (Driscoll *et al.* 2010a, b; Penman *et al.* 2011) and regionally (Yates *et al.* 2003; Watson 2009; Pastro *et al.* 2011; Andersen *et al.* 2012; Enright & Fontaine 2014). However, achieving this must be scientific and evidence-based (Sutherland *et al.* 2004; Pullin & Knight 2005; Boaz & Gough 2010; Segan *et al.* 2011; Cook *et al.* 2013a, b; Pullin & Knight 2013; Dicks *et al.* 2014; Ferraro & Hanauer 2014). Formal processes of addressing key conservation issues, such as ecologically sustainable fire regimes should be approached with systematic review and evidence synthesis (Pullin & Stewart 2006; Gough *et al.* 2012; Collaboration for Environmental Evidence 2013; Cook *et al.* 2013a, b; Gough *et al.* 2013; Pullin & Knight 2013; Bilotta *et al.* 2014; Walsh *et al.* 2014; Doerr *et al.* 2015). A systematic review of fire regimes and management is recommended, particularly for fire sensitive vegetation in the Wet Tropics.

A number of recent reports have considered the impact of climate change on fire regimes and their combined impact on vegetation in Australia (Williams *et al.* 2009; Low 2011; Murphy *et al.* 2012; Williams *et al.* 2012b; CSIRO & Bureau of Meteorology 2015). Their reviews represent the best synthesis of information regarding the interaction of climate change, fire and biodiversity, including vegetation. Each of these reports details potential impacts for different regions and ecosystems throughout Australia. However, as these reviews consider entire regions or entire ecosystems they do not focus on fine-scale or local impacts within one region. Indeed, the linkage between regional planning and local action is critical, but often lacking (Pressey *et al.* 2013). Consequently, to understand how climate change will impact vulnerable regions or ecosystems, such as the Wet Tropics, a more detailed, regional focus and analysis is required (Hughes 2011; Low 2011; Williams & Crimp 2012; Williams *et al.* 2012; CSIRO & Bureau of Meteorology 2015). This study is an ideal example of an intra-regional approach to the matters discussed at broader scales. Intra-regional variability can help improve broader regional understanding and predictions. There are important details and complexities at a local scale within regions that are not represented by broader, generic regional summaries. Linking continental and regional scale assessments to a regional and local scale assessment, such as this, can provide a comprehensive multi-scaled approach to biodiversity conservation, which helps to ensure effective climate change mitigation and adaptation considerations (Lindenmayer & Franklin 2002; Mackey *et al.* 2002). This study has direct implication for other regions of Australia and globally.

One simple conservation and management issue presented here and in other national and regional reports (Williams *et al.* 2009; Low 2011; Murphy *et al.* 2012; Williams *et al.* 2012b; CSIRO & Bureau of Meteorology 2015), is that reducing landscape pressures, such as fire, is the best option for mitigating climate change impacts on ecosystems (Driscoll *et al.* 2012; Williams *et al.* 2012b; Scheffer *et al.* 2015). Reducing landscape pressures can ameliorate climate change impacts (Gill *et al.* 2014) and by managing stressors, such as fire, can build resilience to climate change (Scheffer *et al.* 2015). This requires ecologically appropriate fire regimes for vegetation types that consider future climate and bushfire risk pressures. It is also critical to plan and manage the protection of climate and pyric refugia (Murphy *et al.* 2012; Reside *et al.* 2014), particularly for vegetation that is climate- and fire-sensitive. Appropriate management of fire and anthropogenic ignitions, is possibly the best strategy to address potential impacts on vegetation from changes in climate and fire danger.

6.5 Future research, integration and implementation

While there are a number of identifiable areas for future research, the largest gap in knowledge is perhaps not in the science, but rather in the synthesis of evidence (Pullin & Knight 2013) and the integration of science into management, policy and legislation. This is needed in fire management (Cary *et al.* 2003; Dovers *et al.* 2004), climate change (Steffen *et al.* 2009) and more so for the interaction between them (Sullivan 2008; Williams *et al.* 2009; Driscoll *et al.* 2012). A lack of systematic evidence synthesis and uptake has contributed to discrepancies between evidence and management of forests in the Wet Tropics (Appendix

1.1). More systematic reviews are required to inform management regarding effective strategies for achieving conservation outcomes in a rapidly changing environment (Pullin & Stewart 2006; Gough *et al.* 2012; Collaboration for Environmental Evidence, 2013; Cook *et al.* 2013a, b; Gough *et al.* 2013; Pullin & Knight 2013; Bilotta *et al.* 2014; Walsh *et al.* 2014; Doerr *et al.* 2015). For example, a systematic review of fire regimes in the Wet Tropics (including for rain forest, tall eucalypt forests and savannas) could help inform decision-making on how to best address potential threats to vegetation from climate change and fire.

This thesis demonstrated a missing link between local on-ground physical conditions and broader regional models and projections (Williams *et al.* 2009; Low 2011; Murphy *et al.* 2012; Williams *et al.* 2012b; CSIRO & Bureau of Meteorology 2015). It detected intra-regional variability that has important implications for climate change mitigation and adaptations strategies at the local scale. Similar intra-regional research should be undertaken in other areas of Australia.

Studies of the conservation value or refugial value of long unburnt vegetation are rare in comparison to fire response studies. Thus, long unburnt vegetation is under-valued under-appreciated by ecologists and land managers. Long-term ecological studies have become recognised as being critical for understanding landscape and environmental change processes and for biodiversity conservation (Likens & Lindenmayer 2011; Lindenmayer *et al.* 2012b; Youngentob *et al.* 2013). Most studies of long unburnt vegetation conclude that long unburnt areas are under-represented, threatened by too frequent fire and are important for biodiversity conservation, as refugia and as areas from which recolonisation of biota can occur (Woinarski 1990; Bowman & Panton 1995; Bradstock *et al.* 2002; Woinarski *et al.* 2004; Andersen *et al.* 2005; Bradstock *et al.* 2005; Ooi *et al.* 2006; Edwards & Russell-Smith 2009; Andersen *et al.* 2012; Kitzberger *et al.* 2012; Nimmo *et al.* 2012; Scott *et al.* 2012; Watson *et al.* 2012; Griffiths & Brook 2014; Kelly *et al.* 2015; Ziembicki *et al*. 2015; Croft *et al*. 2016; Swan *et al*. 2016). More work on long-term studies, especially long unburnt or fire-free vegetation requires more attention (Driscoll *et al.* 2010a; Croft *et al*. 2016).

There is a need for an evaluation of the health and resilience of the Wet Tropics tall eucalypt forests. This study identified that tall eucalypt forests are particularly vulnerable to climate change and potential shift to alternative stable states. It is strongly recommended that an ecosystem risk assessment, consistent with the International Union for Conservation of Nature’s (IUCN) Red List of ecosystems (Rodríguez *et al.* 2011; Keith *et al.* 2013; Rodríguez *et al.* 2015) is undertaken for the tall eucalypt forests of the Wet Tropics. A similar risk evaluation approach of tall eucalypt forests in Victoria indicated that they were critically endangered and had 92% chance of collapse by 2067 (Burns *et al.* 2015). They recommended immediate protection of remaining unburnt and unlogged forests; a recommendation repeated here for Wet Tropics tall eucalypt forests.

Tall eucalypt forests in the Wet Tropics support a suite of dependent flora and fauna (Harrington & Sanderson 1994). Evaluations of forest health, resilience and risk evaluation should address particular keystone species at risk of extinction. The structural and habitat components of tall eucalypt forests must be examined for such species. For example, the habitat requirements of the northern bettong *Bettongia tropica* (Winter 1997a) relating to its primary food source (mycophagous truffles) and how these are affected by fire are unknown (Claridge & Trappe 2004; Maser *et al.* 2008), yet their habitat is regularly burnt every 3-5 years (Department of National Parks Recreation Sport and Racing 2013; Queensland Herbarium 2014), which may actually suppress this food source (Trappe *et al.* 2006; Maser *et al.* 2008). Another tall eucalypt forest indicator species is the yellow-bellied glider *Petaurus australis*, a social tree hollow dependent possum. As there is little unlogged tall eucalypt forest remaining, a forest inventory of hollow-bearing trees needs to be considered to ensure there is sufficient tree-hollow recruitment following large-scale systematic logging of large hollow-bearing trees throughout tall eucalypt forests of the region. It takes over 210 years for a eucalypt to develop a suitable tree hollow large enough to house a yellow-bellied glider (Wormington & Lamb 1999; Gibbons & Lindenmayer 2002; Koch *et al.* 2008), thus, fire regimes that prevent the ongoing recruitment of old hollow-bearing trees, will cause population declines (Bluff 2016; Croft *et al*. 2016). [Interestingly, the duration of hollow development in tall eucalypts (210+ years) is uncannily similar to the natural fire frequency for these communities (230+ years) (Chen 1990)]. Loss of large hollow-bearing trees in tall eucalypt forests is a widespread result from logging and too frequent fire (Lindenmayer *et al.* 2012a). Logging removal of old hollow-bearing trees in the Wet Tropics means that much of the tall eucalypt forests are now devoid of tree-hollows, which potentially explains the observed declines in gliders throughout the Wet Tropics (Winter 1997b, 2004) except in areas which remain unlogged (unpublished report, Rupert Russell Queensland Parks and Wildlife Service, Mossman).

A priority research area is to better understand pre- European vegetation structure and fire regimes, to help resolve controversy associated with contemporary management objectives (Appendix 1.1). Evidence and clarity are required to disentangle causes of recent vegetation change (Harrington & Sanderson 1994; Johansen & Phinn 2005; Tng *et al.* 2011) between a lack of fire and natural vegetation recovery from European disturbance (Birtles 1982, 1988, 1997a, 1997b; Frawley 1988, 1991; Unwin *et al.* 1988; Winter *et al.* 1991a; Crome 1992; Frost 1997; Haberle *et al.* 2006; Turton 2008). A comparison of vegetation change between logged and unlogged areas in the Wet Tropics would be useful evidence to test whether there are differences in vegetation change in areas not affected by European disturbance. This comparison has either not been quantified (Harrington & Sanderson 1994), or has erroneously included logged areas with unlogged areas (Tng *et al.* 2011).

The potential causes of recent vegetation change should also be considered carefully. Climatic changes in rainfall were attributed to observed vegetation thickening at rain forest boundaries in the leeward areas of the region (Johansen & Phinn 2005), which is consistent with observed increase in rainfall for that part of the region described here (Chapter 5). Climate change is also related to changed concentration of gases in the atmosphere and the impact of elevated carbon dioxide on various vegetation types may be an issue (see for example Bowman *et al.* 2010). A greenhouse experiment comparing the growth of seedlings of dominant species from each of rain forest, tall eucalypt forest and savanna in controlled ambient and enriched carbon dioxide enclosures was originally conceived as part of this research, albeit outside the scope of this study.

Little research has been done to evaluate the extent of resilience of tall eucalypt forest and rain forest species to repeated fires. Although it has been shown that many rain forest species (predominantly pioneers) can tolerant a low frequency of fire (Unwin 1983; Williams 2000; Marrinan *et al.* 2005; Campbell & Clarke 2006; Williams *et al.* 2012c), other endemic tall eucalypt forest sclerophyllous understorey species do not fare so well (Campbell & Clarke 2006; Williams *et al.* 2012), indicating fire sensitivity. The resilience of dominant tall eucalypt canopy species, such *E. grandis* and *E. resinifera*, particularly young individuals, to repeated fires needs to be better understood (Ashton 1981; Ashton & Attiwill 1994; Gill & Catling 2002; Gill 2012). Although some tall eucalypt forest species have the advantage of epicormic shooting from branches following fire, they can only do this once they have attained maturity and have reached the mid-storey (Gill & Catling 2002; Gill 2012; Williams *et al.* 2012c). This evidence indicates that regular fires have the ability to exacerbate expansion of pioneer rain forest species in tall eucalypt forest understorey, while killing endemic sclerophyllous species and young recruits. It is critical that the lifecycles of these species are maintained and that there remains ongoing recruitment to old age (particularly for tree-hollow recruitment considering the widespread loss of hollow-bearing trees due to timber harvesting); a scenario which seems unlikely under current prescribed burning regimes (Department of National Parks Recreation Sport and Racing 2013; Queensland Herbarium 2014).

6.6 Research refinements and improvements

There are several improvements that could be made to the overall research. Specific improvements to techniques, new approaches and data gaps were discussed in each of the Chapters 2-5.

Vegetation in this study was classified broadly into three groups, however, there are multiple unique vegetation types within each classification (1.4.1), which deserve independent consideration in their own right. Savanna included multiple open woodland and forest types. Tall eucalypt forests contain multiple ‘tall open’ and ‘open’ forest types, which exist between rain forest and savanna vegetation in the Wet Tropics. These include tall open forest types dominated by *E. grandis*, types dominated by *E. resinifera* and open forest types dominated by *Syncarpia glomulifera*, *Corymbia intermedia*, *E. uvida* (Hill 1999) and *E. reducta*. Rain forest vegetation also includes multiple structural types; mesophyll and microphyll types, as well as types containing Araucariaceae. The latter is of particular interest, as Araucariaceae are sclerophyllous, rather than mesophyllous soft-leaved rain forest vegetation and these types also occur frequently in the leeward uplands of the Wet Tropics. Of particularly note, is the occurrence of the bunya pine *A. bidwilli* on the Carbine tableland (see Appendix 1.1). Accordingly, a more detailed vegetation analysis is meritorious.

Improvements to the methodological approach in Chapter 2 would be to incorporate meteorological variables, such as extremes (rather than climate and averages) into distribution models of vegetation. Additionally, the ability to incorporate fire danger parameters into distribution models of vegetation would be valuable. Improvements to existing thin plate smoothing spline techniques, currently using only three geographic variables (latitude, longitude and elevation) for climate (Hutchinson & Xu 2013), should consider additional geographic variables and meteorological data (Jones *et al.* 2009), including regional-scale meteorology (Ashcroft *et al.* 2009). This would improve distribution models using interpolated climate data.

The identification of an appropriate ecological modelling approach (Chapter 2) was complicated, but there may better model options (Appendix 2.1). Other modelling techniques, such as boosted regression trees, which can cater for more complex non-linear relationships should be considered. Ecologists adopting modelling techniques should remain aware of the pitfalls of using complex and multiple techniques without appropriate evaluation of their data first and selection of an approach that can allow direct model evaluations. One particular suitable method was identified that could appropriately account for spatial autocorrelation in the response and predictor variables for a large dataset, the residuals autocovariate approach (Crase *et al.* 2012). This method is worthy of recognition and promotion as a simple approach to addressing spatial dependence in distribution models, particularly with large datasets. This model can be applied to multiple statistical techniques.

It is unclear whether the microclimatic gradient (Chapter 3 and 4) reflects the climate of the region (i.e. exogenous effect) or is a consequence of the vegetation gradient (i.e. an endogenous effect). To resolve this requires controlled experiments comparing microclimate conditions with standard meteorological measurements from adjacent clearings that meet meteorological site standards (Canterford 1997) along environmental gradients. To improve microclimate and fire danger information, accurate rainfall measurements need to be taken in areas not beneath a canopy for each vegetation type. Surrogates were needed in this research for rain forest and tall eucalypt forest vegetation.

Empirical micrometeorology data in complex terrain has been shown to improve vegetation model predictions (Ashcroft 2006; Ashcroft *et al.* 2008). Incorporating meteorological or topoclimate data by pre-processing spatial interpolations of climate, can improve spatial climate data. This pre-processing should be discerned from downscaling techniques, which are a post-processing method and therefore retain inherent inaccuracies. Recent global climate models, for example, had a typical spatial resolution between 100 -200 km, which, in themselves, are generally much coarser than meteorological observations (McInnes *et al.* 2015). Regional downscaling of global climate models, therefore, can remain inaccurate. However, empirical meteorological observations can be used to improve model performance and accuracy, as demonstrated here (Chapter 3). This concept has been further developed in the Wet Tropics, with downscaling of higher resolution (5 km grid) daily meteorological models supported by empirical data from micrometeorological sampling (Storlie *et al.* 2013). However, Storlie *et al.* (2013) sampled only within rain forest vegetation and did not account for vegetation feedbacks on microclimate. Nonetheless, micrometeorological sampling is required for intra-regional studies to improve climate change predictions and to accurately determine potential impacts and develop on ground adaptation and mitigation strategies.

Due to the presence of microclimatic feedbacks from vegetation, including vegetation type in distribution models for species may help to improve predictions of their distribution. For example, indications of microclimatic buffering of habitat have been repeatedly demonstrated within these rain forests (Shoo *et al.* 2010; Storlie *et al.* 2014).

Further research is required to relate FFDI (Chapter 4) to actual landscape fire occurrence in order to identify thresholds when savanna, tall eucalypt forest and rain forest will burn. Unfortunately, adequate fire history information was not available for this research. Assessment of satellite detection of hotspots and fire scars to establish the ability to reliably map fires in closed canopy forests, including rain forests and tall eucalypt forests with a rain forest understorey proved unsuccessful. Preliminary work conducted as part of this research, indicate satellite imagery is not reliable for this purpose and that hotspot information, rather than fire scars, is more reliable.

The time series analysis in Chapter 5, utilised a linear regression approach, however, climatic trends are not necessarily linear, as trends show natural variability, including cyclic patterns, which may display highly variation for some variables such as rainfall (Suppiah *et al.* 2010; McInnes *et al.* 2015). It is possible that there was difficulty in detecting statistically significant trends with linear regression for the shorter length of the time-series analysis (1957-

2010). Assessment of alternative time series, start and end points and how they influence trends should be considered. Climate change trends show an accelerating trajectory for temperature (IPCC 2013; Allen *et al.* 2014), which is certainly non-linear. Analysis of climate and fire danger data, testing for more complex trends, may determine whether the patterns observed in this study are accelerating or decelerating.

This study examined the potential affects of climate change on meteorological and fire danger conditions on vegetation types. However, other elements of climate change and atmospheric conditions are also likely to affect vegetation. Increasing concentration of carbon dioxide in the atmosphere is known to produce an enrichment affect on plant growth and water use efficiency (Ainsworth and Long 2005; Kimball *et al*. 1993). How this affect, interacting with meteorological and fire danger changes requires further consideration.

Overall, the approach and analyses undertaken in this thesis have necessarily adopted unconventional means of addressing a complex issue; the nexus between climate change, fire regimes and vegetation. The complexities of alternative stable states, vegetation feedbacks, influence of fire and capacity of spatially interpolated climate to inform accurate future predictions of distributions have been investigated, rather than ignored. The results have highlighted these inherent complexities and have provided insights to help inform predictions of how climate change, interacting with fire might affect vegetation and their associated biota.

6.7 Conclusions

The aim of this thesis was to determine if climate change interacting with fire would affect the distribution of vegetation types. Investigation of vegetation, climate and fire interactions illuminated inherent complexities in the system that makes simple modelling approaches more challenging. These complexities required exploration to understand their extent and magnitude. There is some evidence to suggest that climate and fire danger could be changing in a way that increases the risk to fire-sensitive vegetation of collapse and tipping into alternative stable states. Although there was regional variability in average fire danger patterns, climate change appears to be causing an increase in extreme fire danger conditions in the Wet Tropics. More anthropogenic ignitions during extreme fire danger conditions are likely to result in more frequent and intense fires, which have the potential to affect vegetation distribution. This may result in fire sensitive vegetation tall eucalypt forests and rain forests becoming more flammable and more likely to burn. An increase in fire frequency in these vegetation types, risks their degradation or transition to an alternative vegetation state. Climate change induced effects on fire regimes are not expected to adversely affect savannas, which are a more stable and fire tolerant vegetation type. Savanna may benefit from changing conditions by expanding into areas currently occupied by fire sensitive communities. Tall eucalypt forest, already a threatened vegetation type, is particularly vulnerable and the most at risk ecosystem in the region.

A comparison of different vegetation types within overlapping environmental niches showed signs of alternative stable states of vegetation. This provided insight into the relative vulnerability or stability of vegetation types. Suitable areas of tall eucalypt forest and rain forest were occupied by savanna and maintained presumably by the presence of frequent fires. Tall eucalypt forest occupied less than 70% of its preferred niche and was affected by both rain forest and savanna alternative stable states. However, they are more immediately at risk from an increase in fire, than from slow encroachment of rain forest invasion in the long-term; a change process that would take over 2,000 years.

Will climate change interacting with fire affect the distribution of vegetation types? The combined evidence presented here, suggest that the mechanisms driving vegetation distributions have changed and are expected to accelerate. Should fire frequency and intensity increase sufficiently to affect vegetation distributions, then this will most likely result in expansion of savanna at the expense of rain forest and tall eucalypt forests, mediated by fire. However, changes in fire danger alone are not enough to mediate vegetation change. They need to be coupled with anthropogenic ignitions for changes in fire potential to be realised. Fire risk reflects only fire potential, but ignitions result in fires. Inappropriate fire regimes have the potential to exacerbate risk to vegetation, but alternatively could be used to mitigate risk. How fire is managed in the environment today, could affect vegetation distribution in the future. The overriding implication is not so much about how vegetation will be affected by changes in climate or fire risk, but how fire and ignition management will affect them. We have the opportunity to either mitigate predicted climate change increases in fire danger or exacerbate them, leading to potential ecosystem collapse. The greater threat to vegetation will be from fire, rather a direct change in climate. We can manage fire. Never mind the warming, watch out for the fire!

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APPENDICES

Appendix 1.1 Supplementary essay on tall eucalypt forests of the Australian Wet Tropics.

In consideration of tall eucalypt forest in the Wet Tropics and the vulnerability of this vegetation type to climate change and an increase in extreme fire danger, special attention needs to be given to this restricted vegetation community.

1.1.1 Tall eucalypt forest facts

Tall eucalypt forests occur in three broad regions of Australia, including southeastern Australia and Tasmania, southwestern Australia and east coastal Australia (Ashton 1981; Ashton & Attiwill 1994; Gill & Catling 2002; Gill 2012). The latter region is considered a sub-tropical province, with tall eucalypt forests occurring in association with montane environments, which experience cooler, more temperate conditions. Thus, the forests appear to be more affiliated with temperate climates than tropical ones. In addition to tall eucalypt forests occurring in northeast NSW and southeast Queensland, there are some important outliers, including the Carnarvon Range, the Clarke Range (Central Queensland Coast) and the Wet Tropics, which is the northern-most occurrence.

Tall eucalypt forests in the Wet Tropics and probably throughout the subtropical province, are an elevationally restricted mountain ecosystem, occurring at an average elevation of 800 metres (Table 2.2, Fig. 2.1). Throughout the subtropical province, tall eucalypt forests contain common eucalypt species, including *E. grandis*, *E. resinifera* and *Syncarpia glomulifera* and a comparable suite of other flora and fauna. All these species reach their northern-most range in the Wet Tropics, but only at high elevations. This indicates that the tall eucalypt forests in the Wet Tropics have more affinity with temperate eucalypt forests, than surrounding tropical savannas. Both temperate eucalypt forests and elevation restricted mountain ecosystems are identified as two of the most vulnerable Australian ecosystems to tipping points (Laurance *et al.* 2011a), further indicating the vulnerability of tall eucalypt forests to climate change and destabilisation. This is further exacerbated by the large edge to area ratio of tall eucalypt forest making them more vulnerable to external influence and rapid change (Harrington & Sanderson 1994).

Tall eucalypt forests in the Wet Tropics are officially listed as endangered, along with a range of species dependent on these forests. All vegetation communities (regional ecosystems) under the broad vegetation grouping ‘tall eucalypt forest’, are listed as endangered (7.11.14, 7.12.21, 7.12.22, 7.3.42, 7.8.15 and 7.8.16) or of concern (7.11.31, 7.11.32, 7.12.52) (Accad *et al.* 2013). The biodiversity status assigned to these regional ecosystems does not consider the threat of increased fire (short-term fire intolerance) or the potential for destabilisation and abrupt shifts as described in this thesis. Instead, they are listed because of a perceived risk of rain forest encroachment (long-term fire intolerance) and a loss of ability to regenerate. This will be discussed later.

Tall eucalypt forests in the Wet Tropics also support a suite of dependent flora and fauna (Harrington & Sanderson 1994; Williams *et al.* 1996b; Yeates & Monteith 2008), including species that are listed in Australian and Queensland legislation as being of concern or in decline. These include several listed flora, including: bunya pine *A. bidwilli* (least concern, northern population genetically distinct, very restricted, highly susceptible and threatened; IUCN) (Thomas 2011), Mt Spurgeon pine *Prumnopitys ladei* (near threatened Queensland), cypress orchid *Dendrobium callitrophilum* (vulnerable Australia, Queensland), Nitchaga heath-myrtle *Triplarina nitchaga* (vulnerable Australia, Queensland) and *Eucalyptus lockyeri* subsp. *lockyeri* (rare Queensland). They also include several listed fauna: northern bettong *Bettongia tropica* (endangered Australia, Queensland), spotted-tail Quoll *Dasyurus maculatus gracilis* (endangered Queensland), yellow-bellied glider *Petaurus australis unnamed subsp.* (vulnerable Australia, Queensland), white-footed dunnart *Sminthopsis leucopus* (near threatened Queensland), golden-tipped bat *Kerivoula papuensis* (near threatened Queensland), glossy-black cockatoo *Calyptorhynchus lathami* (vulnerable Queensland), masked owl *Tyto novaehollandiae kimberli* (vulnerable Queensland), grey goshawk *Accipiter novaehollandiae* (near threatened Queensland), Atherton legless-lizard *Delma mitella* (vulnerable Australia, near threatened Queensland), robust burrowing snake *Simoselaps warro* (near threatened Queensland), magnificent broodfrog *Pseudophryne covaceviche* (vulnerable Queensland) and the armoured mist frog *Litoria lorica* (critically endangered Australia, endangered Queensland). Most of these species are endemic to tall eucalypt forests and adjacent areas, or are dependent on specific habitat features, canopy species or tree hollows, not found in surrounding savannas or rain forests. Accordingly, the loss of tall eucalypt forests in the region could contribute to localised extinctions. The biodiversity status of these species may need to be upgraded in light of the findings of this study and associated arguments.

1.1.2 Disturbance, vegetation change and controversy at the rain forest boundary

There remains controversy, in the Wet Tropics (Winter *et al.* 1991a; Stanton *et al.* 2014a, b; Tng *et al.* 2014) and elsewhere in Australia (Kohen 1995; Kohen 1996; Griffiths 2001; Zylstra 2006; Hateley 2010), regarding the natural (pre-European) structure and composition of tall eucalypt forests and the drivers of post-European vegetation change. Changes observed in the Wet Tropics, relate to post-European rain forest thickening and encroachment into adjacent tall eucalypt forests (1.4.1) and since the 1940s (Harrington & Sanderson 1994) and elsewhere in northeastern Australia (Russell-Smith *et al.* 2004a, b). Although vegetation change has been widely reported, only three studies have empirically quantified change patterns (Harrington & Sanderson 1994; Johansen & Phinn 2005; Tng *et al.* 2011). Vegetation change broadly encompasses thickening of rain forest vegetation in two main areas, the coastal savanna (open forest) (for example, Jackson *et al.* 2011) and the leeward tall eucalypt forests (Harrington & Sanderson 1994; Johansen & Phinn 2005; Tng *et al.* 2011). While regular Indigenous burning of coastal open forest may have suppressed rain forest thickening, it remains a spurious argument for the tall eucalypt forests, especially as there is myriad evidence to the contrary. The controversy exists because individuals, land management practitioners and authors have observed vegetation change patterns in short time frames and attribute this to one cause, a reduction in fire. However, fire cannot be universally applied to explain all vegetation change patterns without examination of available evidence. Unfortunately, a lack of evidence synthesis and systematic review mean that the array of available evidence is not immediately available to practitioners and is often ignored. Accordingly, subjective opinions that are not evidence-based, replace objective evidence-based understanding of ecological change processes. This lack of robust evidence uptake can lead land managers and agencies astray in their quest for ecologically sustainable land management (6.2.5).

Much of the literature on this topic claim that rain forest thickening in the Wet Tropics is due to a reduction in fire frequency and interval associated with the cessation of traditional Aboriginal burning practices (Ash 1988; Unwin *et al.* 1988; Stocker & Unwin 1989; Unwin 1989; Harrington & Sanderson 1994; Hopkins *et al.* 1996; Russell-Smith & Stanton 2002; Stanton *et al.* 2014a, b). However, despite their best intentions, none of these authors provide any empirical evidence of causation. Furthermore, some of the proposed evidence of vegetation change is not evidence-based at all. For example, descriptions of vegetation structure are argued to be a demonstration of change and of cause (Stanton *et al.* 2014a, b), but they are neither. Furthermore, there is a lack of substantial evidence to back up the argument and much of the diverse literature and evidence is ignored. In another example, an argument of vegetation change caused by a cessation of Indigenous burning, an often cited example, was provided at only one site (Hopkins *et al.* 1996). However, this example occurred prior to European arrival (Hopkins *et al.* 1996) and was more likely to be an isolated occurrence than an extensive trend. The site in question was on a knoll along a ridge that was most likely an Indigenous trail to traverse from the lowlands to the uplands and today is still remains as a well-used walking track (www.nprsr.qld.gov.au/parks/daintree-mount-sorrow). Other examples of old Indigenous camp sites and trails along spurs in the near vicinity are known to the author (pers. obs.).

There is also a common assumption among authors (Ash 1988; Unwin *et al.* 1988; Stocker & Unwin 1989; Unwin 1989; Harrington & Sanderson 1994; Hopkins *et al.* 1996; Russell-Smith & Stanton 2002; Stanton *et al.* 2014a, b) that the natural structure of tall eucalypt forests excludes a rain forest understorey, which is deemed to be deleterious to tall eucalypt forests and, therefore, must be prevented. In the absence of sound historic data, or any evidence synthesis of pre-European structure of tall eucalypt forests and the likely cause of post-European vegetation change, these views and assumptions have become widely adopted by fire managers and key agencies. However, there is a diverse range of evidence that indicates to the contrary of these assumptions. It is important that the breadth of fragmentary evidence is considered to discern between pre- and post-European vegetation structures and disturbance regimes (Gill 2012).

Distinguishing the relative influence of contemporary disturbances from previous indigenous or natural disturbance regimes on environmental change is critical in order to identify healthy resilient ecosystems and sustainable disturbance regimes from degraded unhealthy ones (Kirkpatrick 1994; Chazdon 2003; Gill 2012). The bulk of post-European vegetation change is most likely attributable to European disturbance regimes, which include disruption to traditional Aboriginal fire regimes. Indeed, the legacy of European disturbances to the environment in Australia are widely recognised as being catastrophic compared to Aboriginal impacts (Benson 1991; Flannery 1994; Kirkpatrick 1994; Powell 1994; Kohen 1995; Benson & Redpath 1997; Bowman 2001). European impacts in the Wet Tropics are also well documented. These highly destructive European practices, included clearing, timber harvesting and grazing (Birtles 1982, 1988, 1997a, 1997b; Frawley 1988, 1991; Unwin *et al.* 1988; Winter *et al.* 1991a; Crome 1992; Frost 1997; Haberle *et al.* 2006; Turton 2008) and were systematic and widespread in the region, up until broad-scale forest protection associated with listing of the Wet Tropics as a World Heritage Area in 1988 (Winter *et al.* 1991a). Ironically, disturbance by Europeans in the Wet Tropics included an increase in fire frequency (Haberle 2005; Haberle *et al.* 2006, 2010), not a decrease as speculated. In fact, European impacts in the Wet Tropics since the 1880s represent the most significant period of disturbance to the region in 23,000 years (Haberle *et al.* 2006).

Clearing and timber harvesting are without doubt the most destructive of European disturbance regimes to the natural environment and evidence suggests these activities were followed by an increase in fire frequency. These practices have fundamentally changed the vegetation structure of tall eucalypt forests and have degraded the health and resilience of these forests (Lindenmayer *et al*. 2011). There is also evidence that logging of tall eucalypt forests further increases their risk to bushfire (Lindenmayer *et al.* 2009; Lindenmayer *et al.* 2011; Price & Bradstock 2012; Bradstock & Price 2014; Taylor *et al.* 2014) and perverse management practices can result in landscape traps (Lindenmayer *et al*. 2011). This also holds true in wet tropical forests elsewhere, where fire usually occurs following anthropogenic disturbances (Haberle *et al.* 2010). Accordingly, evaluations of the natural structure of tall eucalypt forests must consider the catastrophic disturbances imposed by European activities and recovery pathways following these disturbances.

Evidence of vegetation change associated with tall eucalypt forests in the Wet Tropics (Harrington & Sanderson 1994; Tng *et al.* 2011), is benchmarked against a baseline vegetation structure from the 1940s, which was the earliest available aerial photography for the region. However, the 1940s is not a suitable benchmark for assessing the natural structure of these forests, as this period does not represent a natural pre-European state. Instead, it is more likely to represent highly disturbed forests, following more than 60 years of systematic clearing, logging and burning (Birtles 1982, 1988, 1997a, 1997b ; Frawley 1988, 1991; Unwin *et al.* 1988; Winter *et al.* 1991a; Crome 1992; Frost 1997; Haberle *et al.* 2006; Turton 2008). Vegetation changes since the 1940s could represent a number of different factors. They could represent natural vegetation recovery pathways following European disturbance, a cessation of Indigenous fire regimes, a reduction in fire frequency, a response to elevated atmospheric carbon dioxide or climatic change influences. Examination of a breadth of available evidence is required to elucidate the truth behind recent vegetation changes.

Surprisingly, little work has been done to establish the capacity of Indigenous burning practices to trigger widespread landscape change upon their removal. The only evidence-based consideration of contemporary Indigenous fire regimes and European disturbances, clearly indicates that vegetation change is not due to the cessation of Indigenous burning practices (Hill *et al.* 2000, 2001). These findings are supported by archaeological evidence. Archaeology of rain forest Indigenous groups indicate very low occupancy and regional evidence of increased burning in recent, pre-European history, were attributable to climate not anthropogenic burning (Cosgrove *et al*. 2007). Palynological evidence of vegetation change and fire history indicate climate to be the major driver of vegetation distributions, perhaps with minor interaction with Indigenous activity (Haberle 2005; Haberle *et al.* 2006, 2010; Moss *et al.* 2007). This is consistent with other regions, demonstrating climate, not Indigenous fire determined the distribution of fire-sensitive vegetation (Sakaguchi *et al.* 2013). Evidence of Indigenous occupation of tall eucalypt forests is noticeably absent compared to other vegetation types and there is no evidence of active Indigenous burning of tall eucalypt forests anywhere in Australia (Kohen 1995; Kohen 1996; Griffiths 2001; Zylstra 2006; Hateley 2010). For Australia generally, Indigenous fire regimes are indistinguishable above background evidence levels, but there is a widespread post-European increase in the frequency and area burnt by fire (Enright & Thomas 2008; Bowman & Haberle 2010; Mooney *et al.* 2011). In the Wet Tropics, the most significant change in entire the pollen record is from European clearing and burning from the 1880s, associated with the timber and farming industry (Haberle *et al.* 2006). Archaeological evidence indicates Indigenous fire regimes had little influence on vegetation distribution, particularly tall eucalypt forests. Available evidence demonstrates a natural fire regime for tall eucalypt forests with intervals around 230 years and much longer time periods for rain forest (Chen 1990). This is far outside the realm of human generations to actively manage. It seems unlikely, therefore, that a cessation of Indigenous burning practices could trigger observed vegetation changes, particularly in tall eucalypt forests.

There is other evidence of causal factors for post-European vegetation change. Climatic trends observed in the Wet Tropics (Chapter 5; Suppiah *et al.* 2007, 2010; Hilbert *et al.* 2014; McInnes *et al.* 2015), indicate it is getting warmer and wetter (at least in the western part of the region, where tall eucalypt forests occur) (Chapter 5). For example, observed thickening of rain forest near their boundaries and in tall eucalypt forests (Harrington & Sanderson 1994; Johansen & Phinn 2005; Tng *et al.* 2011), coincides with an observed increase in rainfall (Fig.7, p.9 Suppiah *et al.* 2007; Chapter 5) for the same period (1940-2008) as observed vegetation change. Johansen & Phinn (2005) also observed vegetation changes between 1988 and 1999, and attributed this change to regeneration of vegetation and potential increase in rainfall during this period. This post-European period also coincides with elevated atmospheric carbon dioxide, which has demonstrated an influence on vegetation change in other regions (Stokes *et al.* 2005; Buitenwerf *et al.* 2012; Higgins & Scheiter 2012; Beringer *et al.* 2014; Murphy *et al.* 2014). Consideration of the autecology of tall eucalypt forests themselves indicates their affiliation with rain forest (Chapter 2; Tng *et al.* 2012, 2013, 2014), thus suggesting vegetation change being a natural recovery pathway. The Wet Tropics is not an isolated example and comparable evidence and patterns are presented for tall eucalypt forests elsewhere (Lindenmayer *et al.* 2011; Burns *et al.* 2015).

1.1.3 Natural fire regimes in tall eucalypt forest

Much of the evidence regarding fire regimes in tall eucalypt forest in Australia, suggest that fire intervals are associated with rare natural events, rather than anthropogenic causes (Ashton 1981; Kirkpatrick 1994; Gill & Catling 2002; Bradstock 2008). In fact, there is no evidence of Indigenous peoples burning tall eucalypt forests anywhere in Australia (Kohen 1995; Kohen 1996; Griffiths 2001; Zylstra 2006; Hateley 2010). Fire intervals for tall eucalypt forest are widely accepted as being variable to centennial scale (Jackson 1968; Kirkpatrick 1994; Gill & Catling 2002; Jackson & Brown 2005; Bradstock 2008; Bowman & Wood 2009; Bradstock 2010), outside the range of one to several human generations. Evidence of fire intervals in the Wet Tropics suggest a return time over 230 years (Chen 1990).

The two sources of fire ignitions in the Wet Tropics are lightning and anthropogenic ignitions, with anthropogenic causes being the most prevalent (Ash 1988; Fensham 1997; Preece 2007). Ignition of tall eucalypt forests is most likely to be caused by encroachment from adjacent savanna fire, rather than by lightning or direct anthropogenic ignitions. Due to the fine fuels of savanna vegetation, there is unlikely to be any long-distance fire spotting to cause ignition within a tall eucalypt forest. Lightning is a rare event in the region broadly (Kuleshov *et al*. 2006) and is highly unlikely to occur in association with wet forest vegetation (Kilinc & Beringer 2007). However, anecdotal evidence of natural lightning ignitions, resulting in fire, within tall eucalypt forest in the Wet Tropics, which were under very wet conditions (Hopkins *et al.* 1993). This was evidence enough for the authors to consider that lightning was effective and frequent enough to maintain the forest structure. Perhaps the frequency of natural lightning ignitions reflects the natural fire intervals of tall eucalypt forests indicating by charcoal evidence of around 230 years (Chen 1990).

Evidence here has demonstrated that tall eucalypt forests present a feedback on microclimate (Chapter 3) and fire danger (Chapter 4) and despite broader macroclimatic conditions, occasions of ‘High’ fire danger in tall eucalypt forest are extremely rare (Chapter 5). The presence of alternative vegetation states, particularly for tall eucalypt forest, suggest that too frequent fire (as well as too little fire) has a significant influence on the distribution. Enough influence to be concerned that continuation of frequent fire, following decades of unnatural (European) disturbance, has the capacity to influence the structure, composition and perhaps distribution of tall eucalypt forests. With indications of natural centennial scale fire interval, European forest degradation, increased fire frequency and a potential increased risk of extreme fire danger conditions, the natural fire regime of tall eucalypt forests has been and will continue to be affected. The only mitigating action available, is to reduce anthropogenic fires and to restore the health and resilience of these forests to a pre-European condition.

1.1.4 Tall eucalypt forest structure

Pre-European condition and structure of tall eucalypt forests needs to be better understood so that researchers, fire managers and key agencies formulate a clearer position of what they are managing fire in these forests for. However, only two remote inaccessible areas of tall eucalypt forest in the region are known for remaining unlogged and with minimal disturbance. These include one small area on Mt Elliott in the south and a larger area on the northwestern side of the Carbine tableland in the north (Winter *et al.* 1991a). The author can attest to the strikingly different structure, composition, function and age classes of overstorey, midstorey and understorey in these unlogged forests compared with all other eucalypt forests in the region (pers. obs.). Both areas include a substantial component of rain forest, with little grass in the understorey. These two areas represent the best available baseline with which to compare the structure of tall eucalypt forests. Future research is required to compare these unlogged areas with areas that have been logged elsewhere. This comparison has either not been quantified (Harrington & Sanderson 1994), or has erroneously included logged areas with unlogged areas (Tng *et al.* 2011). In any case, these two areas represent the healthiest and most resilient areas of tall eucalypt forests and are likely to be the best pyric and climate refugia for tall eucalypt forest. These areas, particularly the larger area at Mt Carbine, require active fire suppression to protect their refugial value.

Consideration of the autecology and physiology of dominant tall eucalypt forest canopy species can indicate important habitat associations and adaptations. For example, *E. grandis* demonstrates autecological adaptations associated with an affiliation with rain forest vegetation (Tng *et al.* 2012, 2013) and infrequent fire. This species does not have a lignotuber or thick bark (Carr *et al.* 1982), which are indicators that this species is fire sensitive. They instead invest their energy in accelerated growth rate, in order to outcompete rain forest species (Duff 1987), particularly following a wildfire event or canopy gap. This allows them to persist as a canopy species, regardless of the type of understorey. The dense timber of eucalypt trees can easily cause gap creation in a rain forest understorey, when huge limbs fall from a great height ('widow-makers'). The pyre of dense timber at the base of mature *E. grandis* is a common occurrence, persisting indefinitely and serving as a fuel source for the rare occasion of a natural fire event. This species possesses a smooth, barkless trunk and generally have no low branches to prevent rain forest creepers and climbers from taking hold and reaching into the eucalypt canopy. Both bark and low branches are readily shed to prevent rain forest species climbing the trunk and also to feed the stockpile of fuel at the base of a tree. *E. grandis* also provides tree hollows for the yellow-bellied glider (*P. australis*). It is due to the presence of old-growth *E. grandis* trees that the gliders have persisted in the Wet Tropics. It takes at least 200 years for a eucalypt to develop a tree hollow large enough to support a glider of this size glider (Wormington & Lamb 1999; Gibbons & Lindenmayer 2002; Koch *et al.* 2008). *E. grandis* is clearly adapted to rain forest conditions and long fire-free periods in excess of 200 years, but does not demonstrate adaptations or evidence of tolerance to frequent fire.

Throughout Australia, tall eucalypt forests are described as having a rain forest or shrubby understorey (Ashton 1981; Tracey 1982; Ashton & Attiwill 1994; Griffiths 2001; Gill & Catling 2002; Campbell & Clarke 2006; Zylstra 2006; Hateley 2010). Tall eucalypt forests in the Wet Tropics, from their earliest descriptions, indicate an understorey of rain forest or sclerophyll species to 15 metres, but not a grassy understorey (p. 47 Tracey 1982). This is consistent with early images of tall eucalypt forests in the region (see for example Cairns & Johnston 1985; www.queenslandplaces.com.au/atherton-shire-and-tableland). The presence of a grassy understorey in these systems is not widespread and may be an indication of how recent the disturbance has been to tall eucalypt forests in the Wet Tropics compared to elsewhere in Australia. For example, an equivalent level of disturbance to tall eucalypt forests in the Central Highlands of Victoria had occurred by the 1840s (Griffiths 2001; Hateley 2010), not the 1940s. The presence of a grassy understorey beneath giant eucalypt trees is an ecological oddity. The purpose of growing to 50 metres or so tall, is to compete with other tall or fast growing species, not because of grass. Conversely, a grassy understorey in these forests is indicative of a disturbed system (Brook 1989; Garrity *et al.* 1997; MacDonald 2004). Tall eucalypt forests descriptions with a grassy *Imperata* understorey have appeared more recently (Harrington & Sanderson 1994; Harrington *et al.* 2000; Harrington *et al.* 2005; Stanton *et al.* 2014a, b). However, these descriptions are probably examples of European degraded systems, not natural pre-European undisturbed forests. It has possibly become more widespread as a result of a fire-driven landscape trap (Lindenmayer *et al.* 2011; Grady & Hoffmann 2012; Werner 2012; Tepley *et al*. 2016). This structural condition of tall eucalypt forest probably expanded greatly after 1880s, but has evidently displayed understorey thickening since the 1940s.

Evidence indicates that a grassy understorey is associated with frequent disturbance and probably outside the tolerance of tall eucalypt forest, suggesting that it is unnatural. Tall eucalypt forests in Queensland with a grassy understorey are often dominated by the grass, *Imperata cylindrica*. *I. cylindrica* is one of the 10 most invasive weeds worldwide (MacDonald 2004) and is a fire climax community, resprouting after being burnt (Brook 1989; Garrity *et al.* 1997; MacDonald 2004). In the Wet Tropics *Imperata* is an invasive post-disturbance species (Rasiah *et al.* 2004). It is characteristic of sites where rain forest was cleared and burnt and is maintained by fire, which is used to prevent rain forest from returning (Stocker 1981). It is also prevalent after fire associated with other cyclone disturbance (Webb 1958). It has deleterious effects on rain forest and tall eucalypt tree recruitment, including *E. grandis* and *E. resinifera* (Otsamo *et al.* 1995; Turvey 1996; Otsamo *et al.* 1997). To return degraded systems with *Imperata*, to healthy resilient ones, requires long fire free periods and the suppression of *Imperata* requires fire prevention (Brook 1989). Applying regular fire in tall, long-lived, fire sensitive eucalypt forests just to maintain a grassy *Imperata* understorey holds no merit. Instead, *Imperata* should be seen as an indicator of a degraded system and threat to natural regeneration of forest structure and composition.

The thickening of the rain forest understorey in tall eucalypt forests is inaccurately deemed a ‘contraction’ of tall eucalypt forests (Harrington & Sanderson 1994). Contraction implies the loss, or retreat, of the tall eucalypt forest, but this is not the trend being observed. What is being observed is a natural recovery or regeneration following systematic European disturbance to these forests. The belief that tall eucalypt forests, growing in excess of 50 metres, naturally occur with a grassy understorey from 1940s air photo imagery (Harrington & Sanderson 1994), is a misinterpretation of the natural structure of tall eucalypt forests and the failure to recognise an appropriate structural benchmark with which to compare, such as the 1880s (Haberle *et al*. 2005).

1.1.5 Tall eucalypt forest and fire management

Currently, local fire managers and agencies have adopted the view that the long-term shade intolerance of tall eucalypt forests, associated with rain forest thickening, is the greatest threat to those communities (Department of National Parks Recreation Sport and Racing 2013; Queensland Herbarium 2014; Tng *et al.* 2014). This rationale is based on the supposition, by multiple authors, that recent rain forest understorey thickening in tall eucalypt forest and adjacent savanna (Harrington & Sanderson 1994; Johansen & Phinn 2005; Tng *et al.* 2011), is attributed to a reduction in fire frequency since the cessation of Indigenous burning practices (Ash 1988; Unwin *et al.* 1988; Stocker & Unwin 1989; Unwin 1989; Harrington & Sanderson 1994; Hopkins *et al.* 1996; Russell-Smith & Stanton 2002; Stanton *et al.* 2014a, b). To the contrary, there is ample opposing evidence from multiple disciplines indicating alternative drivers of this vegetation change. Regardless, the supposition has become part of a cultural paradigm with fire managers and agencies in the region, despite other available evidence. Despite warnings of the importance of considering the breadth of fragmentary evidence when discerning between pre- and post-European fire regimes (Gill 2012), there remains a lack of integration of this information into management. Perhaps a history of hubris in forest management (Lindenmayer & Laurance 2012) has prevented the acknowledgement of compelling evidence that forestry operations have been a key causal factor in forest degradation and vegetation change.

Current regional fire management practices prescribe fire in tall eucalypt forests to arrest the processes of rain forest or shrubby understorey thickening, in favour of a grassy understorey (Department of National Parks Recreation Sport and Racing 2013; Queensland Herbarium 2014; Stanton *et al.* 2014a, b; Tng *et al.* 2014), believing that rain forest understories represent a “loss” or “contraction” of tall eucalypt forests (Harrington & Sanderson 1994; Stanton *et al.* 2014a, b). Because many pioneer rain forest species in these ecosystems survive a low frequency of fire (Williams *et al.* 2012c), the recommended fire interval for these forests is astoundingly so frequent (every three to ten years) (Department of National Parks Recreation Sport and Racing 2013; Queensland Herbarium 2014), as to risk the persistence of fire sensitive tall eucalypt forest species. For example, tall eucalypt forest dominated by *E. grandis* are recommended to be burnt every 3-5 years, where it has a grassy understorey, or 6-10 years with a shrubby understorey (regional ecosystem 7.12.21, Queensland Herbarium 2014). Fires this frequent will prevent recruitment of mature tree dominants, as it takes at least 15 years for *E. grandis* takes to reach maturity (Florence 1996) and further exacerbate the short-term fire intolerance of canopy and understorey species. Tall eucalypt canopy trees in southeastern Australia do not survive fire until they are more than 25 to 30 years old (Ashton 1981). Two intense fires within this time frame are sufficient to cause an extinction event, which has been observed in tall eucalypt forests elsewhere (Gill 2012). Fire intervals in tall eucalypt forests are naturally much longer than this and usually require periods of prolonged drought and extreme fire weather (Gill & Catling 2002; Bradstock 2008, 2010). These are circumstances that are likely to become more common in the Wet Tropics and elsewhere in Australia, due to climate change. Evidence of natural fire intervals for tall eucalypt forests in the Wet Tropics is in the order of 230 years (Chen 1990). Despite the guidelines specifying mosaic burning, the minimum fire interval should represent the amount of time for species to recover before a second fire occurs and the maximum interval equivalent to the age before dominant species senesce (Department of National Parks Recreation Sport and Racing 2013). For tall eucalypt forests, this should be an interval range of 15-300 years, not 3-10 years. The recommended fire regimes clearly ignore scientific evidence and require immediate review (Department of National Parks Recreation Sport and Racing 2013),

The official recommended fire guidelines for tall eucalypt forest (Department of National Parks Recreation Sport and Racing 2013; Queensland Herbarium 2014), are not evidence-based, nor the result of a synthesis of relevant information. As a result, these fire regimes will maintain tall eucalypt forests in a degraded state. Fire regimes that maintain tall eucalypt forests, or other vegetation types, in a degraded state, diminish the resilience of that ecosystem and potentially risk an abrupt transition to an alternative stable state. In many instances, fire management practitioners may be unknowingly maintaining these ecosystems in a degraded state consistent with a fire-driven landscape trap (Lindenmayer *et al.* 2011) or fire trap (Grady & Hoffmann 2012; Werner 2012; Tepley *et al*. 2016). This scenario indicates that current management activities are likely to be exacerbating, rather than mitigating likely climate change impacts. Prescribed fire in tall eucalypt forest at short intervals could become a catalyst that triggers tipping points and result in transition to an alternative vegetation state. This is not an unlikely scenario, as there are examples where this has occurred in tall eucalypt forests in southern Australia (Gill 2012). These fire regimes have the capacity to cause widespread loss of tall eucalypt forests and interventions to reduce fire disturbance need to be implemented to prevent this from occurring (Bowman *et al.* 2014). Consideration needs to be given to the creation of climate change and pyric refugia (Reside *et al.* 2014) for fire sensitive vegetation. Without diligent management of forest health and resilience by practitioners, tall eucalypt forests and rain forest boundaries are exposed to potential fire-induced tipping points and alternative stable states, even within the short-term.

1.1.6 The future of tall eucalypt forests

Two opposing processes affect the distribution of vegetation along the environmental gradient. These include short-term fire intolerance and long-term shade intolerance. Rain forest and tall eucalypt forest display short-term fire intolerance, whereas tall eucalypt forest and savanna display long-term shade intolerance. These opposing conditions between pyrophobic and pyrophytic vegetation are well documented (Kitzberger *et al.* 2016). Tall eucalypt forests are challenged by both opposing forces. Tall eucalypt forests are wedged between these two pressures, both of which exert strong controls on its distribution, including the present of alternative vegetation states (Chapter 2). However, an evaluation of the risks and extent of these two forces requires consideration.

Long-term shade intolerance associated with rain forest thickening has been observed since the 1940s (Harrington & Sanderson 1994; Johansen & Phinn 2005; Tng *et al.* 2011). While this could be associated with natural forest recovery pathways, fire managers and agencies recognise this process as a threat. However, this process is so slow that it would take more than 2,000 years (assuming no fire disturbance) for rain forest thickening to impact 75% of the tall eucalypt forest (Tng *et al.* 2011). This potential change, attributed to long-term shade intolerance (Chapter 2), is dwarfed by short-term fire intolerance that could cause abrupt change of vegetation, tipping into an alternative stable state, which is predicted to occur within the next 30 (Hilbert 2010) to 50 years (Burns *et al.* 2015). However, a sustained increase in the intensity and frequency of fires, which could result from increasing extreme fire danger, may result in change in a much shorter timeframe. The rate of change from these opposing forces is also documented for other regions (Kitzberger *et al.* 2016) and it is the fire events that are of greatest concern.

Tall eucalypt forests in the Wet Tropics are clearly identified as being under threat from fire and climate change and are vulnerable to tipping points. Vegetation change or shifts associated with climate change, are likely to be driven by change in stochastic events, such as fire, or extreme weather (Scheffer *et al.* 2001; Gonzalez *et al.* 2010; Higgins & Scheiter 2012; Halofsky *et al.* 2013). To understand how such disturbances will influence vegetation change, it is important to consider the legacy effects of past disturbances (Loudermilk *et al.* 2013), which will affect the resilience or vulnerability of ecosystems to climate induced shifts (Scheffer *et al.* 2001; Folke *et al.* 2004; Tompkins & Adger 2004; Parks & Bernier 2010; Baker *et al.* 2012; Knox & Clarke 2012; Warszawski *et al.* 2013). Past disturbances from human colonisation have altered vegetation stable states in some situations are subsequently maintained by positive feedbacks of recurring fire (Tepley *et al.* 2016). It has also been discussed here, that these forests may be in a degraded state and are being maintained in this state with frequent fire intervals that maintain a landscape trap. This is of concern. These management practices will exacerbate likely climate change impacts and have the potential to trigger catastrophic ecosystem collapse and transition to an alternative vegetation type. Building ecosystem resilience to climate change by reducing other stressors such as fire is critical to avoid potential ecosystem collapse (Gill *et al.* 2014; Scheffer *et al.* 2015).

Appendix 2.1 Process for assessing and selecting an appropriate model technique for predicting vegetation distribution.

Vegetation modelling analysis consisted of an iterative process of testing and development, before final selection of one thorough and robust spatial model technique. The iterative process consisted of an assessment of model techniques, initial tests with those techniques, model evaluation, performance, review, and comparison between and within model techniques, including a multi-model technique ensemble approach.

Predictions from different distribution model techniques can be highly variable (Araújo & New 2007; Aguirre-Gutiérrez *et al.* 2013) and can contribute the greatest source of variability and uncertainty (Buisson *et al.* 2010). A multi-model ensemble approach (Araújo & New 2007; Aguirre-Gutiérrez *et al.* 2013) is often recommended to address the issue of model variability. An ensemble of multiple model techniques was explored for this reason and a number of model techniques were considered and tested, with the view of adopting an ensemble of model techniques. Three model techniques were considered, including generalised linear models (GLM), classification and regression trees (CART) and MaxEnt suitability distribution model. Comparisons of these three model techniques indicate GLMs to be the more accurate methodology (Bedia *et al.* 2011), with MaxEnt generally performing poorly. Elsewhere GLMs are shown to outperform MaxEnt (Khatchikian *et al.* 2011; Royle *et al.* 2012), as are CART analyses (Clark *et al.* 2012), however, there are some exceptions (Gastón & García-Viñas 2011; Rupprecht *et al.* 2011). Although three model techniques were tested, a single analysis technique eventually became the preferred approach.

Iterative Analysis Process

Initially data presented itself in the format of 'presence only', with one column of data for the response variable, vegetation, with one of three vegetation types represented at any one point. Data in this form lends itself to particular analysis techniques, which accommodate presence only data. Three techniques were explored, including MaxEnt, multinomial logistic regression and classification regression tree analysis.

The first model approach tested was a suitability distribution model, also known as statistical species, ecological niche or habitat distribution models (Guisan & Thuiller 2005). The use of a distribution model for vegetation was preferred over mechanistic 'dynamic global vegetation model' approaches, as these latter techniques tend to be coarse and consider ecological processes rather than distribution *per se*. A maximum-entropy model via MaxEnt software (Phillips *et al.* 2004; Elith *et al.* 2011) and based on a machine-learning algortihm, was used as the suitability distribution model for each vegetation type. MaxEnt has been repeatedly demonstrated to perform well when compared with other suitability distribution models using presence-only data (Elith *et al.* 2006; Peterson *et al.* 2007). Combinations of predictor variables were used with each vegetation type and model performance was evaluated by area under the curve (AUC) of the receiver operating characteristic.

The second method tested was a multinomial generalised linear model (logistic regression). The generalised linear models (GLM) contained multivariate response variables consisting of the three vegetation types and combinations of predictor variables. Model performance and selection was evaluated by Akaike Information Criterion (AICc) and percent explained deviance of the model. The analysis sequence described by Logan (2010) was used, including tests for model assumptions. Multinomial logistic regression has been recently used in modelling vegetation distributions in relation to climate change (Ackerly *et al.* 2015). However, there are limitations in using this technique (Ackerly *et al.* 2015), which can be avoided by modelling vegetation separately, such as with binomial logistic regression.

The third complementary model technique considered was classification and regression tree (CART) analysis. The analysis sequence described by Logan (2010) was used, including tests for model assumptions.

Each of the three model techniques described were initially evaluated by testing each individual predictor variable by itself, before adding multiple predictor variables into more complex models. In many cases model performance was quite low, leading to enquiry as to how to improve model performance.

It was realised that the response data, could be evaluated as presence and absence data, rather than just presence only data. The multivariate response data (vegetation) was based on dominant regional ecosystems, which were non-overlapping, discrete map areas. Thus, the presence of one vegetation type, infers the absence of all other vegetation types. Where it is available, presence and absence data should be used, rather than presence only data, as this can significantly improve model performance and will make use of all the data available (Brotons *et al.* 2004; Elith *et al.* 2011; Kent & Carmel 2011; Li *et al.* 2011; Yackulic *et al.* 2013). Accordingly, the one column of presence only vegetation data was extracted into three columns of binary data (presence and absence) for each vegetation type. Given that this data now presented in the form of binary data (presence and absence), it was appropriate to explore model techniques that could utilise this data.

Model techniques that make use of presence and absence data included GLMs and classification trees, but not the MaxEnt approach (Ward *et al.* 2009; Elith *et al.* 2011; Yackulic *et al.* 2013). Instead of using multinomial (multivariate) GLMs for all vegetation types, binomial GLMs (with a bivariate response) could instead be used and could be readily incorporated into both the GLM technique and the CART technique.

Aside from some general assumptions and uncertainties of distribution models (Wiens *et al.* 2009), individual model techniques may themselves have their own assumptions and uncertainties to be addressed, not all of which may be explicit (Soberón & Nakamura 2009).

Indeed a review of the literature indicates that many modellers choose to ignore the assumptions of their models and fail to test and address these assumptions. Standard statistical methods such as GLMs and CART have clear assumptions of these models which need to be met, including those of data linearity, normality, dispersion, homogeneity of variance and collinearity.

Despite the multitude of predictive model techniques available, there remains no consensus regarding preferred model evaluation metrics. In fact, some commonly used model evaluation metrics are inappropriately used and may not represent the actual predictive performance of the model, nor be suiTable 2.for model comparisons nor evaluating relative performance between model techniques. It is also evident that model evaluation metrics perform inconsistently under different circumstances and can, for example, vary along environmental gradients (Pottier *et al.* 2013). This suggests that multiple evaluation metrics are required to adequately assess a model's performance, for model comparison and for comparisons between different model techniques. Multiple evaluation metrics have been adopted in ensemble modelling software such as BIOMOD (Thuiller 2003; Thuiller *et al.* 2009). Here we selected a suite of evaluation metrics considered most appropriate for the purposes of this study. They include AICc, explained deviance and TSS.

AUC represents the "area under the curve" (AUC) of the plotted receiver operating characteristic (ROC) (Franklin 2010). It is a widely used metric that incorporates sensitivity (true positive rate) and specificity (1-false positive rate). AUC values above 0.5 indicate a result that is better than random, with values greater than 0.7 of moderate performance and values over 0.9 of high performance (Swets 1988). AUC is the primary evaluation metric used in MaxEnt. However, there is also criticism of this metric as a performance measure being unreliable and incoherent (Termansen *et al.* 2006; Lobo *et al.* 2008; Hand 2009; Liu *et al.* 2011; Golicher *et al.* 2012; Hand & Anagnostopoulos 2013) and inappropriate for binary (presence-absence) data (Allouche *et al.* 2006; Li & Guo 2013). As this is the only evaluation metric available in the MaxEnt technique, results from this approach do not provide actual probability, but rather a prediction based on density of parameter inputs (Phillips *et al.* 2006; Li *et al.* 2011).

Ensemble model techniques need to consider whether one method is superior to others, whether the individual techniques are statistically robust, whether techniques make use of all the data, whether input data is consistent (presence only data in some techniques vs presence and absence data in others), appropriateness of evaluation metric for intercomparability, whether assumptions of each model technique have been met and whether spatial autocorrelation been assessed and can be incorporated. Ensemble modelling should only be approached with the use of a standardised platform for analysis and evaluation such BIOMOD (Thuiller 2003; Thuiller *et al.* 2009). However, an ensemble model approach may be inferior to single model techniques that can be readily compared, have appropriate model evaluations, can have their model assumptions met and can account for spatial autocorrelation. Currently, spatial autocorrelation and model assumption evaluations are not included as part of ensemble model software such as BIOMOD (Thuiller 2003; Thuiller *et al.* 2009). Each individual model technique must be separately evaluated against its model assumptions and for spatial autocorrelation issues prior to inclusion in the ensemble forecasting method. It is presently difficult to include spatial autocorrelation into a unified ensemble forecasting package, although not impossible (Marmion *et al.* 2009).

The enquiry here, into best-practice ecological modelling techniques included an assessment of model techniques, testing, evaluation, consideration of model evaluation metrics and comparison between and within model techniques, including a multi-model technique ensemble approach. Following this enquiry, there was clear evidence of model superiority, flexibility, performance and comparability. GLMs were able to make use of all the data (presence and absence), had robust model comparison and selection techniques available, had model assumptions that could be readily evaluated, had a range of appropriate model evaluation techniques available and could account for spatial autocorrelation. For these reasons, the ensemble forecasting approach was abandoned for a rigorous and robust single model approach. This approach may indeed be more reliable and accurate than a consensus ensemble model approach, which ignores assumptions of the model.

Appendix 2.2 Testing spatial GLM analysis options and identifying techniques that are computationally viable with a large dataset.

A number of spatial analysis methods were tested for addressing spatial autocorrelation in GLMs, however, most of the methods tested were found to be computationally intensive and could not operate within the computing limitations specified in this study.

Hierarchical Bayesian spatial GLMs were attempted using the R packages ‘spBayes’ (Finley & Banerjee 2013) and ‘geoRglm’ (Christensen & Ribeiro Jr 2014), however, both methods were unable to function within the computing limitations of this study. Bayesian approximations were a potential solution to formal Bayesian algorithms, as they are less-computer intensive. Integrated nested Laplace approximations (INLA) (Rue *et al.* 2009) have been identified as being an advantage over Bayesian hierarchical models using Markov chain Monte Carlo (MCMC) algorithms, which are computationally prohibitive for large datasets (Eidsvik *et al.* 2012). Despite this claim, INLA was also unable to compute a spatial analysis with the dataset of this study. A latent Gaussian model equivalent to GLM was tested with INLA via the random walk (rw2d) model defined on a regular grid. Even with a subset of data (<10,000 data points), this model could not compute and would cause the computer to be inoperable.

The Moran eigenvector approach (Diniz-Filho & Bini 2005; Dray *et al.* 2006; Griffith & Peres-Neto 2006; Borcard *et al.* 2011; Dray *et al.* 2012) was also tested with this data. These methods include Moran eigenvector mapping and Moran eigenvector filtering, which are considered to be computationally intensive processes (Dormann *et al.* 2007; Miller *et al.* 2007; Franklin 2010). The Moran eigenvector GLM filtering technique was implemented via the Moran eigenvector filtering function (ME) in the R package ‘spdep’ (Bivand *et al.* 2014). Tests using this technique were used with a random selection of 400 data points. Run time for analysis was not successful and resulted in computer failure after 5-7 hours operation. Clearly this technique was not suitable for larger datasets.

Autocovariate (autologistic) regression method has been identified as a low computation intensity option (Dormann *et al.* 2007; Miller *et al.* 2007; Franklin 2010), but no other methods have been identified. Autocovariate regression spatial GLMs were successfully implemented via ‘spdep’ (Bivand *et al.* 2014) in R software. However, this method is criticised for its performance (Dormann 2007a; Dormann 2009) and is counter-intuitive as it only accounts for spatial dependence in the response variable and not the predictor variables. This has recently led some researchers to develop an alternative, but simple method for addressing SAC with an autocovariate approach, but by using the model’s residual as an autocovariate rather than the model’s response variable as an autocovariate (Crase *et al.* 2012).

The residuals autocovariate (RAC) technique (Crase *et al.* 2012) is a recent method that assesses spatial autocorrelation of a model's residuals, then incorporates a spatial weighting on the residuals as an autocovariate in the model. This technique has been compared with non-spatial models and with standard autocovariate regression models and was found to outperform these techniques (Crase *et al.* 2014). This method is similar to another method − the generalised autoregressive error model (GAR_{err}) − which incorporates spatial weighting on the errors, rather than residuals (Murphy *et al.* 2010). However, the GAR_{err} technique is unable to work with large datasets (Tng *et al.* 2011) and is a more complex approach than the RAC technique. The computational intensity of the RAC method has not previously been compared with other techniques. Nonetheless, the RAC method was tested and successfully implemented for a large dataset within the computing limitations of this study. Of all the methods tested here, the RAC technique represents the most simple, low computational and robust approach to address SAC in distribution models with large datasets. It is this approach that was adopted here, using modified code adopted from Crase *et al.* (2012).

Appendix 2.3 Summary data for a range of geographic and climatic variables for three broad vegetation types (rain forest, tall eucalypt forest and savanna woodland) in the Australian Wet Tropics.

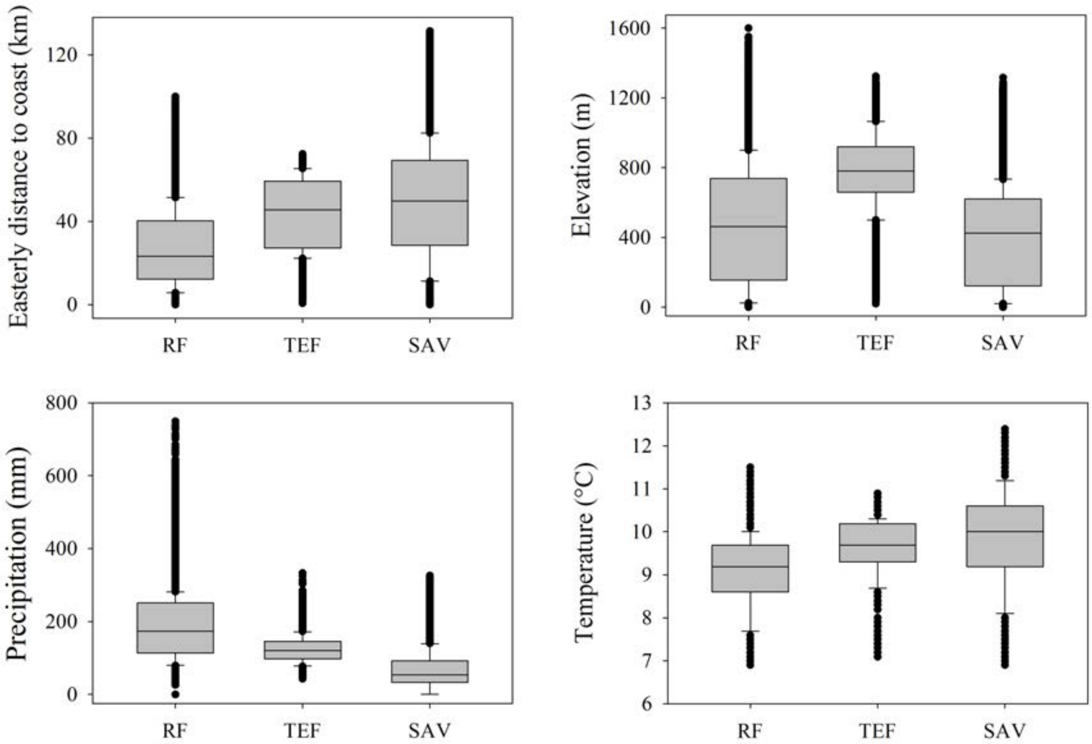

Figure 2.1 Geographic and climatic characteristics of three vegetation types in the Australian Wet Tropics region from 586,045 data points; rain forest (RF), tall eucalypt forest (TEF) and savanna (SAV). Variables consisted of easterly distance to coast, elevation, precipitation (of the driest annual quarter) and temperature (mean diurnal range). Boxes indicate medians (lines) and upper and lower quartiles, bars show 10th and 90th percentiles, and circles represent all outliers.

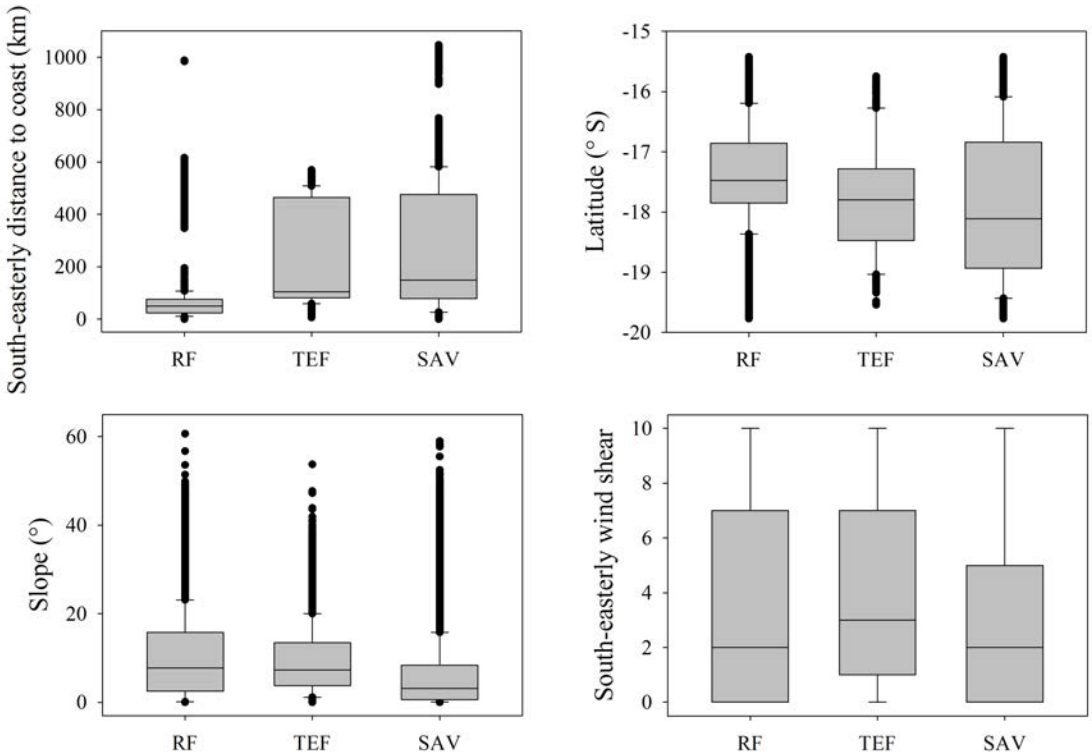

Figure 2.2 Geographic characteristics of three vegetation types in the Australian Wet Tropics region from 586,045 data points; rain forest (RF), tall eucalypt forest (TEF) and savanna (SAV). Boxes indicate medians (lines) and upper and lower quartiles, bars show 10th and 90th percentiles, and circles represent all outliers.

Table 2.1 Percent cover of five categories of topographic aspect in the Wet Tropics for three different vegetation types; rain forest, tall eucalypt forest and savanna.

Aspect	Total %	Rain Forest %	Tall Eucalypt Forest %	Savanna %
Flat	9.36	8.43	5.07	8.7
North East	27.29	26.85	23.69	27.85
South East	21.41	23.92	21.76	20.57
South West	21.77	22.57	26.26	21.78
North West	20.18	18.23	23.23	21.1

Table 2.2 Percent cover of eight category of geology (rock name) in the Wet Tropics for three different vegetation types; including rain forest (RF), tall eucalypt forest (TEF) and savanna woodland (SAV). For more detailed information including composition of rock names in the category 'other', see Appendix 2.4.

Geology	Total %	Rain Forest %	Tall Eucalypt Forest %	Savanna %
Alluvium	16.7	11.5	0.7	18.5
Basalt	5.6	14.9	1.6	2.4
Colluvium	7	0.7	1.1	10
Felsites	8.6	8.6	35.5	8.1
Granitoid	29.1	38.6	51.3	25.9
Mudrock	10.6	18.9	8.1	8.2
Rudite	5.9	1.6	0.3	8
Other	16.4	5.2	1.4	18.9

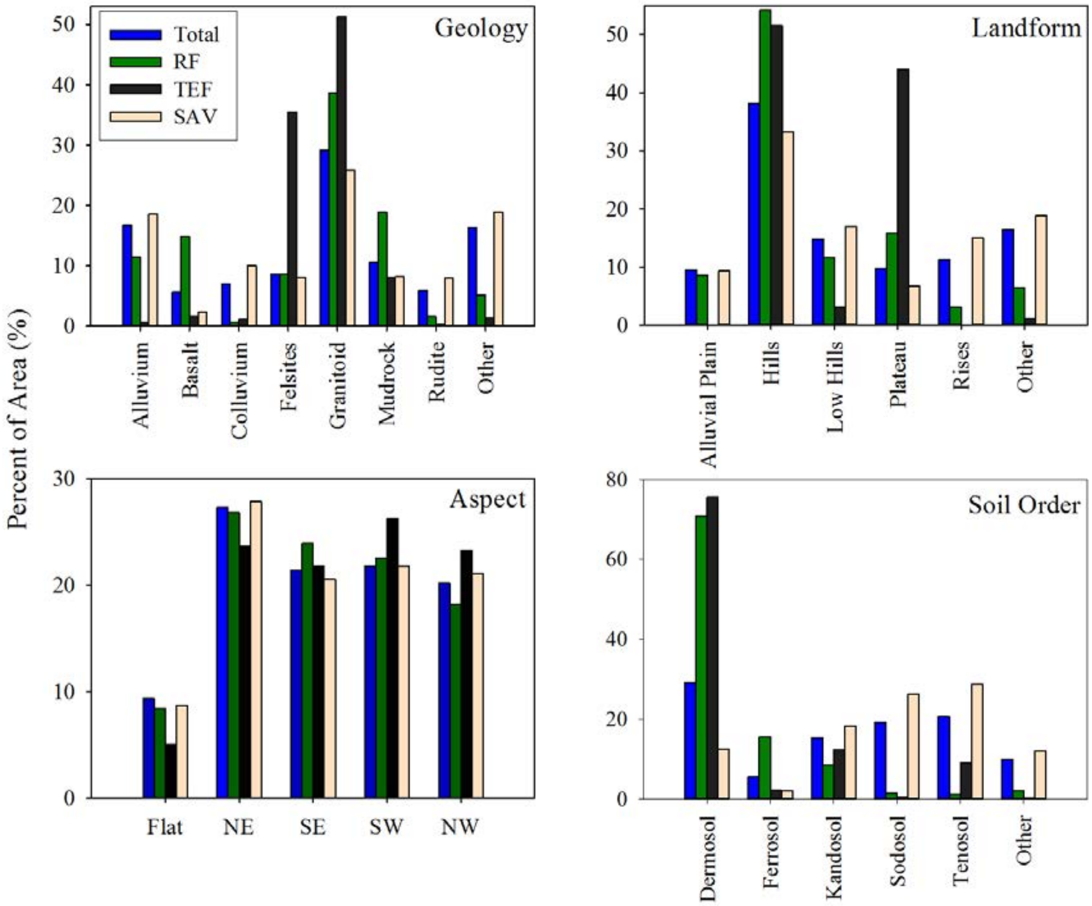

Figure 2.3 Percent cover of four geographic and edaphic characteristics for the total Wet Tropics region and for three vegetation types from 586,045 data points; rain forest (RF), tall eucalypt forest (TEF) and savanna (SAV).

Table 2.3 Percent cover of 6 category of landform pattern in the Wet Tropics for three different vegetation types; rain forest (RF), tall eucalypt forest (TEF) and savanna woodland (SAV). For more detailed information including composition of the category 'other', see Appendix 2.5.

Landform Pattern	Landform Code	Total %	Rain Forest %	Tall Eucalypt Forest %	Savanna %
Alluvial Plain	ALP	9.5	8.6	0	9.3
Hills	HIL	38.2	54.2	51.5	33.3
Low Hills	LOW	14.8	11.7	3.2	17
Plateau	PLT	9.7	15.8	44	6.7
Rises	RIS	11.2	3.2	0.1	15
Other	Other	16.5	6.5	1.2	18.8

Table 2.4 Occurrence of 10 category of relief type in the Wet Tropics region, showing total percentage of the region and percentages occupied by three different vegetation types; rain forest (RF), tall eucalypt forest (TEF) and savanna woodland (SAV). For detailed information including composition of the category 'other', see Appendix 2.6.

Relief	Relief Code	Total %	Rain Forest%	Tall Eucalypt Forest %	Savanna %
Very steep hills 90–300 m 56-100%	VH	23.2	25.1	25	23.3
Steep hills 90–300 m 32–56%	SH	16.6	30.6	27.2	11.3
Level plain <9 m <1%	LP	14.2	10.6	0.1	13.8
Rolling low hills 30–90 m 10–32%	RL	9.5	21	10.7	5.5
Gently undulating plains <9 m 1–3%	GP	7.8	2.6	0.4	9.9
Steep low hills 30–90 m 32–56%	SL	6.8	0.4	0.6	9.6
Gently undulating rises 9-30 m 1–3%	GR	6.5	0.3	0	9.1
Rolling rises 9–30 m 10–32%	RR	6.1	6.7	2.9	6.3
Undulating low hills 30–90 m 3–10%	UL	5.1	2.5	33.1	5.3
Other	Other	4.2	0.4	0	5.9

Table 2.5 Percent cover of 6 category soil order (Australian Soil Classification) in the Wet Tropics for three different vegetation types; rain forest, tall eucalypt forest and savanna woodland. For more detailed information including composition of the category 'other', see Appendix 2.7.

Soil Order	Total %	Rain Forest%	Tall Eucalypt Forest %	Savanna %
Dermosol	29.2	70.9	75.6	12.5
Ferrosol	5.6	15.6	2.3	2.1
Kandosol	15.3	8.6	12.4	18.3
Sodosol	19.2	1.5	0.5	26.3
Tenosol	20.6	1.2	9.1	28.7
Other	10	2.2	0.2	12.1

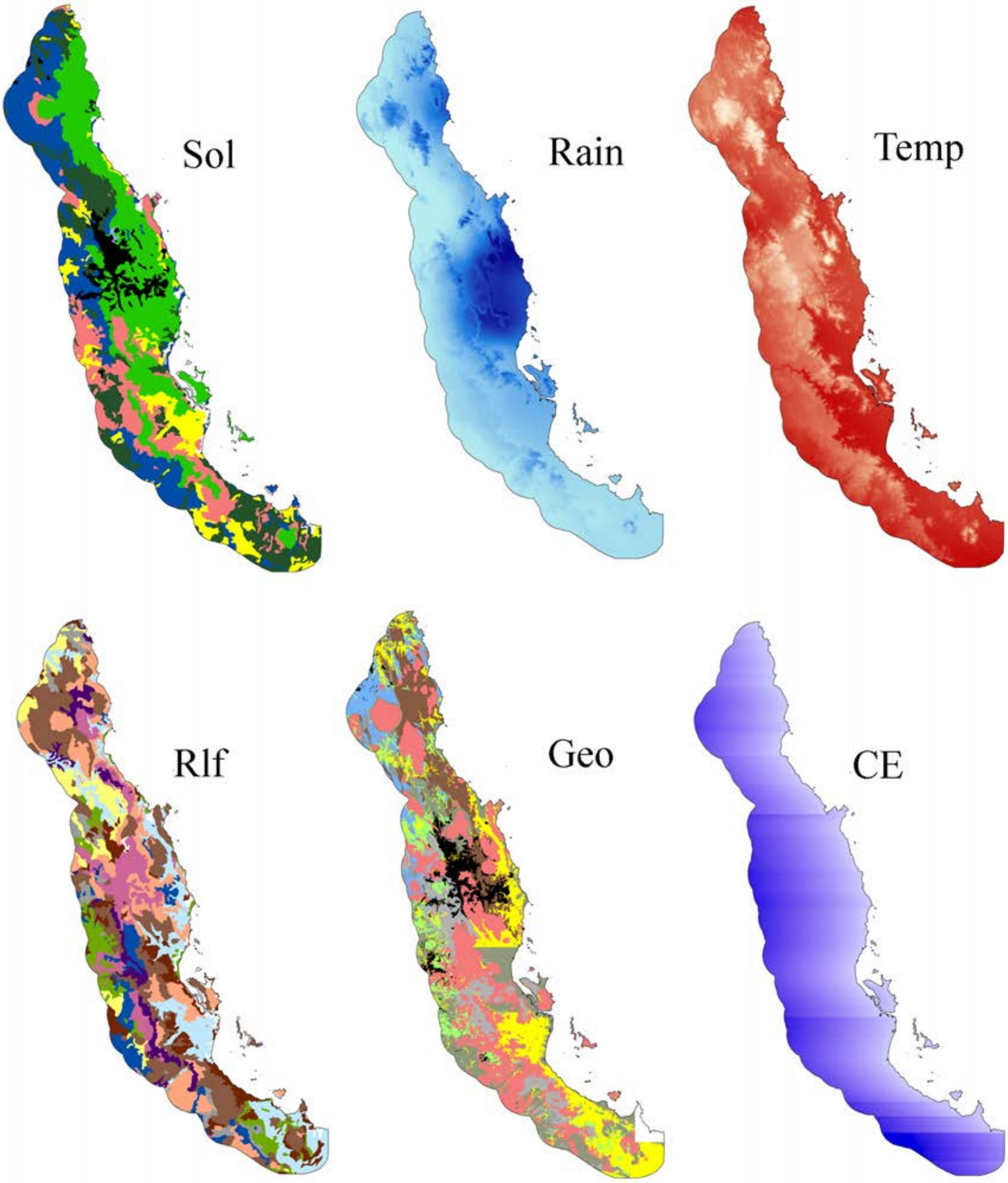

Figure 2.4 Spatial pattern of six variables used to predict vegetation distribution in the Wet Tropics of northeastern Australia. Variables were soil (Sol), precipitation of driest annual quarter (Rain), maximum temperature of the warmest period (Temp), relief (Rlf), geology (Geo) and easterly distance to the coast (CE).

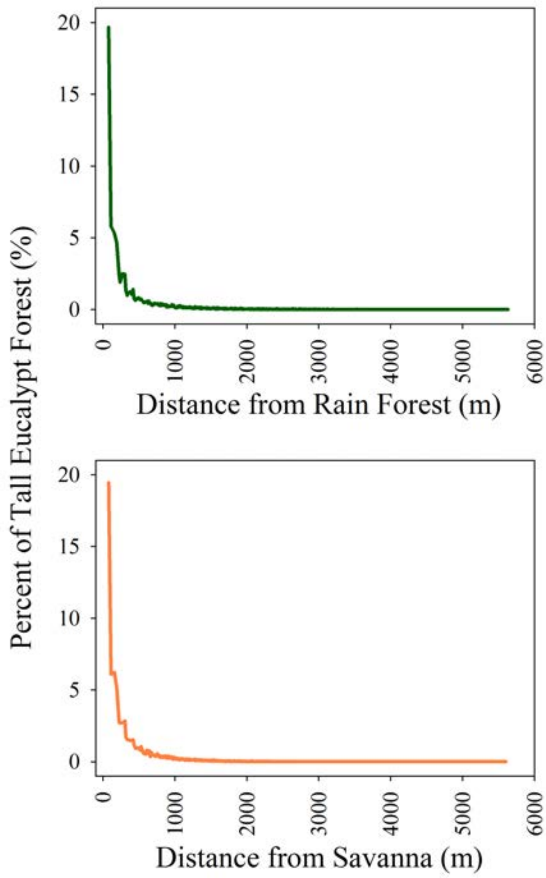

Figure 2.5 The proportion of tall eucalypt forest occurring with distance from rain forest and from savanna boundaries. Spatial RAC GLM indicates distance from rain forest explains 25% of model deviance (TSS 0.64) and distance from savanna explains 19% of model deviance (TSS 0.56).

Table 2.6 Landscape patterns for tall eucalypt forest in areas with high (probability 0.9 or greater), moderate (0.7 or greater) or low (0.5 or greater) predicted probability of occurring. Values represent averages from 187 points for high probability, 2005 points for moderate probability and 4707 points for low probability. All categories present are listed for geology and soil variables.

Variable	$p \geq 0.9$	$p \geq 0.7$	$p \geq 0.5$
Distance to Rain Forest	493.42	1041.53	1027.7
Distance to Savanna	1421.27	782.39	724.31
Elevation	881.98	838.24	859.12
Easterly distance to coast	25582.35	44060.97	48486.92
Temperature: Mean Annual	19.42	19.63	19.5
Temperature: Mean Diurnal Range	9.3	9.81	9.87
Temperature: Mean Coldest Quarter	14.88	15.25	15.22
Precipitation: Annual	2120.03	1893.44	1837.88
Precipitation: Driest Quarter	122.3	126.74	124.95
Geology Types	Felsites, Granitoid	Felsites, Granitoid	Felsites, Granitoid
Soil Types	Dermosol	Dermosol	Dermosol, Kandosol

Appendix 2.4 Occurrence of 8 category of geology (rock name) in the Wet Tropics region, showing total percentage of the region and percentages occupied by three different vegetation types; rain forest (RF), tall eucalypt forest (TEF) and savanna woodland (SAV). Details for twenty-six additional categories, which compose the category 'other' are also provided.

Geology rock name	Total Count	Total %	RF Count	RF %	TEF Count	TEF %	SAV Count	SAV %
Alluvium	97098	16.7	17095	11.5	86	0.7	72120	18.5
Basalt	32613	5.6	22223	14.9	206	1.6	9568	2.4
Colluvium	40434	7	1068	0.7	137	1.1	38908	10
Felsites	50084	8.6	12820	8.6	4585	35.5	31686	8.1
Granitoid	168819	29.1	57621	38.6	6639	51.3	101264	25.9
Mudrock	61580	10.6	28247	18.9	1050	8.1	31842	8.2
Rudite	33977	5.9	2351	1.6	44	0.3	31372	8
Other	95097	16.4	7836	5.2	182	1.4	73863	18.9
-arenite	5141	0.9	90	0.1	0	0	5045	1.3
-arenite-mudrock	13368	2.3	1874	1.3	104	0.8	11367	2.9
- arenite-rudite	586	0.1	77	0.1	7	0.1	499	0.1
- carbonates (limestone or dolomite)	29	0	1	0	0	0	19	0
- chert	113	0	14	0	2	0	96	0
- dioritoid	705	0.1	0	0	0	0	704	0.2
- ferricrete	605	0.1	45	0	0	0	529	0.1
- gabbroid	535	0.1	158	0.1	6	0	371	0.1
- gravel	2	0	0	0	0	0	0	0
- mafites (lavas, clastics & high-level intrusives)	2671	0.5	333	0.2	5	0	2321	0.6
- man-made deposits	195	0	0	0	0	0	195	0
- metamorphic rock	2438	0.4	1047	0.7	17	0.1	1321	0.3
- metamorphosed sedimentary rock	4837	0.8	398	0.3	22	0.2	4415	1.1
- miscellaneous unconsolidated sediments	23979	4.1	1928	1.3	5	0	12303	3.1
- mixed mafites & felsites (mainly volcanics)	5091	0.9	299	0.2	0	0	4685	1.2
- mixed metamorphosed mafites & sedimentary rocks	588	0.1	0	0	0	0	588	0.2
- mixed sedimentary rocks & felsites	1430	0.2	26	0	0	0	1404	0.4
- mixed siliciclastic/ carbonate rocks	129	0	26	0	0	0	103	0
- mixed volcanic & sedimentary rocks	2663	0.5	99	0.1	0	0	2564	0.7
- mud	438	0.1	0	0	0	0	86	0
- poorly consolidated sediments	12408	2.1	13	0	2	0	12388	3.2
- sand	3666	0.6	611	0.4	0	0	1656	0.4
- sedimentary rocks	10307	1.8	27	0	0	0	10148	2.6
- silcrete	104	0	1	0	0	0	102	0
- ultramafic rock	75	0	37	0	0	0	38	0
- water bodies	2994	0.5	732	0.5	12	0.1	916	0.2
Total Count	579702	100	149261	100	12929	100	390623	100

Appendix 2.5 Occurrence of 6 category of landform pattern in the Wet Tropics region, including total percentage of the region and percentages occupied by three different vegetation types; rain forest (RF), tall eucalypt forest (TEF) and savanna woodland (SAV). Details for 10 additional categories, which compose the category 'other' are listed.

Landform Pattern	Total Count	Total %	RF Count	RF %	TEF Count	TEF %	SAV Count	SAV %
Alluvial Plain	54802	9.5	12743	8.6	3	0	36314	9.3
Hills	219903	38.2	80578	54.2	6650	51.5	129684	33.3
Low Hills	85273	14.8	17414	11.7	409	3.2	66142	17
Plateau	55886	9.7	23465	15.8	5674	44	25994	6.7
Rises	64217	11.2	4773	3.2	14	0.1	58328	15
Other	95142	16.5	9645	6.5	152	1.2	73423	18.8
- Alluvial Fan	287	0	0	0	0	0	287	0.1
- Covered Plain	4201	0.7	1249	0.8	0	0	2260	0.6
- Delta	2369	0.4	223	0.2	0	0	1252	0.3
- Dune Field	5261	0.9	585	0.4	0	0	2496	0.6
- Flood Plain	4475	0.8	272	0.2	0	0	4168	1.1
- Meander Plain	19449	3.4	1573	1.1	13	0.1	15097	3.9
- Mountains	11679	2	2429	1.6	89	0.7	7750	2
- Plain	23384	4.1	2569	1.7	45	0.3	20297	5.2
- Sheet Flood Plain	20922	3.6	745	0.5	5	0	19486	5
- Tidal Flat	3115	0.5	0	0	0	0	330	0.1
Total Count	575223	100	148618	100	12902	100	389885	100

Appendix 2.6 Occurrence of 10 category of relief type in the Wet Tropics region, including total percentage of the region and percentages occupied by three different vegetation types; rain forest (RF), tall eucalypt forest (TEF) and savanna woodland (SAV). Details for 3 additional categories, which compose the category 'other' are also provided.

Relief	Total Count	Total %	RF Count	RF %	TEF Count	TEF %	SAV Count	SAV %
Very steep hills 90–300 m 56-100%	133269	23.2	37251	25.1	3225	25	90737	23.3
Steep hills 90–300 m 32–56%	95489	16.6	45549	30.6	3514	27.2	44136	11.3
Level plain <9 m <1%	81961	14.2	15710	10.6	19	0.1	53773	13.8
Rolling low hills 30–90 m 10–32%	54716	9.5	31139	21	1380	10.7	21533	5.5
Gently undulating plains <9 m 1–3%	45139	7.8	3819	2.6	47	0.4	38650	9.9
Steep low hills 30–90 m 32–56%	39044	6.8	592	0.4	74	0.6	37614	9.6
Gently undulating rises 9-30 m 1–3%	37121	6.5	411	0.3	0	0	35409	9.1
Rolling rises 9–30 m 10–32%	35072	6.1	9887	6.7	374	2.9	24513	6.3
Undulating low hills 30–90 m 3–10%	29187	5.1	3703	2.5	4266	33.1	20694	5.3
Other	24225	4.2	557	0.4	3	0	22826	5.9
- Undulating rises 9–30 m 3–10%	21507	3.7	350	0.2	3	0	20371	5.2
- Very steep mountains >300 m 56–100%	2470	0.4	172	0.1	0	0	2296	0.6
- Rolling hills 90–300 m 10–32%	248	0	35	0	0	0	159	0
Total Count	575223	100	148618	100	12902	100	389885	100

Appendix 2.7 Occurrence of 6 category soil order (Australian Soil Classification) in the Wet Tropics region, including total percentage of the region and percentages occupied by three different vegetation types; rain forest (RF), tall eucalypt forest (TEF) and savanna woodland (SAV). Details for 6 additional categories, which compose the category 'other' are also provided.

Soil Order	Total Count	Total %	RF Count	RF %	TEF Count	TEF %	SAV Count	SAV %
Dermosol	168246	29.2	105396	70.9	9755	75.6	48566	12.5
Ferrosol	32090	5.6	23200	15.6	297	2.3	8328	2.1
Kandosol	88171	15.3	12854	8.6	1595	12.4	71280	18.3
Sodosol	110469	19.2	2162	1.5	64	0.5	102378	26.3
Tenosol	118640	20.6	1779	1.2	1171	9.1	112069	28.7
Other	57607	10	3227	2.2	20	0.2	47264	12.1
- Chromosol	22422	3.9	274	0.2	7	0.1	22058	5.7
- Hydrosol	24117	4.2	1732	1.2	13	0.1	16987	4.4
- Kurosol	3178	0.6	478	0.3	0	0	2276	0.6
- Organosol	1869	0.3	688	0.5	0	0	821	0.2
- Podosol	119	0	49	0	0	0	37	0
- Vertosol	5902	1	6	0	0	0	5085	1.3
Total Count	575223	100	148618	100	12902	100	389885	100

Appendix 2.8 Comparison of spatial (residuals autocovariate) non-linear logistic regressions testing for individual variables predicting distribution of 3 vegetation types: a. rain forest, b. tall eucalypt forest and c. savanna.

a. rain forest

Rain Forest	AICc	Exp. Dev. %	TSS	Resid. df
bc19	347647.7	46.7	0.72	568796
Soil	348966.9	46.9	0.74	575216
bc17	349175.4	46.5	0.72	568796
bc15	376713.8	42.3	0.68	568796
bc12	378546.7	42	0.69	568796
bc16	382641.1	41.4	0.69	568796
bc18	383771.8	41.2	0.7	568796
bc13	408091.4	37.5	0.65	568796
bc14	430928.3	34	0.65	568796
bc02	441146.2	32.4	0.62	568796
Coast distance (SE)	456955.4	30	0.56	568796
bc07	460887.7	29.4	0.58	568796
Relief	470941	28.4	0.59	575212
Coast distance (E)	475540.3	27.2	0.54	568796
bc03	485163.1	25.7	0.52	568796
Geology	510745.8	22.8	0.51	579693
Landform	512063.4	22.1	0.5	575216
bc05	532425.7	18.4	0.45	568796
Slope	538443.8	17.5	0.42	568796
Wind (SE)	538691.9	17.5	0.37	568796
bc04	541918.8	17	0.42	568796
bc08	553450	15.2	0.41	568796
bc10	555625.5	14.9	0.41	568796
bc06	555901.6	14.8	0.4	568796
bc01	556828.7	14.7	0.4	568796
Hillshade	559723.4	14.3	0.38	568796
Elevation	560608.5	14.1	0.39	568796
bc11	560653.9	14.1	0.39	568796
Wind (NW)	561515.4	14	0.44	568796
bc09	563863.5	13.6	0.35	568796
Latitude	566923.4	13.2	0.35	568796
Aspect	568834.4	12.9	0.37	568794
Stream distance	569845.2	12.7	0.36	568796

b. tall eucalypt forest

Tall Eucalypt Forest	AICc	Exp. Dev. %	TSS	Resid. df
bc10	82641.78	32.9	0.72	568796
bc08	82701.09	32.9	0.72	568796
Elevation	83029.94	32.6	0.72	568796
bc01	83059.24	32.6	0.72	568796
bc11	83629.97	32.1	0.72	568796

Geology	84046.42	32.2	0.68	579693
Soil	86856.15	29.7	0.66	575216
bc17	87002.06	29.4	0.64	568796
Relief	89744.18	27.4	0.57	575212
Landform	90073.98	27.1	0.57	575216
bc19	90318.88	26.7	0.63	568796
bc12	91082.42	26.1	0.62	568796
bc15	91484.18	25.8	0.63	568796
bc05	92564.63	24.9	0.65	568796
bc06	92972.85	24.5	0.63	568796
bc16	93152.65	24.4	0.64	568796
bc09	93320.55	24.3	0.63	568796
bc18	93818.85	23.9	0.61	568796
bc13	94854.16	23	0.62	568796
bc02	95728.13	22.3	0.61	568796
bc07	96665.91	21.5	0.59	568796
Coast distance (E)	97565.12	20.8	0.61	568796
bc03	97715.18	20.7	0.61	568796
bc04	99068.96	19.6	0.59	568796
bc14	99561.71	19.2	0.55	568796
Latitude	99651.53	19.1	0.52	568796
Stream distance	100089.7	18.8	0.54	568796
Slope	100498	18.4	0.56	568796
Coast distance (SE)	100518.1	18.4	0.54	568796
Hillshade	100676.3	18.3	0.54	568796
Wind (SE)	100814.4	18.2	0.54	568796
Wind (NW)	100912.9	18.1	0.54	568796
Aspect	121001.2	1.8	0.32	568794

c. savanna

Savanna	**AICc**	**Exp. Dev. %**	**TSS**	**Resid. df**
bc19	376620.9	47.1	0.7	568796
bc17	406192	42.9	0.68	568796
bc15	409703.1	42.4	0.66	568796
bc12	419705.7	41	0.66	568796
Soil	440912.1	39	0.66	575216
bc18	444299.3	37.6	0.64	568796
bc16	445866.3	37.4	0.64	568796
bc13	446093.4	37.3	0.63	568796
bc02	496151.6	30.3	0.57	568796
bc14	505382.1	29	0.57	568796
bc07	517642.4	27.3	0.54	568796
Coast distance (SE)	524472.8	26.3	0.51	568796
bc03	538288.5	24.4	0.48	568796
Coast distance (E)	541260.6	24	0.5	568796
Relief	570814.3	21.1	0.5	575212

bc05	595565.7	16.3	0.43	568796
Landform	606048.2	16.2	0.41	575216
Geology	609166.3	16.8	0.42	579693
bc04	610871.5	14.2	0.38	568796
bc08	614072.4	13.7	0.39	568796
bc01	616931.9	13.3	0.38	568796
bc10	617029.6	13.3	0.39	568796
Slope	622191	12.6	0.38	568796
bc11	622392.8	12.6	0.37	568796
Elevation	622440.4	12.6	0.37	568796
Wind (SE)	624561.6	12.3	0.38	568796
bc09	631031.9	11.3	0.34	568796
bc06	631875.3	11.2	0.34	568796
Hillshade	636083.9	10.6	0.35	568796
Wind (NW)	638454	10.3	0.32	568796
Latitude	641636.3	9.9	0.33	568796
Aspect	645438.2	9.3	0.31	568794
Stream distance	646118.6	9.2	0.32	568796

Appendix 3.1 Copy of publication:

Shoo, L. P., Storlie, C., Vanderwal, J., Little, J. & Williams, S. E. (2011) Targeted protection and restoration to conserve tropical biodiversity in a warming world. *Global Change Biology* **17**, 186–193. (8 pages)

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Pages 249-258

Global Change Biology

Global Change Biology (2011) **17**, 186–193, doi: 10.1111/j.1365-2486.2010.02218.x

Targeted protection and restoration to conserve tropical biodiversity in a warming world

LUKE P. SHOO, COLLIN STORLIE, JEREMY VANDERWAL, JEREMY LITTLE and STEPHEN E. WILLIAMS

Centre for Tropical Biodiversity and Climate Change, School of Marine and Tropical Biology, James Cook University of North Queensland, Townsville, Qld 4811, Australia

Abstract

Complex landscapes interact with meteorological processes to generate climatically suitable habitat (refuges) in otherwise hostile environments. Locating these refuges has practical importance in tropical montane regions where a high diversity of climatically specialized species is threatened by climate change. Here, we use a combination of weather data and spatial modeling to quantify thermally buffered environments in a regional tropical rainforest. We do this by constructing a spatial surface of maximum air temperature that takes into account important climate-mediating processes. We find a strong attenuating effect of elevation, distance from coast and foliage cover on maximum temperature. The core habitat of a disproportionately high number of endemic species (45%) is encompassed within just 25% of the coolest identified rainforest. We demonstrate how this data can be used to (i) identify important areas of cool habitat for protection and (ii) efficiently guide restoration in degraded landscapes to expand extant networks of critical cool habitat.

Keywords: adaptation management, climate change, heat stress, montane biodiversity, refugia, temperature buffering

Received 12 January 2010 and accepted 10 March 2010

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Appendix 3.2 Letter and report authored by Jeremy Little and submitted to State Ministers regarding the 'Cessation of timber harvesting at Herberton Range State Forest' in the Australian Wet Tropics, an identified protection priority of cool climate refugia.

Pages 259- 283

17th November 2009

The Hon. Stephen Robertson
Minister for Natural Resources, Mines and Energy
PO BOX 15216, CITY EAST QLD 4002
Sent via post and email (naturalresources@ministerial.qld.gov.au)

RE: Cessation of timber harvesting at Herberton Range State Forest

Dear Minister,

We are writing to you on behalf of the Cairns and Far North Environment Centre (CAFNEC) and the Queensland Conservation Council (QCC) to request urgent and immediate action to halt timber harvesting at Mt Baldy in the Herberton Range State Forest of north-east Queensland as their impact threatens significant conservation values of the area.

Protection of Mt Baldy should be considered one of the highest conservation priorities in the Wet Tropics region due to a combination of both its high biological value and high level of threat (see **Attachment 1** prepared by Mr Jeremy Little, PhD candidate, JCU). Mt Baldy contains natural values worthy of world heritage status, yet was omitted from listing in the Wet Tropics World Heritage Area. More recently Mt Baldy has been identified as being a critical climate refuge for a myriad of wildlife and ecosystems. Currently however there are timber extraction activities occurring in the area which are causing significant environmental harm and are seriously threatening the integrity of this ecosystem.

In 1999, the Queensland Government made a commitment to bring an end to all logging in native forests by 2024. At this time, climate change implications were not taken into consideration. These implications show quite clearly the need to stop degrading ecosystems from activities such as timber harvesting, and take action now to protect climate sensitive habitats. Mt Baldy is a climate sensitive habitat at risk from significant degradation due to timber harvesting and therefore requires immediate protection.

Recent advice from the Department of Environment and Resource Management is that “native forest log timber harvesting on the native State Forests will cease” and that “these areas will in time be converted to National Park or other protected area estate tenures”. The actual timing of this transfer has not been determined, however, **there is an exciting opportunity to act now**. Timber harvesting permits for the Herberton Range State Forest expire on 31st December 2009. We request that a moratorium on timber harvesting is put in place and that no further permits for timber harvesting are issued for this area after that date.

CAFNEC, QCC and ARCS argue that protection from forestry operations and transfer of tenure to a protected area is needed immediately. Any further degradation that is permitted NOW will reduce biological value of the land at the time of transfer. Further, Mt Baldy has been identified as a priority climate refuge. As such, degradation in this area is set to greatly inflate the expense of establishing a network of faunal refuges in the region to minimize biodiversity loss under climate change.

CAFNEC, PO Box 323N, CAIRNS QLD 4870
T: (07) 4032 1746   F: (07) 4053 3779
E: coord@cafnec.org.au www.cafnec.org.au

I look forward to your timely response and trust that the information provided herewith will be of great assistance in resolving this matter.

Yours sincerely,

Sarah Hoyal
Coordinator - CAFNEC

Toby Hutcheon
Coordinator - QCC

CC:
The Hon. Peter Garrett (Federal Minister for the Environment, Heritage and the Arts)
PO BOX 6022, Parliament House, CANBERRA ACT 2600

The Hon. Desley Boyle (Minister for Local Government and Aboriginal and Torres Strait Islander Partnerships and State Member for Cairns), PO BOX 15031, CITY EAST QLD 4002

The Hon. Shane Knuth (State Member for Dalrymple), Stock Exchange Arcade
2/76 Mosman Street, CHARTERS TOWERS QLD 4820

The Hon. Carryn Sullivan (Chair, Environment and Resources Committee), 1/43 Benabrow Avenue, BELLARA QLD 450

The Hon. Jim Turnour (Federal Member for Leichhardt), PO Box 2794, CAIRNS QLD 4870

Senator Jan McLucas, PO BOX 2733, CAIRNS QLD 4870.

The Hon. Tim Mulherin (Minister for Primary Industries, Fisheries and Rural and Regional Queensland), GPO BOX 46, BRISBANE QLD 4001

The Hon. Kate Jones (Minister for Climate Change and Sustainability), PO BOX 15155, CITY EAST QLD 4002

ATTACHMENT 1

CESSATION OF TIMBER HARVESTING AT HERBERTON RANGE STATE FOREST

Jeremy Little, PhD Candidate, James Cook University of North Queensland

EXECUTIVE SUMMARY

Requested Actions:

1. All timber extraction and harvesting operations in the Herberton Range State Forest are to cease without exception with a moratorium effective 31st December 2009.

2. No further permits are issued for any harvesting operations in the Herberton Range State Forest beyond 31st December 2009.

3. Herberton Range State Forest is converted to protected area estate with haste.

4. Rehabilitation efforts are made throughout the Herberton Range State Forest to remediate ecosystem health and improve ecosystem resilience.

5. All the above recommendations are also applied to all native forest areas on State Forest and Timber Reserves within North Queensland as per the Statewide Forest Process intent.

Issue:
Mt Baldy has been identified as being of high conservation significance. This area contains natural values worthy of world heritage status, yet was omitted from listing in the Wet Tropics World Heritage Area. More recently, Mt Baldy has been identified as being a critical climate refuge for myriad wildlife and ecosystems. Currently, however, there are extractive industries operating on Mt Baldy in the Herberton Range State Forest. Government permits for timber harvesting in this area are due to expire in December 2009.

Problem:
The current extractive industries being permitted by the Queensland Government at Mt Baldy are causing significant environmental harm and degradation to Mt Baldy's natural values and are contributing to the degradation of this important climate refuge. It is important that the ecosystem resilience of this location is improved and no further degradation takes place.

Solution:
Mt Baldy has already been identified for transfer to National Park tenure via the Statewide Forest Process, although no timeframes have been given. Current timber harvesting permits in the area, however, are due to expire in December 2009. Given past and recent identification of the importance of this area and timing of permit expiry, it is a timely and opportune time to proceed with tenure conversion of Mt Baldy (Herberton Range State Forest) into a National Park and for inclusion into the Wet Tropics World Heritage Area.

1. INTRODUCTION

Mt Baldy falls within the Herberton Range State Forest in the Wet Tropics bioregion of Far North Queensland and is located immediately adjacent to the town of Atherton (**Figures 1-3**). The Wet Tropics region is an area that has been recognised as being of significant ecological importance, but also an area of high risk to climate change (*ClimateQ* pp 177. Queensland Government, 2009).

In 1988, the rainforests and adjacent forests of the Wet Tropics bioregion were listed as a World Heritage Area. Surprisingly, Mt Baldy was omitted from this nomination for reasons unknown. Consequently, Herberton Range State Forest was divided into Herberton Range Forest Reserve (the only area within the Wet Tropics World Heritage Area [WTWHA]) and the remaining Herberton Range State Forest, which includes Mt Baldy. This has only been a recent conversion and why at this time the entire State Forest was not converted to protected area is astounding. The Mt Baldy section of Herberton Range State Forest, like other sections and surrounding forests, is equally rich in natural values and is clearly also worthy of world heritage status.

Mt Baldy has demonstrated high ecological values. There are a number of listed threatened, vulnerable and rare species found within the Mt Baldy section of Herberton Range State Forest, as well as regional ecosystems that are endangered and of concern. In addition, Mt Baldy has recently been identified as a critical climate refuge and in most need of protection. These facts are indicative of the need to protect the Mt Baldy section of Herberton Range State Forest and to ensure that this ecosystem is not degraded by ongoing inappropriate activities.

Currently, however, Mt Baldy remains as a State Forest; an anomaly outside the World Heritage and protected area estate of the bioregion. Permitted activities (timber harvesting) managed by the Queensland Government occurring within this State Forest, are causing environmental harm and degradation and are clearly inappropriate considering the ecological significance and importance of this area. Recent evidence suggests that these activities ‘permitted’ by the Queensland Government may be expanding in this area, which is in conflict with the necessary actions for protecting this area from further degradation. While there are legislative mechanisms that ‘permit’ timber harvesting in this area, it is also likely that current activities are in breach of statutory and code of practice frameworks.

The Queensland Government in 1999 committed to end all logging in native forest by 2024 (www.forests.org/archive/spacific/queenend.htm). At this time, climate change was not one of the considerations in this decision. Now with climate change pressures, the need to cease logging activities in some areas needs to be brought forward.

“North Queensland Ecotone Forests” on state lands, including Herberton Range State Forest, have been identified as a priority area under Queensland’s Statewide Forests Process (SFP) managed by the Department of Environment and Resource Management (DERM). The SFP process has determined that timber harvesting in these areas should cease and that tenure should be converted to National Park or other protected area estate (Staff, DERM Forest Products, 11/9/2009). No timeframes have been given for this process to occur, however, there is an exciting opportunity to act now. Timber harvesting permits at Herberton Range State Forest expire on 31st December 2009. It is thus requested that this date is used to cease all timber harvesting operations of native forests in the area.

Figure 1: *Locality map showing the location of A: Herberton Range State Forest and B: Herberton Range Forest Reserve in North Queensland near Cairns. Image courtesy GoogleMaps.*

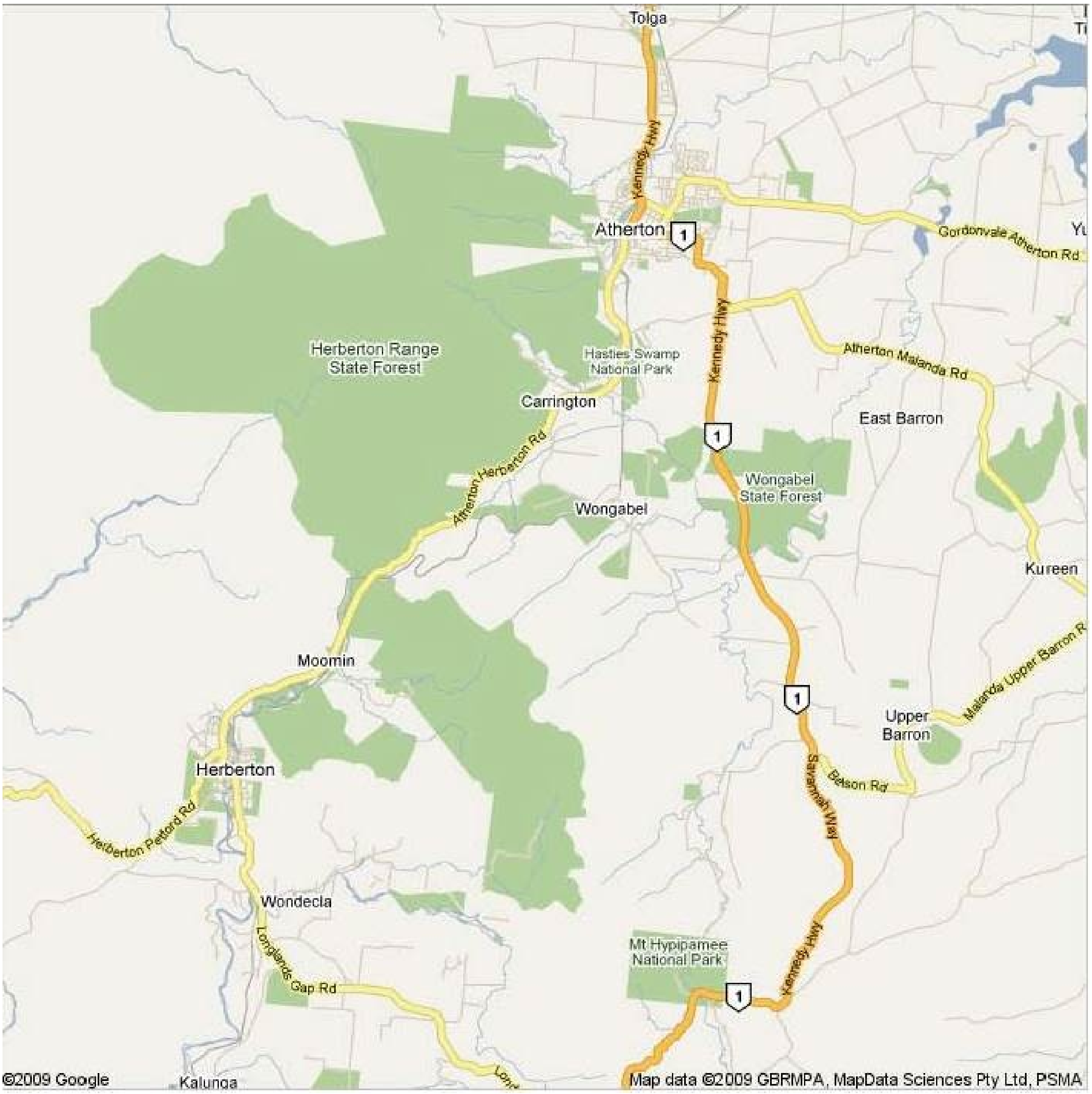

Figure 2: *Locality map of Herberton Range State Forest near Atherton. Image courtesy GoogleMaps.*

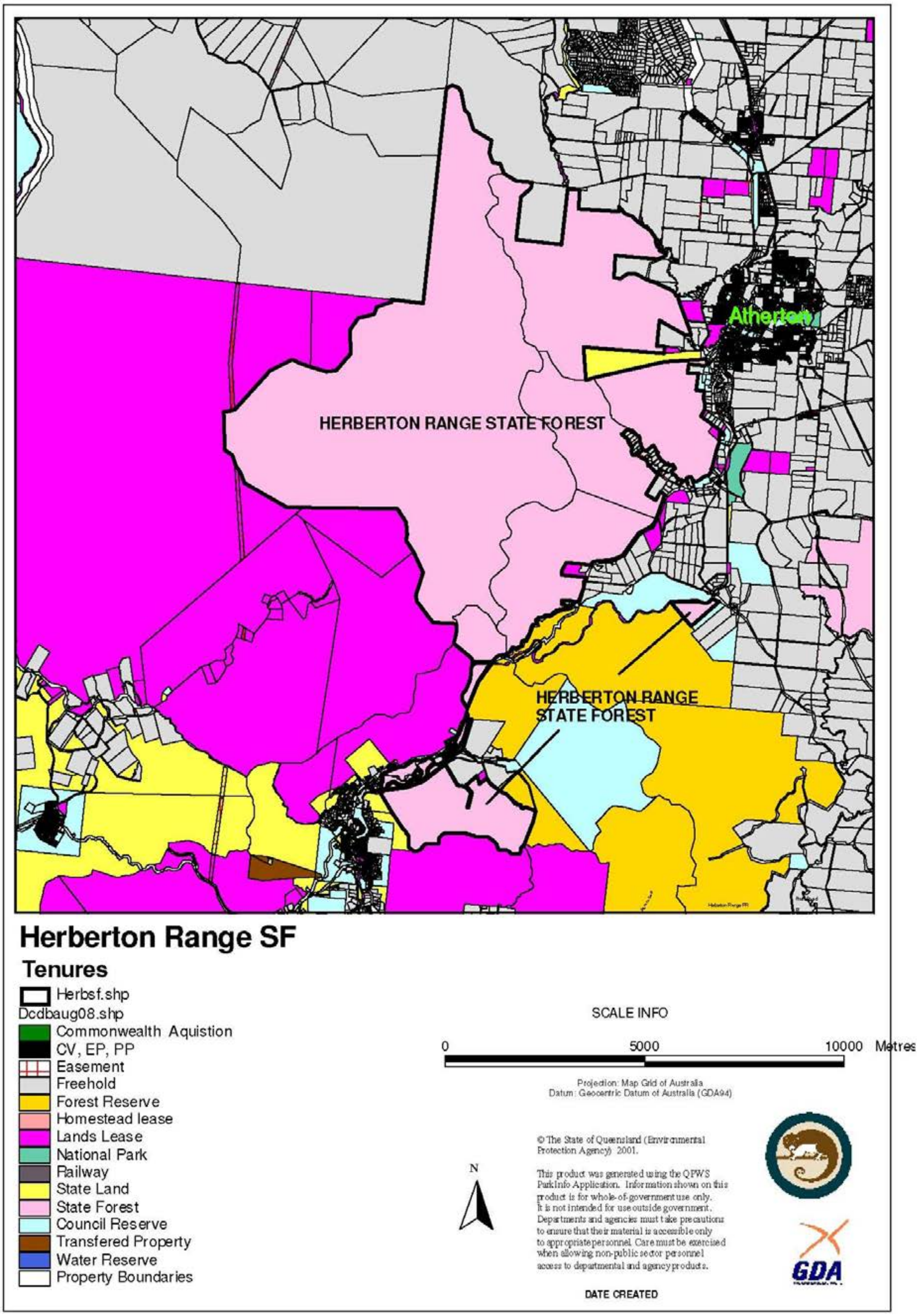

Figure 3: *Tenure map of Herberton Range State Forest. Courtesy of DERM.*

2. ECOLOGICAL VALUES AND CONSERVATION SIGNIFICANCE

World Heritage values

The original Herberton Range State Forest (prior to recent tenure conversion to National Park) was partly within the WTWHA and partly outside. Recent tenure conversions in the WTWHA have seen State Forests become Forest Reserves and some have now become National Park. During this conversion process, Herberton Range State Forest was split into two: Herberton Range State Forest and Herberton Range Forest Reserve.

The remaining area of Herberton Range State Forest, which is outside the WTWHA, was not included in the original World Heritage Area (WHA) nomination for a number of contentious reasons . Accordingly, this area which contains equally, if not greater ecological significance than surrounding protected and World Heritage areas is NOT protected and is currently being logged, grazed, inappropriately burnt and used for bee-keeping. These activities are NOT compatible with protecting the high ecological and (rightly) world heritage values within this estate.

North Queensland Ecotone Forests

Adjacent to the significant rainforests of the Wet Tropics bioregion in North Queensland are eucalypt forests and woodlands, which are referred to as ecotone forests. These ecotone forests are severely limited in their distribution and are restricted to the rainforest edge of the Wet Tropics. The thin band of ecotone forests is no more than 10km wide at its widest point and form a disjunct band on the west of the rainforest clad mountain ranges of no more than 400km in a north- south direction.

Despite their restricted distribution, these ecotone forests contain endemic, endangered, vulnerable and rare species not found in either rainforest, nor in drier tropical savanna woodlands. These ecotone forests are unique and important in their own right and play a pivotal role in sustaining and buffering rainforest boundaries and in landscape connectivity.

A recent example of importance of ecotone forests, is the recent rediscovery of the endangered (but believed extinct) Armoured Mist Frog *Litoria lorica* in ecotone forests of the Wet Tropics (www.news.com.au/couriermail/story/0,23739,24331119-3102,00.html). This species was last observed over 15 years ago in montane rainforest, but was rediscovered by James Cook University researcher Robert Puschendorf. This species was previously not known to occur in open ecotone forests, but only in rainforest. This demonstrates the importance of ecotone forests not only for their endemic biota, but for biota from the adjacent rainforests as well. This is true for the Herberton Range State Forest as well, which is demonstrated in **Figure 4**, showing a rare and charismatic rainforest animal taking refuge in adjacent ecotone forests.

Both buffering and connectivity will become much more important as the changing climate shifts habitats. However, “much of the forest adjoining the Wet Tropics has been fragmented by clearing for agriculture and development, reducing the capacity for species and ecosystems to respond to climate impacts” (*ClimateQ*. pp 180. DERM, 2009). Some of the remaining ecotone forests are not protected within National Park or World Heritage Area, falling rather on private, state or leasehold land. **The most significant of these areas is the Mt Baldy section of Herberton Range State Forest**.

The North Queensland Ecotone Forests have been identified through Queensland’s Statewide Forest Process as requiring a cessation to timber harvesting and conversion to protected area estate. There is no timeframe determined for this to occur.

Figure 4: *The rare Lumholtz Tree-kangaroo in tall open forest, adjacent rainforest. Tall open ecotone forests are currently actively logged at Mt Baldy. Photo taken at Mt Baldy, Herberton Range State Forest, 2008.*

Listed species: Endangered, Vulnerable and Rare species

Tables 1- 3 in the Appendix, lists EVR species that have been identified as being present or likely to be present in Herberton Range State Forest. There is legislative requirement that theses species are protected under the *Environmental Protection and Biodiversity Conservation Act 1999* and/ or the *Nature Conservation Act 1992*. In addition, there is a commitment to do so under the "*Code of practice for native forest timber production on State lands*" (s2.3.2.1, Queensland Government, 2007). Some of these species also have Recovery Plans requiring protection of species habitat and cessation of logging activities.

What is alarming is that there is no known monitoring for any of these species in this area, nor their population health. This is potentially a breach of both federal and state legislation and policy.

Of particular concern is the vulnerable **Yellow-bellied Glider** *Petaurus australis* (**Figure 5**), which requires both tree hollows and feed trees, which are target tree species by timber harvesters. See section on Habitat Trees in Policy Considerations below. Mt Baldy contains an isolated population of this species, which is directly threatened by current timber harvesting. These impacts are conclusive. Population surveys for Yellow-bellied Glider in logged areas at the nearby Koombooloomba State Forest (Nitchaga Creek) showed a dramatic decline in numbers due to timber harvesting (Winter, DERM report), whereas, unlogged areas in the Daintree National Park have shown stable populations over the last fifteen years (Hedges, DERM report). Although it is required by policy, no surveys for this species are known to have occurred by suitably qualified zoologists at Herberton Range State Forest.

Figure 5: *The vulnerable Yellow-bellied Glider Petaurus australis. This species occurs in the Mt Baldy area of Herberton Range State Forest and is directly threatened by timber harvesting activities.*

In addition to listed species known to occur in this area, are additional listed species that are 'likely' to occur but have not been previously recorded or surveyed for. The endangered **Northern Bettong** *Bettongia tropica* is one such species (**Figure 6**). This species is endemic to ecotone forests in the Wet Tropics region. Its distribution and population in the Wet Tropics has been greatly reduced by land clearing, timber harvesting and inappropriate fire regimes.

Although the Northern Bettong has not previously been recorded in Herberton Range State Forest, there is critical habitat in this area. In addition, current research being carried out at James Cook University by Northern Bettong specialist Brooke Bateman, has clearly shown that "Mt Baldy is some of the best habitat for them", particularly under future climate scenarios. Mt Baldy will be "important to facilitate their movement" from other areas and as a climate refuge, as their habitat becomes less favourable with climate change.

Figure 6: *The endangered Northern Bettong Bettongia tropica. This species is likely to occur at Mt Baldy in the Herberton Range State Forest; an area which will also become a critical refuge for this species with a warming climate.*

Another example is that of the tube-nosed insectivorous bat *Murina florium*. Current threats include “forest harvesting operations and” … “there are important sites in the Moomin and Mt Baldy State Forests which are currently not reserved land tenure or included in the WTWHA. Logging still continues in part of the species range, leading to an inferred decline in numbers and fragmentation of populations” (www.environment.gov.au/biodiversity/threatened/publications/action/bats/24.html).

It is likely that current timber harvesting operations are in breach of state and federal legislation for the protection of listed species. There is no known monitoring or assessment on the impact of timber harvesting on the populations of listed species at Herberton Range State Forest. The Queensland Government, therefore, needs to take immediate action to rectify this problem.

Tropical Rainforest and Montane Environments
The rainforests of the Wet Tropics region are widely recognised as being of significant ecological importance both nationally and globally, with the majority of it listed as world heritage. In the recent ClimateQ report, DERM (2009) state that this area “has outstanding conservation value, with the rainforests and landforms supporting a high proportion of Australia’s plant and animal species. The Wet Tropics supports many rare plants and animals found nowhere else on earth, and contains populations of threatened species”.

Yet the Wet Tropics is far from protected. The ClimateQ report goes on to state that the “Wet Tropics rainforests are at risk from climate change (Williams et al, 2003). Many of the highly valued endemic and rare plants and animal species are confined to the higher, cooler areas— such as mountain tops and plateaus” (pp.180. DERM, 2009). These cooler climates on mountain tops are retreating as the climate warms, thus reducing habitat area available for these upland species (**Figure 7**). This is a significant threat to upland specialists. “In his final report Professor Garnaut assessed that under this scenario climate change would force all endemic Australian rainforest vertebrate species to extinction” (pp180. DERM, 2009).

Herberton Range State Forest contains an outlier of tropical rainforest that has not been included in the WTWHA. This rainforest, however, contains significant endemic and restricted biota of the Wet Tropical rainforests, many of which are listed species (see Appendix). It is also has a significant an area of upland mountain range (over 1200m), making it of critical importance as a climate refuge.

Mountainous areas throughout eastern Australia require the same level of protection. Naturally vegetated mountainous areas throughout Queensland that are on state land and are not currently in protected area tenure need immediate transferral to National Park.

Figure 7: *The endemic Golden Bowerbird is restricted to upland rainforest on mountain ranges in the Wet Tropics bioregion and is known from only twelve ranges including the Herberton Range State Forest. This Golden Bowerbird is threatened by climate change, as its habitat area of cool moist rainforest contracts with warmer temperatures.*

Rare or Unusual Ecosystems

Montane heath is known only from four locations in the Wet Tropics, including Hinchinbrook Island and the adjacent Bishops Peak, Mt Windsor Tableland and Mt Baldy. Endemic and significant species can be found in this environment. In some areas where montane heath remains is the endemic and striking Blue-flowering Banksia *Banksia plagiocarpa*, which is known from only two locations. Likewise *B. spinulosa* is known only from two locations in the Wet Tropics, including Mt Wallum in Herberton Range State Forest. There is currently no protection for this population. Indeed Mt Wallum is named after the 'wallum' (heath) vegetation with *B.spinulosa* that grows within a restricted radius of the summit (**Figures 8,9**).

Mt Baldy also contains outstanding groves of **wet cypress-pine forests** with *Callitris macleayana*, which are habitat to the vulnerable Thin Feather-orchid *Tropilis callitrophillus* (which is known from Mt Baldy, but has not been accurately listed in Queensland Government records). These forest groves are extremely restricted and are directly threatened by timber harvesting. The Thin-feathered Orchid is only known from a few mountain ranges in the region.

Figure 8: *Banksia spinulosa montane forest with heath on Mt Wallum, Herberton Range State Forest. This species is restricted to only two mountains in the Wet Tropics region.*

Figure 9: *Ecotone forest with montane heath. Restricted to only two mountains in the Wet Tropics region, including the Herberton Range State Forest.*

Climate Refuge and Climate Change in the Wet Tropics bioregion.
New scientific research funded by the Federal Government Marine and Tropical Sciences Research Facility was recently presented at the 10th International Congress of Ecology, in Brisbane on 16-21 August 2009 on critical climate change refuge areas in the Wet Tropics. Detailed modelling of regional climate has identified patches of unusually cool climate imbedded within upland landscapes of the region. These areas are expected to serve as critical climate refuges that, if properly managed, will maximise resilience and minimise biodiversity loss under climate change. Immediate measures that can and should be taken now include protection of existing rainforest refuges currently not contained within a conservation reserve and restoration of rainforest in areas of degraded land that would otherwise qualify as thermal refugia. Mt Baldy is probably the most significant example of the former in terms of patch size and proximity to other important climate refugia.

It is noteworthy to point out that considerable opportunities exist to promote resilience of biodiversity to climate change through reinstatement of rainforest in priority thermal refugia. However, restoration efforts to date have typically been small in scale (most projects less than five hectares in area) and unit cost of vegetation reinstatement can exceed AU$20,000/ha (Catterall and Harrison, 2006). It is nonsensical to be spending this amount of money in one area while simultaneously incurring losses in existing priority refugia such as Mt Baldy. This is especially true when advice from the DERM is that “native forest log timber harvesting on the native State Forests will cease” and that “these areas will in time be converted to National Park or other protected area estate tenures”. Timing is therefore critical. Any further degradation that is permitted NOW will only inflate the expense of restoration programs that are already underway elsewhere or being negotiated. Degradation at Mt Baldy will also broaden the time gap between habitat demand and habitat availability for vulnerable fauna as we have to wait for functional forest to be restored (e.g. hollow-bearing trees).

3. POLICY IMPLICATIONS

Statewide Forest Process

The “North Queensland Ecotone Forests”, including Mt Baldy, is identified as a priority area under Queensland’s Statewide Forests Process (SFP) managed by The Department of Environment and Resource Management (DERM). The DERM website states that “the government is committed to the SFP as the most appropriate way for determining the long-term management of Queensland’s State-owned forests”. Yet nothing is published to indicate how this will be done.

For the “North Queensland Ecotone Forests”, what is stated is that “The SFP has determined a preferred long-term forest management solution for North Queensland’s ecotone forests, and arrangements to support this are being implemented” (www.derm.qld.gov.au). Again no further commitments have been on this matter.

Advice from staff of DERM Forest Products (11/9/2009) is that:

- “These arrangements principally relate to the cessation of native forest harvesting on these areas and their future management for conservation purposes”;

- “native forest log timber harvesting on the native State Forests will cease, however the actual timing of this is yet to determined”.

- “these areas will in time be converted to National Park or other protected area estate tenures”

- “the formal consultation process with them is yet to be undertaken. This is expected to occur within the next 6 months”.

No negotiation should be entered into. The Government has earmarked this area for protection. The conservation value of this area has been identified as being the most significant in the Wet Tropics.

Advice from staff of DERM Forest Products (11/9/2009) is that timber harvesting is “continuing under permits which are now extended to 31 December 2009.” Here, then is an exciting opportunity to prevent further degradation to the Herberton Range State Forest and to commence proceedings to have this area adequately protected. It is requested here, that a moratorium is placed on all timber harvesting activities as of 1st January 2010, pending conversion of the State Forest into National Park estate.

Figure 10: *Ecotone forest with montane heath. Restricted to only two mountains in the Wet Tropics region, including the Herberton Range State Forest. Photo taken at Mt Wallum, Herberton Range State Forest.*

Forestry

Mt Baldy is within the Herberton Range State Forest wherein there are current permits for timber extraction and grazing, issued by the Queensland Government. Both of these 'permitted' activities are causing "environmental harm" (Forestry Code of Practice, Queensland Government, 2007) and degradation, which threaten the ecosystem resilience of this fragile area.

I believe that these 'permitted' activities (in particular timber harvesting) are in breach of the *Environmental Protection and Biodiversity Conservation Act 1999* (ref. s266B) and also the Queensland Government's own "*Code of practice for native forest timber production on State lands*" (Queensland Government, 2007). There is insufficient proof that adequate protection is being afforded to the listed threatened species.

The destructive activity of timber harvesting has been observed to be expanding in its impact, rather than being reduced. In the last few weeks and months, a number of activities have occurred that indicate timber extraction is moving into new areas and expanding in operation, rather than contracting. New snigging tracks as recent as August 2009 have been observed (for example, at AMG 55 K 329503 8090069 WGS84) at an elevation of 1250 metres above sea level (**Figure 11**). Harvesting activities in mountain areas such as this are inappropriate given their limited distribution and also considering the value of these areas as a climate refuge.

Figure 11: *New snigging tracks for timber harvesting in montane ecotone forest, immediately adjacent to remnant rainforest and at an elevation of 1250 metres above sea level. This track was cleared (presumably for timber harvesting) around August 2009. (Photo taken: August 2009, at AMG 55 K 329503 8090069 WGS84).*

Code of practice for native forest timber production on State lands
Timber harvesting activities that follow guidelines in the "*Code of practice for native forest timber production on State lands"* (Queensland Government, 2007), do not automatically provide for the protection required for listed species and their Recovery Plans under both the *Environmental Protection and Biodiversity Conservation Act 1999* and/ or the *Nature Conservation Act 1992*. The authors of this document have witnessed recent destruction of threatened species habitat in this area, which is in breach of this legislation.

Recently observed forestry activities include:

- feed trees of yellow-bellied gliders have been removed (AMG 55 K 328176 8087966 WGS84).
- mature hollow-bearing trees have been removed (AMG 55 K 329074 8088437 WGS84).
- new snigging tracks into apparently unlogged areas (AMG 55 K 329503 8090069 WGS84).

The Forestry Code of Practice states that "*EVR species, as defined under the Nature Conservation Act 1992, and M and P species, as defined in the Species Management Information System (SMIS), must be protected from the adverse effects of harvesting. The diversity of flora and fauna, including their successional stages, in native forests must be maintained"* (s2.3.2.1, Queensland Government, 2007). The harvesting of old mature trees, as observed at (AMG 55 K 329074 8088437 WGS84), is responsible for removing the critical mature successional stage, where trees become hollow-bearing.

Habitat trees (s6.3)
There are specific details for prescribing habitat tree retention for Greater Gliders, which is listed as common under the *Nature Conservation (Wildlife) Regulation 1994*, but not for other arboreal mammals, including the Yellow-bellied Glider, which is listed as vulnerable. Both of these species occur at Mt Baldy.

It is unlikely that habitat trees are being adequately protected and the decline of yellow-bellied Glider populations in this area is evidence of this. Areas which have not had disturbance from timber harvesting activities have shown stable population numbers (Hedges, internal DERM report). **Figure 11** shows a likely habitat tree for Yellow-bellied Gliders which has been felled in the Herberton Range State Forest.

Feed, Shelter and Nest Trees (s6.4)

Feed trees and shelter trees have been observed to have been removed from the Mt Baldy section of Herberton Range State Forest within the last two years (**Figure 12**):

- feed trees of yellow-bellied gliders have been removed (AMG 55 K 328176 8087966 WG-S84).
- mature hollow-bearing trees have been removed (AMG 55 K 329074 8088437 WGS84).

An active feed tree of Yellow-bellied Gliders was observed in 2008 (AMG: 55K 328176E 8087966N WGS84), in an area that was being actively logged. This tree has not been able to be located since this time and we suspect that it has also been felled.

Figure 12: *Timber harvesting and grazing activities at Mt Baldy. The fallen log observed behind the dark cow is that of Eucalyptus resinifera (only known feed tree of the 'vulnerable' Yellow-bellied Glider). This felled tree has a diameter of at least 1.5 metres! E. resinifera trees of this size would be considered 'old growth' and are also capable of providing tree hollows. (Photo taken: April 2009, at AMG 55 K 329074 8088437 WGS84).*

Climate Change
The Queensland Government has recently articulated its responsibilities and responses to climate change via its publication "***ClimateQ: toward a greener Queensland***" (The State of Queensland, Department of Environment and Resource Management, 2009).

In this document, it is clearly stated that "Queensland is progressively phasing out timber harvesting on Crown Land" (pp 151. DERM, 2009). This is consistent with statements made regarding the Statewide Forest Process for North Queensland Ecotone Forests, but again in this document, there is no commitment to any timeframe.

The ClimateQ document (pp.177. DERM, 2009) also makes commitments to:
- expanding the protected area estate;
- help build resilience of species and ecosystems to cope with climate change; and
- protecting climate-sensitive habitats, and
- connecting landscapes through biodiversity corridors.

Consideration is also given to providing "'climate corridors', improve the resilience of ecosystems to withstand changes to climate variability and enable species to migrate to new habitats" (pp182, 187. ClimateQ. DERM, 2009). This will be important for species such as the endangered Tropical Bettong, as has been shown in research conducted by Brooke Bateman at JCU (see above).

It is critical that we are able to improve ecosystem resilience of sensitive habitats so that these areas are best situated to deal with climate change impacts. Thus, ongoing activities such as timber harvesting which degrade ecosystem health and resilience are counter productive. "Managing the direct effects of climate change on ecosystems is extremely difficult. A broader objective is to restore the health and function of degraded ecosystems to improve their resilience to cope with climate change (Dunlop & Brown, 2008)" (pp182. ClimateQ. DERM, 2009).

Rehabilitating degraded systems is important to improve ecosystems resilience, however, this work can be expensive as stated above. In addition, "natural healthy ecosystems can store between 40–60 per cent more carbon dioxide than degraded ecosystems (Mackey et al, 2008)" (pp182. ClimateQ. DERM, 2009). Thus, preventing degradation is far more cost effective than repairing the damage.

There is a call for immediate action on climate change. We can no longer delay our response. This has been highlighted in the recent report "Climate Change 2009: Faster change and more serious risks" by Steffen, 2009.

4. CONCLUSIONS

Herberton Range State Forest should be considered one of the highest conservation priorities in the Wet Tropics region due to a combination of high biological value and high level of threat. This area contains natural values of high ecological significance and the area has been recognised for protection by the Queensland Government since 1999. At this time climate change was not considered as a threat. Recently, the importance of this area has been highlighted because of climate change threats and thus the ecological value is far greater than previously considered.

Currently, however, there are timber extraction activities, which are causing significant environmental harm and are seriously threatening the integrity of this ecosystem. Degrading climate-sensitive ecosystems and listed species goes against several legislative and policy mechanisms.

Herberton Range State Forest has been identified for transfer to National Park tenure via the Statewide Forest Process, although no timeframes have been given. Government permits for timber harvesting in this area are due to expire in December 2009. Given past and recent identification of the importance of this area and timing of permit expiry, it is a timely and opportune time to proceed with a cessation to timber harvesting in the area and for tenure conversion of Herberton Range State Forest into a National Park and for inclusion into the Wet Tropics World Heritage Area.

Accordingly, we request the following actions:

1. All timber extraction and harvesting operations at Mt Baldy in the Herberton Range State Forest are to cease immediately and without exception with a moratorium effective 1st January 2010.

2. No further permits are issued for any harvesting operations in the Herberton Range State Forest.

3. Herberton Range State Forest is converted to protected area estate with haste.

4. Rehabilitation efforts are made throughout the Herberton Range State Forest to remediate ecosystem health and improve ecosystem resilience.

5. All the above recommendations are also applied to all native forest areas on State Forest and Timber Reserves within North Queensland as per Statewide Forest Process intent.

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APPENDIX

Table 1: Species recorded in Herberton Range State Forest that are listed as endangered, vulnerable or rare under the Queensland Nature Conservation Act 1992 or Australian *Environmental Protection and Biodiversity Conservation Act 1999* (as per Queensland Government records).

Scientific Name	Common Name	Qld	Aust
FAUNA			
Nyctimystes dayi	Australian lacelid	E	E
Litoria nannotis	waterfall frog	E	E
Litoria genimaculata now classified as *L. serrata*	tapping green eyed frog R	R	-
Austrochaperina robusta	robust whistlefrog	R	
Pseudophryne covacevichae	magnificent broodfrog	V	V
Accipiter novaehollandiae	grey goshawk	R	
Cyclopsitta diophthalma macleayana	Macleay's fig-parrot	V	
Ninox rufa queenslandica	rufous owl (southern subspecies)	V	
Dendrolagus lumholtzi	Lumholtz's tree-kangaroo	R	
Petaurus australis unnamed subsp.	yellow-bellied glider (northern subsp)	V	V
Pseudochirulus herbertensis	Herbert River ringtail possum	R	
Pseudochirops archeri	green ringtail possum	R	
Hemibelideus lemuroides	lemuroid ringtail possum	R	
Rhinolophus philippinensis	greater large-eared horseshoe bat	E	E
Kerivoula papuensis	golden-tipped bat	R	
Murina florium	tube-nosed insectivorous bat	V	
Lampropholis robertsi		R	
FLORA			
Cyatheaceae Cyathea celebica		R	
Apocynaceae Tylophora rupicola		E	E
Caesalpiniaceae Caesalpinia robusta	giant mother-in-law vine	R	
Clusiaceae Mammea touriga	brown touriga	R	
Ebenaceae Diospyros sp. (Mt Lewis L.S.Smith 10107)		R	
Elaeocarpaceae Elaeocarpus coorangooloo		R	
Ericaceae Acrotriche baileyana		R	
Sterculiaceae Firmiana papuana lacewood		R	
Menispermaceae Hypserpa smilacifolia		R	
Orchidaceae Chiloglottis longiclavata		R	

Qld- Queensland conservation status under the *Nature Conservation Act 1992*. "The codes are Presumed Extinct (PE), Endangered (E), Vulnerable (V), Rare (R), Common (C) or Not Protected ( )".

Aust- Australian conservation status under the Environmental Protection & Biodiversity Conservation Act 1999. "The values of EPBC are Conservation Dependent (CD), Critically Endangered (CE), Endangered (E), Extinct (EX), Extinct in the Wild (XW) and Vulnerable (V)".

Table 2: Species recorded in Herberton Range State Forest that are listed as endangered, vulnerable or rare under the Queensland Nature Conservation Act 1992 or Australian *Environmental Protection and Biodiversity Conservation Act 1999* (not listed on Queensland Government records).

Scientific Name	**Common Name**	**Qld**	**Aust**
Orchidaceae *Dendrobium aemulum* (C) now classified as *Tropilis callitrophillus* (V, V)	Thin Feather Orchid	V	V
Rubiaceae *Psychotria sp.* undescribed See http://www.chah.gov.au/cgi-bin/anhsir?070=CANB&080=680135			

Codes as above

Table 3: Species not recorded in Herberton Range State Forest but with likely habitat that are listed as endangered, vulnerable or rare under the Queensland Nature Conservation Act 1992 or Australian *Environmental Protection and Biodiversity Conservation Act 1999.*

Scientific Name	**Common Name**	**Qld**	**Aust**
Bettongia tropica	Northern Bettong	E	
Sminthopsis leucopus	White-footed Dunnart	R	
Dasyurus maculatus gracilis	Spotted-tailed Quoll	E	
Antechinus leo	Cinnamon Antechinus	R	
Petrogale mareeba	Mareeba Rock-wallaby	R	
Tyto novaehollandiae kimberlyi	Masked Owl	V	
Delma mitella	Legless Lizard	R	
Simoselaps warro		R	
Myrtaceae Eucalyptus lockeryi subsp. *lockeryi*		R	

Codes as above

Table 4: Regional Ecosystems mapped in Herberton Range State Forest that are listed as Endangered or Of Concern under the Queensland *Vegetation Management Act 1999.*

Regional Ecosystem Code	VMA Status
7.8.19	E
7.3.39c	OC
7.3.42b	OC
7.3.43a	OC
7.3.48a	OC
7.3.49a	OC
7.5.4d	OC
7.8.7a	OC
7.8.7b	OC
7.8.14	OC
7.12.9	OC
7.12.30a	OC
7.12.34	OC
7.12.37a	OC
7.12.50	OC
7.12.52	OC
7.12.57	OC
7.12.59	OC
7.12.66a	OC

VMA- Vegetation Management Act 1999
VMA Status codes are Endangered (E), Of Concern (OC) and Not Of Concern (N).

Appendix 3.3 Ministerial response to the report 'Cessation of timber harvesting at Herberton Range State Forest' (Appendix 3.2).

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- 7 APR 2010

Hon Stephen Robertson MP
Member for Stretton

Queensland Government

Minister for Natural Resources, Mines and Energy and Minister for Trade

Ref MO/10/1191
CTS 04682/10

3 1 MAR 2010

Ms Sarah Hoyal
Coordinator
Cairns and Far North Environment Centre Inc
PO Box 323N
CAIRNS QLD 4870

Dear Ms Hoyal

Thank you for your letter dated 5 March 2010 regarding the cessation of timber harvesting at Herberton Range State Forest and your acknowledgement of the work being done to secure the conservation values of the North Queensland Ecotone Forests.

I can confirm that timber harvesting will cease on all State forest tenured lands, with the exception of two small areas which will remain available for fuel wood harvesting and collection for the next five years. You may be aware that there is a long tradition, particularly in the Ravenshoe and Herberton area, in using fuel wood for domestic heating and cooking with much of the material sourced from State forest areas. A reasonable period of transition is considered appropriate for this low impact use.

In terms of the priorities for conversion of various areas to the protected area estate, Herberton Range State Forest is high priority, and most of the area will transition to the protected area later this year, following the cessation of timber harvesting.

As you identify in your letter, there are complexities and difficulties in managing lands for different uses. The tenure transition plan developed by the Department of Environment and Resource Management recognises the range of issues present including the need for reasonable adjustment arrangements for existing users of various State forests areas. Regarding the details of the plan, Mr Robert Hughes of the department has arranged to meet with you on 31 March 2010 to discuss tenure transfer priorities for various areas, and the process for moving these forward.

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Should you have any further enquiries, please do not hesitate to contact Mr Hughes, Manager, Sustainable Futures Group of the department on telephone 3330 5985.

Yours sincerely

STEPHEN ROBERTSON MP

Appendix 3.4 Gazettal notice regarding the transfer of the Mt Baldy section of Herberton Range State Forest from State Forest to protected area tenure (Baldy Mountain Forest Reserve) on 9 December 2010.

http://www.derm.qld.gov.au/parks_and_forests/managing_parks_and_forests/forest_transfer_processes_in_queensland/index.html; http://www.derm.qld.gov.au/parks_and_forests/managing_parks_and_forests/forest_transfer_processes_in_queensland/wet_tropics_forest_transfer/index.html Accessed 10 July 2011.

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List of Recent Gazettal's

South East			
Forest Reserve	**Area Transferred to Protected Area (~ha)**	**Gazettal Date**	**Name of Protected Area**
Bunyaville Forest Reserve	630	25-Sep-09	Bunyaville Conservation Park
Wickham Forest Reserve	145	25-Sep-09	Wickham National Park Wickham Forest Reserve (SEQ horse trail network)

Sunshine Coast/Burnett			
Forest Reserve	**Area Transferred to Protected Area (~ha)**	**Gazettal Date**	**Name of Protected Area**
Maroochy Forest Reserve 1	270	25-Sep-09	Eumundi Conservation Park
Maroochy Forest Reserve 3	226	25-Sep-09	Eumundi Conservation Park
Tuchekoi Forest Reserve	384	25-Sep-09	Tuchekoi National Park Tuchekoi Forest Reserve (SEQ horse trail network)
Woondum Forest Reserve 1	4046.88	25-Sep-09	Woondum National Park Woondum Forest Reserve 1 (SEQ horse trail network)
Bellthorpe Forest Reserve 1	307	26-Mar-10	Bellthorpe National Park Bellthorpe Forest Reserve 1 (SEQ horse trail network)
Bellthorpe Forest Reserve 1	7347	26-Mar-10	Bellthorpe National Park Bellthorpe Conservation Park (Griffith Uni research centre) Bellthorpe Forest Reserve 2 (SEQ horse trail network and Woodford Folk Festival area)
Beerburrum Forest Reserve 1	1671.32	04-Jun-10	Glass House Mountains National Park Glass House Mountains Conservation Park Beerburrum Forest Reserve 1 (SEQ horse trail network and fire tower)
Beerburrum Forest Reserve 2	66.2	04-Jun-10	Pumicestone National Park
Beerwah Forest Reserve	843.31	04-Jun-10	Glass House Mountains National Park Mooloolah River National Park Beerwah Forest Reserve (Jowarra Day Use Area; Blue Gum area for railway revocation)
Maleny Forest Reserve 1	368.6	04-Jun-10	Glass House Mountains National Park
Mooloolah Forest Reserve	332.63	04-Jun-10	Dularcha National Park Mooloolah Forest Reserve (SEQ horse trail network)
Noosa Forest Reserve	60.14	04-Jun-10	Tewantin National Park
Tewantin Forest Reserve 1	1885.41	04-Jun-10	Tewantin National Park Tewantin National Park Recovery (foliage collection) Tewantin Forest Reserve 1 (SEQ horse trail network; road revocations; communication tower)
Tewantin Forest Reserve 3	67.21	04-Jun-10	Tewantin National Park Tewantin Forest Reserve 3 (SEQ horse trail network)
Woondum Forest Reserve 3	2.55	04-Jun-10	Woondum Conservation Park
Bulburin State Forest	1695	9-Dec-10	Bulburin East Forest Reserve
Mount Stanley State Forest 1	3395	9-Dec-10	Mount Stanley Forest Reserve 1
Mount Stanley State Forest 2	1000	9-Dec-10	Mount Stanley Forest Reserve 2

List of Recent Gazettal's

Wet Tropics			
Forest Reserve	**Area Transferred to Protected Area (~ha)**	**Gazettal Date**	**Name of Protected Area**
Heights of Victory Forest Reserve	421	11-Dec-09	Mount Lewis National Park
Mount Lewis Forest Reserve	21287	11-Dec-09	Mount Lewis National Park Mount Lewis National Park Recovery
Riflemead Forest Reserve 1	627	11-Dec-09	Mount Lewis National Park
Riflemead Forest Reserve 2	1043	11-Dec-09	Mount Lewis National Park
Round Mountain/Lyons Lookout Forest Reserve	4542	11-Dec-09	Mount Lewis National Park
Macalister Range Forest Reserve	5615	04-Jun-10	Macalister Range National Park Macalister Range Forest Reserve (South Edge Road)
Basilisk Forest Reserve	2210	18-Nov-10	Basilisk Range National Park
Koombooloomba Forest Reserve	29281	18-Nov-10	Koombooloomba National Park; Koombooloomba Conservation Park
Little Mulgrave Forest Reserve	10913	9-Dec-10	Little Mulgrave National Park; Mount Peter Conservation Park
Gillies Highway Forest Reserve	415	9-Dec-10	Gadgarra National Park
Gadgarra Forest Reserve	7854	9-Dec-10	Gadgarra National Park
North Ecotone			
State Forest	**Area Transferred to Forest Reserve (~ha)**	**Gazettal Date**	**Name of Forest Reserve**
Abergowrie State Forest	1715	18-Nov-10	Abergowrie Forest Reserve 2
Bilwon State Forest	5918	18-Nov-10	Bilwon Forest Reserve
Cardwell State Forest	960	18-Nov-10	Cardwell Forest Reserve 2
Danbulla State Forest 2	2181	18-Nov-10	Danbulla West Forest Reserve
Formantine State Forest	1711	18-Nov-10	Formantine Forest Reserve
Kuranda State Forest	6427	18-Nov-10	Kuranda West Forest Reserve
Mount Fox State Forest	4303	18-Nov-10	Girringun Forest Reserve
Ravenshoe State Forest 1	2241	18-Nov-10	Ravenshoe Forest Reserve 1
Ravenshoe State Forest 2	250	18-Nov-10	Ravenshoe Forest Reserve 2
Ravenshoe State Forest 3	1715	18-Nov-10	Ravenshoe Forest Reserve 3
Speewah State Forest	176	18-Nov-10	Barron Gorge Forest Reserve
Danbulla State Forest 1	1309	9-Dec-10	Danbulla South Forest Reserve
Herberton Range State Forest	7100	9-Dec-10	Baldy Mountain Forest Reserve
The Bluff State Forest	6304	9-Dec-10	The Bluff Forest Reserve
Tumoulin State Forest	1877	9-Dec-10	Tumoulin Forest Reserve

Appendix 3.5 Calibration for maximum temperature (Tmax, °C) measured in PVC housing against standard Stevenson Screen (SS) housing. Calibrations also used Photosynthetically Active Radiation (PAR, µmol/m^2/s) measurements (where available), which determined the amount of sunlight directly affecting the PVC housing. Results are provided for categories of canopy cover with a. 0-25% canopy cover and b. 26-75% canopy cover. Testing showed it was not necessary to adjust readings from sites with a thick canopy (76-100% canopy).

a. 0-25% canopy cover

Model with PAR	**Estimate**	**SE**	***t***	***P***	**Adj. R^2**
(Intercept)	3.54	2.25	1.58	0.14	0.88
PVC	0.79	0.09	9.22	<0.001	
PAR	0	0	0.58	0.57	

PVC only model	**Estimate**	**SE**	***t***	***P***	**Adj. R^2**
(Intercept)	2.48	0.09	26.16	<0.001	0.96
PVC	0.87	0	213.03	<0.001	

Linear Regression	**Adj. R^2**
Model with PAR: Tmax_SS = 3.544 + (0.794 * Tmax_PVC) + (0.000374 * PARmax)	0.891
PVC only model: Tmax_SS = 2.477 + (0.867 * Tmax_PVC)	0.956

b. 26-75% canopy cover

Model with PAR	**Estimate**	**SE**	***t***	***P***	**Adj. R^2**
(Intercept)	3.99	3.49	1.14	0.28	0.9
PVC	0.82	0.14	6	<0.001	
PAR	0	0	0.16	0.88	

PVC only model	**Estimate**	**SE**	***t***	***P***	**Adj. R^2**
(Intercept)	1.88	0.06	31.8	<0.001	0.99
PVC	0.9	0	371.06	<0.001	

Linear Regression	**Adj. R^2**
Model with PAR: SS_max = 3.99 + (0.82 * PVC_max) + (0.000239 * PAR_max),	0.90
PVC only model: SS_max = 1.88 + (0.90 * PVC_max)	0.99

Appendix 3.6 Pairwise models (GLM) comparing each of ten daily micrometeorological variables within each of three vegetation types; rain forest (RF), tall eucalypt forest (TEF) and savanna (SAV). Pairwise combinations, therefore, were RF:TEF, RF:SAV and TEF:SAV. Micrometeorological variables were recorded within each vegetation type, replicated eight times in eight different ‘transect’ locations; Koombooloomba (AUKO), Mt Baldy (AUMB), Mt Lewis (CUML), Mt Spurgeon (CUMS), Davies Ck (LUDC), Tinnaroo Ck (LUTC), Paluma (SUPA) and Mt Windsor (WUMW). The response variable for each model consists of one of ten microclimate variables for the first vegetation type (in the pairwise analysis) and the explanatory variables were the microclimate variable at the second vegetation type, transect and their interaction. Micrometeorological variables were temperature (a. maximum, b. mean, c. minimum), relative humidity (d. maximum, e. mean, f. minimum), mean wind speed (g.) and soil moisture deficit (SMD; h. maximum, i. mean) and solar exposure (j.). Coefficient estimate, standard error (SE), 95% confidence intervals (95% CI), probability significance (*P*), Akaike Information Criterion (AICc) and percent explained deviance (D^2) relative to the null model are reported.

a. maximum temperature

RF: TEF	**Estimate**	**SE**	**95% CI**	***P***	**AICc**	**D^2**
(Intercept)	-3.63	0.39	-4.4--2.86	0.00	19975.87	87.73
TEF	1.1	0.02	1.07-1.14	0.00		
Transect_AUMB	5.22	0.52	4.21-6.24	0.00		
Transect_CUML	1.53	0.54	0.47-2.59	0.00		
Transect_CUMS	-0.33	0.53	-1.36-0.7	0.53		
Transect_LUDC	-0.74	0.51	-1.75-0.26	0.15		
Transect_LUTC	0.18	0.48	-0.76-1.12	0.71		
Transect_SUPA	-0.86	0.58	-2-0.27	0.14		
Transect_WUMW	-0.04	0.59	-1.2-1.12	0.95		
TEF:Transect_AUMB	-0.3	0.02	-0.34--0.25	0.00		
TEF:Transect_CUML	-0.2	0.02	-0.24--0.15	0.00		
TEF:Transect_CUMS	-0.04	0.02	-0.08-0	0.08		
TEF:Transect_LUDC	0.01	0.02	-0.03-0.05	0.70		
TEF:Transect_LUTC	-0.13	0.02	-0.17--0.09	0.00		
TEF:Transect_SUPA	-0.14	0.02	-0.18--0.09	0.00		
TEF:Transect_WUMW	-0.12	0.02	-0.17--0.07	0.00		

RF:SAV	**Estimate**	**SE**	**95% CI**	***P***	**AICc**	**D^2**
(Intercept)	-5.88	0.64	-7.14--4.62	0.00	23516.49	77.12
SAV	1.1	0.02	1.05-1.15	0.00		
Transect_AUMB	5.43	0.85	3.76-7.1	0.00		
Transect_CUML	-0.71	0.98	-2.64-1.21	0.47		
Transect_CUMS	-3.02	0.93	-4.84--1.2	0.00		
Transect_LUDC	-2.47	0.85	-4.13--0.8	0.00		
Transect_LUTC	3.44	0.75	1.97-4.91	0.00		
Transect_SUPA	-2.22	0.91	-4.01--0.43	0.02		
Transect_WUMW	1.68	0.94	-0.17-3.52	0.07		

SAV:Transect_AUMB	-0.32	0.03	-0.38--0.25	0.00		
SAV:Transect_CUML	-0.17	0.04	-0.24--0.1	0.00		
SAV:Transect_CUMS	-0.05	0.03	-0.12-0.02	0.13		
SAV:Transect_LUDC	0.05	0.03	-0.01-0.12	0.10		
SAV:Transect_LUTC	-0.3	0.03	-0.36--0.25	0.00		
SAV:Transect_SUPA	-0.06	0.03	-0.12-0.01	0.08		
SAV:Transect_WUMW	-0.23	0.03	-0.29--0.16	0.00		

TEF:SAV	**Estimate**	**SE**	**95% CI**	***P***	**AICc**	**D^2**
(Intercept)	-2.67	0.39	-3.43--1.9	0.00	21492.87	83.69
SAV	1.01	0.01	0.98-1.04	0.00		
Transect_AUMB	0.78	0.57	-0.34-1.9	0.17		
Transect_CUML	1.98	0.68	0.65-3.32	0.00		
Transect_CUMS	-0.65	0.57	-1.77-0.47	0.25		
Transect_LUDC	-1.19	0.57	-2.31--0.07	0.04		
Transect_LUTC	4.14	0.49	3.18-5.09	0.00		
Transect_SUPA	-1.13	0.67	-2.44-0.18	0.09		
Transect_WUMW	2.52	0.65	1.25-3.79	0.00		
SAV:Transect_AUMB	-0.06	0.02	-0.11--0.02	0.00		
SAV:Transect_CUML	-0.13	0.02	-0.18--0.08	0.00		
SAV:Transect_CUMS	-0.06	0.02	-0.11--0.02	0.00		
SAV:Transect_LUDC	0.04	0.02	0-0.08	0.07		
SAV:Transect_LUTC	-0.2	0.02	-0.24--0.17	0.00		
SAV:Transect_SUPA	0.06	0.02	0.02-0.11	0.01		
SAV:Transect_WUMW	-0.14	0.02	-0.18--0.09	0.00		

b. mean temperature

RF:TEF	**Estimate**	**SE**	**95% CI**	***P***	**AICc**	**D^2**
(Intercept)	-1.9	0.22	-2.34--1.46	0.00	14118.5	93.94
TEF	1.05	0.01	1.03-1.07	0.00		
Transect_AUMB	2.29	0.31	1.68-2.9	0.00		
Transect_CUML	-3.11	0.31	-3.71--2.51	0.00		
Transect_CUMS	-4.84	0.32	-5.46--4.22	0.00		
Transect_LUDC	-2.83	0.31	-3.43--2.23	0.00		
Transect_LUTC	-3.03	0.28	-3.59--2.48	0.00		
Transect_SUPA	-3.51	0.33	-4.15--2.87	0.00		
Transect_WUMW	-3.79	0.34	-4.47--3.12	0.00		
TEF:Transect_AUMB	-0.13	0.02	-0.16--0.09	0.00		
TEF:Transect_CUML	0.07	0.02	0.04-0.1	0.00		
TEF:Transect_CUMS	0.21	0.02	0.18-0.24	0.00		
TEF:Transect_LUDC	0.12	0.02	0.09-0.15	0.00		
TEF:Transect_LUTC	0.05	0.01	0.02-0.08	0.00		
TEF:Transect_SUPA	0.09	0.02	0.06-0.13	0.00		
TEF:Transect_WUMW	0.12	0.02	0.09-0.16	0.00		

RF:SAV	**Estimate**	**SE**	**95% CI**	***P***	**AICc**	**D^2**
(Intercept)	-3.92	0.31	-4.53--3.31	0.00	16600.86	90.6
SAV	1.13	0.02	1.1-1.16	0.00		
Transect_AUMB	2.53	0.43	1.68-3.38	0.00		
Transect_CUML	-4.13	0.46	-5.03--3.22	0.00		
Transect_CUMS	-7.34	0.47	-8.26--6.43	0.00		
Transect_LUDC	-2.34	0.42	-3.16--1.52	0.00		
Transect_LUTC	-2.32	0.39	-3.08--1.55	0.00		
Transect_SUPA	-3.16	0.44	-4.02--2.31	0.00		
Transect_WUMW	-4.18	0.49	-5.14--3.21	0.00		
SAV:Transect_AUMB	-0.18	0.02	-0.23--0.14	0.00		
SAV:Transect_CUML	0	0.02	-0.04-0.04	0.91		
SAV:Transect_CUMS	0.16	0.02	0.11-0.2	0.00		
SAV:Transect_LUDC	0.04	0.02	0-0.08	0.07		
SAV:Transect_LUTC	-0.04	0.02	-0.08--0.01	0.02		
SAV:Transect_SUPA	0.02	0.02	-0.02-0.06	0.29		
SAV:Transect_WUMW	0.04	0.02	-0.01-0.09	0.09		

TEF:SAV	**Estimate**	**SE**	**95% CI**	***P***	**AICc**	**D^2**
(Intercept)	-2.46	0.14	-2.74--2.18	0.00	10794.29	95.49
SAV	1.09	0.01	1.08-1.11	0.00		
Transect_AUMB	0.96	0.22	0.52-1.4	0.00		
Transect_CUML	3.06	0.25	2.58-3.54	0.00		
Transect_CUMS	-0.29	0.22	-0.72-0.14	0.19		
Transect_LUDC	1.04	0.22	0.61-1.47	0.00		
Transect_LUTC	1.47	0.2	1.08-1.86	0.00		
Transect_SUPA	1.26	0.23	0.8-1.72	0.00		
Transect_WUMW	0.22	0.26	-0.3-0.74	0.41		
SAV:Transect_AUMB	-0.1	0.01	-0.12--0.07	0.00		
SAV:Transect_CUML	-0.23	0.01	-0.25--0.21	0.00		
SAV:Transect_CUMS	-0.11	0.01	-0.13--0.09	0.00		
SAV:Transect_LUDC	-0.09	0.01	-0.11--0.07	0.00		
SAV:Transect_LUTC	-0.12	0.01	-0.14--0.1	0.00		
SAV:Transect_SUPA	-0.11	0.01	-0.13--0.09	0.00		
SAV:Transect_WUMW	-0.09	0.01	-0.12--0.07	0.00		

c. minimum temperature

RF:TEF	**Estimate**	**SE**	**95% CI**	***P***	**AICc**	**D^2**
(Intercept)	-0.3	0.2	-0.69-0.09	0.13	17192.93	91.16
TEF	1	0.01	0.97-1.02	0.00		
Transect_AUMB	2.43	0.3	1.84-3.02	0.00		
Transect_CUML	-4.54	0.31	-5.15--3.94	0.00		
Transect_CUMS	-6.59	0.32	-7.22--5.97	0.00		
Transect_LUDC	-2.67	0.29	-3.24--2.1	0.00		
Transect_LUTC	-5.31	0.29	-5.87--4.75	0.00		

Transect_SUPA	-2.14	0.3	-2.73--1.55	0.00		
Transect_WUMW	-1.69	0.31	-2.29--1.1	0.00		
TEF:Transect_AUMB	-0.13	0.02	-0.16--0.09	0.00		
TEF:Transect_CUML	0.16	0.02	0.13-0.2	0.00		
TEF:Transect_CUMS	0.3	0.02	0.26-0.33	0.00		
TEF:Transect_LUDC	0.11	0.02	0.08-0.15	0.00		
TEF:Transect_LUTC	0.18	0.02	0.14-0.21	0.00		
TEF:Transect_SUPA	0.06	0.02	0.03-0.1	0.00		
TEF:Transect_WUMW	0.02	0.02	-0.02-0.05	0.39		

RF:SAV	**Estimate**	**SE**	**95% CI**	***P***	**AICc**	**D^2**
(Intercept)	-0.92	0.25	-1.4--0.43	0.00	19173.72	87.39
SAV	1.07	0.02	1.04-1.1	0.00		
Transect_AUMB	2.51	0.38	1.77-3.26	0.00		
Transect_CUML	-5.3	0.42	-6.13--4.47	0.00		
Transect_CUMS	-6.13	0.4	-6.91--5.35	0.00		
Transect_LUDC	1.16	0.34	0.51-1.82	0.00		
Transect_LUTC	-5.86	0.36	-6.57--5.16	0.00		
Transect_SUPA	-1.94	0.36	-2.65--1.22	0.00		
Transect_WUMW	0.17	0.37	-0.56-0.9	0.65		
SAV:Transect_AUMB	-0.19	0.02	-0.23--0.14	0.00		
SAV:Transect_CUML	0.09	0.02	0.04-0.13	0.00		
SAV:Transect_CUMS	0.12	0.02	0.07-0.16	0.00		
SAV:Transect_LUDC	-0.15	0.02	-0.19--0.11	0.00		
SAV:Transect_LUTC	0.13	0.02	0.09-0.17	0.00		
SAV:Transect_SUPA	-0.02	0.02	-0.06-0.02	0.43		
SAV:Transect_WUMW	-0.18	0.02	-0.23--0.14	0.00		

TEF:SAV	**Estimate**	**SE**	**95% CI**	***P***	**AICc**	**D^2**
(Intercept)	-0.55	0.11	-0.77--0.33	0.00	13464.63	94.36
SAV	1.07	0.01	1.06-1.08	0.00		
Transect_AUMB	0.45	0.2	0.06-0.84	0.02		
Transect_CUML	2.32	0.23	1.87-2.77	0.00		
Transect_CUMS	0.03	0.19	-0.35-0.4	0.89		
Transect_LUDC	3.24	0.17	2.9-3.57	0.00		
Transect_LUTC	-0.04	0.19	-0.41-0.33	0.85		
Transect_SUPA	0.78	0.2	0.4-1.17	0.00		
Transect_WUMW	1.24	0.2	0.86-1.63	0.00		
SAV:Transect_AUMB	-0.09	0.01	-0.11--0.06	0.00		
SAV:Transect_CUML	-0.21	0.01	-0.24--0.19	0.00		
SAV:Transect_CUMS	-0.13	0.01	-0.15--0.11	0.00		
SAV:Transect_LUDC	-0.23	0.01	-0.25--0.21	0.00		
SAV:Transect_LUTC	-0.07	0.01	-0.09--0.05	0.00		
SAV:Transect_SUPA	-0.11	0.01	-0.13--0.09	0.00		
SAV:Transect_WUMW	-0.16	0.01	-0.18--0.14	0.00		

d. maximum relative humidity

RF:TEF	**Estimate**	**SE**	**95% CI**	***P***	**AICc**	**D^2**
(Intercept)	30.86	11.38	8.56-53.17	0.01	25151.03	79.18
TEF	0.69	0.11	0.47-0.92	0.00		
Transect_AUMB	-33.15	11.54	-55.77--10.52	0.00		
Transect_CUML	-3.87	11.43	-26.28-18.53	0.73		
Transect_CUMS	-27.24	11.48	-49.74--4.74	0.02		
Transect_LUDC	31.14	11.68	8.25-54.03	0.01		
Transect_LUTC	7.98	11.44	-14.43-30.4	0.49		
Transect_SUPA	-25.59	11.49	-48.11--3.08	0.03		
Transect_WUMW	-57.76	11.54	-80.37--35.15	0.00		
TEF:Transect_AUMB	0.33	0.12	0.1-0.56	0.00		
TEF:Transect_CUML	0.05	0.11	-0.18-0.27	0.69		
TEF:Transect_CUMS	0.28	0.12	0.05-0.5	0.02		
TEF:Transect_LUDC	-0.31	0.12	-0.54--0.08	0.01		
TEF:Transect_LUTC	-0.08	0.11	-0.3-0.15	0.51		
TEF:Transect_SUPA	0.25	0.12	0.03-0.48	0.03		
TEF:Transect_WUMW	0.58	0.12	0.35-0.81	0.00		

RF:SAV	**Estimate**	**SE**	**95% CI**	***P***	**AICc**	**D^2**
(Intercept)	80.7	7.33	66.33-95.07	0.00	26379.06	61.66
SAV	0.19	0.07	0.05-0.34	0.01		
Transect_AUMB	-32.56	7.49	-47.24--17.88	0.00		
Transect_CUML	-21.57	7.47	-36.22--6.92	0.00		
Transect_CUMS	-25.25	7.41	-39.77--10.73	0.00		
Transect_LUDC	-4.33	7.68	-19.38-10.73	0.57		
Transect_LUTC	-12.58	7.49	-27.26-2.1	0.09		
Transect_SUPA	-53.21	7.47	-67.85--38.58	0.00		
Transect_WUMW	-34.49	7.43	-49.05--19.94	0.00		
SAV:Transect_AUMB	0.33	0.08	0.19-0.48	0.00		
SAV:Transect_CUML	0.24	0.08	0.09-0.38	0.00		
SAV:Transect_CUMS	0.27	0.07	0.13-0.42	0.00		
SAV:Transect_LUDC	0.05	0.08	-0.1-0.2	0.55		
SAV:Transect_LUTC	0.13	0.08	-0.01-0.28	0.07		
SAV:Transect_SUPA	0.53	0.07	0.39-0.68	0.00		
SAV:Transect_WUMW	0.36	0.07	0.21-0.5	0.00		

TEF:SAV	**Estimate**	**SE**	**95% CI**	***P***	**AICc**	**D^2**
(Intercept)	70.58	7.28	56.31-84.85	0.00	29101.7	64.51
SAV	0.29	0.07	0.15-0.44	0.00		
Transect_AUMB	-22.08	7.43	-36.65--7.52	0.00		
Transect_CUML	-33.86	7.42	-48.39--19.33	0.00		
Transect_CUMS	-18.37	7.33	-32.74--4.01	0.01		
Transect_LUDC	-25.19	7.58	-40.05--10.34	0.00		

Transect_LUTC	-28.94	7.44	-43.52--14.36	0.00
Transect_SUPA	-25.32	7.42	-39.85--10.78	0.00
Transect_WUMW	-13.32	7.37	-27.78-1.13	0.07
SAV:Transect_AUMB	0.23	0.07	0.08-0.37	0.00
SAV:Transect_CUML	0.36	0.07	0.21-0.5	0.00
SAV:Transect_CUMS	0.2	0.07	0.06-0.35	0.01
SAV:Transect_LUDC	0.25	0.08	0.1-0.4	0.00
SAV:Transect_LUTC	0.3	0.07	0.15-0.45	0.00
SAV:Transect_SUPA	0.25	0.07	0.11-0.4	0.00
SAV:Transect_WUMW	0.14	0.07	0-0.29	0.06

e. mean relative humidity

RF:TEF	**Estimate**	**SE**	**95% CI**	***P***	**AICc**	**D^2**
(Intercept)	12.33	1.97	8.46-16.19	0.00	32338.64	85.01
TEF	0.88	0.02	0.84-0.93	0.00		
Transect_AUMB	-11.85	2.35	-16.46--7.24	0.00		
Transect_CUML	6.5	2.21	2.17-10.82	0.00		
Transect_CUMS	-15.31	2.36	-19.93--10.68	0.00		
Transect_LUDC	17.91	2.59	12.83-22.99	0.00		
Transect_LUTC	17.49	2.19	13.19-21.79	0.00		
Transect_SUPA	-5.61	2.39	-10.29--0.93	0.02		
Transect_WUMW	-8.82	2.38	-13.47--4.16	0.00		
TEF:Transect_AUMB	0.14	0.03	0.09-0.19	0.00		
TEF:Transect_CUML	-0.03	0.02	-0.08-0.02	0.18		
TEF:Transect_CUMS	0.16	0.03	0.11-0.21	0.00		
TEF:Transect_LUDC	-0.17	0.03	-0.23--0.12	0.00		
TEF:Transect_LUTC	-0.15	0.02	-0.2--0.11	0.00		
TEF:Transect_SUPA	0.11	0.03	0.05-0.16	0.00		
TEF:Transect_WUMW	0.13	0.03	0.08-0.18	0.00		

RF:SAV	**Estimate**	**SE**	**95% CI**	***P***	**AICc**	**D^2**
(Intercept)	27.85	2.21	23.52-32.19	0.00	33096.23	72.34
SAV	0.75	0.03	0.7-0.8	0.00		
Transect_AUMB	7.88	2.54	2.9-12.85	0.00		
Transect_CUML	12.59	2.6	7.5-17.68	0.00		
Transect_CUMS	4.11	2.5	-0.8-9.01	0.10		
Transect_LUDC	23.43	2.82	17.9-28.96	0.00		
Transect_LUTC	20.8	2.57	15.76-25.84	0.00		
Transect_SUPA	0.24	2.59	-4.83-5.31	0.93		
Transect_WUMW	7.86	2.51	2.93-12.78	0.00		
SAV:Transect_AUMB	-0.06	0.03	-0.11-0	0.06		
SAV:Transect_CUML	-0.04	0.03	-0.1-0.02	0.16		
SAV:Transect_CUMS	0.05	0.03	-0.01-0.11	0.11		
SAV:Transect_LUDC	-0.24	0.03	-0.3--0.17	0.00		
SAV:Transect_LUTC	-0.18	0.03	-0.24--0.12	0.00		

SAV:Transect_SUPA	0.06	0.03	0-0.12	0.04		
SAV:Transect_WUMW	-0.01	0.03	-0.07-0.05	0.72		

TEF:SAV	**Estimate**	**SE**	**95% CI**	***P***	**AICc**	**D^2**
(Intercept)	17.39	1.47	14.5-20.28	0.00	32718.46	86.00
SAV	0.85	0.02	0.82-0.89	0.00		
Transect_AUMB	12.59	1.72	9.21-15.96	0.00		
Transect_CUML	2.53	1.75	-0.91-5.96	0.15		
Transect_CUMS	16.52	1.64	13.31-19.72	0.00		
Transect_LUDC	5.19	1.86	1.54-8.85	0.01		
Transect_LUTC	-0.41	1.75	-3.85-3.03	0.82		
Transect_SUPA	9.9	1.77	6.42-13.37	0.00		
Transect_WUMW	13.95	1.71	10.6-17.3	0.00		
SAV:Transect_AUMB	-0.12	0.02	-0.16--0.08	0.00		
SAV:Transect_CUML	0.04	0.02	-0.01-0.08	0.09		
SAV:Transect_CUMS	-0.1	0.02	-0.14--0.06	0.00		
SAV:Transect_LUDC	-0.05	0.02	-0.09--0.01	0.03		
SAV:Transect_LUTC	0.03	0.02	-0.01-0.07	0.13		
SAV:Transect_SUPA	-0.1	0.02	-0.14--0.06	0.00		
SAV:Transect_WUMW	-0.12	0.02	-0.16--0.08	0.00		

f. minimum relative humidity

RF:TEF	**Estimate**	**SE**	**95% CI**	***P***	**AICc**	**D^2**
(Intercept)	1.76	1.56	-1.3-4.81	0.26	43237.05	74.68
TEF	1.01	0.02	0.97-1.06	0.00		
Transect_AUMB	9.34	2.04	5.33-13.34	0.00		
Transect_CUML	22.03	2.03	18.04-26.01	0.00		
Transect_CUMS	4.31	2.18	0.04-8.58	0.05		
Transect_LUDC	17.58	2.32	13.03-22.13	0.00		
Transect_LUTC	25	1.95	21.19-28.82	0.00		
Transect_SUPA	35.82	2.04	31.81-39.82	0.00		
Transect_WUMW	21.38	2.07	17.33-25.43	0.00		
TEF:Transect_AUMB	-0.03	0.03	-0.09-0.03	0.28		
TEF:Transect_CUML	-0.15	0.03	-0.21--0.09	0.00		
TEF:Transect_CUMS	-0.05	0.03	-0.11-0.01	0.08		
TEF:Transect_LUDC	-0.18	0.03	-0.24--0.11	0.00		
TEF:Transect_LUTC	-0.2	0.03	-0.26--0.15	0.00		
TEF:Transect_SUPA	-0.23	0.03	-0.29--0.17	0.00		
TEF:Transect_WUMW	-0.11	0.03	-0.17--0.05	0.00		

RF:SAV	**Estimate**	**SE**	**95% CI**	***P***	**AICc**	**D^2**
(Intercept)	18.93	1.72	15.56-22.3	0.00	42955.51	57.11
SAV	0.94	0.03	0.88-1	0.00		
Transect_AUMB	19.43	2.24	15.03-23.83	0.00		
Transect_CUML	26.15	2.33	21.59-30.72	0.00		

Transect_CUMS	8.14	2.32	3.59-12.69	0.00		
Transect_LUDC	11.44	2.54	6.47-16.42	0.00		
Transect_LUTC	26.34	2.32	21.8-30.87	0.00		
Transect_SUPA	27.94	2.29	23.45-32.43	0.00		
Transect_WUMW	19.83	2.25	15.42-24.23	0.00		
SAV:Transect_AUMB	-0.21	0.04	-0.3--0.13	0.00		
SAV:Transect_CUML	-0.1	0.04	-0.19--0.01	0.03		
SAV:Transect_CUMS	0.14	0.04	0.06-0.23	0.00		
SAV:Transect_LUDC	-0.09	0.04	-0.17-0	0.05		
SAV:Transect_LUTC	-0.28	0.04	-0.36--0.2	0.00		
SAV:Transect_SUPA	-0.17	0.04	-0.25--0.08	0.00		
SAV:Transect_WUMW	-0.01	0.04	-0.09-0.07	0.83		

TEF:SAV	**Estimate**	**SE**	**95% CI**	***P***	**AICc**	**D^2**
(Intercept)	16.58	0.92	14.77-18.39	0.00	41435.19	82.84
SAV	0.95	0.02	0.92-0.99	0.00		
Transect_AUMB	3.63	1.27	1.15-6.12	0.00		
Transect_CUML	2.74	1.3	0.19-5.28	0.04		
Transect_CUMS	7.33	1.24	4.91-9.75	0.00		
Transect_LUDC	-1.54	1.36	-4.21-1.13	0.26		
Transect_LUTC	-4.39	1.31	-6.97--1.82	0.00		
Transect_SUPA	-4.87	1.3	-7.42--2.31	0.00		
Transect_WUMW	-0.24	1.27	-2.73-2.25	0.85		
SAV:Transect_AUMB	-0.06	0.02	-0.1--0.01	0.01		
SAV:Transect_CUML	0.09	0.02	0.04-0.14	0.00		
SAV:Transect_CUMS	0.1	0.02	0.05-0.15	0.00		
SAV:Transect_LUDC	0.03	0.02	-0.02-0.08	0.20		
SAV:Transect_LUTC	0.06	0.02	0.01-0.1	0.01		
SAV:Transect_SUPA	0.04	0.02	-0.01-0.08	0.13		
SAV:Transect_WUMW	0.1	0.02	0.05-0.15	0.00		

g. mean wind speed

RF:TEF	**Estimate**	**SE**	**95% CI**	***P***	**AICc**	**D^2**
(Intercept)	0	0	0-0	0.00	-8477.1	22.2
TEF	0.12	0.03	0.05-0.18	0.00		
Transect_AUMB	0	0	0-0	0.00		
Transect_LUDC	0	0	0-0	0.00		
TEF:Transect_AUMB	-0.03	0.03	-0.09-0.03	0.53		
TEF:Transect_LUDC	-0.12	0.03	-0.18--0.05	0.15		

RF:SAV	**Estimate**	**SE**	**95% CI**	***P***	**AICc**	**D^2**
(Intercept)	0	0	0-0	0.00	-8242.89	11.6
SAV	0	0	0-0.01	0.00		
Transect_AUMB	0	0	-0.01-0	0.00		
Transect_LUDC	0	0	0-0	0.00		

SAV:Transect_AUMB	0.03	0	0.02-0.03	0.53		
SAV:Transect_LUDC	0	0.01	-0.01-0.01	0.15		

TEF:SAV	**Estimate**	**SE**	**95% CI**	***P***	**AICc**	**D^2**
(Intercept)	0.01	0	0-0.01	0.00	-11241.71	41.03
SAV	0.01	0.02	-0.03-0.04	0.00		
Transect_AUMB	0.02	0.01	0.01-0.03	0.00		
Transect_CUML	0.01	0.01	0-0.02	0.00		
Transect_CUMS	-0.01	0	-0.02-0	0.53		
Transect_LUDC	-0.02	0.01	-0.04--0.01	0.15		
Transect_LUTC	-0.01	0.01	-0.02-0	0.71		
Transect_SUPA	-0.01	0.01	-0.02-0.01	0.14		
Transect_WUMW	0.01	0.01	-0.01-0.02	0.95		
SAV:Transect_AUMB	0.22	0.03	0.17-0.27	0.00		
SAV:Transect_CUML	0.48	0.03	0.43-0.53	0.00		
SAV:Transect_CUMS	0.05	0.02	0.01-0.1	0.08		
SAV:Transect_LUDC	0.29	0.03	0.22-0.35	0.70		
SAV:Transect_LUTC	0.19	0.03	0.14-0.24	0.00		
SAV:Transect_SUPA	0.02	0.03	-0.05-0.08	0.00		
SAV:Transect_WUMW	0.28	0.02	0.23-0.32	0.00		

h. maximum soil moisture deficit

RF:TEF	**Estimate**	**SE**	**95% CI**	***P***	**AICc**	**D^2**
(Intercept)	-45.97	3.04	-51.93--40.01	0.00	34568.38	84.72
TEF	0.9	0.02	0.86-0.94	0.00		
Transect_AUMB	83.97	3.61	76.9-91.05	0.00		
Transect_CUML	73.79	4.32	65.33-82.25	0.00		
Transect_CUMS	-5.5	7.48	-20.17-9.16	0.53		
Transect_LUDC	6.67	5.76	-4.62-17.96	0.15		
Transect_LUTC	18.29	4.18	10.1-26.47	0.71		
Transect_SUPA	82.12	4.57	73.17-91.07	0.14		
Transect_WUMW	177.73	3.9	170.09-185.37	0.95		
TEF:Transect_AUMB	-0.48	0.03	-0.53--0.43	0.00		
TEF:Transect_CUML	-0.39	0.03	-0.45--0.33	0.00		
TEF:Transect_CUMS	0.18	0.05	0.08-0.28	0.08		
TEF:Transect_LUDC	0.13	0.04	0.05-0.2	0.70		
TEF:Transect_LUTC	0.06	0.03	0-0.12	0.00		
TEF:Transect_SUPA	0.17	0.04	0.09-0.24	0.00		
TEF:Transect_WUMW	-0.58	0.03	-0.64--0.53	0.00		

RF:SAV	**Estimate**	**SE**	**95% CI**	***P***	**AICc**	**D^2**
(Intercept)	-17.4	3.97	-25.18--9.62	0.00	34767.76	76.17
SAV	0.61	0.02	0.56-0.66	0.00		
Transect_AUMB	54.47	4.84	44.99-63.96	0.00		
Transect_CUML	70.86	4.78	61.49-80.22	0.00		

Transect_CUMS	22.1	7.2	7.99-36.21	0.53		
Transect_LUDC	-87.95	9.79	-107.15--68.75	0.15		
Transect_LUTC	70.61	4.55	61.7-79.53	0.71		
Transect_SUPA	111.16	4.67	102.01-120.31	0.14		
Transect_WUMW	137.78	5.51	126.99-148.57	0.95		
SAV:Transect_AUMB	-0.19	0.03	-0.26--0.13	0.00		
SAV:Transect_CUML	-0.25	0.03	-0.31--0.19	0.00		
SAV:Transect_CUMS	0.15	0.05	0.04-0.25	0.08		
SAV:Transect_LUDC	0.91	0.07	0.78-1.04	0.70		
SAV:Transect_LUTC	-0.34	0.03	-0.4--0.28	0.00		
SAV:Transect_SUPA	-0.02	0.03	-0.09-0.04	0.00		
SAV:Transect_WUMW	-0.24	0.04	-0.31--0.17	0.00		

TEF:SAV	**Estimate**	**SE**	**95% CI**	***P***	**AICc**	**D^2**
(Intercept)	23.12	2.73	17.76-28.47	0.00	45880.82	76.43
SAV	0.74	0.02	0.7-0.77	0.00		
Transect_AUMB	-11.96	3.53	-18.88--5.03	0.00		
Transect_CUML	52.96	3.35	46.41-59.52	0.00		
Transect_CUMS	24.96	3.9	17.32-32.6	0.53		
Transect_LUDC	-90.75	5.91	-102.32--79.17	0.15		
Transect_LUTC	45.29	3.27	38.88-51.7	0.71		
Transect_SUPA	36.68	3.21	30.39-42.97	0.14		
Transect_WUMW	-45.7	4.13	-53.8--37.6	0.95		
SAV:Transect_AUMB	0.14	0.02	0.09-0.19	0.00		
SAV:Transect_CUML	-0.24	0.02	-0.28--0.2	0.00		
SAV:Transect_CUMS	0	0.03	-0.05-0.05	0.08		
SAV:Transect_LUDC	0.79	0.04	0.71-0.87	0.70		
SAV:Transect_LUTC	-0.33	0.02	-0.37--0.28	0.00		
SAV:Transect_SUPA	-0.25	0.02	-0.3--0.2	0.00		
SAV:Transect_WUMW	0.31	0.03	0.26-0.37	0.00		

i. mean soil moisture deficit

RF:TEF	**Estimate**	**SE**	**95% CI**	***P***	**AICc**	**D^2**
(Intercept)	-47.47	3.01	-53.36--41.57	0.00	34934.99	84.32
TEF	0.91	0.02	0.87-0.95	0.00		
Transect_AUMB	87.06	3.57	80.06-94.07	0.00		
Transect_CUML	68.61	4.28	60.21-77	0.00		
Transect_CUMS	-26.18	7.24	-40.36--12	0.53		
Transect_LUDC	6.56	5.65	-4.51-17.63	0.15		
Transect_LUTC	23.48	4.09	15.47-31.5	0.71		
Transect_SUPA	82.83	4.35	74.3-91.36	0.14		
Transect_WUMW	178.36	3.86	170.81-185.92	0.95		
TEF:Transect_AUMB	-0.49	0.03	-0.54--0.44	0.00		
TEF:Transect_CUML	-0.36	0.03	-0.42--0.31	0.00		
TEF:Transect_CUMS	0.32	0.05	0.22-0.42	0.08		

TEF:Transect_LUDC	0.12	0.04	0.05-0.2	0.70		
TEF:Transect_LUTC	0.03	0.03	-0.03-0.09	0.00		
TEF:Transect_SUPA	0.19	0.04	0.12-0.26	0.00		
TEF:Transect_WUMW	-0.58	0.03	-0.63--0.53	0.00		

RF:SAV	**Estimate**	**SE**	**95% CI**	***P***	**AICc**	**D^2**
(Intercept)	-18.45	3.73	-25.77--11.14	0.00	35062.33	75.91
SAV	0.62	0.02	0.57-0.66	0.00		
Transect_AUMB	55.85	4.63	46.78-64.93	0.00		
Transect_CUML	68.97	4.49	60.18-77.77	0.00		
Transect_CUMS	12.01	6.61	-0.94-24.96	0.53		
Transect_LUDC	-87.69	9.51	-106.32--69.06	0.15		
Transect_LUTC	68.99	4.34	60.49-77.5	0.71		
Transect_SUPA	106.68	4.45	97.96-115.39	0.14		
Transect_WUMW	137.89	5.3	127.5-148.27	0.95		
SAV:Transect_AUMB	-0.2	0.03	-0.27--0.14	0.00		
SAV:Transect_CUML	-0.25	0.03	-0.31--0.19	0.00		
SAV:Transect_CUMS	0.2	0.05	0.11-0.3	0.08		
SAV:Transect_LUDC	0.9	0.06	0.77-1.02	0.70		
SAV:Transect_LUTC	-0.33	0.03	-0.39--0.27	0.00		
SAV:Transect_SUPA	0.02	0.03	-0.05-0.08	0.00		
SAV:Transect_WUMW	-0.24	0.04	-0.31--0.17	0.00		

TEF:SAV	**Estimate**	**SE**	**95% CI**	***P***	**AICc**	**D^2**
(Intercept)	28.76	2.55	23.77-33.75	0.00	46350.38	76.55
SAV	0.71	0.02	0.68-0.74	0.00		
Transect_AUMB	-17.21	3.38	-23.84--10.58	0.00		
Transect_CUML	51.1	3.12	44.98-57.23	0.00		
Transect_CUMS	22.17	3.64	15.03-29.31	0.53		
Transect_LUDC	-96.49	5.68	-107.61--85.36	0.15		
Transect_LUTC	34.72	3.12	28.61-40.83	0.71		
Transect_SUPA	25.91	3.05	19.93-31.88	0.14		
Transect_WUMW	-51.66	3.99	-59.48--43.83	0.95		
SAV:Transect_AUMB	0.16	0.02	0.11-0.21	0.00		
SAV:Transect_CUML	-0.23	0.02	-0.28--0.19	0.00		
SAV:Transect_CUMS	0	0.03	-0.05-0.05	0.08		
SAV:Transect_LUDC	0.82	0.04	0.74-0.89	0.70		
SAV:Transect_LUTC	-0.27	0.02	-0.32--0.23	0.00		
SAV:Transect_SUPA	-0.19	0.02	-0.24--0.15	0.00		
SAV:Transect_WUMW	0.34	0.03	0.29-0.4	0.00		

j. solar exposure

RF:TEF	**Estimate**	**SE**	**95% CI**	***P***	**AICc**	**D^2**
(Intercept)	-249800	108300	-462116.5--37500.07	0.02	56007.01	64.74
TEF	1.1	0.03	1.03-1.17	0.00		

Transect_AUMB	528900	137100	260188.7-797675.8	0.00
Transect_CUMS	426700	170400	92672.81-760730.9	0.01
Transect_LUDC	503100	132900	242657.3-763621.5	0.00
TEF:Transect_AUMB	-0.74	0.04	-0.81--0.67	0.00
TEF:Transect_CUMS	-0.95	0.07	-1.08--0.83	0.00
TEF:Transect_LUDC	-0.75	0.05	-0.85--0.64	0.00

RF:SAV	**Estimate**	**SE**	**95% CI**	***P***	**AICc**	**D^2**
(Intercept)	-803200	145600	-1088665--517828.7	0.00	47917.78	60.74
SAV	0.25	0.01	0.23-0.28	0.00		
Transect_AUMB	315900	189700	-56032.3-687754.2	0.00		
Transect_CUMS	892900	277600	348721.7-1437074	0.53		
Transect_LUDC	263800	200600	-129326.3-656832.3	0.15		
SAV:Transect_AUMB	-0.07	0.01	-0.1--0.04	0.71		
SAV:Transect_CUMS	-0.23	0.02	-0.27--0.19	0.14		
SAV:Transect_LUDC	-0.09	0.02	-0.13--0.05	0.95		

TEF:SAV	**Estimate**	**SE**	**95% CI**	***P***	**AICc**	**D^2**
(Intercept)	23530	138500	-247858.3-294913.2	0.00	154283.8	82.21
SAV	0.2	0.01	0.18-0.22	0.00		
Transect_AUMB	-2011000	214200	-2430456--1590966	0.00		
Transect_CUML	-1312000	207800	-1718784--904218.6	0.00		
Transect_CUMS	341400	187500	-26049.77-708832.1	0.53		
Transect_LUDC	69790	191900	-306369.4-445948.6	0.15		
Transect_LUTC	-416300	363900	-1129589-297017.4	0.71		
Transect_SUPA	-1879000	224800	-2319937--1438873	0.14		
Transect_WUMW	34440	244100	-444076.3-512959	0.95		
SAV:Transect_AUMB	0.3	0.01	0.27-0.33	0.00		
SAV:Transect_CUML	0.2	0.01	0.18-0.23	0.00		
SAV:Transect_CUMS	-0.12	0.01	-0.14--0.09	0.08		
SAV:Transect_LUDC	-0.09	0.02	-0.12--0.05	0.70		
SAV:Transect_LUTC	0.31	0.03	0.25-0.37	0.00		
SAV:Transect_SUPA	0.36	0.01	0.33-0.39	0.00		
SAV:Transect_WUMW	0.13	0.02	0.1-0.16	0.00		

Appendix 3.7 Model selection of pairwise models (GLM) comparing each of ten daily microclimate variables within each of three vegetation types; rain forest (RF), tall eucalypt forest (TEF) and savanna (SAV). Pairwise combinations, therefore, were RF:TEF, RF:SAV and TEF:SAV. Microclimate variables were recorded within each vegetation type, replicated eight times in eight different transect locations; Koombooloomba (AUKO), Mt Baldy (AUMB), Mt Lewis (CUML), Mt Spurgeon (CUMS), Davies Ck (LUDC), Tinnaroo Ck (LUTC), Paluma (SUPA) and Mt Windsor (WUMW). The full model response variable was one of ten microclimate variables for the first vegetation type (in the pairwise analysis) and the explanatory variables were the microclimate variable at the second vegetation type, transect and their interaction. Microclimate variables were temperature (a. maximum, b. mean, c. minimum), relative humidity (d. maximum, e. mean, f. minimum), mean wind speed (g.) and soil moisture deficit (SMD; h. maximum, i. minimum) and solar exposure (j.). Alternative candidate models consisted of the absence of the interaction term (model_1), the absence of the interaction term and 'transect' (model_2), 'transect' only (model_3) and the null model (model_null). Model selection was based on Akaike Information Criterion (AICc) and all tables are ranked by AICc. Delta AICc, Akaike weights (*wi*) and percent explained deviance (D^2) relative to the null model are also reported.

a. maximum temperature

	AICc	**delta AICc**	***wi***	**D^2**
RF:TEF	19975.87	0	1	87.76
RF:TEF_1	20292.57	316.7	0	87.08
RF:TEF_2	24520.95	4545.08	0	74
RF:TEF_3	36607.68	16631.81	0	17.3
RF:TEF_null	37925.45	17949.58	0	0

	AICc	**delta AICc**	***wi***	**D^2**
RF:SAV	23516.49	0	1	77.17
RF:SAV_1	23834.58	318.09	0	75.87
RF:SAV_2	27764.66	4248.16	0	53.47
RF:SAV_3	36607.68	13091.19	0	17.3
RF:SAV_null	37925.45	14408.96	0	0

	AICc	**delta AICc**	***wi***	**D^2**
TEF:SAV	21492.87	0	1	83.73
TEF:SAV_1	21756.89	264.02	0	83.01
TEF:SAV_2	24205.53	2712.66	0	75.06
TEF:SAV_3	33466.82	11973.95	0	9.17
TEF:SAV_null	34087.68	12594.82	0	0

b. mean temperature

	AICc	**delta AICc**	***wi***	**D^2**
RF:TEF	14118.5	0	1	93.95
RF:TEF_1	14590.9	472.4	0	93.45

RF:TEF_2	18251.66	4133.16	0	87.99
RF:TEF_3	35256.26	21137.75	0	13.49
RF:TEF_null	36258.53	22140.03	0	0

	AICc	**delta AICc**	***wi***	**D^2**
RF:SAV	16600.86	0	1	90.63
RF:SAV_1	16860.43	259.57	0	90.19
RF:SAV_2	22933.29	6332.43	0	72.97
RF:SAV_3	35256.26	18655.4	0	13.49
RF:SAV_null	36258.53	19657.67	0	0

	AICc	**delta AICc**	***wi***	**D^2**
TEF:SAV	10794.29	0	1	95.5
TEF:SAV_1	11203.38	409.1	0	95.19
TEF:SAV_2	17807.99	7013.7	0	86.51
TEF:SAV_3	31169.8	20375.52	0	6.52
TEF:SAV_null	31601.02	20806.74	0	0

c. minimum temperature

	AICc	**delta AICc**	***wi***	**D^2**
RF:TEF	17192.93	0	1	91.18
RF:TEF_1	17744.1	551.18	0	90.32
RF:TEF_2	21058.23	3865.31	0	83.25
RF:TEF_3	36309.72	19116.79	0	11.71
RF:TEF_null	37169.42	19976.5	0	0

	AICc	**delta AICc**	***wi***	**D^2**
RF:SAV	19173.72	0	1	87.42
RF:SAV_1	19630.61	456.89	0	86.4
RF:SAV_2	24240.49	5066.77	0	70.62
RF:SAV_3	36309.72	17136	0	11.71
RF:SAV_null	37169.42	17995.7	0	0

	AICc	**delta AICc**	***wi***	**D^2**
TEF:SAV	13464.63	0	1	94.38
TEF:SAV_1	14095.92	631.29	0	93.78
TEF:SAV_2	17491.22	4026.59	0	89.42
TEF:SAV_3	32417.53	18952.9	0	6.12
TEF:SAV_null	32820.8	19356.17	0	0

d. maximum relative humidity

	AICc	**delta AICc**	***wi***	**D^2**
RF:TEF	25151.03	0	1	79.24

RF:TEF_1	26431.44	1280.4	0	74.1
RF:TEF_2	26687.13	1536.1	0	72.88
RF:TEF_3	35435.99	10284.95	0	0.54
RF:TEF_null	35454.43	10303.4	0	0

	AICc	**delta AICc**	***wi***	**D^2**
RF:SAV	26379.06	0	1	61.76
RF:SAV_1	26896.39	517.33	0	57.83
RF:SAV_2	27342.31	963.25	0	54.1
RF:SAV_3	35435.99	9056.93	0	0.54
RF:SAV_null	35454.43	9075.38	0	0

	AICc	**delta AICc**	***wi***	**D^2**
TEF:SAV	29101.7	0	1	64.6
TEF:SAV_1	29250.38	148.68	0	63.62
TEF:SAV_2	29614.83	513.13	0	61.26
TEF:SAV_3	39344.33	10242.63	0	1.68
TEF:SAV_null	39442.11	10340.41	0	0

e. mean relative humidity

	AICc	**delta AICc**	***wi***	**D^2**
RF:TEF	32338.64	0	1	85.05
RF:TEF_1	32934.71	596.07	0	83.41
RF:TEF_2	33873.52	1534.88	0	80.48
RF:TEF_3	44327.93	11989.29	0	1.04
RF:TEF_null	44376.71	12038.07	0	0

	AICc	**delta AICc**	***wi***	**D^2**
RF:SAV	33096.23	0	1	72.42
RF:SAV_1	33324.7	228.47	0	71.16
RF:SAV_2	34419.62	1323.39	0	64.62
RF:SAV_3	44327.93	11231.7	0	1.04
RF:SAV_null	44376.71	11280.48	0	0

	AICc	**delta AICc**	***wi***	**D^2**
TEF:SAV	32718.46	0	1	86.04
TEF:SAV_1	32928.35	209.89	0	85.51
TEF:SAV_2	35235.9	2517.44	0	78.67
TEF:SAV_3	49093.82	16375.36	0	1.46
TEF:SAV_null	49177.12	16458.67	0	0

f. minimum relative humidity

	AICc	**delta AICc**	***wi***	**D^2**

RF:TEF	43237.05	0	1	74.75
RF:TEF_1	43343.94	106.89	0	74.22
RF:TEF_2	45205.02	1967.97	0	64.49
RF:TEF_3	52095.81	8858.75	0	5.3
RF:TEF_null	52408.07	9171.01	0	0

	AICc	**delta AICc**	***wi***	**D^2**
RF:SAV	42955.51	0	1	57.23
RF:SAV_1	43091.59	136.09	0	56.03
RF:SAV_2	44302.3	1346.79	0	44.91
RF:SAV_3	52095.81	9140.3	0	5.3
RF:SAV_null	52408.07	9452.56	0	0

	AICc	**delta AICc**	***wi***	**D^2**
TEF:SAV	41435.19	0	1	82.89
TEF:SAV_1	41495.66	60.46	0	82.67
TEF:SAV_2	43525.05	2089.86	0	75.65
TEF:SAV_3	56918.72	15483.53	0	4.41
TEF:SAV_null	57202.49	15767.3	0	0

g. mean wind speed

	AICc	**delta AICc**	***wi***	**D^2**
RF:TEF_3	-9002.77	0	1	5.07
RF:TEF_null	-8928.65	74.12	0	0
RF:TEF	-8477.1	525.67	0	22.48
RF:TEF_1	-8441.09	561.68	0	20.21
RF:TEF_2	-8414.93	587.84	0	18.45

	AICc	**delta AICc**	***wi***	**D^2**
RF:SAV_3	-9002.77	0	1	11.93
RF:SAV_null	-8928.65	74.12	0	0
RF:SAV	-8242.89	759.88	0	5.07
RF:SAV_1	-8197.88	804.89	0	8.71
RF:SAV_2	-8155.87	846.9	0	5.58

	AICc	**delta AICc**	***wi***	**D^2**
TEF:SAV_3	-11480.15	0	1	24.18
TEF:SAV	-11241.71	238.43	0	41.21
TEF:SAV_1	-10729.58	750.56	0	34.6
TEF:SAV_null	-9968.95	1511.2	0	0
TEF:SAV_2	-9738.49	1741.65	0	19.84

h. maximum SMD

	AICc	delta AICc	*wi*	D^2
RF:TEF	34568.38	0	1	84.77
RF:TEF_1	35656.84	1088.46	0	80.12
RF:TEF_2	41739.3	7170.92	0	13.09
RF:TEF_3	49431.1	14862.72	0	60.92
RF:TEF_null	54394.54	19826.16	0	0

	AICc	delta AICc	*wi*	D^2
RF:SAV	34767.76	0	1	76.26
RF:SAV_1	35276.32	508.55	0	72.89
RF:SAV_2	40002.78	5235.02	0	9.7
RF:SAV_3	49431.1	14663.34	0	60.92
RF:SAV_null	54394.54	19626.77	0	0

	AICc	delta AICc	*wi*	D^2
TEF:SAV	45880.82	0	1	76.49
TEF:SAV_1	47264.14	1383.32	0	69.64
TEF:SAV_2	48743.55	2862.72	0	60.09
TEF:SAV_3	56513.37	10632.55	0	24.55
TEF:SAV_null	58150.52	12269.7	0	0

i. mean SMD

	AICc	delta AICc	*wi*	D^2
RF:TEF	34934.99	0	1	84.38
RF:TEF_1	36083.62	1148.63	0	79.3
RF:TEF_2	41970.43	7035.44	0	13.71
RF:TEF_3	50083.38	15148.39	0	58.55
RF:TEF_null	54735.25	19800.26	0	0

	AICc	delta AICc	*wi*	D^2
RF:SAV	35062.33	0	1	76.01
RF:SAV_1	35614.14	551.81	0	72.3
RF:SAV_2	40150.85	5088.52	0	12.08
RF:SAV_3	50083.38	15021.05	0	58.55
RF:SAV_null	54735.25	19672.92	0	0

	AICc	delta AICc	*wi*	D^2
TEF:SAV	46350.38	0	1	76.61
TEF:SAV_1	47685.81	1335.43	0	70.06
TEF:SAV_2	49132.01	2781.63	0	60.88
TEF:SAV_3	57051.19	10700.81	0	24.11
TEF:SAV_null	58654.3	12303.92	0	0

j. solar exposure

	AICc	delta AICc	*wi*	D^2
RF:TEF	56007.01	0	1	64.87
RF:TEF_1	56394.23	387.22	0	56.49
RF:TEF_2	57143.67	1136.66	0	34.35
RF:TEF_3	57424.66	1417.64	0	30.93
RF:TEF_null	58100.63	2093.61	0	0

	AICc	delta AICc	*wi*	D^2
RF:SAV	47917.78	0	1	60.92
RF:SAV_1	48050.3	132.53	0	57.32
RF:SAV_2	48642.72	724.95	0	37.61
RF:SAV_3	57424.66	9506.88	0	30.93
RF:SAV_null	58100.63	10182.85	0	0

	AICc	delta AICc	*wi*	D^2
TEF:SAV	154283.8	0	1	82.26
TEF:SAV_1	155825.4	1541.62	0	75.75
TEF:SAV_2	158802.9	4519.08	0	55.77
TEF:SAV_3	189920.9	35637.1	0	45.49
TEF:SAV_null	193498	39214.22	0	0

Appendix 3.8 Linear mixed effects models testing the capacity for daily Mareeba meteorological data and vegetation type to predict daily observed micrometeorological patterns at 32 field study sites (recorded daily over a three-year period). Vegetation types were rain forest (RF), tall eucalypt forest (TEF) and savanna (SAV). The response variable for each model was site-based micrometeorology and the predictor variables were daily meteorology data at Mareeba meteorological station, vegetation type and their interaction, with ‘transect’ as a random effect. Models were repeated for each of ten meteorological variables; temperature (a. maximum, b. mean, c. minimum), relative humidity (d. maximum, e. mean, f. minimum), mean wind speed (g.), soil moisture deficit (h. maximum, i. mean) and rainfall (j.; savanna sites only). Coefficient estimate, standard error (SE), 95% confidence intervals (95% CI), t values (*t*), probability (*P*), Akaike Information Criterion (AICc) and percent explained deviance (D^2) relative to the null model are reported.

a. maximum temperature

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	-6.29	0.39	-7.08--5.49	-16.16	0.00	118975	21.73
Mareeba	0.91	0.01	0.89-0.93	99.39	0.00		
SAV	12.14	0.39	11.39-12.9	31.51	0.00		
TEF	5.32	0.33	4.67-5.97	16.08	0.00		
Mareeba:SAV	-0.18	0.01	-0.21--0.16	-13.85	0.00		
Mareeba:TEF	-0.06	0.01	-0.08--0.04	-5.34	0.00		

b. mean temperature

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	-3.49	0.28	-4.08--2.89	-12.43	0.00	94817.2	30.11
Mareeba	0.92	0.01	0.91-0.93	152.50	0.00		
SAV	7.36	0.2	6.98-7.75	37.58	0.00		
TEF	4.91	0.17	4.58-5.24	29.17	0.00		
Mareeba:SAV	-0.15	0.01	-0.17--0.14	-17.75	0.00		
Mareeba:TEF	-0.12	0.01	-0.14--0.11	-16.38	0.00		

c. minimum temperature

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	2.53	0.29	1.89-3.17	8.59	0.00	106787.6	21.56
Mareeba	0.7	0.01	0.69-0.71	111.52	0.00		
SAV	3.35	0.16	3.02-3.67	20.31	0.00		
TEF	2.94	0.14	2.66-3.21	20.76	0.00		
Mareeba:SAV	-0.07	0.01	-0.08--0.05	-7.23	0.00		
Mareeba:TEF	-0.07	0.01	-0.09--0.06	-9.42	0.00		

d. maximum relative humidity

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	97.91	1.17	95.61-100.21	83.48	0.00	152654.1	0.79
Mareeba	0.01	0.01	-0.01-0.04	1.15	0.25		

SAV	-15.79	1.61	-18.94--12.64	-9.83	0.00		
TEF	-3.16	1.38	-5.87--0.45	-2.28	0.02		
Mareeba:SAV	0.14	0.02	0.11-0.18	7.99	0.00		
Mareeba:TEF	0.03	0.02	0-0.06	1.83	0.07		

e. mean relative humidity

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	60.64	1.17	58.34-62.94	51.82	0.00	179867.8	5.28
Mareeba	0.44	0.01	0.41-0.47	30.13	0.00		
SAV	-31.03	1.54	-34.04--28.01	-20.17	0.00		
TEF	-12.07	1.32	-14.66--9.47	-9.12	0.00		
Mareeba:SAV	0.24	0.02	0.2-0.28	11.54	0.00		
Mareeba:TEF	0.11	0.02	0.07-0.14	5.91	0.00		

f. minimum relative humidity

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	39.92	1.21	37.41-42.42	33.10	0.00	202493.4	7.75
Mareeba	0.78	0.01	0.76-0.81	55.52	0.00		
SAV	-26.93	1.03	-28.96--24.91	-26.08	0.00		
TEF	-14.57	0.89	-16.3--12.83	-16.43	0.00		
Mareeba:SAV	-0.04	0.02	-0.07-0	-1.76	0.08		
Mareeba:TEF	0.06	0.02	0.03-0.09	3.48	0.00		

g. mean wind speed

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	0.01	0.02	-0.03-0.05	0.53	0.60	54480.94	7.82
Mareeba	0	0	0-0	0.76	0.45		
SAV	0.06	0.01	0.04-0.08	5.37	0.00		
TEF	-0.01	0.01	-0.03-0.01	-0.72	0.47		
Mareeba:SAV	0.01	0	0.01-0.01	11.62	0.00		
Mareeba:TEF	0	0	0-0.01	4.55	0.00		

h. maximum soil moisture deficit

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	66.62	6.57	52.15-81.08	10.14	0.00	219282.6	3.21
Mareeba	0.09	0	0.08-0.09	35.27	0.00		
SAV	-11.84	1.88	-15.52--8.16	-6.31	0.00		
TEF	4.92	1.68	1.63-8.21	2.93	0.00		
Mareeba:SAV	0.04	0	0.03-0.05	11.80	0.00		
Mareeba:TEF	0.02	0	0.02-0.03	8.03	0.00		

i. mean soil moisture deficit

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**

(Intercept)	77.32	6.18	63.67-90.98	12.51	0.00	206422.7	4.59
Mareeba	0.08	0	0.07-0.08	41.34	0.00		
SAV	-8.34	1.38	-11.05--5.64	-6.04	0.00		
TEF	4.6	1.24	2.18-7.03	3.73	0.00		
Mareeba:SAV	0.04	0	0.03-0.04	15.12	0.00		
Mareeba:TEF	0.02	0	0.02-0.03	10.95	0.00		

j. rainfall

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	1.37	0.42	0.44-2.3	3.28	0.01	33433.76	3.93
Mareeba	0.15	0.01	0.13-0.18	12.94	0.00		

Appendix 3.9 Model selection of linear mixed effects models testing the capacity for daily Mareeba meteorological data and vegetation type (rain forest, tall eucalypt forest and savanna) to predict daily observed micrometeorological conditions at 32 field study sites. Models were repeated for each of ten meteorological variables (response variable); temperature (a. maximum, b. mean, c. minimum), relative humidity (d. maximum, e. mean, f. minimum), mean wind speed (g.), soil moisture deficit (h. maximum, i. mean) and rainfall (j.; savanna sites only). Meteorological data at Mareeba, vegetation type, and their interaction were the explanatory variables, with 'Transect' as a random effect. Alternative candidate models were the full model without the interaction term (model_1), the absence of the interaction term and 'transect' (model_2), 'transect' only (model_3) and the null model (model_null). Model selection was based on Akaike Information Criterion (AICc) and all tables were ranked by AICc. Delta AICc, Akaike weights (*wi*) and percent explained deviance (D^2) relative to the null model are also reported.

a. maximum temperature

	AICc	**delta_AICc**	***wi***	**D^2**
Temp_max	118975	0	1	21.73
Temp_max_1	119170.2	195.14	0	21.59
Temp_max_2	138798.7	19823.71	0	8.68
Temp_max_3	140653.9	21678.91	0	7.46
Temp_max_null	151982	33007	0	0

b. mean temperature

	AICc	**delta_AICc**	***wi***	**D^2**
Temp_mean	94817.2	0	1	30.11
Temp_mean_1	95186.76	369.56	0	29.83
Temp_mean_2	112694.15	17876.94	0	16.92
Temp_mean_3	129096.66	34279.46	0	4.83
Temp_mean_null	135642.54	40825.34	0	0

c. minimum temperature

	AICc	**delta_AICc**	***wi***	**D^2**
Temp_min	106787.6	0	1	21.56
Temp_min_1	106877.8	90.2	0	21.49
Temp_min_2	111407.9	4620.27	0	18.16
Temp_min_3	133992.3	27204.74	0	1.57
Temp_min_null	136123.8	29336.24	0	0

d. maximum relative humidity

	AICc	**delta_AICc**	***wi***	**D^2**
RH_max	152654.1	0	1	0.79
RH_max_1	152725.6	71.57	0	0.74
RH_max_3	152827.5	173.41	0	0.67
RH_max_2	153759.4	1105.32	0	0.07

RH_max_null	153858.4	1204.37	0	0

e. mean relative humidity

	AICc	**delta_AICc**	***wi***	**D^2**
RH_mean	179867.8	0	1	5.28
RH_mean_1	179997.6	129.82	0	5.21
RH_mean_3	185216.2	5348.34	0	2.46
RH_mean_2	185667.9	5800.12	0	2.22
RH_mean_null	189877.2	10009.4	0	0

f. minimum relative humidity

	AICc	**delta_AICc**	***wi***	**D^2**
RH_min	202493.4	0	1	7.75
RH_min_1	202523.1	29.76	0	7.73
RH_min_2	211736.8	9243.36	0	3.53
RH_min_3	213177.8	10684.41	0	2.88
RH_min_null	219484	16990.65	0	0

g. mean wind speed

	AICc	**delta_AICc**	***wi***	**D^2**
Wind_mean	54480.94	0	1	7.82
Wind_mean_1	54671.8	207.41	0	7.49
Wind_mean_3	55332.37	878.32	0	6.36
Wind_mean_2	58545.29	4644.57	0	0.92
Wind_mean_null	59088.18	4091.67	0	0

h. maximum soil moisture deficit

	AICc	**delta_AICc**	***wi***	**D^2**
SMD_max	219282.6	0	1	3.21
SMD_max_1	219419	136.36	0	3.15
SMD_max_2	219899.2	616.57	0	2.94
SMD_max_3	226301.4	7018.76	0	0.11
SMD_max_null	226552.7	7270.1	0	0

i. mean soil moisture deficit

	AICc	**delta_AICc**	***wi***	**D^2**
SMD_mean	206422.7	0	1	4.59
SMD_mean_1	206651.6	228.91	0	4.48
SMD_mean_2	207457.2	1034.52	0	4.11
SMD_mean_3	215978.9	9556.22	0	0.17
SMD_mean_null	216346.6	9923.93	0	0

j. rainfall

	AICc	**delta_AICc**	***wi***	**D^2**
Rain_mm_SAV_2	33433.76	0	1	3.93
Rain_mm_SAV_null	34798.69	1364.93	0	0

Appendix 3.10 Linear mixed effects models testing the relationship between vegetation type and transect with daily observed micrometeorological conditions at 32 field study sites (recorded daily over a three-year period). Vegetation types were rain forest (RF), tall eucalypt forest (TEF) and savanna (SAV). Micrometeorological variables were recorded within each vegetation type, replicated eight times in eight different transect locations; Koombooloomba (AUKO), Mt Baldy (AUMB), Mt Lewis (CUML), Mt Spurgeon (CUMS), Davies Ck (LUDC), Tinnaroo Ck (LUTC), Paluma (SUPA) and Mt Windsor (WUMW). The response variable for each model was site-based micrometeorology and the predictor variables were vegetation type, transect and their interaction, with 'day' as a random effect. Models were repeated for each of eleven micrometeorological variables (response variable); temperature (a. maximum, b. mean, c. minimum), relative humidity (d. maximum, e. mean, f. minimum), mean wind speed (g.), soil moisture deficit (h. maximum, i. mean), rainfall (j.) and solar exposure (k.). Coefficient estimate, standard error (SE), 95% confidence intervals (95% CI), t values (*t*), probability (*P*), Akaike Information Criterion (AICc) and percent explained deviance (D^2) relative to the null model are reported.

a. maximum temperature

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	23.42	0.11	23.2-23.63	216.42	0	106936.9	24.77
SAV	3.65	0.08	3.49-3.82	43.49	0		
TEF	1.18	0.08	1.03-1.33	15.59	0		
TransectAUMB	-3.28	0.09	-3.46--3.1	-35.31	0		
TransectCUML	-3.75	0.08	-3.91--3.59	-45.1	0		
TransectCUMS	-3.91	0.09	-4.08--3.74	-45.02	0		
TransectLUDC	-1.44	0.08	-1.6--1.27	-17.11	0		
TransectLUTC	-5.04	0.08	-5.21--4.88	-60.13	0		
TransectSUPA	-3.88	0.08	-4.04--3.72	-47.18	0		
TransectWUMW	-4.47	0.08	-4.63--4.31	-54.4	0		
SAV:TransectAUMB	2.57	0.13	2.32-2.81	20.48	0		
TEF:TransectAUMB	1.73	0.11	1.51-1.95	15.57	0		
SAV:TransectCUML	5.1	0.11	4.88-5.32	44.93	0		
TEF:TransectCUML	3.32	0.1	3.13-3.51	33.47	0		
SAV:TransectCUMS	3.82	0.11	3.6-4.04	33.73	0		
TEF:TransectCUMS	1.43	0.1	1.24-1.63	14.21	0		
SAV:TransectLUDC	0.72	0.11	0.5-0.94	6.46	0		
TEF:TransectLUDC	0.54	0.1	0.35-0.74	5.52	0		
SAV:TransectLUTC	4.07	0.11	3.85-4.29	36.63	0		
TEF:TransectLUTC	2.86	0.1	2.67-3.05	29.02	0		
SAV:TransectSUPA	3.5	0.12	3.28-3.73	30.4	0		
TEF:TransectSUPA	5.14	0.1	4.94-5.34	51.21	0		
SAV:TransectWUMW	4.16	0.12	3.93-4.39	35.29	0		
TEF:TransectWUMW	2.98	0.1	2.78-3.18	29.15	0		

b. mean temperature

	Estimate	SE	95% CI	*t*	*P*	AICc	D^2
(Intercept)	19	0.08	18.83-19.16	226.38	0	70080.3	38.85
SAV	1.46	0.04	1.38-1.54	35.43	0		
TEF	0.93	0.04	0.86-1	24.96	0		
TransectAUMB	-1.47	0.05	-1.56--1.38	-32.24	0		
TransectCUML	-1.81	0.04	-1.89--1.73	-44.26	0		
TransectCUMS	-2.51	0.04	-2.59--2.42	-58.73	0		
TransectLUDC	-0.03	0.04	-0.11-0.05	-0.65	0.52		
TransectLUTC	-3.26	0.04	-3.34--3.18	-78.91	0		
TransectSUPA	-2.21	0.04	-2.29--2.14	-54.66	0		
TransectWUMW	-3.18	0.04	-3.25--3.1	-78.51	0		
SAV:TransectAUMB	1.05	0.06	0.93-1.17	17.05	0		
TEF:TransectAUMB	0.09	0.05	-0.02-0.2	1.61	0.11		
SAV:TransectCUML	3.75	0.06	3.64-3.86	67.12	0		
TEF:TransectCUML	1.78	0.05	1.68-1.87	36.41	0		
SAV:TransectCUMS	3.63	0.06	3.53-3.74	65.26	0		
TEF:TransectCUMS	1.06	0.05	0.96-1.15	21.27	0		
SAV:TransectLUDC	1.27	0.05	1.16-1.37	23.13	0		
TEF:TransectLUDC	0.45	0.05	0.36-0.55	9.36	0		
SAV:TransectLUTC	3.1	0.05	2.99-3.21	56.7	0		
TEF:TransectLUTC	2.14	0.05	2.05-2.24	44.17	0		
SAV:TransectSUPA	2.59	0.06	2.48-2.7	45.72	0		
TEF:TransectSUPA	1.9	0.05	1.8-2	38.47	0		
SAV:TransectWUMW	3.1	0.06	2.98-3.21	53.37	0		
TEF:TransectWUMW	1.46	0.05	1.36-1.56	29.08	0		

c. minimum temperature

	Estimate	SE	95% CI	*t*	*P*	AICc	D^2
(Intercept)	16.49	0.09	16.31-16.68	174.97	0	85461.02	21.53
SAV	-0.17	0.06	-0.28--0.07	-3.14	0		
TEF	0.37	0.05	0.27-0.47	7.37	0		
TransectAUMB	-0.52	0.06	-0.64--0.4	-8.48	0		
TransectCUML	-0.91	0.05	-1.02--0.8	-16.51	0		
TransectCUMS	-2.24	0.06	-2.36--2.13	-39.16	0		
TransectLUDC	0.56	0.06	0.45-0.67	10.08	0		
TransectLUTC	-2.64	0.06	-2.75--2.54	-47.73	0		
TransectSUPA	-1.66	0.05	-1.77--1.56	-30.59	0		
TransectWUMW	-2.82	0.05	-2.93--2.71	-51.94	0		
SAV:TransectAUMB	0.45	0.08	0.29-0.61	5.41	0		
TEF:TransectAUMB	-0.49	0.07	-0.63--0.34	-6.65	0		
SAV:TransectCUML	3.39	0.07	3.24-3.54	45.24	0		
TEF:TransectCUML	1.85	0.07	1.72-1.98	28.19	0		
SAV:TransectCUMS	3.91	0.07	3.76-4.05	52.27	0		
TEF:TransectCUMS	1.75	0.07	1.62-1.88	26.32	0		
SAV:TransectLUDC	1.32	0.07	1.18-1.47	18	0		

TEF:TransectLUDC	0.64	0.07	0.51-0.77	9.83	0		
SAV:TransectLUTC	3.53	0.07	3.38-3.67	48.04	0		
TEF:TransectLUTC	2.4	0.07	2.27-2.53	36.88	0		
SAV:TransectSUPA	2.27	0.08	2.12-2.42	29.87	0		
TEF:TransectSUPA	1.27	0.07	1.14-1.4	19.18	0		
SAV:TransectWUMW	2.62	0.08	2.47-2.77	33.62	0		
TEF:TransectWUMW	1.3	0.07	1.16-1.43	19.22	0		

d. maximum relative humidity

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	99.8	0.2	99.41-100.19	503	0	139285.6	2.8
SAV	-0.13	0.21	-0.53-0.28	-0.6	0.54		
TEF	-0.12	0.18	-0.47-0.24	-0.6	0.52		
TransectAUMB	-0.83	0.22	-1.26--0.4	-3.8	0		
TransectCUML	-0.72	0.2	-1.11--0.33	-3.6	0		
TransectCUMS	-0.94	0.21	-1.34--0.54	-4.6	0		
TransectLUDC	-0.49	0.21	-0.89--0.09	-2.4	0.02		
TransectLUTC	-0.62	0.2	-1.01--0.23	-3.1	0		
TransectSUPA	-1.09	0.21	-1.51--0.67	-5.1	0		
TransectWUMW	-1.31	0.22	-1.74--0.88	-6	0		
SAV:TransectAUMB	-1.92	0.3	-2.51--1.33	-6.4	0		
TEF:TransectAUMB	0.1	0.26	-0.42-0.62	0.4	0.7		
SAV:TransectCUML	-5.21	0.28	-5.75--4.67	-18.9	0		
TEF:TransectCUML	-1.43	0.24	-1.9--0.97	-6	0		
SAV:TransectCUMS	-5.82	0.28	-6.36--5.28	-21.1	0		
TEF:TransectCUMS	-0.35	0.24	-0.82-0.13	-1.4	0.15		
SAV:TransectLUDC	-2.05	0.27	-2.58--1.51	-7.5	0		
TEF:TransectLUDC	-0.79	0.24	-1.27--0.32	-3.3	0		
SAV:TransectLUTC	-3	0.27	-3.54--2.46	-10.9	0		
TEF:TransectLUTC	-0.83	0.24	-1.29--0.37	-3.5	0		
SAV:TransectSUPA	-0.66	0.3	-1.24--0.07	-2.2	0.03		
TEF:TransectSUPA	-0.09	0.25	-0.59-0.4	-0.4	0.71		
SAV:TransectWUMW	-2.81	0.3	-3.4--2.23	-9.4	0		
TEF:TransectWUMW	0.18	0.26	-0.34-0.69	0.7	0.5		

e. mean relative humidity

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	92.55	0.36	91.85-93.25	260.46	0	154682.3	10.15
SAV	-6.78	0.27	-7.32--6.24	-24.71	0		
TEF	-1.82	0.24	-2.29--1.34	-7.53	0		
TransectAUMB	-0.99	0.29	-1.56--0.41	-3.36	0		
TransectCUML	1.42	0.27	0.89-1.94	5.31	0		
TransectCUMS	-0.25	0.27	-0.79-0.28	-0.93	0.35		
TransectLUDC	0.79	0.27	0.25-1.33	2.87	0		
TransectLUTC	2.01	0.27	1.49-2.53	7.58	0		

TransectSUPA	1.43	0.28	0.88-1.99	5.03	0		
TransectWUMW	0.11	0.29	-0.46-0.69	0.38	0.7		
SAV:TransectAUMB	-4.67	0.4	-5.46--3.88	-11.62	0		
TEF:TransectAUMB	-1.12	0.35	-1.81--0.43	-3.19	0		
SAV:TransectCUML	-10.99	0.37	-11.71--10.27	-29.91	0		
TEF:TransectCUML	-4.26	0.32	-4.89--3.64	-13.41	0		
SAV:TransectCUMS	-9.95	0.37	-10.68--9.23	-26.96	0		
TEF:TransectCUMS	0.53	0.32	-0.1-1.16	1.65	0.1		
SAV:TransectLUDC	-4.13	0.37	-4.85--3.42	-11.29	0		
TEF:TransectLUDC	-2.49	0.32	-3.13--1.86	-7.72	0		
SAV:TransectLUTC	-6.41	0.37	-7.12--5.69	-17.5	0		
TEF:TransectLUTC	-4.08	0.32	-4.7--3.47	-12.95	0		
SAV:TransectSUPA	-6.3	0.4	-7.08--5.52	-15.82	0		
TEF:TransectSUPA	-4.56	0.34	-5.22--3.9	-13.49	0		
SAV:TransectWUMW	-9.04	0.4	-9.82--8.25	-22.59	0		
TEF:TransectWUMW	-2.96	0.35	-3.65--2.28	-8.49	0		

f. minimum relative humidity

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	70.71	0.63	69.48-71.93	113.03	0	184611.2	10.21
SAV	-16.69	0.5	-17.68--15.7	-33.09	0		
TEF	-2.37	0.44	-3.24--1.5	-5.34	0		
TransectAUMB	4.02	0.54	2.96-5.07	7.44	0		
TransectCUML	12.53	0.49	11.57-13.49	25.55	0		
TransectCUMS	7.46	0.5	6.47-8.44	14.79	0		
TransectLUDC	8.08	0.5	7.09-9.07	16.03	0		
TransectLUTC	11.65	0.49	10.7-12.61	23.87	0		
TransectSUPA	13.87	0.52	12.84-14.9	26.49	0		
TransectWUMW	10.72	0.54	9.67-11.78	19.93	0		
SAV:TransectAUMB	-8.19	0.74	-9.63--6.74	-11.07	0		
TEF:TransectAUMB	-7.65	0.65	-8.92--6.38	-11.81	0		
SAV:TransectCUML	-20.36	0.68	-21.68--19.03	-30.14	0		
TEF:TransectCUML	-12.76	0.58	-13.91--11.62	-21.83	0		
SAV:TransectCUMS	-13.42	0.68	-14.75--12.09	-19.77	0		
TEF:TransectCUMS	-1.25	0.59	-2.4--0.09	-2.12	0.03		
SAV:TransectLUDC	-5.57	0.67	-6.89--4.25	-8.27	0		
TEF:TransectLUDC	-5.4	0.59	-6.56--4.23	-9.09	0		
SAV:TransectLUTC	-9.11	0.67	-10.43--7.8	-13.54	0		
TEF:TransectLUTC	-10.93	0.58	-12.07--9.8	-18.85	0		
SAV:TransectSUPA	-19.42	0.73	-20.85--17.98	-26.52	0		
TEF:TransectSUPA	-22.72	0.62	-23.94--21.5	-36.54	0		
SAV:TransectWUMW	-18.87	0.74	-20.31--17.42	-25.65	0		
TEF:TransectWUMW	-14.34	0.64	-15.59--13.08	-22.35	0		

g. mean wind speed

	Estimate	SE	95% CI	*t*	*P*	AICc	D^2
(Intercept)	0.01	0.01	0-0.02	1.29	0.2	-20990.03	-61.21
SAV	0.06	0.01	0.05-0.07	8.79	0		
TEF	0	0.01	-0.02-0.01	-0.63	0.53		
TransectAUMB	0.01	0.01	-0.01-0.02	0.73	0.47		
TransectCUML	0.18	0.01	0.17-0.19	34.91	0		
TransectCUMS	0.01	0	0-0.02	2.34	0.02		
TransectLUDC	0	0.01	-0.02-0.01	-0.38	0.7		
TransectLUTC	0.04	0	0.03-0.05	8.2	0		
TransectSUPA	0.01	0.01	0-0.02	2.15	0.03		
TransectWUMW	0.1	0.01	0.09-0.11	16.74	0		
SAV:TransectAUMB	0.25	0.01	0.23-0.27	25.08	0		
TEF:TransectAUMB	0.09	0.01	0.08-0.11	10.56	0		
SAV:TransectCUML	0.03	0.01	0.01-0.04	3.51	0		
SAV:TransectCUMS	0.15	0.01	0.13-0.16	19.95	0		
SAV:TransectLUDC	0.14	0.01	0.12-0.16	14.45	0		
TEF:TransectLUDC	0.04	0.01	0.02-0.06	4.69	0		
SAV:TransectLUTC	0.09	0.01	0.07-0.1	10.48	0		
SAV:TransectSUPA	0.1	0.01	0.08-0.11	11.08	0		
SAV:TransectWUMW	0.12	0.01	0.1-0.14	13.08	0		

h. maximum soil moisture deficit

	Estimate	SE	95% CI	*t*	*P*	AICc	D^2
(Intercept)	74.08	1.93	70.29-77.87	38.3	0	218368	2.94
SAV	66.46	2.22	62.11-70.8	29.96	0		
TEF	64.33	1.95	60.51-68.15	33.04	0		
TransectAUMB	5.58	2.39	0.89-10.26	2.33	0.02		
TransectCUML	12.12	2.17	7.87-16.38	5.59	0		
TransectCUMS	15.14	2.84	9.58-20.7	5.34	0		
TransectLUDC	28.35	2.37	23.7-33	11.95	0		
TransectLUTC	0.35	2.4	-4.35-5.05	0.15	0.88		
TransectSUPA	68.72	2.11	64.59-72.85	32.61	0		
TransectWUMW	80.77	2.1	76.64-84.89	38.39	0		
SAV:TransectAUMB	-44.91	3.33	-51.44--38.38	-13.48	0		
TEF:TransectAUMB	-50.07	2.91	-55.76--44.37	-17.23	0		
SAV:TransectCUML	-39.48	2.95	-45.27--33.69	-13.37	0		
TEF:TransectCUML	-15.5	2.61	-20.61--10.39	-5.95	0		
SAV:TransectCUMS	-36.24	3.42	-42.94--29.54	-10.6	0		
TEF:TransectCUMS	-18.61	3.12	-24.72--12.5	-5.97	0		
SAV:TransectLUDC	-30.43	3.05	-36.41--24.45	-9.98	0		
TEF:TransectLUDC	-23.27	2.74	-28.64--17.91	-8.5	0		
SAV:TransectLUTC	-73.23	3.25	-79.61--66.85	-22.51	0		
TEF:TransectLUTC	-37.51	2.84	-43.08--31.94	-13.2	0		
SAV:TransectSUPA	-122.88	3.06	-128.88--116.88	-40.14	0		
TEF:TransectSUPA	-110.33	2.62	-115.46--105.2	-42.17	0		

SAV:TransectWUMW	-95.52	3.17	-101.73--89.32	-30.17	0
TEF:TransectWUMW	-109.89	2.87	-115.51--104.27	-38.31	0

i. mean soil moisture deficit

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	78.41	1.39	75.68-81.14	56.28	0	202314.2	5.42
SAV	75.38	1.5	72.44-78.32	50.22	0		
TEF	64.28	1.32	61.69-66.86	48.78	0		
TransectAUMB	2.8	1.62	-0.37-5.97	1.73	0.08		
TransectCUML	15.76	1.47	12.88-18.64	10.74	0		
TransectCUMS	20.42	1.92	16.66-24.19	10.63	0		
TransectLUDC	30.53	1.6	27.38-33.67	19.02	0		
TransectLUTC	-0.37	1.62	-3.55-2.81	-0.23	0.82		
TransectSUPA	68.34	1.43	65.53-71.14	47.81	0		
TransectWUMW	80.03	1.43	77.23-82.82	56.09	0		
SAV:TransectAUMB	-49.79	2.25	-54.21--45.37	-22.08	0		
TEF:TransectAUMB	-44.4	1.97	-48.25--40.55	-22.59	0		
SAV:TransectCUML	-46.24	2	-50.16--42.32	-23.13	0		
TEF:TransectCUML	-21.01	1.76	-24.47--17.55	-11.91	0		
SAV:TransectCUMS	-50.26	2.31	-54.8--45.73	-21.72	0		
TEF:TransectCUMS	-24.15	2.11	-28.29--20.01	-11.44	0		
SAV:TransectLUDC	-43.98	2.06	-48.02--39.94	-21.31	0		
TEF:TransectLUDC	-24.97	1.85	-28.6--21.33	-13.48	0		
SAV:TransectLUTC	-68.62	2.2	-72.93--64.3	-31.17	0		
TEF:TransectLUTC	-34.49	1.92	-38.25--30.72	-17.93	0		
SAV:TransectSUPA	-130.76	2.07	-134.82--126.7	-63.06	0		
TEF:TransectSUPA	-107.33	1.77	-110.81--103.85	-60.53	0		
SAV:TransectWUMW	-102.39	2.15	-106.59--98.18	-47.73	0		
TEF:TransectWUMW	-108.61	1.94	-112.42--104.79	-55.85	0		

j. rainfall (savanna only)

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	1.22	0.35	0.53-1.91	3.45	0	34218.55	0.23
TransectAUMB	-0.54	0.45	-1.42-0.34	-1.21	0.23		
TransectCUML	1.19	0.4	0.41-1.97	2.98	0		
TransectCUMS	0.75	0.39	-0.02-1.52	1.91	0.06		
TransectLUDC	0.19	0.39	-0.58-0.96	0.49	0.63		
TransectLUTC	-0.12	0.48	-1.05-0.82	-0.24	0.81		
TransectSUPA	2.8	0.43	1.95-3.65	6.46	0		
TransectWUMW	0.24	0.47	-0.67-1.15	0.51	0.61		

k. solar exposure

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	2510000	131500	2252346.53-2767848.5	19.09	0	560819.2	4.5
SAV	10460000	147700	10173931.7-10752959.7	70.86	0		
TEF	199500	129700	-54732.32-453763	1.54	0.12		
TransectAUMB	-782900	158000	-1092459.91--473240.3	-4.96	0		
TransectCUML	3200000	97810	3007927.59-3391375.4	32.71	0		
TransectCUMS	-3042000	217500	-3468020.18--2615463.7	-13.99	0		
TransectLUDC	-2118000	158000	-2427908.4--1808374.4	-13.4	0		
TransectLUTC	1424000	101700	1224484.1-1623152.9	14	0		
TransectSUPA	4099000	102400	3898742.14-4300085.1	40.04	0		
TransectWUMW	2676000	124600	2432065.71-2920525.6	21.48	0		
SAV:TransectAUMB	1545000	218100	1117167.2-1972214.9	7.08	0		
TEF:TransectAUMB	2960000	188300	2591126.73-3329168	15.72	0		
SAV:TransectCUML	1098000	163400	777587.53-1418353.5	6.72	0		
SAV:TransectCUMS	2593000	250200	2102043.59-3082971.2	10.36	0		
TEF:TransectCUMS	1798000	233300	1340918.6-2255609.8	7.71	0		
SAV:TransectLUDC	-3117000	205400	-3519151.9--2713951	-15.17	0		
TEF:TransectLUDC	695300	181900	338720.04-1051822.2	3.82	0		
SAV:TransectLUTC	-4621000	284800	-5179656.32--4063203.3	-16.23	0		
SAV:TransectSUPA	-1629000	176500	-1974954.77--1283005.4	-9.23	0		
SAV:TransectWUMW	645100	195300	262395.66-1027854.2	3.3	0		

Appendix 3.11 Model selection of linear mixed effects models testing the relationship between vegetation type and transect with daily observed micrometeorology at 32 field study sites (recorded daily over a three-year period). Vegetation types were rain forest (RF), tall eucalypt forest (TEF) and savanna (SAV). Models were repeated for each of eleven meteorological variables (response variable); temperature (a. maximum, b. mean, c. minimum), relative humidity (d. maximum, e. mean, f. minimum), mean wind speed (g.), soil moisture deficit (h. maximum, i. mean), rainfall (j.) and solar exposure (k.). The response variable for each model was site-based micrometeorology and the predictor variables were vegetation type, transect and their interaction, with 'day' included as a random effect in all models. Alternative candidate models were the full model without the interaction term (model_1), vegetation only (model_2), transect only (model_3) and the null model (model_null). Model selection was based on Akaike Information Criterion (AICc) and all tables are ranked by AICc. Delta AICc, Akaike weights (*wi*) and percent explained deviance (D^2) relative to the null model are also reported.

a. maximum temperature

	AICc	**delta_AICc**	***wi***	**D^2**
Temp_max	106936.9	0	1	24.77
Temp_max_1	112678.4	5741.5	0	20.7
Temp_max_2	117772.3	10835.45	0	17.11
Temp_max_3	139850.8	32913.91	0	1.58
Temp_max_null	142075.3	35138.45	0	0

b. mean temperature

	AICc	**delta_AICc**	***wi***	**D^2**
Temp_mean	70080.3	0	1	38.85
Temp_mean_1	78962.99	8882.69	0	31.07
Temp_mean_2	91503.57	21423.27	0	20.11
Temp_mean_3	109211.53	39131.22	0	4.66
Temp_mean_null	114529.53	44449.23	0	0

c. minimum temperature

	AICc	**delta_AICc**	***wi***	**D^2**
Temp_min	85461.02	0	1	21.53
Temp_min_1	90801.57	5340.55	0	16.6
Temp_min_3	100946.31	15485.28	0	7.28
Temp_min_2	101026.11	15565.09	0	7.19
Temp_min_null	108851.82	23390.8	0	0

d. maximum relative humidity

	AICc	**delta_AICc**	***wi***	**D^2**
RH_max	139285.6	0	1	2.8
RH_max_1	140323.5	1037.83	0	2.06
RH_max_2	141378.1	2092.52	0	1.31

RH_max_3	142320.8	3035.11	0	0.66
RH_max_null	143252.1	3966.48	0	0

e. mean relative humidity

	AICc	**delta_AICc**	***wi***	**D^2**
RH_mean	154682.3	0	1	10.15
RH_mean_1	157002.8	2320.48	0	8.79
RH_mean_2	158032.1	3349.8	0	8.18
RH_mean_3	171634.4	16952.13	0	0.28
RH_mean_null	172107.9	17425.56	0	0

f. minimum relative humidity

	AICc	**delta_AICc**	***wi***	**D^2**
RH_min	184611.2	0	1	10.21
RH_min_1	187679	3067.82	0	8.71
RH_min_2	188966.8	4355.58	0	8.07
RH_min_3	204949.1	20337.89	0	0.3
RH_min_null	205556.3	20945.06	0	0

g. mean wind speed

	AICc	**delta_AICc**	***wi***	**D^2**
Wind_Speed_mean	-20990.03	0	1	-61.21
Wind_Speed_mean_1	-20062.87	927.16	0	-53.96
Wind_Speed_mean_2	-17645.44	3344.59	0	-35.33
Wind_Speed_mean_3	-15292.72	5697.3	0	-17.37
Wind_Speed_mean_null	-13040.57	7949.45	0	0

h. maximum soil moisture deficit

	AICc	**delta_AICc**	***wi***	**D^2**
SMD_max	218368	0	1	2.94
SMD_max_1	222068.7	3700.7	0	1.28
SMD_max_3	222568.9	4200.95	0	1.06
SMD_max_2	224505.2	6137.19	0	0.2
SMD_max_null	224939.7	6571.74	0	0

i. mean soil moisture deficit

	AICc	**delta_AICc**	***wi***	**D^2**
SMD_mean	202314.1	0	1	5.42
SMD_mean_1	209260.6	6946.42	0	2.16
SMD_mean_3	210123.9	7809.75	0	1.76
SMD_mean_2	213142.8	10828.62	0	0.34
SMD_mean_null	213868.2	11554.01	0	0

j. rainfall (savanna only)

	AICc	**delta_AICc**	***wi***	**D^2**
Rainfall_3	34218.55	0	1	0.23
Rainfall_null	34283.63	65.08	0	0

k. solar exposure

	AICc	**delta_AICc**	***wi***	**D^2**
Solar	560819.2	0	1	4.5
Solar_1	562683.2	1864.01	0	4.18
Solar_2	570002	9182.83	0	2.93
Solar_3	583456.5	22637.36	0	0.64
Solar_null	587217.2	26397.98	0	0

Appendix 3.12 Linear mixed effects models testing the relationship between vegetation type and elevation with daily observed micrometeorological conditions at 32 field study sites (recorded daily over a three-year period). Vegetation types were rain forest (RF), tall eucalypt forest (TEF) and savanna (SAV). The response variable for each model was site-based micrometeorology and the predictor variables were vegetation type, elevation and their interaction, with 'day' included as a random effect. Models were repeated for each of eleven micrometeorological variables (response variable); temperature (a. maximum, b. mean, c. minimum), relative humidity (d. maximum, e. mean, f. minimum), mean wind speed (g.), soil moisture deficit (h. maximum, i. mean), rainfall (j.) and solar exposure (k.). Coefficient estimate, standard error (SE), 95% confidence intervals (95% CI), t values (*t*), probability (*P*), Akaike Information Criterion (AICc) and percent explained deviance (D^2) relative to the null model are reported.

a. maximum temperature

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	26.33	0.14	26.05-26.61	185.5	0	111376.3	21.62
SAV	2.42	0.18	2.08-2.77	13.76	0		
TEF	2.45	0.14	2.17-2.73	17.24	0		
Elevation	-0.01	0	-0.01--0.01	-58	0		
SAV:Elevation	0	0	0-0	18.79	0		
TEF:Elevation	0	0	0-0	4.08	0		

b. mean temperature

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	22.42	0.09	22.24-22.61	236.5	0	74340.04	35.1
SAV	2.27	0.09	2.1-2.44	26.26	0		
TEF	1.33	0.07	1.19-1.46	19.04	0		
Elevation	-0.01	0	-0.01--0.01	-100.2	0		
SAV:Elevation	0	0	0-0	6.39	0		
TEF:Elevation	0	0	0-0	6.33	0		

c. minimum temperature

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	20.36	0.11	20.13-20.58	180	0	92081.32	15.42
SAV	1.17	0.12	0.93-1.41	9.65	0		
TEF	0.02	0.1	-0.18-0.21	0.16	0.88		
Elevation	-0.01	0	-0.01-0	-70.01	0		
SAV:Elevation	0	0	0-0	-1.06	0.29		
TEF:Elevation	0	0	0-0	12.97	0		

d. maximum relative humidity

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	100.2	0.3	99.64-100.83	330.3	0	141361.9	1.33

SAV	-4	0.42	-4.81--3.18	-9.6	0		
TEF	-1.42	0.35	-2.09--0.74	-4.1	0		
Elevation	0	0	0-0	-4.4	0		
SAV:Elevation	0	0	0-0	2.2	0.03		
TEF:Elevation	0	0	0-0	2.4	0.02		

e. mean relative humidity

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	94.01	0.48	93.07-94.94	197.3	0	157947.6	8.23
SAV	-10.46	0.57	-11.58--9.34	-18.35	0		
TEF	-5.96	0.47	-6.89--5.03	-12.61	0		
Elevation	0	0	0-0	-1.86	0.06		
SAV:Elevation	0	0	0-0	-5.86	0		
TEF:Elevation	0	0	0-0	3.88	0		

f. minimum relative humidity

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	74.22	0.87	72.52-75.92	85.66	0	188774.7	8.17
SAV	-16.43	1.07	-18.52--14.34	-15.39	0		
TEF	-9.92	0.89	-11.65--8.18	-11.2	0		
Elevation	0.01	0	0-0.01	8.38	0		
SAV:Elevation	-0.01	0	-0.02--0.01	-11.46	0		
TEF:Elevation	0	0	0-0	-1.56	0.12		

g. mean wind speed

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	-0.01	0.01	-0.04-0.02	-0.53	0.59	-17778.62	-36.39
SAV	0.09	0.02	0.05-0.12	4.88	0		
TEF	0.05	0.02	0.02-0.09	3.21	0		
Elevation	0	0	0-0	0.8	0.43		
SAV:Elevation	0	0	0-0	7.17	0		
TEF:Elevation	0	0	0-0	-0.27	0.79		

h. maximum soil moisture deficit

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	66.87	3.49	60.03-73.71	19.18	0	223824.8	0.5
SAV	96.77	5.05	86.87-106.67	19.16	0		
TEF	110.13	4.2	101.89-118.37	26.21	0		
Elevation	0.04	0	0.04-0.05	14.05	0		
SAV:Elevation	-0.1	0.01	-0.11--0.09	-17.55	0		
TEF:Elevation	-0.09	0	-0.1--0.09	-23.13	0		

i. mean soil moisture deficit

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	76.18	2.66	70.97-81.39	28.67	0	212071.8	0.84
SAV	94.02	3.8	86.57-101.47	24.73	0		
TEF	104.19	3.16	97.99-110.39	32.94	0		
Elevation	0.04	0	0.04-0.04	16.96	0		
SAV:Elevation	-0.09	0	-0.1--0.08	-21.92	0		
TEF:Elevation	-0.09	0	-0.09--0.08	-28.77	0		

j. rainfall (savanna sites only)

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	2.94	0.62	1.73-4.16	4.75	0	34282.55	0.01
Elevation	0	0	0-0	-1.76	0.08		

k. solar exposure

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	1610000	342200	938927.3-2280472	4.7	0	569771.9	2.97
SAV	7209000	443200	6339962.33-8078349	16.27	0		
TEF	1561000	385200	805773.51-2316333	4.05	0		
Elevation	-635.9	344.7	-1311.59-39.78	-1.85	0.07		
SAV:Elevation	5987	492.1	5021.93-6951.36	12.17	0		
TEF:Elevation	930.4	396.1	153.92-1706.88	2.35	0.02		

Appendix 3.13 Model selection of linear mixed effects models testing the relationship between vegetation type and elevation with daily observed micrometeorological conditions at 32 field study sites (recorded daily over a three-year period). Vegetation types were rain forest (RF), tall eucalypt forest (TEF) and savanna (SAV). Models were repeated for each of eleven micrometeorological variables (response variable); temperature (a. maximum, b. mean, c. minimum), relative humidity (d. maximum, e. mean, f. minimum), mean wind speed (g.), soil moisture deficit (h. maximum, i. mean), rainfall (j.) and solar exposure (k.). The response variable for each model was site-based micrometeorology and the predictor variables were vegetation type, elevation and their interaction, with 'day' included as a random effect in all models. Alternative candidate models were the full model without the interaction term (model_1), vegetation only (model_2), elevation only (model_3) and the null model (model_null). Model selection was based on Akaike Information Criterion (AICc) and all tables are ranked by AICc. Delta AICc, Akaike weights (*wi*) and percent explained deviance (D^2) relative to the null model are also reported.

a. maximum temperature

	AICc	**delta_AICc**	***wi***	**D^2**
Temp_max	111376.3	0	1	21.62
Temp_max_1	111739.4	363.14	0	21.36
Temp_max_2	117772.3	6396.02	0	17.11
Temp_max_3	130870.9	19494.62	0	7.89
Temp_max_null	142075.3	30699.02	0	0

b. mean temperature

	AICc	**delta_AICc**	***wi***	**D^2**
Temp_mean	74340.04	0	1	35.1
Temp_mean_1	74393.17	53.13	0	35.05
Temp_mean_2	91503.57	17163.53	0	20.11
Temp_mean_3	95057.44	20717.4	0	17
Temp_mean_null	114529.53	40189.49	0	0

c. minimum temperature

	AICc	**delta_AICc**	***wi***	**D^2**
Temp_min	92081.32	0	1	15.42
Temp_min_1	92294.68	213.36	0	15.22
Temp_min_3	96707.59	4626.27	0	11.16
Temp_min_2	101026.11	8944.79	0	7.19
Temp_min_null	108851.82	16770.5	0	0

d. maximum relative humidity

	AICc	**delta_AICc**	***wi***	**D^2**
RH_max	141361.9	0	0.85	1.33
RH_max_1	141365.4	3.46	0.15	1.32

RH_max_2	141378.1	16.22	0	1.31
RH_max_3	143050.8	1688.84	0	0.14
RH_max_null	143252.1	1890.18	0	0

e. mean relative humidity

	AICc	**delta_AICc**	***wi***	**D^2**
RH_mean	157947.6	0	1	8.23
RH_mean_1	158031.3	83.63	0	8.18
RH_mean_2	158032.1	84.46	0	8.18
RH_mean_3	170219.4	12271.7	0	1.1
RH_mean_null	172107.9	14160.22	0	0

f. minimum relative humidity

	AICc	**delta_AICc**	***wi***	**D^2**
RH_min	188774.7	0	1	8.17
RH_min_1	188917.8	143.08	0	8.1
RH_min_2	188966.8	192.13	0	8.07
RH_min_3	202801.1	14026.47	0	1.34
RH_min_null	205556.3	16781.6	0	0

g. mean wind speed

	AICc	**delta_AICc**	***wi***	**D^2**
Wind_Speed_mean	-17778.62	0	1	-36.39
Wind_Speed_mean_1	-17684.89	93.73	0	-35.64
Wind_Speed_mean_2	-17645.44	133.19	0	-35.33
Wind_Speed_mean_3	-13356.59	4422.04	0	-2.44
Wind_Speed_mean_null	-13040.57	4738.05	0	0

h. maximum soil moisture deficit

	AICc	**delta_AICc**	***wi***	**D^2**
SMD_max	223824.8	0	1	0.5
SMD_max_1	224411.8	587.02	0	0.24
SMD_max_2	224505.2	680.36	0	0.2
SMD_max_3	224814.5	989.73	0	0.06
SMD_max_null	224939.7	1114.91	0	0

i. mean soil moisture deficit

	AICc	**delta_AICc**	***wi***	**D^2**
SMD_mean	212071.8	0	1	0.84
SMD_mean_1	212977.3	905.42	0	0.42
SMD_mean_2	213142.8	1070.93	0	0.34
SMD_mean_3	213586	1514.14	0	0.13
SMD_mean_null	213868.2	1796.31	0	0

j. rainfall

	AICc	**delta_AICc**	***wi***	**D^2**
Rain_mm_SAV_3	34282.55	0	0.63	0.01
Rain_mm_SAV_null	34283.63	1.09	0.37	0

k. solar exposure

	AICc	**delta_AICc**	***wi***	**D^2**
Solar	569771.9	0	1	2.97
Solar_1	569958.3	186.47	0	2.94
Solar_2	570002	230.15	0	2.93
Solar_3	586389.9	16618.08	0	0.14
Solar_null	587217.2	17445.3	0	0

Appendix 3.14 Results of linear mixed-effects models examining the relationship between monthly microclimate variables (as recorded over a three year period) and monthly modelled climate (ESOCLIM) for each of 32 study sites within three vegetation types (rain forest, tall eucalypt forest, savanna). Nine climate variables in separate analyses were temperature (mean, maximum and minimum), relative humidity (mean), rain days, rainfall, wind speed (mean), wind run and solar exposure (independent, rainfall dependent). The response variable was average *in situ* microclimate, and the explanatory variables were ESOCLIM climate of the corresponding month, vegetation type, and their interaction. Models were repeated using different random effects, with 'month', 'transect' and 'elevation' used alternately in separate models. Coefficient estimate, standard error (SE), 95% confidence intervals (95% CI), t values (t), probability (P), Akaike Information Criterion (AICc) and percent explained deviance (D^2) relative to the null model are reported.

a. maximum temperature

i. month as random effect

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	-0.7	1.21	-3.15-1.68	-0.58	0.57	1221.31	34.94
ESOCLIM	0.9	0.05	0.79-1	17.47	0.00		
SAV	12.15	1.37	9.46-14.83	8.89	0.00		
TEF	5.88	1.13	3.66-8.1	5.21	0.00		
ESOCLIM:SAV	-0.27	0.06	-0.38--0.16	-4.81	0.00		
ESOCLIM:TEF	-0.12	0.05	-0.22--0.03	-2.57	0.01		

ii. transect as random effect

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	-0.37	0.96	-2.26-1.51	-0.39	0.70	1217.84	39.63
ESOCLIM	0.88	0.04	0.8-0.96	22.01	0.00		
SAV	12.14	1.37	9.46-14.82	8.89	0.00		
TEF	6.1	1.13	3.87-8.32	5.37	0.00		
ESOCLIM:SAV	-0.27	0.06	-0.38--0.16	-4.74	0.00		
ESOCLIM:TEF	-0.13	0.05	-0.22--0.03	-2.70	0.01		

iii. elevation as random effect

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	2.32	0.84	0.62-4.03	2.76	0.01	1079.8	40.96
ESOCLIM	0.84	0.03	0.78-0.9	26.78	0.00		
SAV	9.22	1.24	6.73-11.67	7.45	0.00		
TEF	3	0.98	1-5.02	3.06	0.00		
ESOCLIM:SAV	-0.22	0.04	-0.3--0.13	-4.91	0.00		
ESOCLIM:TEF	-0.1	0.04	-0.17--0.03	-2.66	0.01		

b. mean temperature

i. month as random effect

	Estimate	SE	95% CI	*t*	*P*	AICc	D^2
(Intercept)	-0.19	0.6	-1.46-1.02	-0.31	0.77	710.42	52.96
ESOCLIM	0.93	0.03	0.86-0.99	29.46	0.00		
SAV	5.59	0.57	4.47-6.71	9.79	0.00		
TEF	3.66	0.48	2.7-4.61	7.55	0.00		
ESOCLIM:SAV	-0.15	0.03	-0.2--0.09	-4.99	0.00		
ESOCLIM:TEF	-0.11	0.03	-0.16--0.06	-4.23	0.00		

ii. transect as random effect

	Estimate	SE	95% CI	*t*	*P*	AICc	D^2
(Intercept)	0.7	0.46	-0.22-1.61	1.50	0.13	787.45	57.29
ESOCLIM	0.88	0.02	0.83-0.93	36.33	0.00		
SAV	5.7	0.65	4.42-6.98	8.78	0.00		
TEF	3.71	0.55	2.62-4.79	6.71	0.00		
ESOCLIM:SAV	-0.15	0.03	-0.22--0.08	-4.47	0.00		
ESOCLIM:TEF	-0.11	0.03	-0.17--0.05	-3.77	0.00		

iii. elevation as random effect

	Estimate	SE	95% CI	*t*	*P*	AICc	D^2
(Intercept)	1.16	0.41	0.36-1.97	2.87	0.01	656.7	63.42
ESOCLIM	0.87	0.02	0.83-0.91	44.64	0.00		
SAV	5.32	0.58	4.18-6.46	9.22	0.00		
TEF	3.28	0.48	2.32-4.24	6.78	0.00		
ESOCLIM:SAV	-0.14	0.03	-0.2--0.09	-5.33	0.00		
ESOCLIM:TEF	-0.11	0.02	-0.15--0.06	-4.62	0.00		

c. minimum temperature

i. month as random effect

	Estimate	SE	95% CI	*t*	*P*	AICc	D^2
(Intercept)	1.67	0.61	0.37-2.88	2.73	0.01	905.1	31.81
ESOCLIM	0.96	0.04	0.88-1.05	22.92	0.00		
SAV	3.14	0.57	2.03-4.26	5.54	0.00		
TEF	2.64	0.49	1.67-3.61	5.35	0.00		
ESOCLIM:SAV	-0.14	0.04	-0.22--0.06	-3.64	0.00		
ESOCLIM:TEF	-0.11	0.03	-0.18--0.05	-3.28	0.00		

ii. transect as random effect

	Estimate	SE	95% CI	*t*	*P*	AICc	D^2
(Intercept)	2.34	0.44	1.48-3.21	5.35	0.00	893.34	50.57
ESOCLIM	0.92	0.03	0.86-0.97	32.02	0.00		
SAV	3.2	0.56	2.09-4.31	5.67	0.00		

TEF	2.61	0.49	1.64-3.57	5.30	0.00		
ESOCLIM:SAV	-0.14	0.04	-0.22--0.07	-3.71	0.00		
ESOCLIM:TEF	-0.11	0.03	-0.18--0.04	-3.24	0.00		

iii. elevation as random effect

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	2.29	0.39	1.53-3.05	5.93	0.00	766.2	57.64
ESOCLIM	0.92	0.02	0.87-0.96	39.98	0.00		
SAV	3.38	0.55	2.3-4.46	6.17	0.00		
TEF	2.74	0.45	1.86-3.62	6.12	0.00		
ESOCLIM:SAV	-0.15	0.03	-0.21--0.09	-4.95	0.00		
ESOCLIM:TEF	-0.12	0.03	-0.17--0.07	-4.37	0.00		

d. mean relative humidity

i. month as random effect

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	60.96	7.4	46.26-75.51	8.23	0.00	1819.24	24.17
ESOCLIM	0.41	0.09	0.23-0.6	4.39	0.00		
SAV	-57.81	6.09	-69.77--45.84	-9.49	0.00		
TEF	-30.95	5.29	-41.35--20.54	-5.85	0.00		
ESOCLIM:SAV	0.58	0.08	0.43-0.74	7.51	0.00		
ESOCLIM:TEF	0.34	0.07	0.21-0.48	5.13	0.00		

ii. transect as random effect

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	64.25	5.8	52.85-75.66	11.07	0.00	1989.5	20.78
ESOCLIM	0.37	0.07	0.22-0.51	5.02	0.00		
SAV	-58.68	7.96	-74.33--43.03	-7.37	0.00		
TEF	-31.28	6.92	-44.88--17.67	-4.52	0.00		
ESOCLIM:SAV	0.59	0.1	0.39-0.79	5.85	0.00		
ESOCLIM:TEF	0.35	0.09	0.18-0.52	3.97	0.00		

iii. elevation as random effect

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	63.39	5.35	52.88-73.91	11.86	0.00	1948.16	15.78
ESOCLIM	0.37	0.07	0.24-0.51	5.58	0.00		
SAV	-55.85	7.39	-70.4--41.32	-7.56	0.00		
TEF	-30.2	6.42	-42.83--17.59	-4.71	0.00		
ESOCLIM:SAV	0.56	0.09	0.38-0.75	6.01	0.00		
ESOCLIM:TEF	0.34	0.08	0.18-0.5	4.23	0.00		

e. wind run

i. month as random effect

	Estimate	SE	95% CI	*t*	*P*	AICc	D^2
(Intercept)	-3.46	45.12	-94.86-86.09	-0.08	0.94	2818.68	4.98
ESOCLIM	0.03	0.32	-0.6-0.67	0.09	0.93		
SAV	-80.16	50.77	-179.92-18.94	-1.58	0.12		
TEF	-0.72	48.57	-96.15-94.13	-0.01	0.99		
ESOCLIM:SAV	0.92	0.36	0.22-1.63	2.57	0.01		
ESOCLIM:TEF	0.1	0.34	-0.57-0.78	0.31	0.76		

ii. transect as random effect

	Estimate	SE	95% CI	*t*	*P*	AICc	D^2
(Intercept)	16.14	39.94	-62.42-94.69	0.40	0.69	2754.97	5.57
ESOCLIM	-0.08	0.28	-0.63-0.47	-0.30	0.76		
SAV	-81.01	44.75	-169.01-6.98	-1.81	0.07		
TEF	-5.65	42.74	-89.69-78.39	-0.13	0.90		
ESOCLIM:SAV	0.9	0.32	0.28-1.52	2.85	0.01		
ESOCLIM:TEF	0.12	0.3	-0.48-0.71	0.39	0.70		

iii. elevation as random effect

	Estimate	SE	95% CI	*t*	*P*	AICc	D^2
(Intercept)	6.79	30.11	-52.43-66.01	0.23	0.82	2617.82	2.45
ESOCLIM	0.01	0.21	-0.41-0.43	0.06	0.96		
SAV	-81.25	35.11	-150.29--12.22	-2.31	0.02		
TEF	2.1	32.37	-61.57-65.74	0.07	0.95		
ESOCLIM:SAV	0.88	0.24	0.4-1.35	3.61	0.00		
ESOCLIM:TEF	0.03	0.23	-0.43-0.48	0.11	0.91		

f. mean wind speed

i. month as random effect

	Estimate	SE	95% CI	*t*	*P*	AICc	D^2
(Intercept)	-0.07	1.4	-2.83-2.69	-0.05	0.96	899.58	14.22
ESOCLIM	0.01	0.14	-0.27-0.29	0.07	0.95		
SAV	-2.26	1.62	-5.44-0.92	-1.40	0.16		
TEF	0.13	1.53	-2.87-3.14	0.09	0.93		
ESOCLIM:SAV	0.44	0.16	0.12-0.76	2.69	0.01		
ESOCLIM:TEF	0.05	0.15	-0.26-0.35	0.30	0.77		

ii. transect as random effect

	Estimate	SE	95% CI	*t*	*P*	AICc	D^2
(Intercept)	0.31	1.23	-2.11-2.73	0.25	0.80	830.76	16.94
ESOCLIM	-0.01	0.12	-0.25-0.23	-0.11	0.91		
SAV	-2.26	1.4	-5.01-0.49	-1.62	0.11		

TEF	0.05	1.32	-2.55-2.65	0.04	0.97		
ESOCLIM:SAV	0.42	0.14	0.15-0.7	3.00	0.00		
ESOCLIM:TEF	0.04	0.13	-0.22-0.3	0.31	0.76		

iii. elevation as random effect

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	0.27	0.92	-1.53-2.07	0.30	0.77	691.31	9.67
ESOCLIM	0.01	0.09	-0.17-0.18	0.10	0.92		
SAV	-2.28	1.09	-4.43--0.13	-2.09	0.04		
TEF	-0.04	0.98	-1.96-1.88	-0.04	0.97		
ESOCLIM:SAV	0.41	0.1	0.2-0.61	3.95	0.00		
ESOCLIM:TEF	0.03	0.1	-0.16-0.22	0.29	0.78		

g. rain days

i. month as random effect

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	11.81	2.46	6.89-16.66	4.81	0.00	2290.83	0.52
ESOCLIM	0.17	0.17	-0.17-0.52	0.98	0.33		
SAV	2.04	2.09	-2.08-6.15	0.97	0.33		
TEF	-0.3	1.88	-3.99-3.39	-0.16	0.87		
ESOCLIM:SAV	-0.31	0.16	-0.62--0.01	-2.01	0.05		
ESOCLIM:TEF	-0.05	0.14	-0.32-0.23	-0.33	0.74		

ii. transect as random effect

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	12.61	1.89	8.88-16.35	6.67	0.00	2330.26	0.52
ESOCLIM	0.14	0.12	-0.11-0.38	1.10	0.27		
SAV	1.19	2.24	-3.21-5.6	0.53	0.60		
TEF	-0.84	2.02	-4.8-3.12	-0.42	0.68		
ESOCLIM:SAV	-0.28	0.17	-0.61-0.05	-1.65	0.10		
ESOCLIM:TEF	-0.03	0.15	-0.32-0.26	-0.23	0.82		

iii. elevation as random effect

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	10.27	1.93	6.32-14.12	5.32	0.00	2338.77	0.33
ESOCLIM	0.21	0.12	-0.04-0.45	1.67	0.10		
SAV	4.01	2.59	-1.11-9.27	1.55	0.13		
TEF	2.25	2.26	-2.31-6.91	0.99	0.34		
ESOCLIM:SAV	-0.39	0.17	-0.71--0.06	-2.32	0.02		
ESOCLIM:TEF	-0.12	0.15	-0.41-0.17	-0.82	0.42		

h. rainfall

i. month as random effect

	Estimate	SE	95% CI	*t*	*P*	AICc	D^2
(Intercept)	191.72	23.49	145.05-238.41	8.16	0.00	4624.14	0.37
ESOCLIM	0	0.09	-0.18-0.19	0.04	0.97		
SAV	-6.02	27.22	-59.52-47.46	-0.22	0.83		
TEF	7.25	24.19	-40.3-54.8	0.30	0.76		
ESOCLIM:SAV	-0.28	0.13	-0.54--0.02	-2.16	0.03		
ESOCLIM:TEF	-0.02	0.1	-0.22-0.18	-0.23	0.82		

ii. transect as random effect

	Estimate	SE	95% CI	*t*	*P*	AICc	D^2
(Intercept)	195.48	22.27	151.66-239.87	8.78	0.00	4626.55	0.41
ESOCLIM	0.01	0.08	-0.15-0.17	0.14	0.89		
SAV	-10.86	27.52	-64.97-43.31	-0.40	0.69		
TEF	3.32	24.45	-44.77-51.45	0.14	0.89		
ESOCLIM:SAV	-0.28	0.13	-0.54--0.02	-2.16	0.03		
ESOCLIM:TEF	-0.03	0.1	-0.23-0.17	-0.29	0.77		

iii. elevation as random effect

	Estimate	SE	95% CI	*t*	*P*	AICc	D^2
(Intercept)	189.94	21.48	146.5-232.19	8.84	0.00	4631.74	0.34
ESOCLIM	0.01	0.08	-0.16-0.17	0.08	0.94		
SAV	-4.4	28.88	-61.17-53.74	-0.15	0.88		
TEF	9.46	25.55	-40.84-61.13	0.37	0.71		
ESOCLIM:SAV	-0.28	0.13	-0.54--0.02	-2.14	0.03		
ESOCLIM:TEF	-0.02	0.1	-0.23-0.18	-0.24	0.81		

i. solar exposure

i. month as random effect

	Estimate	SE	95% CI	*t*	*P*	AICc	D^2
(Intercept)	-3408000	2792000	-8936900.11-2083386.3	-1.22	0.22	9947.69	3.88
ESOCLIM	264500	140600	-12019.54-542916.9	1.88	0.06		
SAV	2393000	3291000	-4079828.1-8864843.8	0.73	0.47		
TEF	-1393000	3027000	-7346320.07-4559756.5	-0.46	0.65		
ESOCLIM:SAV	460800	165300	135708.41-785969.9	2.79	0.01		
ESOCLIM:TEF	183600	152400	-116019.74-483203	1.21	0.23		

ii. transect as random effect

	Estimate	SE	95% CI	*t*	*P*	AICc	D^2
(Intercept)	-1698000	2124000	-5876867.54-2485618.4	-0.80	0.43	9777.86	5.16
ESOCLIM	248200	100500	50560.31-445850.3	2.47	0.01		
SAV	990000	2392000	-3712215.54-5693394.5	0.41	0.68		

TEF	-2523000	2201000	-6850447.96-1804615.8	-1.15	0.25		
ESOCLIM:SAV	459200	119900	223382.92-695100.8	3.83	0.00		
ESOCLIM:TEF	176600	110500	-40692.2-393974	1.60	0.11		

iii. elevation as random effect

	Estimate	**SE**	**95% CI**	***t***	***P***	**AICc**	**D^2**
(Intercept)	272500	1653000	-2979808.26-3536542.6	0.17	0.87	9643.6	2.91
ESOCLIM	254000	72540	111349.38-396690.5	3.50	0.00		
SAV	-1609000	2143000	-5856671.56-2605777.4	-0.75	0.45		
TEF	-5119000	1669000	-8404737.91--1823650.3	-3.07	0.00		
ESOCLIM:SAV	473200	86660	302770.4-643635.1	5.46	0.00		
ESOCLIM:TEF	170600	79780	13725.65-327527.8	2.14	0.03		

Appendix 3.15 Model selection of linear mixed effects models examining the relationship between monthly microclimate variables (as recorded over a three year period) and monthly modelled climate (ESOCLIM) for each of 32 study sites within three vegetation types (rain forest, tall eucalypt forest, savanna). Nine climate variables were analysed in separate analyses; temperature (mean, maximum and minimum), relative humidity (mean), rain days, rainfall, wind speed (mean), wind run and solar exposure (independent, rainfall dependent). The response variable was average *in situ* microclimate and the explanatory variables were ESOCLIM climate of the corresponding month, vegetation type, and their interaction with 'month', 'transect' and 'elevation' used as a random effect in separate models. Alternative candidate models were the full model without the interaction term (model_1), ESOCLIM data only (model_2), vegetation type only (model_3) and the null model (model_null). Model selection was based on Akaike Information Criterion (AICc) and all tables are ranked by AICc. Delta AICc, Akaike weights (*wi*) and percent explained deviance (D^2) relative to the null model are also reported.

a. maximum temperature

i. month as random effect

	AICc	**delta_AICc**	***wi***	**D^2**
Temp_max	1221.31	0	1	34.94
Temp_max_1	1239.62	18.31	0	33.72
Temp_max_3	1424.31	203	0	23.64
Temp_max_2	1685.29	463.98	0	9.44
Temp_max_null	1858.03	636.72	0	0

ii. transect as random effect

	AICc	**delta_AICc**	***wi***	**D^2**
Temp_max	1217.84	0	1	39.63
Temp_max_1	1235.49	17.64	0	38.53
Temp_max_2	1696.71	478.86	0	15.15
Temp_max_3	1782.41	564.56	0	10.95
Temp_max_null	1996.19	778.34	0	0

iii. elevation as random effect

	AICc	**delta_AICc**	***wi***	**D^2**
Temp_max	1079.8	0	1	40.96
Temp_max_1	1099.05	19.25	0	39.66
Temp_max_2	1117.25	37.44	0	38.42
Temp_max_3	1775.5	695.69	0	1.98
Temp_max_null	1807.12	727.32	0	0

b. mean temperature

i. month as random effect

	AICc	delta_AICc	*wi*	D^2
Temp_mean	710.42	0	1	52.96
Temp_mean_1	732.66	22.25	0	51.17
Temp_mean_3	1138.2	427.78	0	23.54
Temp_mean_2	1174.42	464	0	20.94
Temp_mean_null	1481.33	770.91	0	0

ii. transect as random effect

	AICc	delta_AICc	*wi*	D^2
Temp_mean	787.45	0	1	57.29
Temp_mean_1	804.58	17.12	0	56.11
Temp_mean_2	1207.3	419.84	0	33.57
Temp_mean_3	1721.44	933.98	0	5.2
Temp_mean_null	1811.23	1023.78	0	0

iii. elevation as random effect

	AICc	delta_AICc	*wi*	D^2
Temp_mean	656.7	0	1	63.42
Temp_mean_1	682.78	26.08	0	61.69
Temp_mean_2	730.85	74.15	0	58.71
Temp_mean_3	1726.2	1069.5	0	1.96
Temp_mean_null	1756.38	1099.68	0	0

c. minimum temperature

i. month as random effect

	AICc	delta_AICc	*wi*	D^2
Temp_min	905.1	0	0.99	31.81
Temp_min_1	915.62	10.52	0.01	30.68
Temp_min_2	1016.7	111.6	0	22.61
Temp_min_3	1197.61	292.51	0	8.88
Temp_min_null	1309.25	404.15	0	0

ii. transect as random effect

	AICc	delta_AICc	*wi*	D^2
Temp_min	893.34	0	1	50.57
Temp_min_1	904.1	10.76	0	49.73
Temp_min_2	1006.93	113.59	0	43.7
Temp_min_3	1759.08	865.74	0	1.42
Temp_min_null	1780.22	886.88	0	0

iii. elevation as random effect

	AICc	delta_AICc	*wi*	D^2
Temp_min	766.2	0	1	57.64
Temp_min_1	788.23	22.03	0	56.16
Temp_min_2	808.69	42.48	0	54.77
Temp_min_3	1766.72	1000.52	0	0.76
Temp_min_null	1776.05	1009.85	0	0

d. mean relative humidity

i. month as random effect

	AICc	delta_AICc	*wi*	D^2
RH_mean	1819.24	0	1	24.17
RH_mean_1	1867.97	48.73	0	21.94
RH_mean_3	1923.49	104.26	0	19.52
RH_mean_2	2316.36	497.12	0	2.91
RH_mean_null	2383.52	564.28	0	0

ii. transect as random effect

	AICc	delta_AICc	*wi*	D^2
RH_mean	1989.5	0	1	20.78
RH_mean_1	2018.34	28.84	0	19.46
RH_mean_3	2259.87	270.36	0	9.68
RH_mean_2	2360.34	370.84	0	5.56
RH_mean_null	2496.86	507.35	0	0

iii. elevation as random effect

	AICc	delta_AICc	*wi*	D^2
RH_mean	1948.16	0	1	15.78
RH_mean_1	1978.96	30.81	0	14.25
RH_mean_2	2029.4	81.24	0	11.87
RH_mean_3	2250.87	302.71	0	2.31
RH_mean_null	2299.68	351.52	0	0

e. wind run

i. month as random effect

	AICc	delta_AICc	*wi*	D^2
Wind_Run	2818.68	0	1	4.98
Wind_Run_1	2830.39	11.71	0	4.44
Wind_Run_3	2842.85	24.18	0	3.95
Wind_Run_2	2948.27	129.59	0	0.3
Wind_Run_null	2955.1	136.43	0	0

ii. transect as random effect

	AICc	delta_AICc	*wi*	D^2
Wind_Run	2754.97	0	1	5.57
Wind_Run_1	2770.04	15.06	0	4.9
Wind_Run_3	2776.78	21.81	0	4.6
Wind_Run_2	2903.39	148.42	0	0.16
Wind_Run_null	2906.01	151.04	0	0

iii. elevation as random effect

	AICc	delta_AICc	*wi*	D^2
Wind_Run	2617.82	0	1	2.45
Wind_Run_1	2647.21	29.39	0	1.19
Wind_Run_2	2655.47	37.65	0	0.72
Wind_Run_3	2664.19	46.37	0	0.47
Wind_Run_null	2672.68	54.86	0	0

f. mean wind speed

i. month as random effect

	AICc	delta_AICc	*wi*	D^2
Wind_Speed	899.58	0	1	14.22
Wind_Speed_1	911.73	12.15	0	12.63
Wind_Speed_3	923.31	23.73	0	11.3
Wind_Speed_2	1028.16	128.58	0	0.92
Wind_Speed_null	1035.56	135.98	0	0

ii. transect as random effect

	AICc	delta_AICc	*wi*	D^2
Wind_Speed	830.76	0	1	16.94
Wind_Speed_1	847.18	16.41	0	14.84
Wind_Speed_3	857.23	26.47	0	13.6
Wind_Speed_2	981.07	150.31	0	0.76
Wind_Speed_null	986.47	155.71	0	0

iii. elevation as random effect

	AICc	delta_AICc	*wi*	D^2
Wind_Speed	691.31	0	1	9.67
Wind_Speed_1	722.65	31.34	0	4.91
Wind_Speed_2	730.92	39.61	0	3.25
Wind_Speed_3	744.64	53.33	0	1.69
Wind_Speed_null	753.13	61.82	0	0

g. rain days

i. month as random effect

	AICc	**delta_AICc**	***wi***	**D^2**
Rain_Days_3	2290.12	0	0.39	0.28
Rain_Days	2290.83	0.71	0.27	0.52
Rain_Days_1	2292.01	1.89	0.15	0.29
Rain_Days_null	2292.4	2.28	0.12	0
Rain_Days_2	2293.79	3.67	0.06	0.03

ii. transect as random effect

	AICc	**delta_AICc**	***wi***	**D^2**
Rain_Days_3	2328.38	0	0.47	0.34
Rain_Days_1	2329.84	1.46	0.23	0.36
Rain_Days	2330.26	1.88	0.18	0.52
Rain_Days_null	2332.08	3.7	0.07	0
Rain_Days_2	2333.25	4.87	0.04	0.04

iii. elevation as random effect

	AICc	**delta_AICc**	***wi***	**D^2**
Rain_Days_null	2336.14	0	0.48	0
Rain_Days_2	2337.64	1.5	0.23	0.02
Rain_Days	2338.77	2.63	0.13	0.33
Rain_Days_3	2338.97	2.83	0.12	0.05
Rain_Days_1	2340.52	4.38	0.05	0.08

h. rainfall

i. month as random effect

	AICc	**delta_AICc**	***wi***	**D^2**
Rainfall_3	4624.01	0	0.41	0.24
Rainfall	4624.14	0.14	0.39	0.37
Rainfall_1	4625.61	1.61	0.19	0.25
Rainfall_null	4631.13	7.13	0.01	0
Rainfall_2	4633.18	9.17	0	0

ii. transect as random effect

	AICc	**delta_AICc**	***wi***	**D^2**
Rainfall	4626.55	0	0.46	0.41
Rainfall_3	4627.43	0.88	0.29	0.25
Rainfall_1	4627.86	1.31	0.24	0.29
Rainfall_null	4635	8.45	0.01	0
Rainfall_2	4636.4	9.85	0	0.01

iii. elevation as random effect

	AICc	**delta_AICc**	***wi***	**D^2**
Rainfall	4631.74	0	0.45	0.34
Rainfall_3	4632.78	1.04	0.27	0.18
Rainfall_1	4633.06	1.33	0.23	0.22
Rainfall_null	4636.94	5.2	0.03	0
Rainfall_2	4637.9	6.16	0.02	0.02

i. solar exposure

i. month as random effect

	AICc	**delta_AICc**	***wi***	**D^2**
Solar_Exposure	9947.69	0	0.94	3.88
Solar_Exposure_1	9953.11	5.42	0.06	3.79
Solar_Exposure_3	9983.7	36.01	0	3.47
Solar_Exposure_2	10316.95	369.26	0	0.23
Solar_Exposure_null	10338.55	390.86	0	0

ii. transect as random effect

	AICc	**delta_AICc**	***wi***	**D^2**
Solar_Exposure	9777.85	0	1	5.16
Solar_Exposure_1	9791.89	14.03	0	4.99
Solar_Exposure_3	9929.36	151.51	0	3.63
Solar_Exposure_2	10263.85	485.99	0	0.36
Solar_Exposure_null	10298.76	520.91	0	0

iii. elevation as random effect

	AICc	**delta_AICc**	***wi***	**D^2**
Solar_Exposure	9643.6	0	1	2.91
Solar_Exposure_1	9676.3	32.7	0	2.53
Solar_Exposure_2	9712.42	68.82	0	2.13
Solar_Exposure_3	9890.02	246.43	0	0.36
Solar_Exposure_null	9921.38	277.79	0	0

Appendix 4.1 Copy of publication:

Little, J. K., Prior, L. D., Williamson, G. J., Williams, S. E. & Bowman, D. M. J. S. (2012) Fire weather risk differs across rain forest–savanna boundaries in the humid tropics of north-eastern Australia. *Austral Ecology* **37**, 915-925 (11 pages).

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Pages 345- 357

Austral ECOLOGY A Journal of ecology in the Southern Hemisphere

Ecological Society of Australia

Austral Ecology (2012) **37**, 915–925

Fire weather risk differs across rain forest–savanna boundaries in the humid tropics of north-eastern Australia

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Abstract Alternative stable state theory has been applied to understanding the control by landscape fire activity of pyrophobic tropical rain forest and pyrophytic eucalypt savanna boundaries, which are often separated by tall eucalypt forests. We evaluate the microclimate of three vegetation types across an elevational gradient and their relative fire risk as measured by McArthur's Forest Fire Danger Index (FFDI). Microclimatic data were collected from rain forest, tall eucalypt forest and savanna sites on eight vegetation boundaries throughout the humid tropics in north Queensland over a 3-year period and were compared with data from a nearby meteorological station. There was a clear annual pattern in daily FFDI with highest values in the austral winter dry season and lowest values in the austral summer wet season. There was a strong association of the meteorological station FFDI values with those from the three vegetation types, albeit they were substantially lower. The rank order of FFDI values among the vegetation types decreased from savanna, tall eucalypt forest, then rain forest, a pattern that was consistent across each transect. Only very rarely would rain forest be flammable, despite being adjacent to highly flammable savannas. These results demonstrate the very strong effect of vegetation type on microclimate and fire risk, compared with the weak effect of elevation, consistent with a fire–vegetation feedback. This study is the first demonstration of how vegetation type influences microclimate and fire risk across a topographically complex tropical forest–savanna gradient.

Key words: alternative stable state theory, feedback, fire ecology, fire weather danger rating, forest boundary.

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Appendix 5.1 Linear regression equations used in calibrating official meteorological site data to newer site data for Cairns (site 31010 to site 310111) and Mareeba (site 31066 to 31190 to 310210).

Cairns: **Site 31010 to 31011**	**Equation:** **Site31011=b+(x*Site31010)**	**Adjusted R^2**	***p*-value**
Rainfall	0.149 + (0.885 * Site31010)	0.896	<0.001
Temperature: mean	3.606 + (0.814 * Site31010)	0.823	<0.001
Temperature: maximum	1.971 + (0.929 * Site31010)	0.864	<0.001
Temperature: minimum	2.910 + (0.870 * Site31010)	0.891	<0.001
Relative humidity: mean	33.730 + (0.567 * Site31010)	0.564	<0.001
Relative humidity: minimum	14.399 + (0.679 * Site31010)	0.584	<0.001
Wind speed	9.752 + (0.366 * Site31010)	0.0366	<0.001

Mareeba: **Site 031066 to 031210**	**Equation:** **Site31210=b+(x*Site31066)**	**Adjusted R^2**	***p*-value**
Rainfall	0.553 + (0.449 * Site31066)	0.493	<0.001

Mareeba: **Site 031190 to 031210**	**Equation:** **Site31210=b+(x*Site31190)**	**Adjusted R^2**	***p*-value**
Temperature: mean	1.826 + (0.938 * Site31190)	0.939	<0.001
Temperature: maximum	0.952 + (0.970 * Site31190)	0.976	<0.001
Temperature: minimum	-0.345 + (1.019 * Site31190)	0.988	<0.001
Relative humidity: mean	3.653 + (0.883 * Site31190)	0.769	<0.001
Relative humidity: minimum	9.063 + (0.710 * Site31190)	0.678	<0.001
Wind speed	5.056 + (0.708 * Site31190)	0.722	<0.001

Mareeba: **Site 031066 to 031190**	**Equation:** **Site31190=b+(x*Site31066)**	**Adjusted R^2**	***p*-value**
Temperature: mean	3.869 + (0.714 * Site31066)	0.767	<0.001
Temperature: maximum	2.278 + (0.913 * Site31066)	0.861	<0.001
Temperature: minimum	5.971 + (0.633 * Site31066)	0.348	<0.001
Relative humidity: mean	41.269 + (0.453 * Site31066)	0.508	<0.001
Relative humidity: minimum	16.754 + (0.730 * Site31066)	0.479	<0.001
Wind speed	10.170 + (0.109 * Site31066)	0.0212	0.01

Appendix 5.2 Raw, calibrated and homogenised climate time -series data at Cairns (1890-2010) and Mareeba (1957-2010).

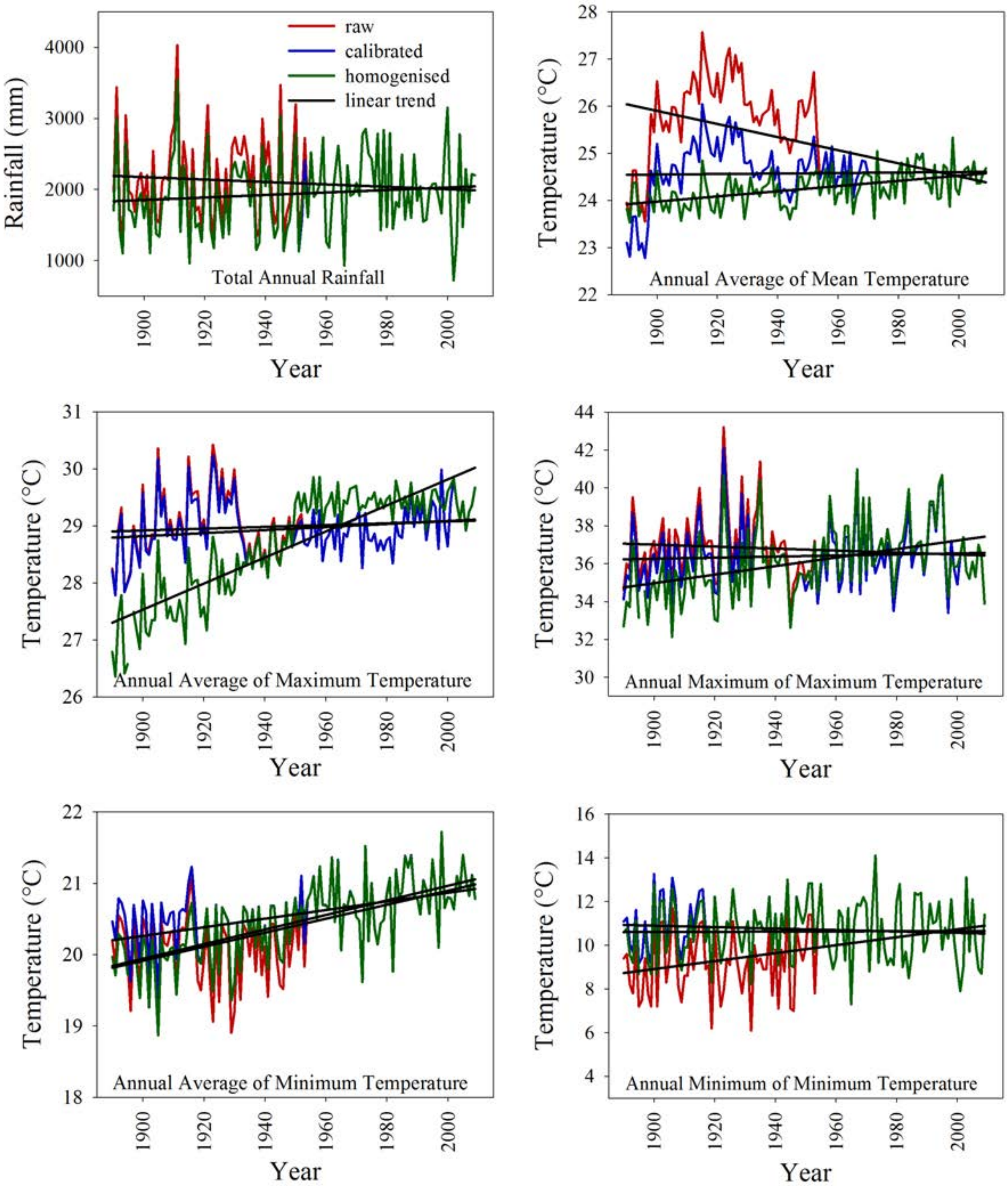

Figure 5.2.1 Raw, calibrated and homogenised climate time -series data at Cairns (1890-2010) for annual rainfall and temperature.

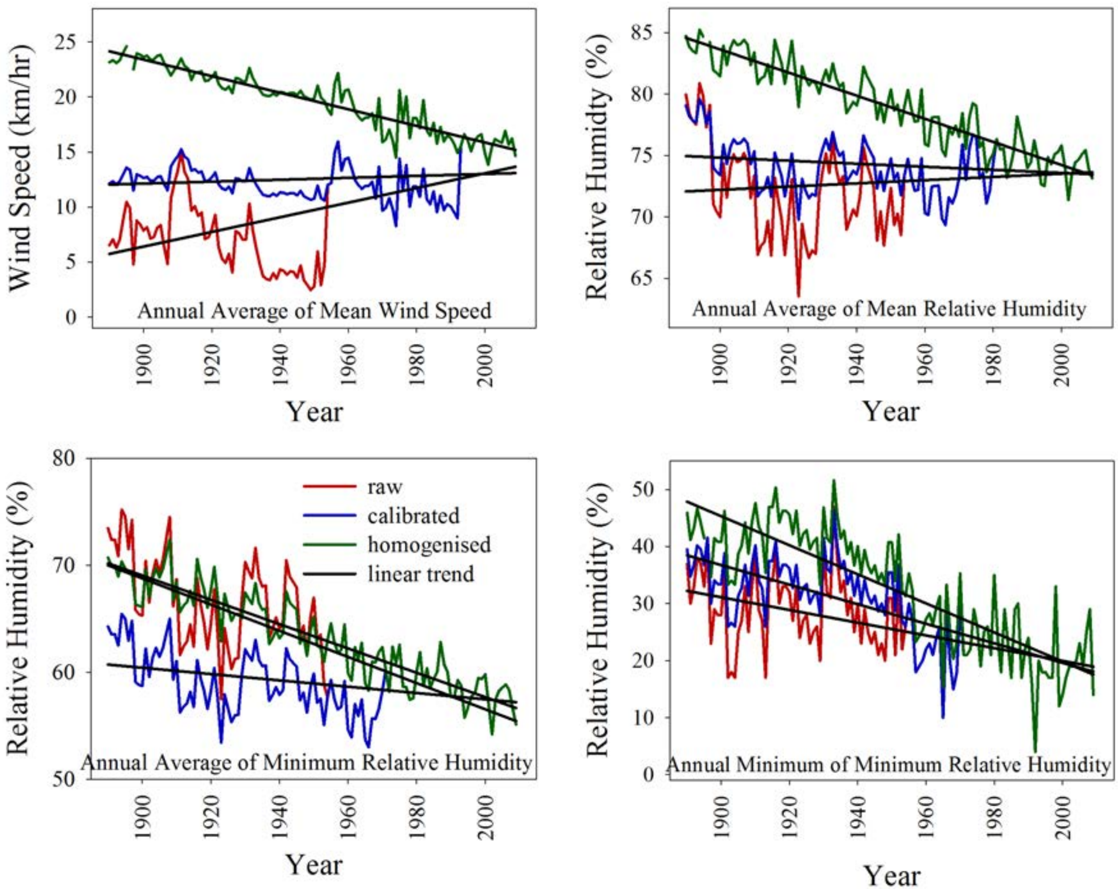

Figure 5.2.2 Raw, calibrated and homogenised climate time -series data at Cairns (1890-2010) for annual wind speed and relative humidity.

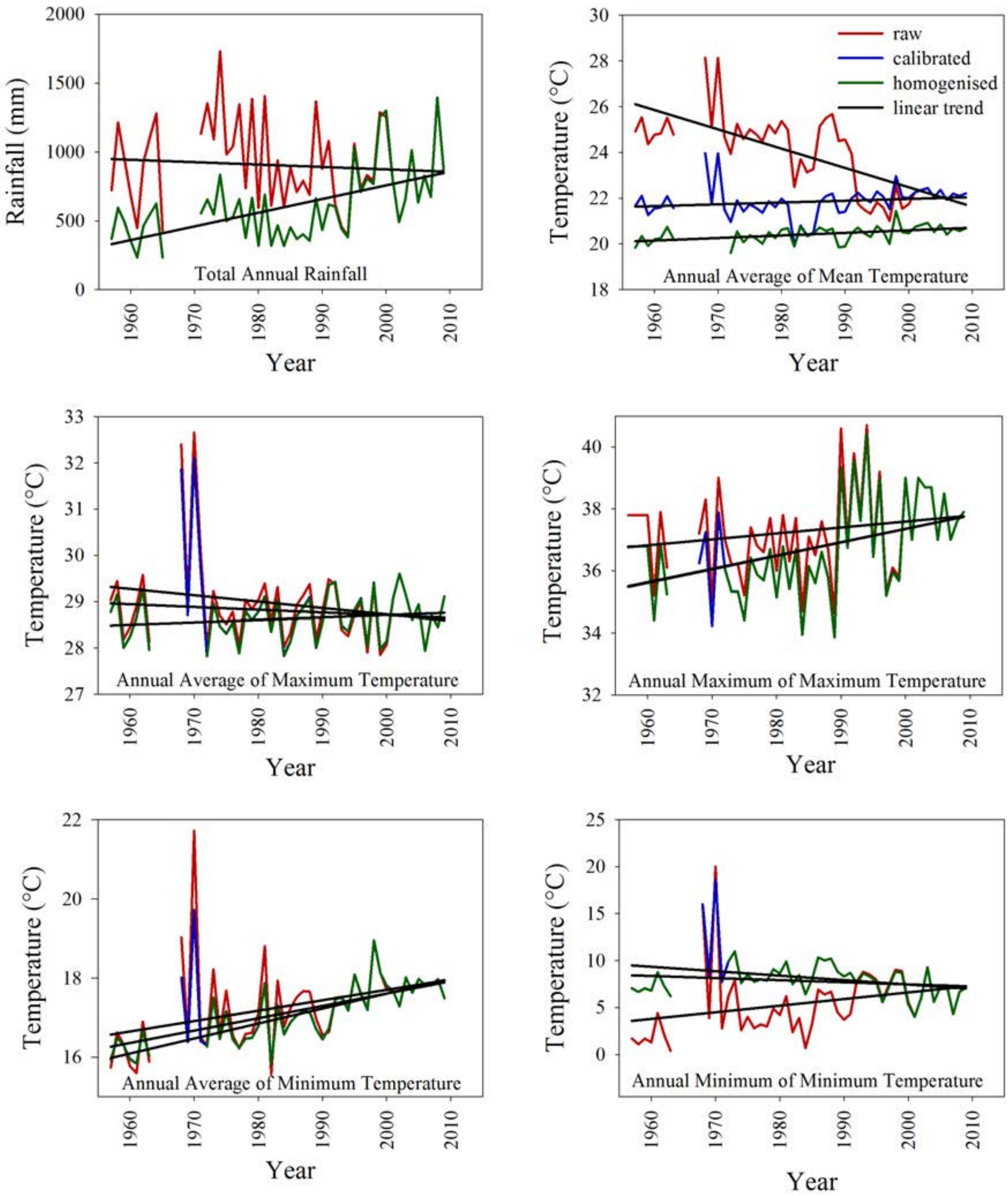

Figure 5.2.3 Raw, calibrated and homogenised climate time -series data at Mareeba (1957-2010) for annual rainfall and temperature.

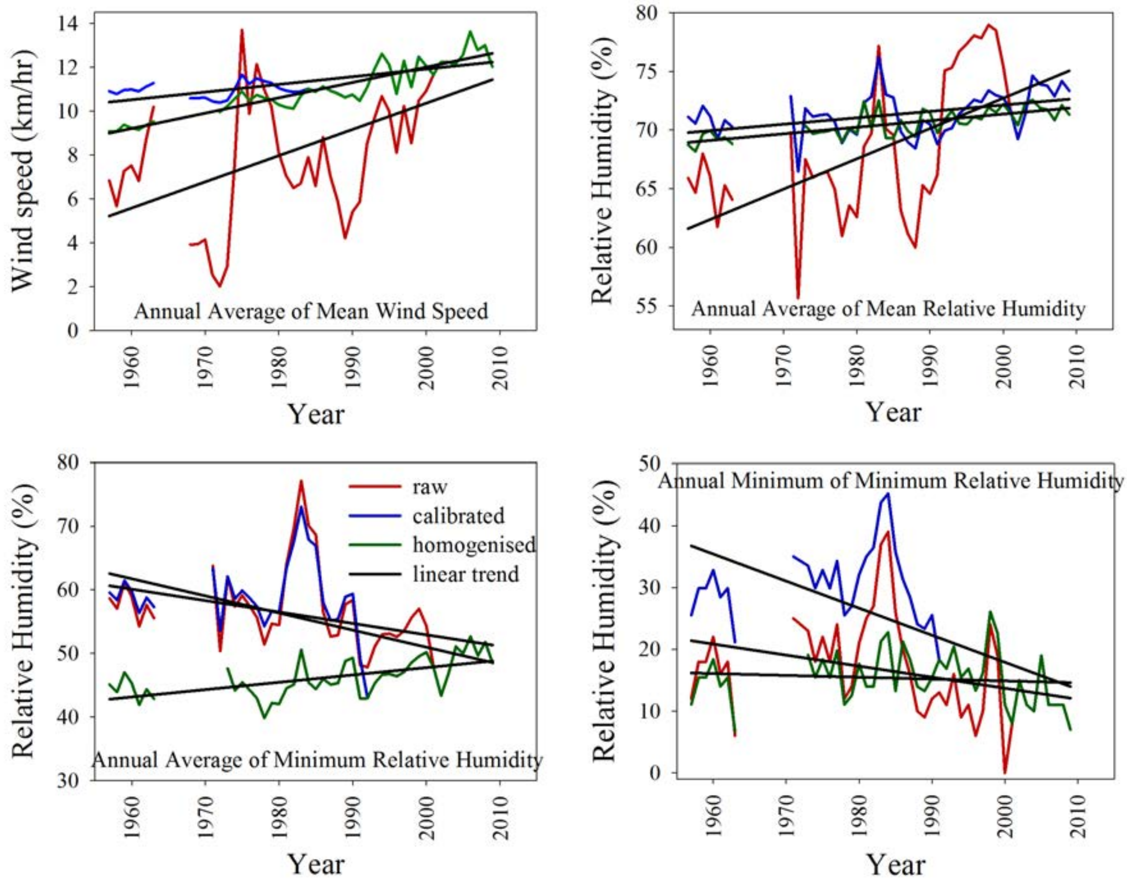

Figure 5.2.4 Raw, calibrated and homogenised climate time -series data at Mareeba (1957-2010) for annual wind speed and relative humidity.

Appendix 5.3 Annual linear trend in FFDI and climatic variables for Cairns from 1890 to 2010. Trends that are significant at the 95% level ($p < 0.05$) are indicated by shading; near significant trends are in bold ($p < 0.15$).

Location	**Variable**	**AdjR^2 (%)**	**F-statistic**	**Residual Std. Error**	***p*-value**	**Year Coefficient**	**Intercept Coefficient**
Global	SOI mean	0	1.06	6.45	0.3	-0.02	0.82
Global	SOI max.	-0.01	0.14	7.17	0.71	-0.01	11.92
Global	SOI min.	0.01	2.61	8.41	**0.11**	-0.04	-10.4
Cairns	FFDI mean	0.62	197.7	0.57	**0**	0.02	3.82
Cairns	Σ FFDI	0.62	197.9	208.2	**0**	7.7	1393.57
Cairns	FFDI max. annual	0.5	119.2	4.84	**0**	0.14	10.08
Cairns	FFDI 99%	0.63	207.9	2.25	**0**	0.09	8.04
Cairns	FFDI 95%	0.72	314.1	1.24	**0**	0.06	6.59
Cairns	FFDI 90%	0.75	356	0.94	**0**	0.05	6.03
Cairns	FFDI 50%	0.48	110.9	0.57	**0**	0.02	4.11
Cairns	FFDI days ≥25	0.2	31.58	0.53	**0**	0.01	-0.19
Cairns	FFDI days ≥12	0.58	166.4	8.26	**0**	0.28	-5.7
Cairns	Rain total	0.01	2.06	539.3	0.15	2.01	1822.34
Cairns	Rain days ≥5 mm	0	0.62	12.56	0.43	-0.03	72.2
Cairns	Wind mean	0.88	844.9	0.98	**0**	-0.08	24.21
Cairns	Wind max.	0	0.41	6.74	0.52	-0.01	34.07
Cairns	Temp. mean	0.26	43.75	0.33	**0**	0.01	23.9
Cairns	Temp. max. annual	0.17	25.79	1.67	**0**	0.02	34.73
Cairns	Temp. max. mean daily	0.74	345.7	0.46	**0**	0.02	27.29
Cairns	Temp. max. 99%	0.27	44.22	1.14	**0**	0.02	32.9
Cairns	Temp. max. 95%	0.52	128	0.63	**0**	0.02	31.42
Cairns	Temp. max. 90%	0.59	170.6	0.56	**0**	0.02	30.72
Cairns	Temp. max. days ≥35 °C	0.09	13.27	3.2	**0**	0.03	0.87
Cairns	Temp. min. annual	-0.01	0.04	1.37	0.84	0	10.59
Cairns	Temp. min. mean daily	0.44	96	0.42	**0**	0.01	19.81
Cairns	R.Hum. mean	0.85	686.1	1.34	**0**	-0.09	84.6
Cairns	R.Hum. min. annual	0.69	270.2	5.79	**0**	-0.25	47.93
Cairns	R.Hum. min. mean daily	0.83	601.9	1.73	**0**	-0.11	70.23
Cairns	R.Hum. min. 1%	0.73	300.1	4.58	**0**	-0.22	53.27
Cairns	R.Hum. min. 5%	0.81	481.3	3.09	**0**	-0.18	59.35

Cairns	R.Hum. min. 10%	0.8	462	2.82	**0**	-0.16	61.24
Cairns	KBDI mean	0.07	9.75	14.82	**0**	0.12	105.13
Cairns	KBDI max.	0.05	6.67	9.4	**0.01**	0.06	185.05
Cairns	KBDI 99%	0.04	6.5	10.21	**0.01**	0.07	183.1
Cairns	KBDI 95%	0.05	6.9	12.49	**0.01**	0.09	176.54
Cairns	KBDI 90%	0.06	9.19	14	**0**	0.11	169.66

Appendix 5.4 Annual linear trend in FFDI and climatic variables for Cairns and Mareeba from 1957 to 2010. Linear trends for rain forest, tall eucalypt forest and savanna (reconstructed from Mareeba data) are also provided. Trends that are significant at the 95% level ($p < 0.05$) are indicated by shading; near significant trends are in bold ($p < 0.15$).

Location	Climate Variable	AdjR^2 (%)	F-statistic	Residual Std. Error	*p*-value	Year Coefficient	Intercept Coefficient
Global	SOI mean	-0.01	0.44	6.26	0.51	-0.04	-0.01
Global	SOI max.	-0.01	0.33	6.71	0.57	0.03	10.54
Global	SOI min.	0	0.92	8.35	0.34	-0.07	-12.15
Cairns	FFDI mean	0.02	1.87	0.6	0.18	0.01	5.68
Cairns	Σ FFDI	0.02	1.87	218.7	0.18	2.61	2075.06
Cairns	FFDI max. annual	-0.02	0.14	5.64	0.71	0.02	23.72
Cairns	FFDI 99%	-0.02	0.11	2.35	0.74	0.01	16.48
Cairns	FFDI 95%	0.03	2.5	1.26	**0.12**	0.02	11.9
Cairns	FFDI 90%	0.08	5.5	1.03	**0.02**	0.02	10.08
Cairns	FFDI 50%	0.02	1.88	0.56	0.18	0.01	5.41
Cairns	FFDI days ≥25	-0.02	0.03	0.77	0.87	0	0.6
Cairns	FFDI days ≥12	0.05	4.04	10.85	**0.05**	0.19	17.3
Cairns	Rain total	-0.02	0.02	535.9	0.9	-0.62	2047.38
Cairns	Rain days ≥5 mm	0	0.84	11.16	0.36	0.09	66.05
Cairns	Wind mean	0.49	51.72	1.29	**0**	-0.08	19.34
Cairns	Wind max.	0.09	5.99	4.91	**0.02**	-0.1	37.19
Cairns	Temp. mean	0.1	6.65	0.37	**0.01**	0.01	24.21
Cairns	Temp. max. annual	0.02	1.84	1.64	0.18	-0.02	37.51
Cairns	Temp. max. mean daily	-0.02	0.05	0.24	0.83	0	29.41
Cairns	Temp. max. 99%	0	1	1.01	0.32	-0.01	35.09
Cairns	Temp. max. 95%	0.07	4.73	0.42	**0.03**	-0.01	33.45
Cairns	Temp. max. 90%	0.06	4.53	0.33	**0.04**	-0.01	32.73
Cairns	Temp. max. days ≥35 °C	-0.01	0.56	3.52	0.46	-0.02	4.58
Cairns	Temp. min. annual	-0.02	0.01	1.49	0.92	0	10.59
Cairns	Temp. min. mean daily	0.08	5.48	0.46	**0.02**	0.01	20.57
Cairns	R.Hum. mean	0.37	32.47	1.48	**0**	-0.07	77.75
Cairns	R.Hum. min. annual	0.12	8.42	5.8	**0.01**	-0.15	26.79
Cairns	R.Hum. min. mean daily	0.34	28.8	1.72	**0**	-0.08	61.73
Cairns	R.Hum. min. 1%	0.08	5.52	4.44	**0.02**	-0.09	34.11

Cairns	R.Hum. min. 5%	0.21	15.26	2.89	**0**	-0.1	43.93
Cairns	R.Hum. min. 10%	0.31	24.42	2.23	**0**	-0.1	48.12
Cairns	KBDI mean	-0.02	0	12.51	0.96	0	116.3
Cairns	KBDI max.	0	1.22	6.92	0.27	-0.07	193.49
Cairns	KBDI 99%	0.01	1.37	7.54	0.25	-0.08	192.37
Cairns	KBDI 95%	0	1.13	9.35	0.29	-0.09	187.81
Cairns	KBDI 90%	-0.01	0.73	10.38	0.4	-0.08	183.01
Mareeba	FFDI mean	0.06	3.62	0.95	**0.06**	**-0.02**	8.66
Mareeba	Σ FFDI	0.06	3.61	347	**0.06**	**-6.44**	3161.51
Mareeba	FFDI max. annual	0.03	2.37	5.33	**0.13**	**0.08**	25.9
Mareeba	FFDI 99%	-0.02	0.02	3.72	0.89	-0.01	22.49
Mareeba	FFDI 95%	-0.02	0	2.23	1	0	16.52
Mareeba	FFDI 90%	0.4	-0.01	1.67	0.53	-0.01	14.28
Mareeba	FFDI 50%	0.03	2.27	1.07	**0.14**	**-0.02**	7.96
Mareeba	Rain total	0.3	21.61	225.3	**0**	9.82	340.73
Mareeba	Wind mean	0.85	265.7	0.45	**0**	0.07	8.92
Mareeba	Wind max.	0.7	106.7	3.61	**0**	0.36	8.14
Mareeba	Temp. mean	0.25	15.96	0.31	**0**	0.01	20.09
Mareeba	Temp. max. annual	0.1	6.34	1.47	**0.02**	0.04	35.6
Mareeba	Temp. max. mean daily	0.01	1.41	0.48	0.24	0.01	28.48
Mareeba	Temp. max. 99%	0.09	5.41	1.23	**0.02**	0.03	34.44
Mareeba	Temp. max. 95%	0.11	6.42	0.95	**0.01**	0.02	32.49
Mareeba	Temp. max. 90%	0.1	6.2	0.82	**0.02**	0.02	31.45
Mareeba	Temp. min. annual	0.01	1.53	1.51	0.22	-0.02	8.36
Mareeba	Temp. min. mean daily	0.61	72.92	0.5	**0**	0.04	15.88
Mareeba	R.Hum. mean	0.54	53.44	0.8	**0**	0.06	68.88
Mareeba	R.Hum. min. annual	-0.02	0.06	4.46	0.8	-0.01	15.82
Mareeba	R.Hum. min. mean daily	0.36	25.94	2.72	**0**	0.14	42.31
Mareeba	KBDI mean	-0.02	0.01	17.09	0.91	0.02	93.48
Mareeba	KBDI max.	0	0.83	13.87	0.37	0.12	163.61
Mareeba	KBDI 99%	0.05	3.09	13.12	**0.09**	**0.23**	157.95
Mareeba	KBDI 95%	0.03	2.43	13.87	**0.13**	**0.21**	153.82
Mareeba	KBDI 90%	0.05	3.11	13.77	**0.09**	**0.24**	147.11
Rain Forest	FFDI mean	0.05	3.14	0.18	**0.08**	**0**	1.33
Rain Forest	Σ FFDI	0.05	3.13	65.42	**0.08**	**-1.13**	485.41

Rain Forest	FFDI max. annual	0.03	2.37	1.02	**0.13**	**0.02**	4.64
Rain Forest	FFDI 99%	-0.02	0.02	0.71	0.89	0	3.98
Rain Forest	FFDI 95%	-0.02	0	0.43	1	0	2.84
Rain Forest	FFDI 90%	-0.01	0.4	0.32	0.53	0	2.41
Rain Forest	FFDI 50%	0.03	2.27	0.21	**0.14**	**0**	1.19
Rain Forest	Wind mean	0.85	266.5	0	**0**	0	0.16
Rain Forest	Wind max.	0.7	106.7	0.02	**0**	0	0.16
Rain Forest	Temp. mean	0.25	15.96	0.28	**0**	0.01	15
Rain Forest	Temp. max. annual	0.1	6.34	1.34	**0.02**	0.03	26.07
Rain Forest	Temp. max. mean daily	0.01	1.41	0.43	0.24	0	19.6
Rain Forest	Temp. max. 99%	0.09	5.41	1.12	**0.02**	0.02	25.01
Rain Forest	Temp. max. 95%	0.11	6.42	0.87	**0.01**	0.02	23.24
Rain Forest	Temp. max. 90%	0.1	6.2	0.74	**0.02**	0.02	22.29
Rain Forest	Temp. min. annual	0.01	1.53	1.06	0.22	-0.01	8.38
Rain Forest	Temp. min. mean daily	0.61	72.92	0.35	**0**	0.03	13.63
Rain Forest	R.Hum. mean	0.54	53.44	0.35	**0**	0.03	91.09
Rain Forest	R.Hum. min. annual	-0.02	0.06	3.49	0.8	-0.01	52.3
Rain Forest	R.Hum. min. mean daily	0.36	25.94	2.13	**0**	0.11	73.04
Rain Forest	KBDI mean	-0.02	0	4.54	0.95	0	93.51
Rain Forest	KBDI max.	0	0.8	3.73	0.38	0.03	112.28
Rain Forest	KBDI 99%	0.04	3	3.53	**0.09**	**0.06**	110.76
Rain Forest	KBDI 95%	0.03	2.31	3.73	**0.14**	**0.06**	109.67
Rain Forest	KBDI 90%	0.04	2.9	3.71	**0.1**	**0.06**	107.89
Tall Eucalypt Forest	FFDI mean	0.06	3.62	0.26	**0.06**	**0**	2.33
Tall Eucalypt Forest	Σ FFDI	0.06	3.61	94.38	**0.06**	**-1.75**	851.53
Tall Eucalypt Forest	FFDI max. annual	0.03	2.37	1.45	**0.13**	**0.02**	7.02
Tall Eucalypt Forest	FFDI 99%	-0.02	0.02	1.01	0.89	0	6.1
Tall Eucalypt Forest	FFDI 95%	-0.02	0	0.61	1	0	4.47
Tall Eucalypt Forest	FFDI 90%	-0.01	0.4	0.45	0.53	0	3.86
Tall Eucalypt Forest	FFDI 50%	0.03	2.27	0.29	**0.14**	**0**	2.14
Tall Eucalypt Forest	Wind mean	0.85	265.8	0.02	**0**	0	0.42
Tall Eucalypt Forest	Wind max.	0.7	106.7	0.16	**0**	0.02	0.39
Tall Eucalypt Forest	Temp. mean	0.25	15.96	0.25	**0**	0.01	17.44
Tall Eucalypt Forest	Temp. max. annual	0.1	6.34	1.25	**0.02**	0.03	29.22
Tall Eucalypt Forest	Temp. max. mean daily	0.01	1.41	0.41	0.24	0	23.18

Tall Eucalypt Forest	Temp. max. 99%	0.09	5.41	1.05	**0.02**	0.02	28.24
Tall Eucalypt Forest	Temp. max. 95%	0.11	6.42	0.81	**0.01**	0.02	26.59
Tall Eucalypt Forest	Temp. max. 90%	0.1	6.2	0.69	**0.02**	0.02	25.7
Tall Eucalypt Forest	Temp. min. annual	0.01	1.53	0.95	0.22	-0.01	10.7
Tall Eucalypt Forest	Temp. min. mean daily	0.61	72.92	0.31	**0**	0.03	15.41
Tall Eucalypt Forest	R.Hum. mean	0.54	53.44	0.44	**0**	0.03	86.25
Tall Eucalypt Forest	R.Hum. min. annual	-0.02	0.06	3.76	0.8	-0.01	38.68
Tall Eucalypt Forest	R.Hum. min. mean daily	0.36	25.94	2.29	**0**	0.11	61.01
Tall Eucalypt Forest	KBDI mean	-0.02	0	5.77	0.95	0	103.1
Tall Eucalypt Forest	KBDI max.	0	0.8	4.74	0.38	0.04	126.92
Tall Eucalypt Forest	KBDI 99%	0.04	3	4.49	**0.09**	**0.08**	124.99
Tall Eucalypt Forest	KBDI 95%	0.03	2.31	4.74	**0.14**	**0.07**	123.61
Tall Eucalypt Forest	KBDI 90%	0.04	2.9	4.72	**0.1**	**0.08**	121.35
Savanna	FFDI mean	0.06	3.62	0.42	**0.06**	**-0.01**	4.8
Savanna	Σ FFDI	0.06	3.6	152	**0.06**	**-2.82**	1751
Savanna	FFDI max. annual	0.03	2.37	2.34	**0.13**	**0.04**	12.35
Savanna	FFDI 99%	-0.02	0.02	1.63	0.89	0	10.86
Savanna	FFDI 95%	-0.02	0	0.98	1	0	8.24
Savanna	FFDI 90%	-0.01	0.4	0.73	0.53	0	7.26
Savanna	FFDI 50%	0.03	2.27	0.47	**0.14**	**-0.01**	4.49
Savanna	Rain total	0.26	17.58	50.52	**0**	2	169.41
Savanna	Wind mean	0.85	266.2	0.05	**0**	0.01	1.67
Savanna	Wind max.	0.7	106.7	0.39	**0**	0.04	1.59
Savanna	Temp. mean	0.25	15.96	0.24	**0**	0.01	19.25
Savanna	Temp. max. annual	0.1	6.34	1.07	**0.02**	0.03	31.7
Savanna	Temp. max. mean daily	0.01	1.41	0.35	0.24	0	26.53
Savanna	Temp. max. 99%	0.09	5.41	0.9	**0.02**	0.02	30.86
Savanna	Temp. max. 95%	0.11	6.42	0.69	**0.01**	0.02	29.44
Savanna	Temp. max. 90%	0.1	6.2	0.59	**0.02**	0.01	28.68
Savanna	Temp. min. annual	0.01	1.53	0.96	0.22	-0.01	11.18
Savanna	Temp. min. mean daily	0.61	72.92	0.32	**0**	0.03	15.95
Savanna	R.Hum. mean	0.54	53.44	0.54	**0**	0.04	76.52
Savanna	R.Hum. min. annual	-0.02	0.06	3.34	0.8	-0.01	24.81
Savanna	R.Hum. min. mean daily	0.36	25.94	2.03	**0**	0.1	44.63
Savanna	KBDI mean	-0.02	0	6.95	0.95	0	91.04

Savanna	KBDI max.	0	0.8	5.71	0.38	0.05	119.79
Savanna	KBDI 99%	0.04	3	5.41	**0.09**	**0.09**	117.47
Savanna	KBDI 95%	0.03	2.31	5.71	**0.14**	**0.08**	115.8
Savanna	KBDI 90%	0.04	2.9	5.69	**0.1**	**0.09**	113.08

Appendix 5.5 Linear seasonal trend ('December-January-February') in FFDI and climatic variables for Cairns (1890 - 2010 and 1957 - 2010) and Mareeba (1957 - 2010). Linear trends for rain forest, tall eucalypt forest and savanna (reconstructed from Mareeba data) are also included. Trends that are significant at the 95% level ($p < 0.05$) are indicated by shading; near significant trends are in bold ($p < 0.15$).

Years	Location	Variable	AdjR^2 (%)	F-statistic	Residual Std. Error	*p*-value	Year Coefficient	Intercept Coefficient
1890-2010	Global	SOI mean	0	1.3	8.56	0.26	-0.03	1.4
1890-2010	Global	SOI max.	-0.01	0.34	8.43	0.56	-0.01	5.65
1890-2010	Global	SOI min.	0.02	2.95	9.72	0.09	-0.04	-2.62
1890-2010	Cairns	FFDI mean	0.04	6.32	1.06	**0.01**	0.01	3.71
1890-2010	Cairns	Σ FFDI	0.04	6.36	95.44	**0.01**	0.63	335.03
1890-2010	Cairns	FFDI max. annual	0.25	40.42	4.29	**0**	0.07	8.73
1890-2010	Cairns	FFDI 99%	0.31	55.02	2.8	**0**	0.05	7.89
1890-2012	Cairns	FFDI 95%	0.29	49.21	1.91	**0**	0.04	6.88
1890-2010	Cairns	FFDI 90%	0.22	34.18	1.54	**0**	0.02	6.4
1890-2010	Cairns	FFDI 50%	-0.01	0.22	1.31	0.64	0	3.9
1890-2010	Cairns	FFDI days ≥25	0.04	5.7	0.2	**0.02**	0	-0.03
1890-2010	Cairns	FFDI days ≥12	0.21	31.68	2.37	**0**	0.04	-0.5
1890-2010	Cairns	Rain total	0.02	3.9	387.5	**0.05**	1.99	824.85
1890-2010	Cairns	Rain days ≥5 mm	0.01	2.42	7.37	0.12	0.03	26.45
1890-2010	Cairns	Wind mean	0.87	803.1	1.38	**0**	-0.1	24.64
1890-2010	Cairns	Wind max.	0.04	5.77	6.19	**0.02**	-0.04	30.66
1890-2010	Cairns	Temp. mean	0.34	61.12	0.49	**0**	0.01	26.08
1890-2010	Cairns	Temp. max. annual	0.17	25.47	1.81	**0**	0.02	34.43
1890-2010	Cairns	Temp. max. mean daily	0.54	141.6	0.68	**0**	0.02	29.78
1890-2010	Cairns	Temp. max. 99%	0.15	22.57	1.71	**0**	0.02	33.77
1890-2010	Cairns	Temp. max. 95%	0.25	41.67	1.09	**0**	0.02	32.58
1890-2010	Cairns	Temp. max. 90%	0.41	83.98	0.81	**0**	0.02	31.8
1890-2010	Cairns	Temp. max. days ≥35 °C	0.06	9.04	2.95	**0**	0.02	0.84

1890-2010	Cairns	Temp. min. annual	0.23	37.34	1.01	**0**	0.02	18.84
1890-2010	Cairns	Temp. min. mean daily	0.61	188.1	0.37	**0**	0.01	22.38
1890-2010	Cairns	R.Hum. mean	0.49	116.8	2.36	**0**	-0.07	84.67
1890-2010	Cairns	R.Hum. min. annual	0.43	91.51	6.85	**0**	-0.17	54.77
1890-2010	Cairns	R.Hum. min. mean daily	0.44	96.36	2.91	**0**	-0.07	70.41
1890-2010	Cairns	R.Hum. min. 1%	0.39	68.77	6.61	**0**	-0.15	54.99
1890-2010	Cairns	R.Hum. min. 5%	0.57	153.2	4.26	**0**	-0.14	60.88
1890-2010	Cairns	R.Hum. min. 10%	0.58	156.8	3.67	**0**	-0.12	62.74
1890-2010	Cairns	KBDI mean	0	0.56	27.94	0.46	-0.05	94.79
1890-2010	Cairns	KBDI max.	-0.01	0.11	24.7	0.74	-0.02	171.11
1890-2010	Cairns	KBDI 99%	-0.01	0.12	25.29	0.73	-0.02	170.04
1890-2010	Cairns	KBDI 95%	-0.01	0.23	27.4	0.63	-0.03	166.08
1890-2010	Cairns	KBDI 90%	0	0.48	29.68	0.49	-0.05	161.3
1957-2010	Global	SOI mean	-0.02	0	9.36	0.97	0	-1.15
1957-2010	Global	SOI max.	-0.02	0	8.85	1	0	4.26
1957-2010	Global	SOI min.	-0.02	0	10.81	0.98	0	-7.17
1957-2010	Cairns	FFDI mean	-0.01	0.61	1.18	0.44	-0.01	4.63
1957-2010	Cairns	Σ FFDI	-0.01	0.6	106.8	0.44	-0.72	417.66
1957-2010	Cairns	FFDI max. annual	-0.01	0.38	5.53	0.54	0.03	15.1
1957-2010	Cairns	FFDI 99%	-0.01	0.3	3.45	0.59	0.02	12.93
1957-2010	Cairns	FFDI 95%	-0.02	0.02	2.49	0.9	0	10.33
1957-2010	Cairns	FFDI 90%	-0.02	0.03	1.94	0.87	0	8.85
1957-2010	Cairns	FFDI 50%	0.01	0.01	1.38	1.34	-0.01	4.42
1957-2010	Cairns	FFDI days ≥25	-0.02	0.16	0.29	0.69	0	0.06
1957-2010	Cairns	FFDI days ≥12	-0.02	0	3.36	0.97	0	3.1
1957-2010	Cairns	Rain total	-0.02	0	451.8	0.95	0.25	1026.43
1957-2010	Cairns	Rain days ≥5 mm	0	0.85	7.99	0.36	0.06	27.25
1957-2010	Cairns	Wind mean	0.34	28.37	1.53	**0**	-0.07	16.56

1957-2010	Cairns	Wind max.	0.06	4.57	6.01	**0.04**	-0.11	31.38
1957-2010	Cairns	Temp. mean	0.03	2.8	0.47	**0.1**	0.01	26.88
1957-2010	Cairns	Temp. max. annual	0.05	3.83	1.66	**0.06**	-0.03	37.69
1957-2010	Cairns	Temp. max. mean daily	0.01	1.47	0.53	0.23	-0.01	31.96
1957-2010	Cairns	Temp. max. 99%	0.06	4.22	1.62	**0.05**	-0.03	36.78
1957-2010	Cairns	Temp. max. 95%	0.01	1.8	0.93	0.19	-0.01	34.68
1957-2010	Cairns	Temp. max. 90%	0.02	2.27	0.65	**0.14**	-0.01	33.92
1957-2010	Cairns	Temp. max. days ≥35 °C	0	1.02	3.08	0.32	-0.03	3.99
1957-2010	Cairns	Temp. min. annual	0.03	2.6	0.94	**0.11**	0.01	20
1957-2010	Cairns	Temp. min. mean daily	0.12	8.46	0.4	**0.01**	0.01	23.4
1957-2010	Cairns	R.Hum. mean	0.06	4.18	2.96	**0.05**	-0.05	79.69
1957-2010	Cairns	R.Hum. min. annual	0.01	1.32	7.88	0.26	-0.08	39.73
1957-2010	Cairns	R.Hum. min. mean daily	0	1.14	3.4	0.29	-0.03	63.98
1957-2010	Cairns	R.Hum. min. 1%	-0.01	0.26	6.57	0.61	-0.03	40.59
1957-2010	Cairns	R.Hum. min. 5%	0.02	2.33	4.98	**0.13**	-0.07	48.59
1957-2010	Cairns	R.Hum. min. 10%	0.02	1.82	4.26	0.18	-0.05	51.92
1957-2010	Cairns	KBDI mean	0.01	1.39	26.27	0.24	-0.27	96.98
1957-2010	Cairns	KBDI max.	0.01	1.38	22.35	0.25	-0.23	176.04
1957-2010	Cairns	KBDI 99%	0.01	1.42	22.72	0.24	-0.24	175.17
1957-2010	Cairns	KBDI 95%	0.01	1.72	24.58	0.2	-0.28	171.47
1957-2010	Cairns	KBDI 90%	0.01	1.75	27.84	0.19	-0.32	166.19
1957-2010	Mareeba	FFDI mean	0.09	5.28	1.89	**0.03**	-0.04	8.04
1957-2010	Mareeba	Σ FFDI	0.09	5.29	170.2	**0.03**	-3.9	725.8
1957-2010	Mareeba	FFDI max. annual	-0.01	0.42	6.79	0.52	0.04	19.67
1957-2010	Mareeba	FFDI 99%	-0.01	0.36	4.9	0.55	-0.03	19.03
1957-2010	Mareeba	FFDI 95%	-0.02	0.14	3.54	0.71	-0.01	14.74
1957-2010	Mareeba	FFDI 90%	0	1.06	2.82	0.31	-0.03	13.07
1957-2010	Mareeba	FFDI 50%	0.07	4.41	2.01	**0.04**	-0.04	7.38

1957-2010	Mareeba	Rain total	0.27	18.76	169	**0**	6.86	181.04
1957-2010	Mareeba	Wind mean	0.15	9.21	0.79	**0**	0.02	9.34
1957-2010	Mareeba	Wind max.	0.67	96.42	2.75	**0**	0.26	7.84
1957-2010	Mareeba	Temp. mean	0.48	43.06	0.55	**0**	0.04	21.61
1957-2010	Mareeba	Temp. max. annual	0.07	4.31	1.43	**0.04**	0.03	35.12
1957-2010	Mareeba	Temp. max. mean daily	0.01	1.59	0.81	0.21	0.01	30.67
1957-2010	Mareeba	Temp. max. 99%	0.11	6.26	1.32	**0.02**	0.03	34.41
1957-2010	Mareeba	Temp. max. 95%	0.05	3.5	1.27	**0.07**	0.02	33.4
1957-2010	Mareeba	Temp. max. 90%	0.02	2.03	1.23	0.16	0.02	32.75
1957-2010	Mareeba	Temp. min. annual	0.1	6.17	1.37	**0.02**	0.03	15.29
1957-2010	Mareeba	Temp. min. mean daily	0.69	104.5	0.59	**0**	0.06	18.21
1957-2010	Mareeba	R.Hum. mean	0.38	28.34	2.15	**0**	0.11	69.04
1957-2010	Mareeba	R.Hum. min. annual	-0.02	0.01	7.11	0.91	-0.01	24.86
1957-2010	Mareeba	R.Hum. min. mean daily	0.28	18.52	4.28	**0**	0.18	43.65
1957-2010	Mareeba	KBDI mean	0.08	4.7	32.73	**0.04**	-0.71	102.08
1957-2010	Mareeba	KBDI max.	0	0.79	31.56	0.38	-0.28	155.02
1957-2010	Mareeba	KBDI 99%	0	1.1	32.39	0.3	-0.34	154.84
1957-2010	Mareeba	KBDI 95%	0	1.04	34.1	0.31	-0.35	151.03
1957-2010	Mareeba	KBDI 90%	0.01	1.44	35.65	0.24	-0.43	148.98
1957-2010	Rain Forest	FFDI mean	0.08	4.62	0.35	**0.04**	-0.01	1.21
1957-2010	Rain Forest	Σ FFDI	0.08	4.63	31.27	**0.04**	-0.67	109.43
1957-2010	Rain Forest	FFDI max. annual	-0.01	0.42	1.3	0.52	0.01	3.44
1957-2010	Rain Forest	FFDI 99%	-0.01	0.36	0.94	0.55	-0.01	3.32
1957-2010	Rain Forest	FFDI 95%	-0.02	0.14	0.68	0.71	0	2.49
1957-2010	Rain Forest	FFDI 90%	0	1.06	0.54	0.31	-0.01	2.17
1957-2010	Rain Forest	FFDI 50%	0.07	4.41	0.39	**0.04**	-0.01	1.08
1957-2010	Rain Forest	Wind mean	0.15	9.21	0	**0**	0	0.17
1957-2010	Rain Forest	Wind max.	0.67	96.42	0.02	**0**	0	0.16

1957-2010	Rain Forest	Temp. mean	0.48	43.06	0.51	**0**	0.03	16.39
1957-2010	Rain Forest	Temp. max. annual	0.06	3.91	1.36	**0.05**	0.03	25.6
1957-2010	Rain Forest	Temp. max. mean daily	0.01	1.62	0.74	0.21	0.01	21.58
1957-2010	Rain Forest	Temp. max. 99%	0.11	6.33	1.23	**0.02**	0.03	24.93
1957-2010	Rain Forest	Temp. max. 95%	0.05	3.51	1.16	**0.07**	0.02	24.06
1957-2010	Rain Forest	Temp. max. 90%	0.02	2	1.12	0.16	0.02	23.48
1957-2010	Rain Forest	Temp. min. annual	0.1	6.17	0.96	**0.02**	0.02	13.22
1957-2010	Rain Forest	Temp. min. mean daily	0.69	104.5	0.41	**0**	0.04	15.26
1957-2010	Rain Forest	R.Hum. mean	0.38	28.34	0.95	**0**	0.05	91.16
1957-2010	Rain Forest	R.Hum. min. annual	-0.02	0.01	5.57	0.91	-0.01	59.38
1957-2010	Rain Forest	R.Hum. min. mean daily	0.28	18.52	3.35	**0**	0.14	74.09
1957-2010	Rain Forest	KBDI mean	0.08	4.7	8.8	**0.04**	-0.19	95.7
1957-2010	Rain Forest	KBDI max.	0	0.79	8.49	0.38	-0.08	109.94
1957-2010	Rain Forest	KBDI 99%	0	1.1	8.71	0.3	-0.09	109.89
1957-2010	Rain Forest	KBDI 95%	0	1.04	9.17	0.31	-0.09	108.87
1957-2010	Rain Forest	KBDI 90%	0.01	1.44	9.59	0.24	-0.11	108.31
1957-2010	Tall Eucalypt Forest	FFDI mean	0.09	5.28	0.51	**0.03**	-0.01	2.16
1957-2010	Tall Eucalypt Forest	Σ FFDI	0.09	5.29	46.28	**0.03**	-1.06	195.34
1957-2010	Tall Eucalypt Forest	FFDI max. annual	-0.01	0.42	1.85	0.52	0.01	5.33
1957-2010	Tall Eucalypt Forest	FFDI 99%	-0.01	0.36	1.33	0.55	-0.01	5.15
1957-2010	Tall Eucalypt Forest	FFDI 95%	-0.02	0.14	0.96	0.71	0	3.99
1957-2010	Tall Eucalypt Forest	FFDI 90%	0	1.06	0.77	0.31	-0.01	3.53
1957-2010	Tall Eucalypt Forest	FFDI 50%	0.07	4.41	0.55	**0.04**	-0.01	1.99
1957-2010	Tall Eucalypt Forest	Wind mean	0.15	9.21	0.03	**0**	0	0.44
1957-2010	Tall Eucalypt Forest	Wind max.	0.67	96.42	0.12	**0**	0.01	0.38
1957-2010	Tall Eucalypt Forest	Temp. mean	0.48	43.06	0.44	**0**	0.03	18.64
1957-2010	Tall Eucalypt Forest	Temp. max. annual	0.06	3.91	1.26	**0.05**	0.02	28.78
1957-2010	Tall Eucalypt Forest	Temp. max. mean daily	0.01	1.62	0.69	0.21	0.01	25.04

1957-2010	Tall Eucalypt Forest	Temp. max. 99%	0.11	6.33	1.14	**0.02**	0.03	28.16
1957-2010	Tall Eucalypt Forest	Temp. max. 95%	0.05	3.51	1.08	**0.07**	0.02	27.35
1957-2010	Tall Eucalypt Forest	Temp. max. 90%	0.02	2	1.04	0.16	0.01	26.81
1957-2010	Tall Eucalypt Forest	Temp. min. annual	0.1	6.17	0.86	**0.02**	0.02	15.04
1957-2010	Tall Eucalypt Forest	Temp. min. mean daily	0.69	104.5	0.37	**0**	0.04	16.87
1957-2010	Tall Eucalypt Forest	R.Hum. mean	0.38	28.34	1.17	**0**	0.06	86.34
1957-2010	Tall Eucalypt Forest	R.Hum. min. annual	-0.02	0.01	6	0.91	-0.01	46.31
1957-2010	Tall Eucalypt Forest	R.Hum. min. mean daily	0.28	18.52	3.61	**0**	0.15	62.15
1957-2010	Tall Eucalypt Forest	KBDI mean	0.08	4.7	11.19	**0.04**	-0.24	105.84
1957-2010	Tall Eucalypt Forest	KBDI max.	0	0.79	10.79	0.38	-0.1	123.95
1957-2010	Tall Eucalypt Forest	KBDI 99%	0	1.1	11.08	0.3	-0.12	123.89
1957-2010	Tall Eucalypt Forest	KBDI 95%	0	1.04	11.66	0.31	-0.12	122.59
1957-2010	Tall Eucalypt Forest	KBDI 90%	0.01	1.44	12.19	0.24	-0.15	121.88
1957-2010	Savanna	FFDI mean	0.09	5.28	0.83	**0.03**	-0.02	4.53
1957-2010	Savanna	Σ FFDI	0.09	5.3	74.52	**0.03**	-1.71	408.42
1957-2010	Savanna	FFDI max. annual	-0.01	0.42	2.97	0.52	0.02	9.62
1957-2010	Savanna	FFDI 99%	-0.01	0.36	2.15	0.55	-0.01	9.34
1957-2010	Savanna	FFDI 95%	-0.02	0.14	1.55	0.71	-0.01	7.46
1957-2010	Savanna	FFDI 90%	0	1.06	1.23	0.31	-0.01	6.73
1957-2010	Savanna	FFDI 50%	0.07	4.41	0.88	**0.04**	-0.02	4.24
1957-2010	Savanna	Rain total	0.25	17.36	39.42	**0**	1.51	65.6
1957-2010	Savanna	Wind mean	0.16	10.12	0.08	**0**	0	1.71
1957-2010	Savanna	Wind max.	0.68	102	0.29	**0**	0.03	1.55
1957-2010	Savanna	Temp. mean	0.45	40.03	0.43	**0**	0.03	20.45
1957-2010	Savanna	Temp. max. annual	0.05	3.5	1.08	**0.07**	0.02	31.39
1957-2010	Savanna	Temp. max. mean daily	0	0.79	0.61	0.38	0.01	28.21
1957-2010	Savanna	Temp. max. 99%	0.09	5.38	0.99	**0.03**	0.02	30.88
1957-2010	Savanna	Temp. max. 95%	0.04	2.96	0.93	**0.09**	0.02	30.17

1957-2010	Savanna	Temp. max. 90%	0.02	1.93	0.88	0.17	0.01	29.65
1957-2010	Savanna	Temp. min. annual	0.08	5.28	0.87	**0.03**	0.02	15.64
1957-2010	Savanna	Temp. min. mean daily	0.69	103.6	0.37	**0**	0.04	17.45
1957-2010	Savanna	R.Hum. mean	0.38	28.34	1.46	**0**	0.08	76.63
1957-2010	Savanna	R.Hum. min. annual	5.32	0.01	-0.02	0.91	-0.01	31.58
1957-2010	Savanna	R.Hum. min. mean daily	0.28	18.52	3.2	**0**	0.14	45.63
1957-2010	Savanna	KBDI mean	0.08	4.7	13.48	**0.04**	-0.29	94.4
1957-2010	Savanna	KBDI max.	0	0.79	13	0.38	-0.12	116.21
1957-2010	Savanna	KBDI 99%	0	1.1	13.34	0.3	-0.14	116.14
1957-2010	Savanna	KBDI 95%	0	1.04	14.05	0.31	-0.14	114.57
1957-2010	Savanna	KBDI 90%	0.01	1.44	14.69	0.24	-0.18	113.72

Appendix 5.6 Linear seasonal trend ('March-April-May') in FFDI and climatic variables for Cairns (1890 - 2010 and 1957 - 2010) and Mareeba (1957 - 2010). Linear trends for rain forest, tall eucalypt forest and savanna (reconstructed from Mareeba data) are also included. Trends that are significant at the 95% level ($p < 0.05$) are indicated by shading; near significant trends are in bold ($p < 0.15$).

Years	Location	Variable	AdjR^2 (%)	F-statistic	Residual Std. Error	*p*-value	Year Coefficient	Intercept Coefficient
1890-2010	Global	SOI mean	0	1.53	8.06	0.22	-0.03	1.04
1890-2010	Global	SOI max.	-0.01	0.13	8.4	0.72	-0.01	5.7
1890-2010	Global	SOI min.	0.02	3.15	9.4	**0.08**	-0.04	-3.64
1890-2010	Cairns	FFDI mean	0.37	71.52	0.91	**0**	0.02	2.59
1890-2010	Cairns	Σ FFDI	0.37	71.52	83.37	**0**	1.84	238.68
1890-2010	Cairns	FFDI max. annual	0.35	64.35	4.05	**0**	0.08	6.37
1890-2010	Cairns	FFDI 99%	0.51	125.2	2.18	**0**	0.06	6.02
1890-2012	Cairns	FFDI 95%	0.54	139.2	1.5	**0**	0.05	5.25
1890-2010	Cairns	FFDI 90%	0.54	140.3	1.32	**0**	0.04	4.64
1890-2010	Cairns	FFDI 50%	0.26	43.19	1.07	**0**	0.02	2.54
1890-2010	Cairns	FFDI days ≥25	0	1.49	0.16	0.23	0	-0.01
1890-2010	Cairns	FFDI days ≥12	0.25	41.58	1.91	**0**	0.03	-0.91
1890-2010	Cairns	Rain total	-0.01	0.35	337.7	0.55	-0.52	761.87
1890-2010	Cairns	Rain days ≥5 mm	0.02	4.05	7.31	**0.05**	-0.04	28.79
1890-2010	Cairns	Wind mean	0.68	252.1	1.54	0	-0.06	24.06
1890-2010	Cairns	Wind max.	0	0.52	5.73	0.47	-0.01	30.51
1890-2010	Cairns	Temp. mean	0.31	55.18	0.46	**0**	0.01	23.96
1890-2010	Cairns	Temp. max. annual	0.21	32.92	1.43	**0**	0.02	31.76
1890-2010	Cairns	Temp. max. mean daily	0.65	223.3	0.64	**0**	0.02	27.24
1890-2010	Cairns	Temp. max. 99%	0.33	59.65	1.2	**0**	0.02	31.19
1890-2010	Cairns	Temp. max. 95%	0.47	108	0.81	**0**	0.02	30.44
1890-2010	Cairns	Temp. max. 90%	0.49	117.3	0.76	**0**	0.02	29.9
1890-2010	Cairns	Temp. max. days ≥35 °C	0.02	3.18	0.75	**0.08**	0	0.04

1890-2010	Cairns	Temp. min. annual	0.04	6.22	1.8	**0.01**	0.01	14.47
1890-2010	Cairns	Temp. min. mean daily	0.29	48.93	0.56	**0**	0.01	20.62
1890-2010	Cairns	R.Hum. mean	0.67	247.1	2.06	**0**	-0.08	86.68
1890-2010	Cairns	R.Hum. min. annual	0.54	142.1	6.56	**0**	-0.2	56.03
1890-2010	Cairns	R.Hum. min. mean daily	0.63	207.2	2.66	**0**	-0.1	72.72
1890-2010	Cairns	R.Hum. min. 1%	0.56	152.9	5.22	**0**	-0.17	57.37
1890-2010	Cairns	R.Hum. min. 5%	0.65	222.6	3.74	**0**	-0.15	61.87
1890-2010	Cairns	R.Hum. min. 10%	0.68	246.8	3.43	**0**	-0.14	64.55
1890-2010	Cairns	KBDI mean	0.06	8.47	22.92	**0**	0.17	54.62
1890-2010	Cairns	KBDI max.	0.1	13.86	24.38	**0**	0.24	114.03
1890-2010	Cairns	KBDI 99%	0.11	15.45	24.28	**0**	0.25	111.08
1890-2010	Cairns	KBDI 95%	0.09	12.2	25.63	**0**	0.23	104.86
1890-2010	Cairns	KBDI 90%	0.06	9.33	26.77	**0**	0.21	98.61
1957-2010	Global	SOI mean	0	1.16	7.68	0.29	-0.07	0.39
1957-2010	Global	SOI max.	-0.02	0.18	8.17	0.67	-0.03	5.54
1957-2010	Global	SOI min.	0.03	2.6	8.99	0.11	-0.13	-4.34
1957-2010	Cairns	FFDI mean	0.09	5.96	1.03	**0.02**	0.02	3.84
1957-2010	Cairns	Σ FFDI	0.09	5.96	94.69	**0.02**	2.02	353.38
1957-2010	Cairns	FFDI max. annual	0.02	2.25	5.03	**0.14**	0.07	12.61
1957-2010	Cairns	FFDI 99%	0.07	4.85	2.62	**0.03**	0.05	10.72
1957-2010	Cairns	FFDI 95%	0.09	6.1	1.87	**0.02**	0.04	8.53
1957-2010	Cairns	FFDI 90%	0.12	8.12	1.61	**0.01**	0.04	7.4
1957-2010	Cairns	FFDI 50%	0.1	6.84	1.12	**0.01**	0.03	3.49
1957-2010	Cairns	FFDI days ≥25	-0.02	0	0.19	1	0	0.04
1957-2010	Cairns	FFDI days ≥12	0.07	4.81	2.77	**0.03**	0.05	0.77
1957-2010	Cairns	Rain total	0	1.18	316.7	0.28	-3	806.65
1957-2010	Cairns	Rain days ≥5 mm	0.01	1.31	6.61	0.26	-0.07	26.92
1957-2010	Cairns	Wind mean	0.24	17.63	2.09	**0**	-0.08	20.29

1957-2010	Cairns	Wind max.	0.09	6.1	3.76	**0.02**	-0.08	32.8
1957-2010	Cairns	Temp. mean	0.09	6.1	0.47	**0.02**	0.01	24.51
1957-2010	Cairns	Temp. max. annual	-0.02	0.06	1.48	0.82	0	33.86
1957-2010	Cairns	Temp. max. mean daily	-0.02	0.01	0.4	0.94	0	29.54
1957-2010	Cairns	Temp. max. 99%	-0.02	0.05	1.27	0.83	0	33.52
1957-2010	Cairns	Temp. max. 95%	-0.02	0.06	0.66	0.8	0	32.51
1957-2010	Cairns	Temp. max. 90%	0.01	1.7	0.55	0.2	-0.01	32.06
1957-2010	Cairns	Temp. max. days ≥35 °C	-0.02	0.01	0.92	0.94	0	0.37
1957-2010	Cairns	Temp. min. annual	0.02	1.9	2.05	0.17	0.02	14.82
1957-2010	Cairns	Temp. min. mean daily	0.02	2.29	0.59	**0.14**	0.01	21.38
1957-2010	Cairns	R.Hum. mean	0.3	24.05	2.56	**0**	-0.11	81.9
1957-2010	Cairns	R.Hum. min. annual	0.03	2.75	7.95	**0.1**	-0.12	39.11
1957-2010	Cairns	R.Hum. min. mean daily	0.25	18.36	3.14	**0**	-0.12	66.81
1957-2010	Cairns	R.Hum. min. 1%	0.06	4.34	5.67	**0.04**	-0.1	43.62
1957-2010	Cairns	R.Hum. min. 5%	0.15	10.68	4.11	**0**	-0.12	51.04
1957-2010	Cairns	R.Hum. min. 10%	0.2	14.13	3.84	**0**	-0.13	54.5
1957-2010	Cairns	KBDI mean	0.04	3.31	20.23	**0.07**	0.32	60.27
1957-2010	Cairns	KBDI max.	0.14	9.94	20.05	**0**	0.55	118.16
1957-2010	Cairns	KBDI 99%	0.15	10.19	20.13	**0**	0.56	116.13
1957-2010	Cairns	KBDI 95%	0.13	8.92	21.03	**0**	0.55	108.25
1957-2010	Cairns	KBDI 90%	0.11	7.64	22.63	**0.01**	0.55	99.96
1957-2010	Mareeba	FFDI mean	-0.02	0	1.46	0.99	0	5.94
1957-2010	Mareeba	Σ FFDI	-0.02	0	134.6	0.99	0.02	546.67
1957-2010	Mareeba	FFDI max. annual	-0.01	0.67	4.05	0.42	0.03	13.67
1957-2010	Mareeba	FFDI 99%	-0.02	0.19	3.54	0.67	0.01	12.6
1957-2010	Mareeba	FFDI 95%	-0.01	0.48	2.59	0.49	0.02	10.16
1957-2010	Mareeba	FFDI 90%	-0.02	0.2	2.33	0.65	0.01	9.11
1957-2010	Mareeba	FFDI 50%	-0.02	0.04	1.35	0.84	0	5.83

1957-2010	Mareeba	Rain total	0.02	1.78	104	0.19	1.3	124.98
1957-2010	Mareeba	Wind mean	0.75	139.4	0.79	**0**	0.09	8.76
1957-2010	Mareeba	Wind max.	0.64	86.11	3.48	**0**	0.31	8.01
1957-2010	Mareeba	Temp. mean	0.36	27.9	0.44	**0**	0.02	19.96
1957-2010	Mareeba	Temp. max. annual	-0.01	0.67	1.22	0.42	0.01	32.53
1957-2010	Mareeba	Temp. max. mean daily	-0.02	0.29	0.57	0.59	0	28.17
1957-2010	Mareeba	Temp. max. 99%	0	0.77	1.26	0.38	0.01	31.95
1957-2010	Mareeba	Temp. max. 95%	0.01	1.68	0.87	0.2	0.01	30.88
1957-2010	Mareeba	Temp. max. 90%	0.04	2.9	0.78	**0.1**	0.01	30.14
1957-2010	Mareeba	Temp. min. annual	-0.01	0.71	2.06	0.4	0.02	11.71
1957-2010	Mareeba	Temp. min. mean daily	0.48	44.79	0.69	**0**	0.04	16.58
1957-2010	Mareeba	R.Hum. mean	0.21	12.75	1.49	**0**	0.05	71.29
1957-2010	Mareeba	R.Hum. min. annual	0	1.11	6.14	0.3	0.06	26.13
1957-2010	Mareeba	R.Hum. min. mean daily	0.19	11.86	3.75	**0**	0.12	46.89
1957-2010	Mareeba	KBDI mean	-0.01	0.38	22.57	0.54	0.14	44.3
1957-2010	Mareeba	KBDI max.	0.04	2.93	24.5	**0.09**	0.41	73.42
1957-2010	Mareeba	KBDI 99%	0.04	2.9	24.43	**0.1**	0.41	72.56
1957-2010	Mareeba	KBDI 95%	0.05	3.37	24.37	**0.07**	0.44	67.73
1957-2010	Mareeba	KBDI 90%	0.04	2.96	24.38	**0.09**	0.41	64.17
1957-2010	Rain Forest	FFDI mean	-0.02	0.01	0.27	0.93	0	0.81
1957-2010	Rain Forest	Σ FFDI	-0.02	0.01	25.04	0.93	0.02	74.74
1957-2010	Rain Forest	FFDI max. annual	-0.01	0.67	0.78	0.42	0.01	2.29
1957-2010	Rain Forest	FFDI 99%	-0.02	0.19	0.68	0.67	0	2.08
1957-2010	Rain Forest	FFDI 95%	-0.01	0.48	0.5	0.49	0	1.62
1957-2010	Rain Forest	FFDI 90%	-0.02	0.2	0.45	0.65	0	1.41
1957-2010	Rain Forest	FFDI 50%	-0.02	0.04	0.26	0.84	0	0.78
1957-2010	Rain Forest	Wind mean	0.75	139.4	0	**0**	0	0.16
1957-2010	Rain Forest	Wind max.	0.64	86.11	0.02	**0**	0	0.16

1957-2010	Rain Forest	Temp. mean	0.36	27.9	0.4	**0**	0.02	14.88
1957-2010	Rain Forest	Temp. max. annual	-0.01	0.67	1.1	0.42	0.01	23.28
1957-2010	Rain Forest	Temp. max. mean daily	-0.02	0.29	0.52	0.59	0	19.31
1957-2010	Rain Forest	Temp. max. 99%	0	0.77	1.14	0.38	0.01	22.76
1957-2010	Rain Forest	Temp. max. 95%	0.01	1.68	0.79	0.2	0.01	21.78
1957-2010	Rain Forest	Temp. max. 90%	0.04	2.9	0.71	**0.1**	0.01	21.1
1957-2010	Rain Forest	Temp. min. annual	-0.01	0.71	1.44	0.4	0.01	10.71
1957-2010	Rain Forest	Temp. min. mean daily	0.48	44.79	0.48	**0**	0.03	14.12
1957-2010	Rain Forest	R.Hum. mean	0.21	12.75	0.66	**0**	0.02	92.15
1957-2010	Rain Forest	R.Hum. min. annual	0	1.11	4.81	0.3	0.05	60.38
1957-2010	Rain Forest	R.Hum. min. mean daily	0.19	11.86	2.93	**0**	0.1	76.63
1957-2010	Rain Forest	KBDI mean	-0.01	0.38	6.07	0.54	0.04	80.16
1957-2010	Rain Forest	KBDI max.	0.04	2.93	6.59	0.09	0.11	87.99
1957-2010	Rain Forest	KBDI 99%	0.04	2.9	6.57	**0.1**	0.11	87.76
1957-2010	Rain Forest	KBDI 95%	0.05	3.37	6.56	**0.07**	0.12	86.46
1957-2010	Rain Forest	KBDI 90%	0.04	2.96	6.56	**0.09**	0.11	85.5
1957-2010	Tall Eucalypt Forest	FFDI mean	-0.02	0	0.4	0.99	0	1.59
1957-2010	Tall Eucalypt Forest	Σ FFDI	-0.02	0	36.62	0.99	0	146.6
1957-2010	Tall Eucalypt Forest	FFDI max. annual	-0.01	0.67	1.1	0.42	0.01	3.7
1957-2010	Tall Eucalypt Forest	FFDI 99%	-0.02	0.19	0.96	0.67	0	3.4
1957-2010	Tall Eucalypt Forest	FFDI 95%	-0.01	0.48	0.7	0.49	0	2.74
1957-2010	Tall Eucalypt Forest	FFDI 90%	-0.02	0.2	0.63	0.65	0	2.46
1957-2010	Tall Eucalypt Forest	FFDI 50%	-0.02	0.04	0.37	0.84	0	1.56
1957-2010	Tall Eucalypt Forest	Wind mean	0.75	139.4	0.03	**0**	0	0.42
1957-2010	Tall Eucalypt Forest	Wind max.	0.64	86.11	0.15	**0**	0.01	0.38
1957-2010	Tall Eucalypt Forest	Temp. mean	0.36	27.9	0.35	**0**	0.02	17.33
1957-2010	Tall Eucalypt Forest	Temp. max. annual	-0.01	0.67	1.03	0.42	0.01	26.62
1957-2010	Tall Eucalypt Forest	Temp. max. mean daily	-0.02	0.29	0.48	0.59	0	22.92

1957-2010	Tall Eucalypt Forest	Temp. max. 99%	0	0.77	1.07	0.38	0.01	26.13
1957-2010	Tall Eucalypt Forest	Temp. max. 95%	0.01	1.68	0.74	0.2	0.01	25.22
1957-2010	Tall Eucalypt Forest	Temp. max. 90%	0.04	2.9	0.66	**0.1**	0.01	24.59
1957-2010	Tall Eucalypt Forest	Temp. min. annual	-0.01	0.71	1.29	0.4	0.01	12.8
1957-2010	Tall Eucalypt Forest	Temp. min. mean daily	0.48	44.79	0.43	**0**	0.03	15.84
1957-2010	Tall Eucalypt Forest	R.Hum. mean	0.21	12.75	0.81	**0**	0.03	87.57
1957-2010	Tall Eucalypt Forest	R.Hum. min. annual	0	1.11	5.17	0.3	0.05	47.38
1957-2010	Tall Eucalypt Forest	R.Hum. min. mean daily	0.19	11.86	3.16	**0**	0.11	64.87
1957-2010	Tall Eucalypt Forest	KBDI mean	-0.01	0.38	7.72	0.54	0.05	86.08
1957-2010	Tall Eucalypt Forest	KBDI max.	0.04	2.93	8.38	**0.09**	0.14	96.04
1957-2010	Tall Eucalypt Forest	KBDI 99%	0.04	2.9	8.36	**0.1**	0.14	95.75
1957-2010	Tall Eucalypt Forest	KBDI 95%	0.05	3.37	8.34	**0.07**	0.15	94.1
1957-2010	Tall Eucalypt Forest	KBDI 90%	0.04	2.96	8.34	**0.09**	0.14	92.88
1957-2010	Savanna	FFDI mean	-0.02	0	0.64	0.99	0	3.61
1957-2010	Savanna	Σ FFDI	-0.02	0	58.95	0.99	0.01	331.8
1957-2010	Savanna	FFDI max. annual	-0.01	0.67	1.77	0.42	0.01	6.99
1957-2010	Savanna	FFDI 99%	-0.02	0.19	1.55	0.67	0.01	6.52
1957-2010	Savanna	FFDI 95%	-0.01	0.48	1.14	0.49	0.01	5.45
1957-2010	Savanna	FFDI 90%	-0.02	0.2	1.02	0.65	0	5
1957-2010	Savanna	FFDI 50%	-0.02	0.04	0.59	0.84	0	3.56
1957-2010	Savanna	Rain total	0.01	1.33	22.78	0.26	0.25	59.27
1957-2010	Savanna	Wind mean	0.75	139.4	0.08	**0**	0.01	1.66
1957-2010	Savanna	Wind max.	0.64	86.11	0.37	**0**	0.03	1.57
1957-2010	Savanna	Temp. mean	0.36	27.9	0.33	**0**	0.02	19.14
1957-2010	Savanna	Temp. max. annual	-0.01	0.67	0.88	0.42	0.01	29.47
1957-2010	Savanna	Temp. max. mean daily	-0.02	0.29	0.41	0.59	0	26.3
1957-2010	Savanna	Temp. max. 99%	0	0.77	0.91	0.38	0.01	29.05
1957-2010	Savanna	Temp. max. 95%	0.01	1.68	0.63	0.2	0.01	28.27

1957-2010	Savanna	Temp. max. 90%	0.04	2.9	0.57	**0.1**	0.01	27.73
1957-2010	Savanna	Temp. min. annual	-0.01	0.71	1.3	0.4	0.01	13.3
1957-2010	Savanna	Temp. min. mean daily	0.48	44.79	0.44	**0**	0.03	16.39
1957-2010	Savanna	R.Hum. mean	0.21	12.75	1.01	**0**	0.04	78.16
1957-2010	Savanna	R.Hum. min. annual	0	1.11	4.59	0.3	0.05	32.53
1957-2010	Savanna	R.Hum. min. mean daily	0.19	11.86	2.8	**0**	0.09	48.05
1957-2010	Savanna	KBDI mean	-0.01	0.38	9.3	0.54	0.06	70.6
1957-2010	Savanna	KBDI max.	0.04	2.93	10.09	**0.09**	0.17	82.59
1957-2010	Savanna	KBDI 99%	0.04	2.9	10.06	**0.1**	0.17	82.24
1957-2010	Savanna	KBDI 95%	0.05	3.37	10.04	**0.07**	0.18	80.25
1957-2010	Savanna	KBDI 90%	0.04	2.96	10.05	**0.09**	0.17	78.78

Appendix 5.7 Linear seasonal trend (‘June-July-August’) in FFDI and climatic variables for Cairns (1890 - 2010 and 1957 - 2010) and Mareeba (1957 - 2010). Linear trends for rain forest, tall eucalypt forest and savanna (reconstructed from Mareeba data) are also included. Trends that are significant at the 95% level ($p < 0.05$) are indicated by shading; near significant trends are in bold ($p < 0.15$).

Years	Location	Variable	AdjR^2 (%)	F-statistic	Residual Std. Error	*p*-value	Year Coefficient	Intercept Coefficient
1890-2010	Global	SOI mean	0	1.08	8.55	0.3	-0.02	1.16
1890-2010	Global	SOI max.	0	0.72	9.09	0.4	-0.02	5.16
1890-2010	Global	SOI min.	0.01	2.25	8.79	**0.14**	-0.03	-2.45
1890-2010	Cairns	FFDI mean	0.66	233.4	0.81	**0**	0.03	3.84
1890-2010	Cairns	Σ FFDI	0.66	233.4	74.39	**0**	2.96	353.12
1890-2010	Cairns	FFDI max. annual	0.56	155.8	2.99	**0**	0.1	7.78
1890-2010	Cairns	FFDI 99%	0.6	180.3	2.31	**0**	0.08	7.3
1890-2012	Cairns	FFDI 95%	0.65	226.6	1.64	**0**	0.06	6.03
1890-2010	Cairns	FFDI 90%	0.71	289.4	1.28	**0**	0.06	5.35
1890-2010	Cairns	FFDI 50%	0.64	210.5	0.77	**0**	0.03	3.87
1890-2010	Cairns	FFDI days ≥25	0.01	1.98	0.09	0.16	0	-0.01
1890-2010	Cairns	FFDI days ≥12	0.46	104.6	3.22	**0**	0.09	-2.02
1890-2010	Cairns	Rain total	0	1.54	56.21	0.22	-0.18	121.27
1890-2010	Cairns	Rain days ≥5 mm	0.03	4.44	3.91	**0.04**	-0.02	8.67
1890-2010	Cairns	Wind mean	0.59	172.4	1.55	**0**	-0.05	23.84
1890-2010	Cairns	Wind max.	0	0.43	4.84	0.52	0.01	29.15
1890-2010	Cairns	Temp. mean	0.01	1.9	0.6	0.17	0	21.17
1890-2010	Cairns	Temp. max. annual	0.19	29.1	1.16	**0**	0.02	28.16
1890-2010	Cairns	Temp. max. mean daily	0.61	191.6	0.65	**0**	0.02	24.39
1890-2010	Cairns	Temp. max. 99%	0.24	39.19	0.99	**0**	0.02	27.78
1890-2010	Cairns	Temp. max. 95%	0.29	49.28	0.89	**0**	0.02	27.11
1890-2010	Cairns	Temp. max. 90%	0.39	77.8	0.8	**0**	0.02	26.52
1890-2010	Cairns	Temp. max. days ≥35 °C	NA	NA	NA	NA	NA	NA

1890-2010	Cairns	Temp. min. annual	-0.01	0.14	1.41	0.71	0	10.57
1890-2010	Cairns	Temp. min. mean daily	0.06	8.46	0.84	**0**	0.01	16.92
1890-2010	Cairns	R.Hum. mean	0.81	519.1	2	**0**	-0.12	85.17
1890-2010	Cairns	R.Hum. min. annual	0.69	268.2	5.42	**0**	-0.23	51.52
1890-2010	Cairns	R.Hum. min. mean daily	0.77	403.5	2.82	**0**	-0.15	70.62
1890-2010	Cairns	R.Hum. min. 1%	0.67	235.6	5.29	**0**	-0.22	53.88
1890-2010	Cairns	R.Hum. min. 5%	0.71	282.9	4.45	**0**	-0.2	58.4
1890-2010	Cairns	R.Hum. min. 10%	0.74	344	3.86	**0**	-0.19	61.4
1890-2010	Cairns	KBDI mean	0.17	25.69	22.05	**0**	0.29	115.38
1890-2010	Cairns	KBDI max.	0.18	28.17	14.04	**0**	0.19	157.64
1890-2010	Cairns	KBDI 99%	0.18	27.97	14.25	**0**	0.2	156.78
1890-2010	Cairns	KBDI 95%	0.18	27.88	14.9	**0**	0.2	153.47
1890-2010	Cairns	KBDI 90%	0.18	28.02	15.54	**0**	0.21	149.48
1957-2010	Global	SOI mean	-0.01	0.72	7.89	0.4	-0.06	0.41
1957-2010	Global	SOI max.	-0.02	0.19	8.43	0.66	-0.03	3.91
1957-2010	Global	SOI min.	0.01	1.42	7.94	0.24	-0.08	-3.49
1957-2010	Cairns	FFDI mean	0.06	4.28	0.89	**0.04**	0.02	6.56
1957-2010	Cairns	Σ FFDI	0.06	4.28	82.33	**0.04**	1.49	603.85
1957-2010	Cairns	FFDI max. annual	0.01	1.65	3.61	0.2	0.04	16.35
1957-2010	Cairns	FFDI 99%	-0.01	0.43	2.53	0.52	0.01	14.97
1957-2010	Cairns	FFDI 95%	0.01	1.58	1.8	0.21	0.02	11.91
1957-2010	Cairns	FFDI 90%	0.05	3.77	1.46	**0.06**	0.02	10.3
1957-2010	Cairns	FFDI 50%	0.1	6.72	0.86	**0.01**	0.02	6.16
1957-2010	Cairns	FFDI days ≥25	0	0.99	0.14	0.32	0	-0.01
1957-2010	Cairns	FFDI days ≥12	0.04	3.06	4.46	0.09	0.07	4.68
1957-2010	Cairns	Rain total	-0.02	0.02	51.79	0.88	-0.07	102
1957-2010	Cairns	Rain days ≥5 mm	-0.02	0.1	3.45	0.75	0.01	5.89
1957-2010	Cairns	Wind mean	0.34	28.61	1.93	**0**	-0.09	21.55

1957-2010	Cairns	Wind max.	0.31	24.37	3.56	**0**	-0.15	35.82
1957-2010	Cairns	Temp. mean	0.04	3.24	0.63	**0.08**	0.01	21.02
1957-2010	Cairns	Temp. max. annual	0	0.83	0.88	0.37	0.01	29.45
1957-2010	Cairns	Temp. max. mean daily	-0.01	0.6	0.48	0.44	0	26.47
1957-2010	Cairns	Temp. max. 99%	0	0.79	0.73	0.38	0.01	29.1
1957-2010	Cairns	Temp. max. 95%	-0.02	0.19	0.53	0.66	0	28.56
1957-2010	Cairns	Temp. max. 90%	-0.02	0.11	0.49	0.74	0	28.17
1957-2010	Cairns	Temp. max. days ≥35 °C	NA	NA	NA	NA	NA	NA
1957-2010	Cairns	Temp. min. annual	-0.02	0.14	1.52	0.71	0	10.72
1957-2010	Cairns	Temp. min. mean daily	0.01	1.75	0.85	0.19	0.01	17.19
1957-2010	Cairns	R.Hum. mean	0.35	29.53	2.14	**0**	-0.1	76.52
1957-2010	Cairns	R.Hum. min. annual	0.16	10.88	5.71	**0**	-0.16	33.25
1957-2010	Cairns	R.Hum. min. mean daily	0.25	19.13	2.95	**0**	-0.11	59.48
1957-2010	Cairns	R.Hum. min. 1%	0.11	7.23	5.19	**0.01**	-0.12	35.58
1957-2010	Cairns	R.Hum. min. 5%	0.11	7.73	4.61	**0.01**	-0.11	41.77
1957-2010	Cairns	R.Hum. min. 10%	0.15	10.42	4.14	**0**	-0.12	46.04
1957-2010	Cairns	KBDI mean	0.02	2.23	19.28	**0.14**	0.25	135.91
1957-2010	Cairns	KBDI max.	-0.02	0.03	10.33	0.86	-0.02	176.89
1957-2010	Cairns	KBDI 99%	-0.02	0.02	10.44	0.88	-0.01	176.21
1957-2010	Cairns	KBDI 95%	-0.02	0	11.07	0.96	0	173.49
1957-2010	Cairns	KBDI 90%	-0.02	0.01	11.96	0.92	0.01	170.04
1957-2010	Mareeba	FFDI mean	0.02	1.99	1.3	0.17	-0.02	8.89
1957-2010	Mareeba	Σ FFDI	0.02	1.99	119.7	0.17	-1.65	817.89
1957-2010	Mareeba	FFDI max. annual	-0.02	0	4.58	1	0	19.65
1957-2010	Mareeba	FFDI 99%	-0.02	0.07	4.11	0.79	-0.01	18.05
1957-2010	Mareeba	FFDI 95%	-0.02	0.2	2.66	0.66	-0.01	14.7
1957-2010	Mareeba	FFDI 90%	-0.01	0.42	2.39	0.52	-0.02	12.9
1957-2010	Mareeba	FFDI 50%	0.03	2.16	1.29	0.15	-0.02	8.4

1957-2010	Mareeba	Rain total	0.09	5.59	0.11	**0.02**	0.31	12.7
1957-2010	Mareeba	Wind mean	0.72	121.9	1.05	**0**	0.11	8.55
1957-2010	Mareeba	Wind max.	0.68	97.88	3.64	**0**	0.34	7.62
1957-2010	Mareeba	Temp. mean	0.06	3.99	0.53	**0.05**	-0.01	17.8
1957-2010	Mareeba	Temp. max. annual	-0.02	0.09	1.6	0.77	0	30.13
1957-2010	Mareeba	Temp. max. mean daily	-0.01	0.59	0.7	0.45	-0.01	25.68
1957-2010	Mareeba	Temp. max. 99%	-0.01	0.41	1.28	0.52	0.01	29.31
1957-2010	Mareeba	Temp. max. 95%	0	1.16	0.97	0.29	0.01	28.06
1957-2010	Mareeba	Temp. max. 90%	-0.02	0.32	0.9	0.58	0	27.4
1957-2010	Mareeba	Temp. min. annual	0.03	2.43	1.48	**0.13**	-0.02	8.48
1957-2010	Mareeba	Temp. min. mean daily	0.22	13.72	0.8	**0**	0.03	12.96
1957-2010	Mareeba	R.Hum. mean	0.1	5.84	1.73	**0.02**	0.04	69.22
1957-2010	Mareeba	R.Hum. min. annual	-0.01	0.59	6.9	0.45	0.05	19.47
1957-2010	Mareeba	R.Hum. min. mean daily	0.2	12	4.35	**0**	0.15	41.39
1957-2010	Mareeba	KBDI mean	0.05	3.07	21.75	**0.09**	0.37	94.12
1957-2010	Mareeba	KBDI max.	0.08	4.93	16.53	**0.03**	0.36	119.19
1957-2010	Mareeba	KBDI 99%	0.08	4.8	16.63	**0.03**	0.36	118.7
1957-2010	Mareeba	KBDI 95%	0.07	4.48	17.03	**0.04**	0.35	116.71
1957-2010	Mareeba	KBDI 90%	0.07	4.09	17.63	**0.05**	0.35	114.19
1957-2010	Rain Forest	FFDI mean	0.02	1.94	0.25	0.17	0	1.37
1957-2010	Rain Forest	Σ FFDI	0.02	1.94	22.96	0.17	-0.31	126.08
1957-2010	Rain Forest	FFDI max. annual	-0.02	0	0.88	1	0	3.44
1957-2010	Rain Forest	FFDI 99%	-0.02	0.07	0.79	0.79	0	3.13
1957-2010	Rain Forest	FFDI 95%	-0.02	0.2	0.51	0.66	0	2.49
1957-2010	Rain Forest	FFDI 90%	-0.01	0.42	0.46	0.52	0	2.14
1957-2010	Rain Forest	FFDI 50%	0.03	2.16	0.25	0.15	0	1.28
1957-2010	Rain Forest	Wind mean	0.72	121.9	0.01	**0**	0	0.16
1957-2010	Rain Forest	Wind max.	0.68	97.88	0.02	**0**	0	0.15

1957-2010	Rain Forest	Temp. mean	0.06	3.99	0.49	**0.05**	-0.01	12.89
1957-2010	Rain Forest	Temp. max. annual	-0.02	0.09	1.45	0.77	0	21.1
1957-2010	Rain Forest	Temp. max. mean daily	-0.01	0.59	0.64	0.45	0	17.05
1957-2010	Rain Forest	Temp. max. 99%	-0.01	0.41	1.16	0.52	0.01	20.35
1957-2010	Rain Forest	Temp. max. 95%	0	1.16	0.88	0.29	0.01	19.22
1957-2010	Rain Forest	Temp. max. 90%	-0.02	0.32	0.82	0.58	0	18.62
1957-2010	Rain Forest	Temp. min. annual	0.03	2.43	1.03	**0.13**	-0.02	8.46
1957-2010	Rain Forest	Temp. min. mean daily	0.22	13.72	0.56	**0**	0.02	11.59
1957-2010	Rain Forest	R.Hum. mean	0.1	5.84	0.77	**0.02**	0.02	91.23
1957-2010	Rain Forest	R.Hum. min. annual	-0.01	0.59	5.4	0.45	0.04	55.16
1957-2010	Rain Forest	R.Hum. min. mean daily	0.2	12	3.41	**0**	0.11	72.32
1957-2010	Rain Forest	KBDI mean	0.05	3.07	5.85	**0.09**	0.1	93.56
1957-2010	Rain Forest	KBDI max.	0.08	4.93	4.45	**0.03**	0.1	100.3
1957-2010	Rain Forest	KBDI 99%	0.08	4.8	4.47	**0.03**	0.1	100.17
1957-2010	Rain Forest	KBDI 95%	0.07	4.48	4.58	**0.04**	0.09	99.64
1957-2010	Rain Forest	KBDI 90%	0.07	4.09	4.74	**0.05**	0.09	98.96
1957-2010	Tall Eucalypt Forest	FFDI mean	0.02	1.99	0.35	0.17	0	2.4
1957-2010	Tall Eucalypt Forest	Σ FFDI	0.02	1.99	32.56	0.17	-0.45	220.35
1957-2010	Tall Eucalypt Forest	FFDI max. annual	-0.02	0	1.25	1	0	5.32
1957-2010	Tall Eucalypt Forest	FFDI 99%	-0.02	0.07	1.12	0.79	0	4.89
1957-2010	Tall Eucalypt Forest	FFDI 95%	-0.02	0.2	0.72	0.66	0	3.97
1957-2010	Tall Eucalypt Forest	FFDI 90%	-0.01	0.42	0.65	0.52	0	3.49
1957-2010	Tall Eucalypt Forest	FFDI 50%	0.03	2.16	0.35	0.15	-0.01	2.26
1957-2010	Tall Eucalypt Forest	Wind mean	0.72	121.9	0.05	**0**	0	0.41
1957-2010	Tall Eucalypt Forest	Wind max.	0.68	97.88	0.16	**0**	0.01	0.37
1957-2010	Tall Eucalypt Forest	Temp. mean	0.06	3.99	0.43	**0.05**	-0.01	15.61
1957-2010	Tall Eucalypt Forest	Temp. max. annual	-0.02	0.09	1.36	0.77	0	24.58
1957-2010	Tall Eucalypt Forest	Temp. max. mean daily	-0.01	0.59	0.6	0.45	0	20.81

1957-2010	Tall Eucalypt Forest	Temp. max. 99%	-0.01	0.41	1.08	0.52	0.01	23.89
1957-2010	Tall Eucalypt Forest	Temp. max. 95%	0	1.16	0.82	0.29	0.01	22.83
1957-2010	Tall Eucalypt Forest	Temp. max. 90%	-0.02	0.32	0.77	0.58	0	22.27
1957-2010	Tall Eucalypt Forest	Temp. min. annual	0.03	2.43	0.93	**0.13**	-0.01	10.78
1957-2010	Tall Eucalypt Forest	Temp. min. mean daily	0.22	13.72	0.5	**0**	0.02	13.58
1957-2010	Tall Eucalypt Forest	R.Hum. mean	0.1	5.84	0.95	**0.02**	0.02	86.44
1957-2010	Tall Eucalypt Forest	R.Hum. min. annual	-0.01	0.59	5.81	0.45	0.04	41.76
1957-2010	Tall Eucalypt Forest	R.Hum. min. mean daily	0.2	12	3.67	**0**	0.12	60.24
1957-2010	Tall Eucalypt Forest	KBDI mean	0.05	3.07	7.44	**0.09**	0.13	103.12
1957-2010	Tall Eucalypt Forest	KBDI max.	0.08	4.93	5.65	**0.03**	0.12	111.7
1957-2010	Tall Eucalypt Forest	KBDI 99%	0.08	4.8	5.69	**0.03**	0.12	111.53
1957-2010	Tall Eucalypt Forest	KBDI 95%	0.07	4.48	5.82	**0.04**	0.12	110.85
1957-2010	Tall Eucalypt Forest	KBDI 90%	0.07	4.09	6.03	**0.05**	0.12	109.98
1957-2010	Savanna	FFDI mean	0.02	1.99	0.57	0.17	-0.01	4.9
1957-2010	Savanna	Σ FFDI	0.02	1.99	52.43	0.17	-0.72	450.51
1957-2010	Savanna	FFDI max. annual	-0.02	0	2.01	1	0	9.61
1957-2010	Savanna	FFDI 99%	-0.02	0.07	1.8	0.79	0	8.91
1957-2010	Savanna	FFDI 95%	-0.02	0.2	1.17	0.66	-0.01	7.44
1957-2010	Savanna	FFDI 90%	-0.01	0.42	1.05	0.52	-0.01	6.65
1957-2010	Savanna	FFDI 50%	0.03	2.16	0.56	0.15	-0.01	4.68
1957-2010	Savanna	Rain total	0.04	3.04	7.92	**0.09**	0.13	16.6
1957-2010	Savanna	Wind mean	0.72	121.9	0.11	**0**	0.01	1.63
1957-2010	Savanna	Wind max.	0.68	97.88	0.39	**0**	0.04	1.53
1957-2010	Savanna	Temp. mean	0.06	3.99	0.41	**0.05**	-0.01	17.49
1957-2010	Savanna	Temp. max. annual	-0.02	0.09	1.16	0.77	0	27.73
1957-2010	Savanna	Temp. max. mean daily	-0.01	0.59	0.51	0.45	0	24.5
1957-2010	Savanna	Temp. max. 99%	-0.01	0.41	0.93	0.52	0.01	27.14
1957-2010	Savanna	Temp. max. 95%	0	1.16	0.7	0.29	0.01	26.23

1957-2010	Savanna	Temp. max. 90%	-0.02	0.32	0.66	0.58	0	25.75
1957-2010	Savanna	Temp. min. annual	0.03	2.43	0.94	**0.13**	-0.01	11.25
1957-2010	Savanna	Temp. min. mean daily	0.22	13.72	0.5	**0**	0.02	14.09
1957-2010	Savanna	R.Hum. mean	0.1	5.84	1.18	**0.02**	0.03	76.75
1957-2010	Savanna	R.Hum. min. annual	-0.01	0.59	5.16	0.45	0.04	27.54
1957-2010	Savanna	R.Hum. min. mean daily	0.2	12	3.26	**0**	0.11	43.94
1957-2010	Savanna	KBDI mean	0.05	3.07	8.96	**0.09**	0.15	91.12
1957-2010	Savanna	KBDI max.	0.08	4.93	6.81	**0.03**	0.15	101.45
1957-2010	Savanna	KBDI 99%	0.08	4.8	6.85	**0.03**	0.15	101.25
1957-2010	Savanna	KBDI 95%	0.07	4.48	7.02	**0.04**	0.15	100.43
1957-2010	Savanna	KBDI 90%	0.07	4.09	7.27	**0.05**	0.14	99.39

Appendix 5.8 Linear seasonal trend ('September-October-November') in FFDI and climatic variables for Cairns (1890 - 2010 and 1957 - 2010) and Mareeba (1957 - 2010). Linear trends for rain forest, tall eucalypt forest and savanna (reconstructed from Mareeba data) are also included. Trends that are significant at the 95% level ($p < 0.05$) are indicated by shading; near significant trends are in bold ($p < 0.15$).

Years	**Location**	**Variable**	**AdjR^2 (%)**	**F-statistic**	**Residual Std. Error**	***p*-value**	**Year Coefficient**	**Intercept Coefficient**
1890-2010	Global	SOI mean	-0.01	0.02	8.85	0.89	0	-0.1
1890-2010	Global	SOI max.	-0.01	0.09	9.15	0.76	0.01	4.04
1890-2010	Global	SOI min.	-0.01	0	9.3	0.98	0	-4.42
1890-2010	Cairns	FFDI mean	0.42	88.47	1.01	**0**	0.02	5.17
1890-2010	Cairns	Σ FFDI	0.42	88.47	92.03	**0**	2.25	470.13
1890-2010	Cairns	FFDI max. annual	0.44	96.18	5.14	**0**	0.13	8.98
1890-2010	Cairns	FFDI 99%	0.51	127.1	3.55	**0**	0.1	8.18
1890-2012	Cairns	FFDI 95%	0.6	178.4	1.99	**0**	0.07	7.13
1890-2010	Cairns	FFDI 90%	0.61	186.5	1.49	**0**	0.05	6.75
1890-2010	Cairns	FFDI 50%	0.32	58.44	0.94	**0**	0.02	5.31
1890-2010	Cairns	FFDI days ≥25	0.16	23.47	0.46	**0**	0.01	-0.14
1890-2010	Cairns	FFDI days ≥12	115.5	4.54	0.49	**0**	0.13	-2.22
1890-2010	Cairns	Rain total	0.03	4.13	106.7	**0.04**	0.56	123.88
1890-2010	Cairns	Rain days ≥5 mm	-0.01	0	4.9	0.99	0	8.53
1890-2010	Cairns	Wind mean	0.84	619.9	1.26	**0**	-0.08	24.39
1890-2010	Cairns	Wind max.	-0.01	0.31	4.38	0.58	-0.01	28.61
1890-2010	Cairns	Temp. mean	0.03	4.42	0.51	**0.04**	0	24.42
1890-2010	Cairns	Temp. max. annual	0.24	38.88	1.39	**0**	0.02	31.94
1890-2010	Cairns	Temp. max. mean daily	0.62	198.3	0.61	**0**	0.02	27.72
1890-2010	Cairns	Temp. max. 99%	0.3	51.42	1.01	**0**	0.02	31.49
1890-2010	Cairns	Temp. max. 95%	0.43	90.03	0.78	**0**	0.02	30.45
1890-2010	Cairns	Temp. max. 90%	0.44	96.8	0.75	**0**	0.02	29.96
1890-2010	Cairns	Temp. max. days ≥35 °C	0.09	12.16	0.49	**0**	0	-0.05

1890-2010	Cairns	Temp. min. annual	0	0.61	1.75	0.44	0	14.18
1890-2010	Cairns	Temp. min. mean daily	0.3	51.37	0.73	**0**	0.01	19.3
1890-2010	Cairns	R.Hum. mean	0.71	300.6	2.23	**0**	-0.1	81.93
1890-2010	Cairns	R.Hum. min. annual	0.58	165.6	7.41	**0**	-0.25	50.98
1890-2010	Cairns	R.Hum. min. mean daily	0.7	287	2.82	**0**	-0.12	67.17
1890-2010	Cairns	R.Hum. min. 1%	0.64	210.1	6.21	**0**	-0.24	53.64
1890-2010	Cairns	R.Hum. min. 5%	0.71	293	4.29	**0**	-0.19	58.13
1890-2010	Cairns	R.Hum. min. 10%	0.72	304.5	3.69	**0**	-0.17	59.9
1890-2010	Cairns	KBDI mean	0	1.08	20.92	0.3	0.06	158.04
1890-2010	Cairns	KBDI max.	0.04	5.4	11.07	**0.02**	0.07	182.88
1890-2010	Cairns	KBDI 99%	0.03	5.33	11.3	**0.02**	0.07	182.38
1890-2010	Cairns	KBDI 95%	0.04	5.49	12.08	**0.02**	0.07	180.27
1890-2010	Cairns	KBDI 90%	0.03	5.12	13.27	**0.03**	0.08	177.8
1957-2010	Global	SOI mean	-0.02	0.04	9.38	0.85	-0.02	0.52
1957-2010	Global	SOI max.	-0.02	0.03	9.93	0.87	-0.01	4.97
1957-2010	Global	SOI min.	-0.02	0.07	9.69	0.79	-0.02	-3.9
1957-2010	Cairns	FFDI mean	-0.02	0.03	1.13	0.86	0	7.61
1957-2010	Cairns	Σ FFDI	-0.02	0.03	103.2	0.86	0.16	692.28
1957-2010	Cairns	FFDI max. annual	-0.02	0.06	6.3	0.81	0.01	22.08
1957-2010	Cairns	FFDI 99%	-0.02	0.02	4.23	0.9	0	18.69
1957-2010	Cairns	FFDI 95%	-0.01	0.4	2.1	0.53	0.01	13.83
1957-2010	Cairns	FFDI 90%	-0.01	0.39	1.59	0.53	0.01	11.83
1957-2010	Cairns	FFDI 50%	-0.01	0.23	1.19	0.63	0	7.03
1957-2010	Cairns	FFDI days ≥25	-0.02	0.02	0.67	0.89	0	0.5
1957-2010	Cairns	FFDI days ≥12	0.02	1.97	6.06	0.17	0.07	8.61
1957-2010	Cairns	Rain total	0.02	2.32	114.8	**0.13**	1.53	130.17
1957-2010	Cairns	Rain days ≥5 mm	0.02	1.85	4.91	0.18	0.06	6.58
1957-2010	Cairns	Wind mean	0.4	36.92	1.63	**0**	-0.09	18.95

1957-2010	Cairns	Wind max.	0.29	22.59	2.89	**0**	-0.12	32.5
1957-2010	Cairns	Temp. mean	0.01	1.49	0.52	0.23	0.01	24.52
1957-2010	Cairns	Temp. max. annual	-0.02	0	1.44	0.98	0	34.09
1957-2010	Cairns	Temp. max. mean daily	0.01	1.59	0.4	0.21	0	29.74
1957-2010	Cairns	Temp. max. 99%	-0.01	0.28	0.87	0.6	0	33.18
1957-2010	Cairns	Temp. max. 95%	-0.01	0.31	0.54	0.58	0	32.38
1957-2010	Cairns	Temp. max. 90%	-0.02	0.08	0.53	0.78	0	31.77
1957-2010	Cairns	Temp. max. days ≥35 °C	-0.01	0.64	0.63	0.43	0	0.27
1957-2010	Cairns	Temp. min. annual	-0.02	0.11	1.87	0.74	-0.01	14.62
1957-2010	Cairns	Temp. min. mean daily	0.02	1.94	0.77	0.17	0.01	20.37
1957-2010	Cairns	R.Hum. mean	0.04	3.41	2.42	**0.07**	-0.04	73.11
1957-2010	Cairns	R.Hum. min. annual	0.04	3.19	7.75	**0.08**	-0.12	29.37
1957-2010	Cairns	R.Hum. min. mean daily	0.09	6.53	3.01	**0.01**	-0.07	56.82
1957-2010	Cairns	R.Hum. min. 1%	0.04	3.43	6.59	**0.07**	-0.11	33.22
1957-2010	Cairns	R.Hum. min. 5%	0.08	5.65	4.44	**0.02**	-0.09	41.62
1957-2010	Cairns	R.Hum. min. 10%	0.15	10.07	3.2	**0**	-0.09	45.85
1957-2010	Cairns	KBDI mean	0.04	3.46	8.85	**0.07**	-0.14	193.99
1957-2010	Cairns	KBDI max.	0.01	1.55	19.89	0.22	-0.22	170.53
1957-2010	Cairns	KBDI 99%	0.05	3.59	9.04	**0.06**	-0.15	193.76
1957-2010	Cairns	KBDI 95%	0.05	3.51	9.67	**0.07**	-0.16	192.53
1957-2010	Cairns	KBDI 90%	0.04	2.98	10.91	**0.09**	-0.16	190.72
1957-2010	Mareeba	FFDI mean	0	0.8	1.69	0.38	-0.01	12.07
1957-2010	Mareeba	Σ FFDI	0	0.8	153.5	0.38	-1.33	1098.01
1957-2010	Mareeba	FFDI max. annual	-0.01	0.69	5.31	0.41	0.04	26.06
1957-2010	Mareeba	FFDI 99%	-0.01	0.72	4.45	0.4	0.04	23.13
1957-2010	Mareeba	FFDI 95%	-0.02	0.05	3.55	0.82	0.01	20.2
1957-2010	Mareeba	FFDI 90%	-0.02	0.26	2.77	0.61	0.01	17.04
1957-2010	Mareeba	FFDI 50%	0.03	2.45	1.35	**0.12**	-0.02	11.42

1957-2010	Mareeba	Rain total	0.06	3.91	44.76	**0.05**	0.83	31.37
1957-2010	Mareeba	Wind mean	0.69	108	0.59	**0**	0.06	9.18
1957-2010	Mareeba	Wind max.	0.77	157.6	2.19	**0**	0.26	8.52
1957-2010	Mareeba	Temp. mean	-0.02	0	0.5	0.96	0	21.04
1957-2010	Mareeba	Temp. max. annual	0.12	7.11	1.53	**0.01**	0.04	35.12
1957-2010	Mareeba	Temp. max. mean daily	0.06	3.97	0.7	**0.05**	0.01	29.59
1957-2010	Mareeba	Temp. max. 99%	0.07	4.66	1.46	**0.04**	0.03	34.56
1957-2010	Mareeba	Temp. max. 95%	0.08	5.09	1.37	**0.03**	0.03	33.21
1957-2010	Mareeba	Temp. max. 90%	0.09	5.31	1.13	**0.03**	0.02	32.14
1957-2010	Mareeba	Temp. min. annual	-0.01	0.65	1.69	0.42	0.01	11.17
1957-2010	Mareeba	Temp. min. mean daily	0.32	22.74	0.85	**0**	0.04	15.64
1957-2010	Mareeba	R.Hum. mean	0.1	5.87	1.72	**0.02**	0.04	65.24
1957-2010	Mareeba	R.Hum. min. annual	-0.02	0.03	5.12	0.85	0.01	17.46
1957-2010	Mareeba	R.Hum. min. mean daily	0.14	8.2	3.71	**0.01**	0.1	36.69
1957-2010	Mareeba	KBDI mean	-0.01	0.38	16.69	0.54	0.1	143.34
1957-2010	Mareeba	KBDI max.	0.04	3.04	12.97	**0.09**	0.22	158.65
1957-2010	Mareeba	KBDI 99%	0.04	3.01	13.06	**0.09**	0.22	158.21
1957-2010	Mareeba	KBDI 95%	0.04	2.87	13.23	**0.1**	0.22	156.82
1957-2010	Mareeba	KBDI 90%	0.03	2.63	13.64	0.11	0.21	155.26
1957-2010	Rain Forest	FFDI mean	-0.01	0.77	0.32	0.38	0	1.98
1957-2010	Rain Forest	Σ FFDI	-0.01	0.77	29.36	0.38	-0.25	180.18
1957-2010	Rain Forest	FFDI max. annual	-0.01	0.69	1.02	0.41	0.01	4.67
1957-2010	Rain Forest	FFDI 99%	-0.01	0.72	0.85	0.4	0.01	4.11
1957-2010	Rain Forest	FFDI 95%	-0.02	0.05	0.68	0.82	0	3.54
1957-2010	Rain Forest	FFDI 90%	-0.02	0.26	0.53	0.61	0	2.94
1957-2010	Rain Forest	FFDI 50%	0.03	2.45	0.26	**0.12**	0	1.86
1957-2010	Rain Forest	Wind mean	0.69	103.6	0	**0**	0	0.16
1957-2010	Rain Forest	Wind max.	0.77	157.6	0.01	**0**	0	0.16

1957-2010	Rain Forest	Temp. mean	-0.02	0	0.46	0.96	0	15.87
1957-2010	Rain Forest	Temp. max. annual	0.12	7.11	1.39	**0.01**	0.04	25.63
1957-2010	Rain Forest	Temp. max. mean daily	0.06	3.97	0.64	**0.05**	0.01	20.61
1957-2010	Rain Forest	Temp. max. 99%	0.07	4.66	1.33	**0.04**	0.03	25.13
1957-2010	Rain Forest	Temp. max. 95%	0.08	5.09	1.25	**0.03**	0.03	23.89
1957-2010	Rain Forest	Temp. max. 90%	0.09	5.31	1.03	**0.03**	0.02	22.92
1957-2010	Rain Forest	Temp. min. annual	-0.01	0.65	1.18	0.42	0.01	10.34
1957-2010	Rain Forest	Temp. min. mean daily	0.32	22.74	0.6	**0**	0.03	13.46
1957-2010	Rain Forest	R.Hum. mean	0.1	5.87	0.76	**0.02**	0.02	89.48
1957-2010	Rain Forest	R.Hum. min. annual	-0.02	0.03	4.01	0.85	0.01	53.59
1957-2010	Rain Forest	R.Hum. min. mean daily	0.14	8.2	2.9	**0.01**	0.08	68.64
1957-2010	Rain Forest	KBDI mean	-0.01	0.38	4.49	0.54	0.03	106.8
1957-2010	Rain Forest	KBDI max.	0.04	3.04	3.49	**0.09**	0.06	110.92
1957-2010	Rain Forest	KBDI 99%	0.04	3.01	3.51	**0.09**	0.06	110.8
1957-2010	Rain Forest	KBDI 95%	0.04	2.87	3.56	**0.1**	0.06	110.43
1957-2010	Rain Forest	KBDI 90%	0.03	2.63	3.67	**0.11**	0.06	110
1957-2010	Tall Eucalypt Forest	FFDI mean	0	0.8	0.46	0.38	0	3.26
1957-2010	Tall Eucalypt Forest	Σ FFDI	0	0.8	41.75	0.38	-0.36	296.57
1957-2010	Tall Eucalypt Forest	FFDI max. annual	-0.01	0.69	1.44	0.41	0.01	7.06
1957-2010	Tall Eucalypt Forest	FFDI 99%	-0.01	0.72	1.21	0.4	0.01	6.27
1957-2010	Tall Eucalypt Forest	FFDI 95%	-0.02	0.05	0.97	0.82	0	5.47
1957-2010	Tall Eucalypt Forest	FFDI 90%	-0.02	0.26	0.75	0.61	0	4.61
1957-2010	Tall Eucalypt Forest	FFDI 50%	0.03	2.45	0.37	**0.12**	-0.01	3.08
1957-2010	Tall Eucalypt Forest	Wind mean	0.69	107.9	0.03	**0**	0	0.43
1957-2010	Tall Eucalypt Forest	Wind max.	0.77	157.6	0.1	**0**	0.01	0.41
1957-2010	Tall Eucalypt Forest	Temp. mean	-0.02	0	0.4	0.96	0	18.19
1957-2010	Tall Eucalypt Forest	Temp. max. annual	0.12	7.11	1.3	**0.01**	0.03	28.81
1957-2010	Tall Eucalypt Forest	Temp. max. mean daily	0.06	3.97	0.59	**0.05**	0.01	24.13

1957-2010	Tall Eucalypt Forest	Temp. max. 99%	0.07	4.66	1.24	**0.04**	0.03	28.34
1957-2010	Tall Eucalypt Forest	Temp. max. 95%	0.08	5.09	1.16	**0.03**	0.02	27.19
1957-2010	Tall Eucalypt Forest	Temp. max. 90%	0.09	5.31	0.96	**0.03**	0.02	26.29
1957-2010	Tall Eucalypt Forest	Temp. min. annual	-0.01	0.65	1.06	0.42	0.01	12.46
1957-2010	Tall Eucalypt Forest	Temp. min. mean daily	0.32	22.74	0.53	**0**	0.02	15.26
1957-2010	Tall Eucalypt Forest	R.Hum. mean	0.1	5.87	0.94	**0.02**	0.02	84.26
1957-2010	Tall Eucalypt Forest	R.Hum. min. annual	-0.02	0.03	4.32	0.85	0.01	40.07
1957-2010	Tall Eucalypt Forest	R.Hum. min. mean daily	0.14	8.2	3.13	**0.01**	0.09	56.28
1957-2010	Tall Eucalypt Forest	KBDI mean	-0.01	0.38	5.71	0.54	0.03	119.95
1957-2010	Tall Eucalypt Forest	KBDI max.	0.04	3.04	4.44	**0.09**	0.07	125.19
1957-2010	Tall Eucalypt Forest	KBDI 99%	0.04	3.01	4.47	**0.09**	0.08	125.04
1957-2010	Tall Eucalypt Forest	KBDI 95%	0.04	2.87	4.53	**0.1**	0.07	124.57
1957-2010	Tall Eucalypt Forest	KBDI 90%	0.03	2.63	4.67	**0.11**	0.07	124.03
1957-2010	Savanna	FFDI mean	0	0.8	0.74	0.38	-0.01	6.29
1957-2010	Savanna	Σ FFDI	0	0.8	67.23	0.38	-0.58	572.2
1957-2010	Savanna	FFDI max. annual	-0.01	0.69	2.32	0.41	0.02	12.42
1957-2010	Savanna	FFDI 99%	-0.01	0.72	1.95	0.4	0.02	11.13
1957-2010	Savanna	FFDI 95%	-0.02	0.05	1.56	0.82	0	9.85
1957-2010	Savanna	FFDI 90%	-0.02	0.26	1.21	0.61	0.01	8.47
1957-2010	Savanna	FFDI 50%	0.03	2.45	0.59	**0.12**	-0.01	6.01
1957-2010	Savanna	Rain total	0.07	4.56	15.51	**0.04**	0.31	17.57
1957-2010	Savanna	Wind mean	0.69	106.9	0.06	**0**	0.01	1.7
1957-2010	Savanna	Wind max.	0.77	157.6	0.23	**0**	0.03	1.63
1957-2010	Savanna	Temp. mean	-0.02	0	0.38	0.96	0	19.97
1957-2010	Savanna	Temp. max. annual	0.12	7.11	1.11	**0.01**	0.03	31.35
1957-2010	Savanna	Temp. max. mean daily	0.06	3.97	0.51	**0.05**	0.01	27.34
1957-2010	Savanna	Temp. max. 99%	0.07	4.66	1.06	**0.04**	0.02	30.95
1957-2010	Savanna	Temp. max. 95%	0.08	5.09	1	**0.03**	0.02	29.96

1957-2010	Savanna	Temp. max. 90%	0.09	5.31	0.82	**0.03**	0.02	29.19
1957-2010	Savanna	Temp. min. annual	-0.01	0.65	1.07	0.42	0.01	12.96
1957-2010	Savanna	Temp. min. mean daily	0.32	22.74	0.54	**0**	0.02	15.79
1957-2010	Savanna	R.Hum. mean	0.1	5.87	1.17	**0.02**	0.03	74.04
1957-2010	Savanna	R.Hum. min. annual	-0.02	0.03	3.83	0.85	0.01	26.04
1957-2010	Savanna	R.Hum. min. mean daily	0.14	8.2	2.77	**0.01**	0.08	40.42
1957-2010	Savanna	KBDI mean	-0.01	0.38	6.88	0.54	0.04	111.4
1957-2010	Savanna	KBDI max.	0.04	3.04	5.34	**0.09**	0.09	117.7
1957-2010	Savanna	KBDI 99%	0.04	3.01	5.38	**0.09**	0.09	117.53
1957-2010	Savanna	KBDI 95%	0.04	2.87	5.45	**0.1**	0.09	116.95
1957-2010	Savanna	KBDI 90%	0.03	2.63	5.62	**0.11**	0.09	116.31

Appendix 5.9 Historic climate trends at Cairns (1890-2010) and Mareeba (1957-2010).

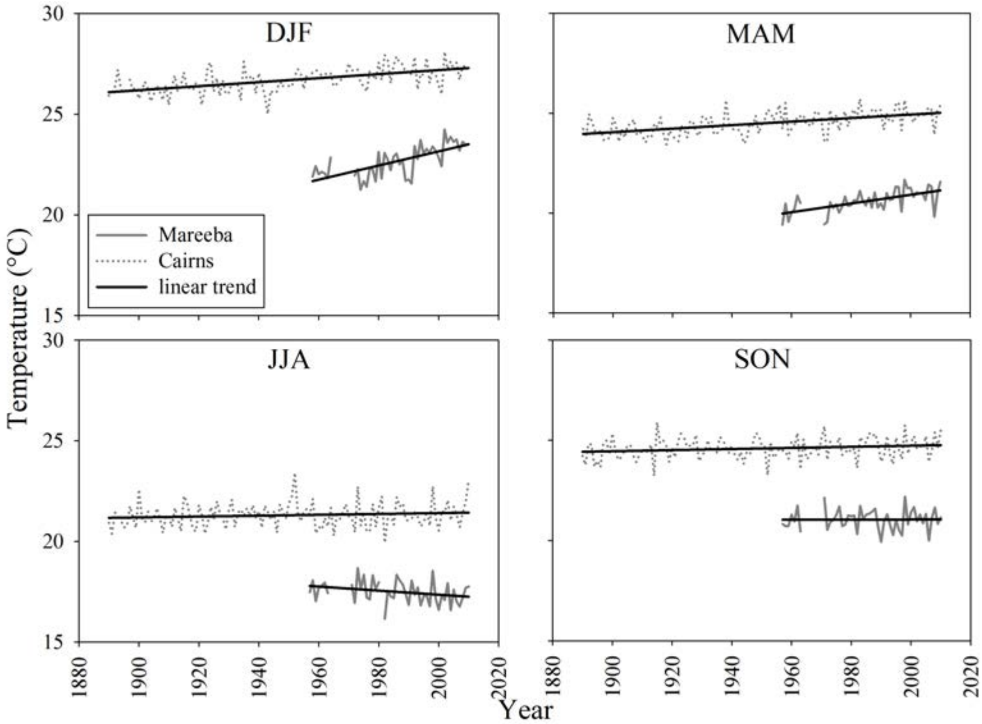

Figure 5.9.1 Historic seasonal average temperature at Cairns and Mareeba for the period December-January-February (DJF), March-April-May (MAM), June-July-August (JJA) and September-October-November (SON).

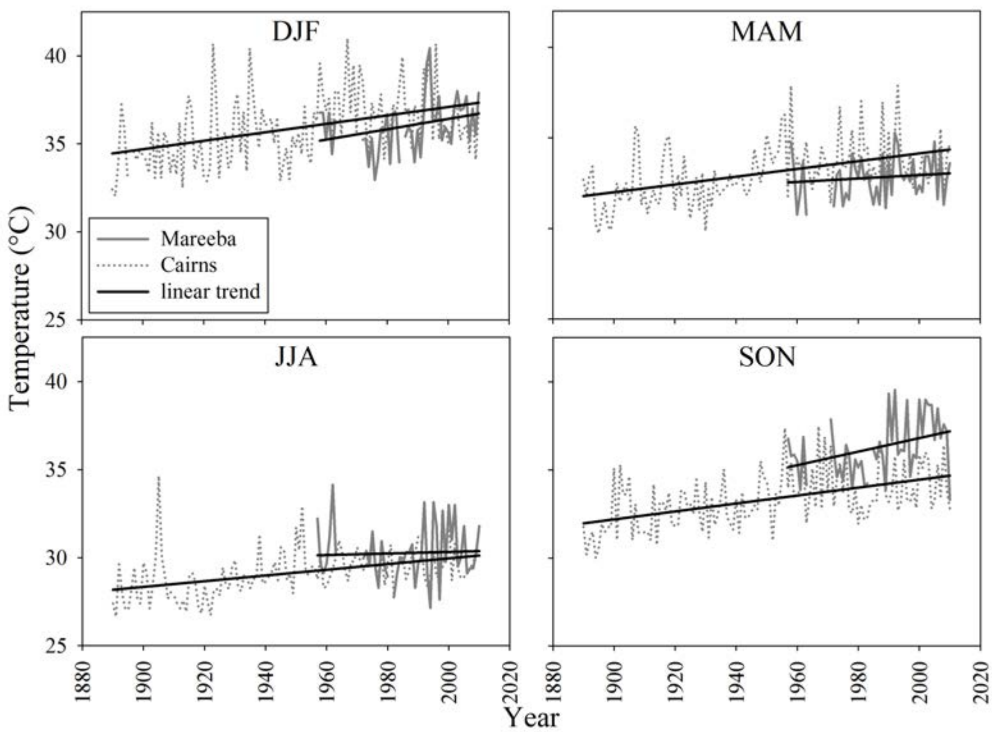

Figure 5.9.2 Historic seasonal extreme maximum temperature (hottest record during season) at Cairns and Mareeba for the period December-January-February (DJF), March-April-May (MAM), June-July-August (JJA) and September-October-November (SON).

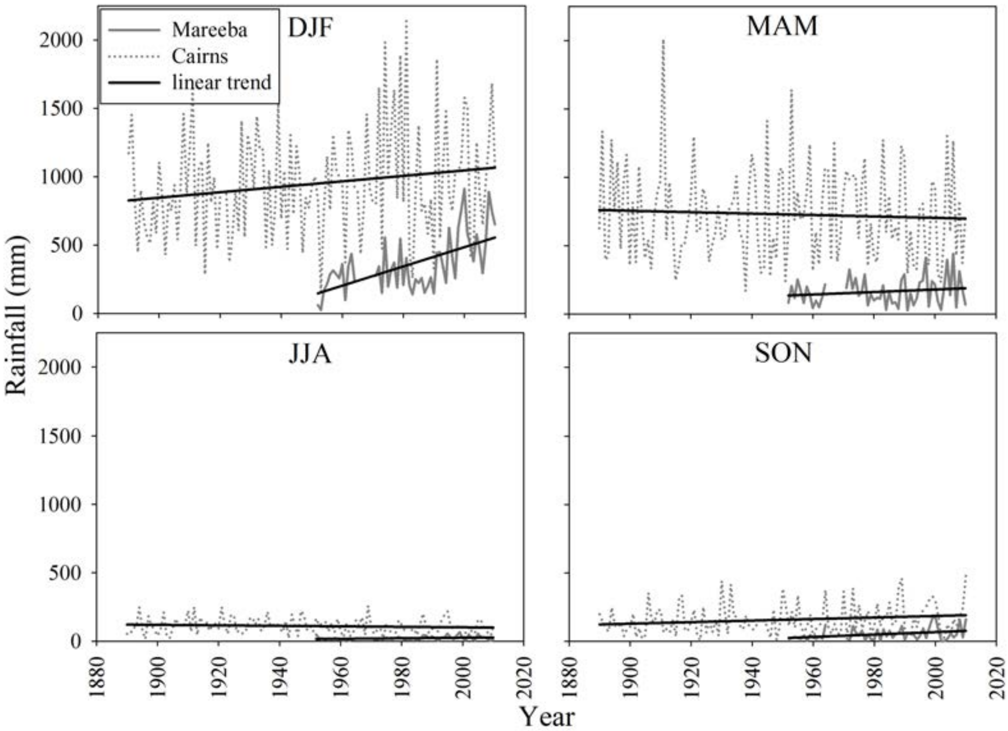

Figure 5.9.3 Total seasonal rainfall at Cairns and Mareeba for the period December-January-February (DJF), March-April-May (MAM), June-July-August (JJA) and September-October-November (SON). The seasonal trends for Cairns were significant for SON (1890-2010 only, Table 5.4) and trends for Mareeba were significant during DJF and JJA.

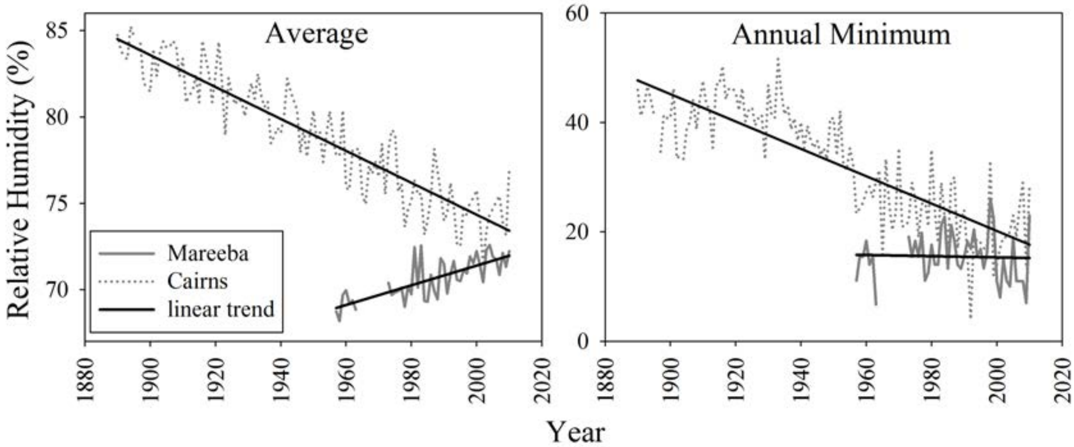

Figure 5.9.4 Historic relative humidity at Cairns and Mareeba. Both these trends were significant for Cairns (Table 5.4 and 5.5), but only the average trend was significant at Mareeba (Table 5.5).

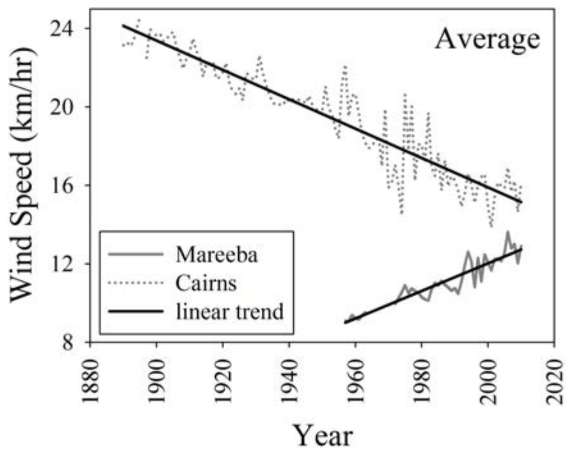

Figure 5.9.5 Historic wind speed at Cairns and Mareeba. Trends for Cairns and Mareeba were both significant (Tables 5.4 and 5.5).

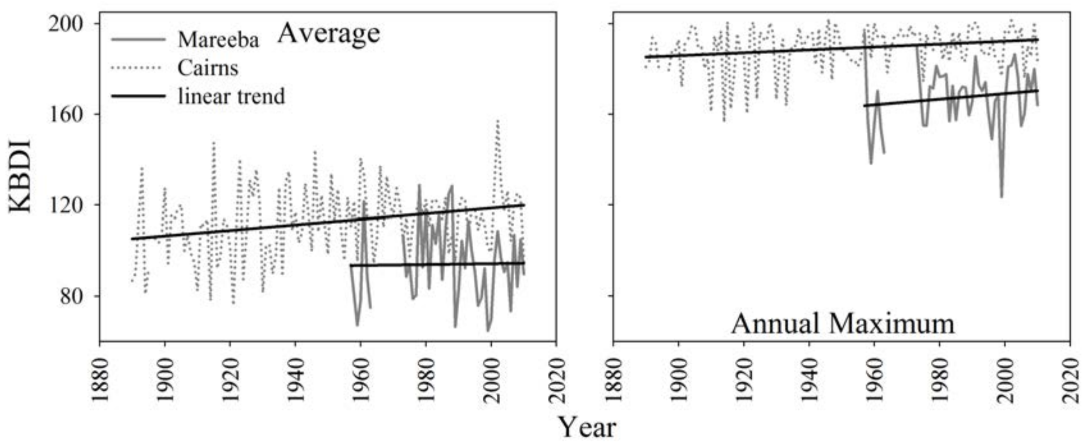

Figure 5.9.6 Historic annual Keetch-Byram Drought Index (KBDI) at Cairns and Mareeba, including average and annual maximum. Trends were significant for Cairns from 1890 to 2010 (Table 5.4).