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Connecting Sediment Load Targets to Ecological Outcomes for Seagrass

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http://www.nesptropical.edu.au

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ACRONYMS

AIMS............. Australian Institute of Marine Science
AMC………….Annual Mean Concentration
BFD............... Burdekin Falls Dam
BGC.............. Biogeochemical model
BOM............. Bureau of Meteorology
BSL…………..Burdekin Sediment Load
bPAR………...Benthic Photosynthetically Active Radiation
CI……………..Confidence interval
CSIRO........... Commonwealth Scientific Industrial Research Organisation
DEM.............. Digital Elevation Model
DIN……………Dissolved Inorganic Nitrogen
DS…………….Desired state
EMS…………..Environmental Modelling Suite
ERT............... Ecologically Relevant Target
GBRWHA...... Great Barrier Reef World Heritage Area
GL................. Gigalitre
GLM………….Generalized linear models
HO .... *Halophila ovalis*
IMOS............. Integrated Marine Observing System
JCU............... James Cook University
kt.................. kiloton
K_d……………..Diffuse attenuation co-efficient
ML................. Megalitre
MMP............. Marine Monitoring Program
MRT………….Multi-variate regression trees
Mt.................. Megatonne
NASA............ National Aeronautics and Space Administration
NESP............ National Environmental Science Program
NQDT............ North Queensland Dry Tropics
P/A…………...Presence/Absence of seagrass species
PAR.............. Photosynthetically Active Radiation
PoT............... Port of Townsville
RECOM......... Relocatable Coastal Model
RelExp……….Relative tidal exposure
RIMReP........ Reef Integrated Monitoring and Reporting Program
RMSE………..Root mean square error
RRRC............ Reef and Rainforest Research Centre Limited
S1................. Deep subtidal seagrass community
S2................. Shallow subtidal seagrass community
Sed_{dom}……….Dominant sediment type
SHOC………..Sparse Hydrodynamic Ocean Code
SIEF.............. Science Industry Endowment Fund
SPM.............. Suspended particulate matter
TSS............... Total Suspended Sediment
TWQ............. Tropical Water Quality

WCI…………..Water Clarity Index
WQIP .... Water Quality Improvement Plan
ZC .... *Zostera muelleri* subsp. *capricorni*

ABBREVIATIONS

km……………kilometers
m……………..meters
m^{-2} s^{-1}………..per square meter per second
mol m^{-2} d^{-1}…..moles (of photons) per square meter per day
Sed_{dom}………dominant sediment type
RelExp………relative tidal exposure index

GLOSSARY

Benthic Photosynthetically Active Radiation (bPAR)

An estimate of the quantum of photosynthetically active radiation reaching the benthos based on a remote sensing algorithm.

Colonising

A seagrass life-history strategy with traits including fast shoot turnover and time to sexual reproduction, low physiological resistance (e.g. to low light events), and an ability to rapidly recover from disturbances from seeds in a seed bank, and from lateral expansion and shoot production.

Condition/state

Relative quantities of characteristics of the seagrass such as biomass and spatial extent.

Confidence intervals

A range of plausible values for an unknown parameter. Most commonly, and throughout this report, a 95% confidence interval is used.

Desired state

Desired state is an aspirational target for reporting on ecological health and for guiding management decisions.

Ecological values

The perceived importance of an ecosystem, which is underpinned by the biotic and/or abiotic components and processes that characterise that ecosystem.

eReefs

A coupled hydrodynamic-biogeochemical model, and an application of the CSIRO Environmental Modelling Suite.

Fine sediment

Sediment grain size that is less than 20 µm in size.

Growing season

The period of the year when seagrass typically grows the fastest and reaches the highest levels of extent and biomass for the year. The precise period is defined in different ways depending on the application, and also on the location but is typically in the range of August to December in the Great Barrier Reef.

Indicator

A measurable quality of the ecological or environmental system. Sometimes used synonymously with 'metric'.

K_d

The diffuse attenuation coefficient (Kd) is a measure of how light dissipates with depth in water and expressed as per meter (m^{-1}).

Metric

A measurable quality of the ecological or environmental system. Sometimes used synonymously with 'indicator'.

Opportunistic

A seagrass life-history strategy with intermediate (between colonising and persistent) and adaptable traits including shoot turnover and time to sexual reproduction, high physiological resistance (e.g. to low light events), and a poor ability to recover from disturbances due to limited or no seed bank and slow rates of lateral expansion and shoot production.

Persistent

A seagrass life-history strategy with traits including slow shoot turnover and time to sexual reproduction, high physiological resistance (e.g. to low light events), and a poor ability to recover from disturbances due to limited or no seed bank and slow rates of lateral expansion and shoot production.

Pre-development

Refers to the period of time before the rate of human-induced modification of the Great Barrier Reef catchments rapidly accelerated ca. 1850. This term is applied in this report synonymously with "pre-industrial", which is the label for scenarios run by the Source catchments and eReefs models.

R

A free software environment for statistical computing and graphics.

Resilience

The capacity to provide ecological services in the future, based on being able to retain condition and function in the face of disturbances.

Secchi depth

The water depth at which a secchi disk (a black and white disk) is no longer visible, and is therefore taken as a measure of water transparency.

SLIM

An unstructured-mesh hydrodynamic model that simulates flow from the river to the coastal ocean, and has been used in connectivity models of the GBR.

Total suspended solids

A measure (typically mg/L) of the amount of sediment in suspension in the water. Based on a sediment grain size of less than 63 μm in this report.

Suspended particulate matter (SPM)

The suspended matter in the water column of estuarine and marine waters comprised of fine mineral particles, organic matter, living organisms such as bacteria and plankton, and other particles. SPM is deleterious to marine organisms and ecosystems because it can stick to organisms, and contribute to reductions in water clarity.

Water clarity

Describes how far light can travel through the water column and is affected by suspended particulate matter.

Water year

Describes the period 1st October to 30th September in the following year such that a single wet season (see below), fits within a single water year

Wet season

The period of the year when most of the rainfall and river discharge occurs. The exact time-period can be defined in various ways, but in this report it refers to November to April.

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We thank the Port of Townsville Limited for their support and funding of the long-term seagrass monitoring program for Cleveland Bay. We would like to thank the many James Cook University and Fisheries Queensland staff who have contributed to the monitoring program over the years. We also acknowledge funding from the Great Barrier Reef Foundation for supporting this work. The authors would like to thank Marites Magno-Canto (AIMS) for supplying satellite derived monthly mean benthic light data. Thanks also go to Graeme Curwen for his assistance developing maps, Ryan Turner (Queensland Department of Environment and Science) for providing sediment data, and Barbara Robson (AIMS) and Robin Ellis (Queensland Department of Environment and Science) for helpful discussions.

The eReefs model simulations were produced as part of the eReefs project (eReefs.info), a collaboration between the Science Industry Endowment Fund (SIEF), the Commonwealth Scientific Industrial Research Organisation (CSIRO), the Australian Institute of Marine Science (AIMS), the Bureau of Meteorology (BOM), and the Great Barrier Reef Foundation (GBRF), with support from BHP Billiton Mitsubishi Alliance, the Australian and Queensland governments, and with observations obtained through the Integrated Marine Observing System (IMOS).

EXECUTIVE SUMMARY

The ecological health of the Great Barrier Reef (GBR) is threatened by multiple pressures originating from locations both within and adjacent to the coastal zone, as well as global-scale pressures from climate change. Pollutant loads discharged from rivers are among the greatest risks to seagrass meadows of the GBR and have caused declines in seagrass area and density throughout the GBR, with variable levels of recovery depending on both the region and subsequent pressures. Turbidity plumes in particular are problematic for seagrass, as fine sediment reduces light available to seagrass and is easily resuspended. Seagrass decline has cascading consequences, including dugong and turtle mortality, and reductions in dugong fecundity.

The Reef 2050 Water Quality Improvement Plan (WQIP) (State of Queensland, 2018) seeks to improve the quality of water entering the GBR from adjacent catchments. The existing 2018 WQIP sediment load reduction targets are "ecologically relevant targets" (ERT) based on light requirements for seagrass, set using the eReefs Environmental Modelling Suite (EMS) to assess the load reduction required to achieve an acceptable light level for seagrasses. Building upon this, the purpose of this project is to compare seagrass state directly with catchment sediment loads, to provide an additional evidence base for the construction of ERTs. The specific objectives of this project were to:

1. define 'desired state' for seagrass meadows as an ecological benchmark,
2. examine the relationships between catchment inputs of sediment and seagrass desired state based on long-term monitoring data and eReefs, and
3. compare against the 2018 WQIP ERTs based on the sediment loads under which seagrass condition meets the criteria of 'desired state'.

Desired state

'Desired state' is defined in this study as an aspirational target for guiding management decisions, which has been identified as a priority information need for the management of the GBR. Seagrass desired state was determined as a case study in Cleveland Bay. Routine monitoring of seagrasses in the bay has been undertaken for the Port of Townsville since 2007. Multivariate regression trees were used to classify the seagrass data from that monitoring program into seven different community types based on observed presence and absence of seven seagrass species in different habitat conditions. A 'desired state' of biomass and spatial extent was determined for two subtidal and five intertidal communities. This was based on data from years in which these indicators were not significantly different to maximum values observed over the entire study period. The assumptions and implications of this approach are discussed throughout this report. Desired state is now being investigated for the entire GBR data set in NESP 5.4. Of the five intertidal and two subtidal communities defined in Cleveland Bay, the analysis of desired state relative to sediment loads considered the area and biomass of the shallow subtidal community, and the total area and mean biomass across all seven seagrass communities. Deep subtidal seagrass was included in the mean biomass, but not in the total area, because area of this community is much more difficult to accurately survey than the other six seagrass communities in Cleveland Bay.

Relationships between catchment sediment loads and seagrass state

Determining the relationships between sediment loads and the state of seagrass ecosystems is important but extremely challenging for a number of reasons. Monitoring captures only a small

amount of the spatial and temporal variability in stressors affecting ecological systems, making it difficult to distinguish between correlation and causality. Furthermore, there are multiple timescales involved: for example, sediment loads may affect seagrass in the short-term through sediment plumes and over longer timescales through the resuspension of this newly deposited and historical sediment, and seagrasses have both short and long-term responses to environmental condition. To deal with these challenges, the project used two different modelling approaches to explore the relationship between sediment loads and seagrass communities in Cleveland Bay: the process-based eReefs model, which is the GBR-wide application of the CSIRO EMS, and simple statistical models built from monitoring data.

The eReefs coupled hydrodynamic-biogeochemical model is a powerful tool to support science and management of the GBR, such as developing the targets in the WQIP. In order to relate eReefs output to measured seagrass biomass and distribution in Cleveland Bay, we needed a finer spatial resolution than the 1km or 4km eReefs grid. Therefore, we used the eReefs Relocatable Coastal Model (RECOM) to assess the effects of sediment loads on predicted benthic light and seagrass distribution and biomass in Cleveland Bay, which had a resolution of approximately 500 m. Our initial findings identified some challenges in modelling sediment dynamics with eReefs. The eReefs team responded to this information by updating the sediment module, which improved eReefs performance in predicting Secchi depth for the GBR as a whole. However, despite these improvements, differences between seagrass monitoring data and eReefs-RECOM prediction of seagrass extent and biomass in Cleveland Bay meant that we were unable to use the model in assessing the impact of catchment sediment loads on seagrass state at the study site. Therefore, we were also unable to use eReefs to develop a broadly-applicable (i.e. for all 35 basins of the GBR) approach to setting ERTs for seagrass. The insights gained in this project will inform further model refinements in eReefs for application in nearshore areas.

The second modelling approach taken was a comparison of seagrass condition (biomass and area) in Cleveland Bay to discharge ('flow') and sediment loads by fitting linear statistical models to 12 years of monitoring data. The data (Figure 1) demonstrated that the Burdekin River dominates sediment delivery to Cleveland Bay. Annual changes in the area and biomass of shallow subtidal seagrass were significantly correlated with annual sediment loads from the Burdekin River. Neither area nor biomass were significantly correlated to annual sediment loads, but area was significantly correlated to 4-year antecedent sediment loads for both the shallow subtidal community and all communities combined. The trajectory of decline and recovery differed between biomass and area. Prior to our analysis, 'fine sediment' (<20μm) was hypothesised to be an important driver of ecological change, but differentiating between fine sediment and TSS did not improve correlation with seagrass indicators.

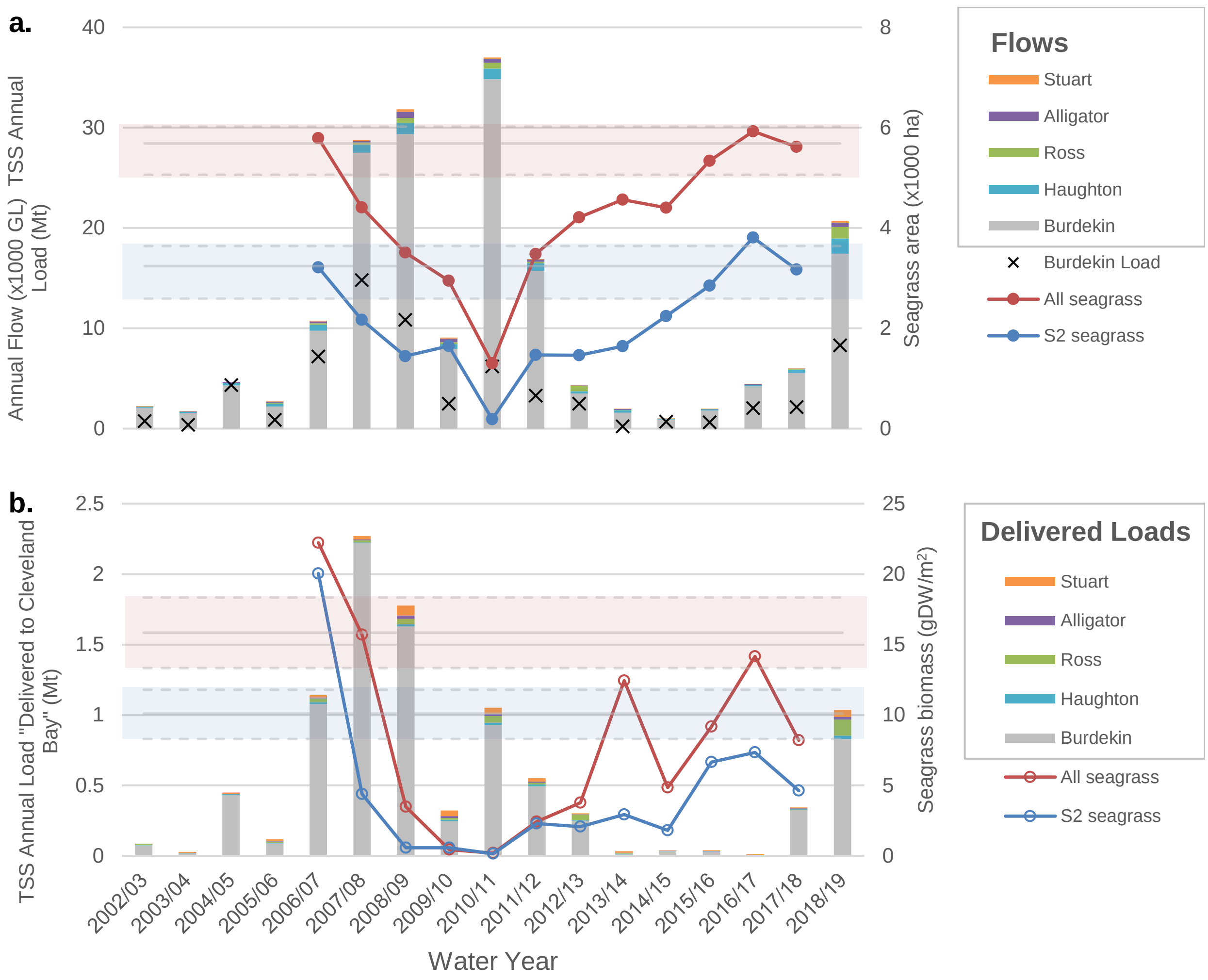


Figure 1. Time series with bars showing a) annual flows and b) delivered annual sediment (Total Suspended Solids, TSS) loads from the Burdekin River and other local rivers and creeks over a water year (October to September); and lines indicating seagrass a) area and b) biomass for the shallow subtidal seagrass community (denoted as S2) and all seagrass communities combined at the end of the water year. For context, the total Burdekin River TSS load is also indicated in a). From Lambert et al., in preparation.

The project had originally aimed to develop a spatially explicit habitat model to link seagrass condition to local benthic light conditions, and use that model to differentiate between the impact of local sediment resuspension and turbidity caused directly by riverine inputs. There was insufficient data to develop such a model, but we were able to assess how spatially explicit light data relates to seagrass area and biomass. Satellite-derived benthic light (bPAR) maps were used to calculate the area of potential seagrass habitat in Cleveland Bay, based on the area with average annual benthic light above a range of different levels. Root mean square error (RMSE) between observed seagrass area and predicted habitat was minimised (i.e. best fit) when annual average or growth season average was 4 to 7 mol/m^2/d. However, data collected in this project and from other data sources suggests that the bPAR model tends to overpredict benthic light relative to *in-situ* light in Cleveland Bay. Therefore, these levels (4 – 7 mol/m^2/d) are only relevant for bPAR as a data source. For this reason, we did not proceed with the spatially explicit habitat models in this project.

Comparison to the ERTs in the WQIP

The three strongest relationships between sediment loads and Cleveland Bay seagrass condition ($R^2>0.55$, $p<0.01$) were used to estimate “sediment load thresholds”, above which seagrass was predicted to decline or fail to meet desired state (Table I). The WQIP defined “baseline loads” for fine sediment from the Burdekin River in 2012-2013 as 3.26 Mt/yr, of which 2.786 Mt/yr were attributed to anthropogenic processes (Brodie et al. 2017), and proposed a reduction of load reduction target of 0.84 Mt/yr (i.e. 30% of the anthropogenic load) in order to meet seagrass light requirements in receiving waters. The three different models used in this project suggest that annual average fine sediment loads from the Burdekin River of 1.9-2.2 Mt/yr are required for the seagrass to meet desired state, or to avoid decline in biomass or area, in Cleveland Bay. This represents a reduction of 1.06-1.36 Mt/yr or 38-49% of anthropogenic load. Achieving these loads reductions would not guarantee that seagrass in Cleveland Bay achieves the desired state, but similarity between estimates generated from independent approaches strengthens confidence in these targets, while highlighting the challenges in quantifying the effects of terrestrial activities on downstream ecosystems.

Table 1. Predicted thresholds for Burdekin River TSS and fine sediment load, and equivalent load reduction compared with WQIP targets. See Chapter 3 for further information on how these thresholds were calculated.

Burdekin River metric	*Seagrass indicator[3]*	*Source equation*	*TSS threshold (Mt)*	*Fine sediment (<20 μm) load threshold (Mt)*	*R^2*	*p-value*	*Annual fine-sediment load target (Mt/yr)*	*Fine sediment load reduction[1] (Mt/yr)*	*Fine sediment load reduction[2] (% anthropogenic)*
1-year load	$\Delta Biomass_{subtidal} > 0$	5	2.7	2.2	0.71	0.001	**2.2**	1.06	38%
4-year load	$Area_{subtidal} \geq DS_{subtidal}$	6	9.9	7.9	0.56	0.005	**2.0**	1.26	45%
4-year load	$Area_{totall} \geq DS_{total}$	7	9.3	7.4	0.69	0.0008	**1.9**	1.36	49%
	WQIP Burdekin Catchment Target[4]						**2.4**	**0.84**	**30%**

[1] Load reduction based on the 2012-2013 fine sediment total baseline load of 3.26 Mt/yr for the Burdekin River (Brodie et al. 2017)
[2] Load reduction (% anthropogenic) is based on 2012-2013 fine sediment total anthropogenic load of 2.786 Mt/yr (Brodie et al. 2017)
[3] DS = minimum Desired State
[4] State of Queensland (2018)

Conclusion and Recommendations

Ecologically Relevant Targets are criteria that, if met, correspond to desired ecological outcomes for the GBR (e.g. desired state) and achievement of the over-arching objective of Reef Plan. Setting ERTs is important for addressing anthropogenic stressors on environmental systems, but is challenging for a number of reasons. Ecological state depends on interactions and feedbacks between natural and anthropogenic processes interacting across a range of spatial and temporal scales. Even where long-term monitoring data is available, it may not have sufficient spatial and temporal resolution, and assigning causality for observed changes is difficult. In the context of these challenges for setting ERTs, the project has made six main contributions:

1. The data needs for relating catchment loads to ecological outcomes are non-trivial, requiring compilation and re-analysis of a large number of different data sets. We highlight the complex nature of accessing and using data needed to quantify targets.
2. Defining a ‘desired state’ for seagrass communities in Cleveland Bay demonstrated how the spatial and temporal variability of ecological systems can be incorporated in the setting of ecological targets. The desired state case study is a demonstration of how to overcome multiple challenges in setting quantitative targets to satisfy over-arching management objectives. The approach will be refined as it is applied to other locations with different ecological characteristics.
3. By considering multiple indicators of ecological response (desired spatial extent for all seagrass and avoiding decline in area or biomass for subtidal seagrass) and stressors over multiple timescales (1- and 4-year TSS loads), we produced a range of estimates for sediment load reduction targets (Table 1). Allowing for model uncertainty, our findings were comparable to the existing 2018 WQIP Ecologically Relevant Targets, which were determined from an entirely different method. This highlights the importance of using multiple independently modelling approaches and data sources to increase confidence in recommendations for systems where uncertainty is high.
4. Defining long-term seagrass light requirements is non-trivial, because seagrass response to light availability depends on species, light history and other environmental factors. However, our analysis of seagrass spatial extent and bPAR estimated from the satellite light product suggested that defining seagrass potential habitat by areas where bPAR exceeded 4-7 mol/m^2/day, correlates well to seagrass spatial extent metrics.
5. Our models found stronger correlations between seagrass variables and river flow than sediment load. This suggests the need to examine other mechanisms by which high flow events affect seagrass state (which could include nutrients and herbicides, for example).
6. We were unable to explore the relative contributions of recent catchment sediment loads to the legacy effects of catchment inputs (including fine sediment, organics and nutrients) via sediment resuspension. Further refinement of eReefs/RECOM to capture these fine-scale inshore processes is needed to explore the relative contributions of these two processes to seagrass light availability.

Future work which builds upon this project could incorporate wider ecosystem effects. For example, further work is needed to explore whether feedbacks in the system are likely to create possible tipping points beyond which recovery would become difficult or impossible. Seagrass response is also likely to occur on shorter timescales than wider ecosystem effects, for example if seagrass decline caused large decline in dugong or turtle numbers, recovery of seagrass would not necessarily correspond to recovery of the dugong or turtle populations.

1.0 BACKGROUND AND OBJECTIVES

1.1 Introduction

Coastal ecosystems are threatened by multiple activities both within and adjacent to the coastal zone. These can be broadly summarized as global-scale stressors, namely climate change, and regional to local-scale stressors including urban, industrial and agricultural run-off, dredging and trawling (Grech et al. 2012). Global scale declines in coastal habitat and ecosystem function have led to a call for enhanced conservation by improving legislation, policies and planning frameworks to tackle these cumulative pressures (Griffiths et al. 2019, Unsworth et al. 2019). An additional challenge lies in the charisma problem that coastal habitats face, with their invaluable contribution to human well-being not adequately recognized (Duarte et al. 2008, Unsworth et al. 2019). For example, seagrass meadows alone support 20% of the world's biggest fisheries through nursery habitat provision (Unsworth et al. 2018), and are essential to the livelihoods of many coastal communities dependent on fish for protein (Unsworth et al. 2014, Nordlund et al. 2017), and yet protection for seagrasses is inadequate in most places (Griffiths et al. 2019). There are notable exceptions where seagrass meadows are at the fore-front of conservation efforts, including in the Great Barrier Reef (GBR) where multiple levels of legislation and policy protect seagrass meadows (Griffiths et al. 2019). But the most insidious threats such as run-off, are also the most complicated to manage. The research outlined in this report tackles one aspect of this management challenge: sediment load reduction targets for rivers discharging into the coastal zone.

Delivery of sediment and nutrients by river runoff to the GBR lagoon has increased following development of the adjacent catchments (ca. 1850), which has enhanced the influence of terrestrially-derived constituents within the GBR lagoon (Kroon et al. 2012, Lewis et al. 2014, Bainbridge et al. 2018). Suspended particular matter (SPM) within the lagoon is comprised of both terrestrially-sourced and internally produced organic matter that binds with the fine sediment, can travel over broad distances and can be more easily resuspended following initial deposition (Bainbridge et al. 2012, Bainbridge et al. 2018). While the increase in sediment loads delivered to the GBR from most river basins since European settlement is undisputed, gaps in the knowledge on the transport and fate this 'anthropogenic load' in the GBR lagoon has led some researchers to question the impacts of the additional loads on marine ecosystems (e.g. Larcombe and Ridd 2018, Larcombe and Ridd 2019). Indeed from the Burdekin River, a large proportion of the sediment load (~ 90%) is deposited within a few kilometres of the river mouth and has restricted mobility once deposited (Lewis et al. 2014, Delandmeter et al. 2015). The relative influence and processes governing the source, transport and fate of SPM is the subject of ongoing complimentary research being undertaken for the National Environmental Science Program (see Project 2.1.5 Lewis et al. (2018)). This recent work, coupled with previous work by Fabricius et al. (2013, 2014, 2016) demonstrates that at several inshore sites in the GBR lagoon, the influence of the new SPM transported past the initial deposition zone in river flood plumes not only has the greatest influence on SPM concentrations (i.e. highest concentrations measured at the location occurs during flood plume periods), but also contributes to higher SPM concentrations (and suppressed photic depth) in subsequent resuspension events in the months following the dissipation of the plume. These findings contradict the views of Larcombe and Ridd (2018, 2019). While the research into SPM dynamics is ongoing, we refer to SPM as sediment, but acknowledge the complexity of water column constituents affecting water clarity and ecological condition in the GBR.

Our study provides an opportunity to examine the influence of newly delivered sediment on seagrass meadows from the inshore GBR and provides new insights that directly address the core debate on the impacts of sediment in the GBR. By applying the new knowledge on the concept of 'deliverable sediment' to the sites (i.e. the sediment that travels beyond the initial deposition zone), we are able to examine the relationships between the deliverable sediment load and seagrass community type and distribution.

The Reef 2050 Water Quality Improvement Plan (WQIP) seeks to improve the quality of water entering the GBR from adjacent catchments. A priority action of the WQIP are the new reef protection regulations which came into effect on the 1st December 2019 (https://www.qld.gov.au/environment/agriculture/sustainable-farming/reef/reef-regulations/about). The WQIP targets are based on the best available independent scientific advice provided by the 2017 Scientific Consensus Statement (Waterhouse et al. 2017). Water quality targets for each of the 35 basins within the GBR are based on load reduction of fine sediment and nutrients (including both dissolved inorganic and particulate forms of nitrogen and phosphorus) and pesticide management to meet targets based on a risk model (Brodie et al. 2017). The fine sediment targets were set for most basins, including the Burdekin, using the eReefs Environmental Modelling Suite (Steven et al. 2019) to assess a required level of load reduction to achieve an acceptable light climate for seagrass (and hence relevant to the current project) (from Brodie et al. 2017).

1.2 Study Approach

The objective of this study was to apply an understanding of the effects of sediment run-off on marine water clarity and benthic light to assess the impact of sediment loads on seagrasses and to compare against ecologically relevant targets for management actions to reduce catchment-derived sediment. The specific objectives of this project were to:

1. define 'desired state' for seagrass meadows as an ecological benchmark,
2. examine the relationships between catchment inputs of fine sediment and seagrass desired state based on long-term monitoring data and eReefs, and
3. compare against the 2018 WQIP ERTs based on the sediment loads under which seagrass condition meets the criteria of 'desired state'.

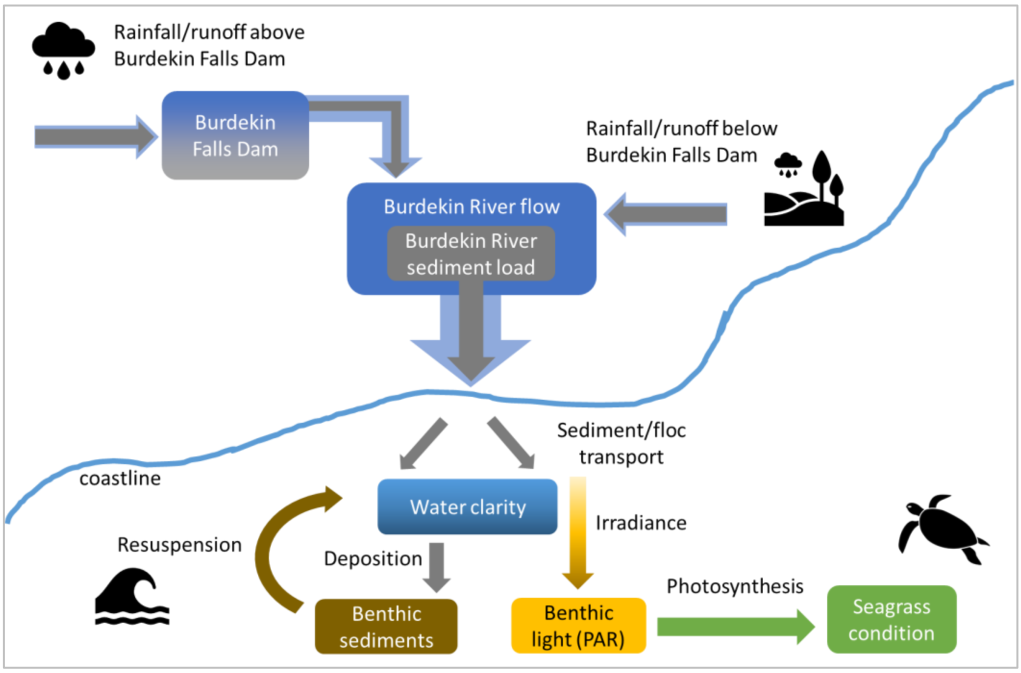


Figure 1. Schematic showing key catchment to ocean processes

This was undertaken in the Burdekin region where sediment loads have had well-documented impacts on water quality (Fabricius et al. 2014, Lewis et al. 2018) and where water quality affects the condition of nearshore habitats, in particular the extensive seagrass meadows (Collier et al. 2012, Petus et al. 2014, McKenzie et al. 2019). This work has demonstrated that setting ecological targets, and linking catchment loads to ecological targets is important but challenging for a number of reasons, and we highlight the uncertainty and assumptions that need to be made. This study is part of a broader range of projects looking into sediments, organic matter and nutrients within the region, as well as benthic light levels and light thresholds (Figure 3). This analysis has drawn upon these new and emerging data sets, and while the data compilation was in itself a large and challenging task, ongoing data collection and data availability will be invaluable to contribute to an evidence-base for management targets.

Figure 2. Sediment from the Burdekin River flood plume dispersing towards Cleveland Bay illustrates the potential influence of river loads on benthic habitats (NASA Worldview 9 February 2019). White areas are clouds.

To meet these objectives, we adopted a step-wise approach, outlined by the chapters in this report (Figure 3):

Chapter 2. Seagrass Desired State: Desired state is an aspirational target for guiding management. Analysis of the diverse seagrass species in Cleveland Bay was used to define unique seagrass communities. Reference subsets of the biomass and area of each community was then used define desired state. This analysis was conducted as a case-study, demonstrating how to overcome the challenges of defining desired, and will be applied and adapted to new areas in NESP TWQ Hub Project 5.4.

Chapter 3: Seagrass condition in relation to sediment loads (Chapter 3): Seagrass condition (spatial extent and biomass) in Cleveland Bay, northeast Australia, to river discharge and associated sediment loads, fitting linear models to 12 years of routine seagrass monitoring data. The strongest relationships were used estimate “sediment load thresholds”, above which seagrass was predicted to decline or fail to meet desired state. These were compared to existing load targets.

Chapter 4. Seagrass condition in relation to benthic light (Chapter 4) The recently developed satellite-derived, spatially-explicit benthic light product, bPAR (Magno-Canto et al. 2019, Robson et al. 2019), was compared to seagrass area and biomass. Potential seagrass habitat was calculated based on the area of Cleveland Bay that exceeded specific bPAR levels (ranging from 2-10 mol/m^2/d), and correlating this to the measured biomass and area of seagrass. The results of this, were not used to estimate ERTs.

Chapter 5: Exploration of eReefs for regional and bay-scale application (Chapter 5): eReefs was used to set the WQIP 2018 targets based on light thresholds. In this section, we take a further step and explore relationships between sediment loads and seagrass using the Relocatable Coastal Model (RECOM). We also investigate accumulation rates of new sediment vs legacy sediment in Cleveland Bay, the impact of different sediment types, and the influence of different river sources.

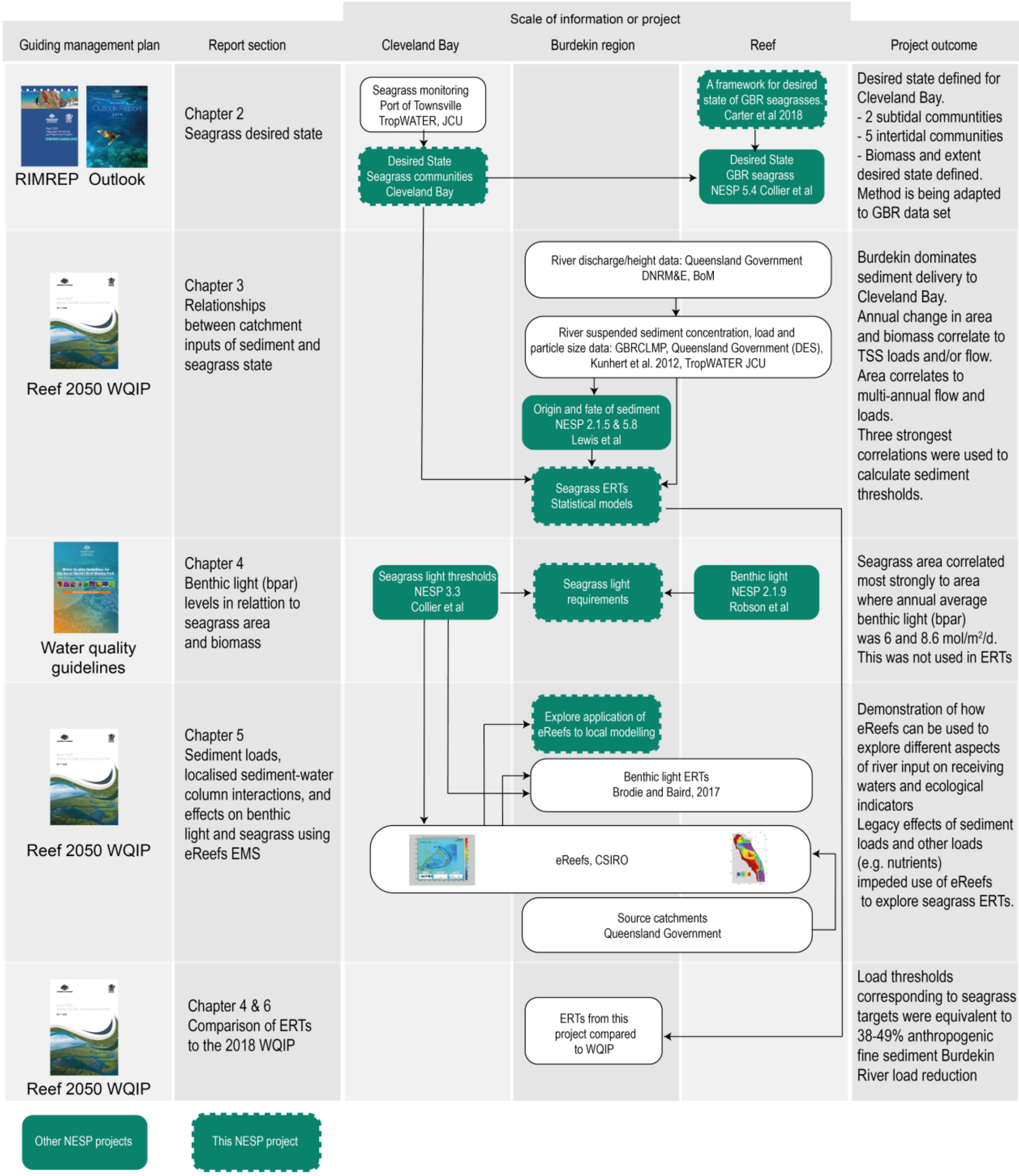


Figure 3. Report outline, simplified conceptualisation of information flow into NESP TWQ Hub Project 3.2.1 to meet objectives. Also shown are the relevant management plans that motivated project objectives, and which may be apply to apply project outcomes in future iterations.

Other projects and publications related to this work are:

1. NESP Projects 2.1.5. and 5.8. What's really damaging the Reef? Tracing the origin and fate of the environmentally detrimental sediment and associated bioavailable nutrients. https://nesptropical.edu.au/index.php/round-5-projects/project-5-8/ (Lewis et al., 2018)

2. Queensland Government RP128G Sources of bioavailable particulate nutrients. https://www.qld.gov.au/environment/agriculture/sustainable-farming/reef/reef-projects-current#RP128G (Garzon-Garcia et al., 2017a, Garzon-Garcia et al., 2017b, Waterhouse et al., 2018)

3. Katharina Fabricius NESP corals and light project (DiPerna et al. 2018, Robson et al. 2019, Strahl et al. 2019).

4. Seagrass light thresholds (Collier et al. 2016).

1.3 The Burdekin Region

The Burdekin Basin (catchment), is one of the largest catchments in Australia (Figure 4) with a total area of 130,400 km^2, and is the single largest source of sediment discharge to the GBR contributing approximate 30% of the total sediment loads (Kroon et al. 2012). It has an annual median discharge of 4,400 GL (range: 250–54,030 GL) over a 99-year gauge record to 2019 (1921–2019) (from MMP report/gauge data). It is a seasonally dry tropical catchment and has extremely variable flow (Figure 5), with high flow and discharge of sediment and nutrients following high rainfall, often associated with tropical cyclones and depressions.

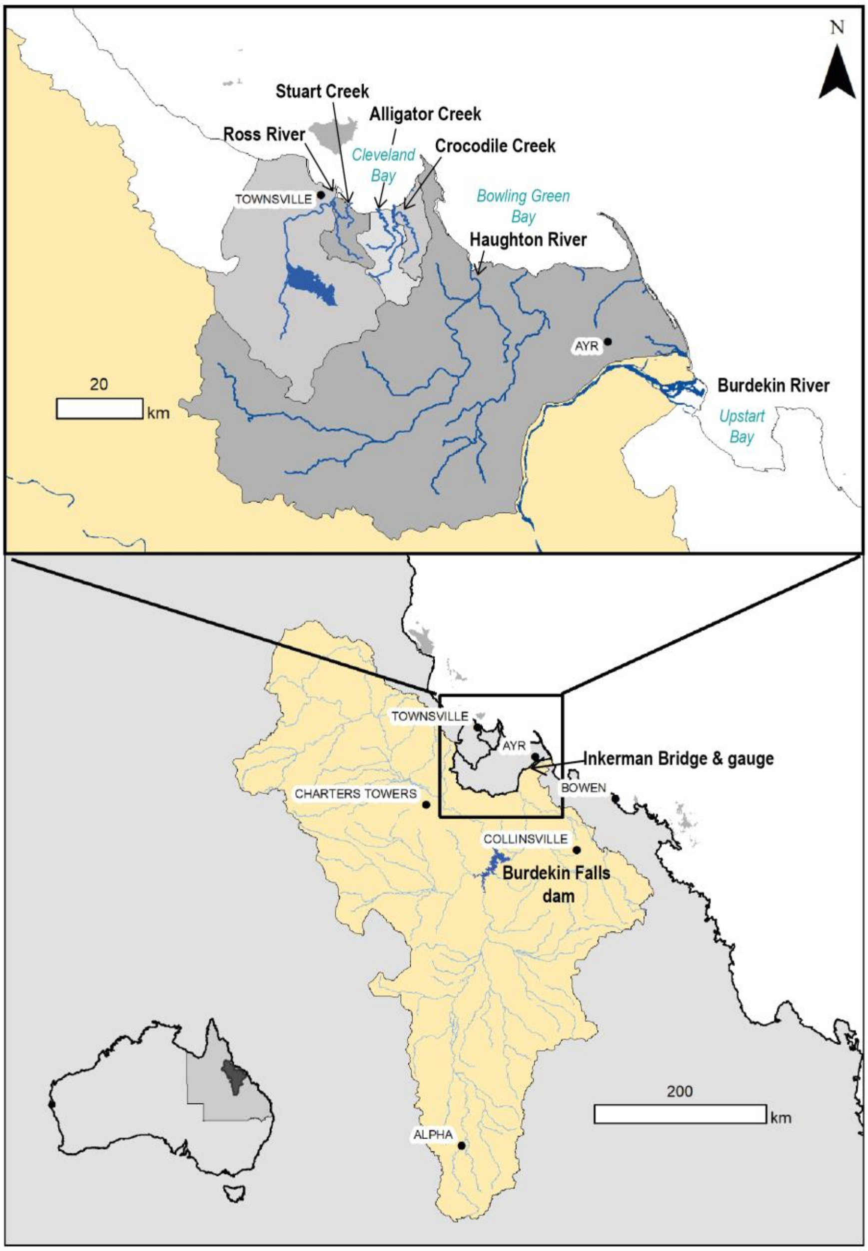


Figure 4. The vast Burdekin basin (yellow). Inset: Local river and creek catchments feeding into Cleveland Bay (Ross River, Stuart, Alligator and Crocodile Creeks), Bowling Green Bay (Haughton River) and Upstart Bay (Burdekin River). Adapted from Lambert et al. in preparation.

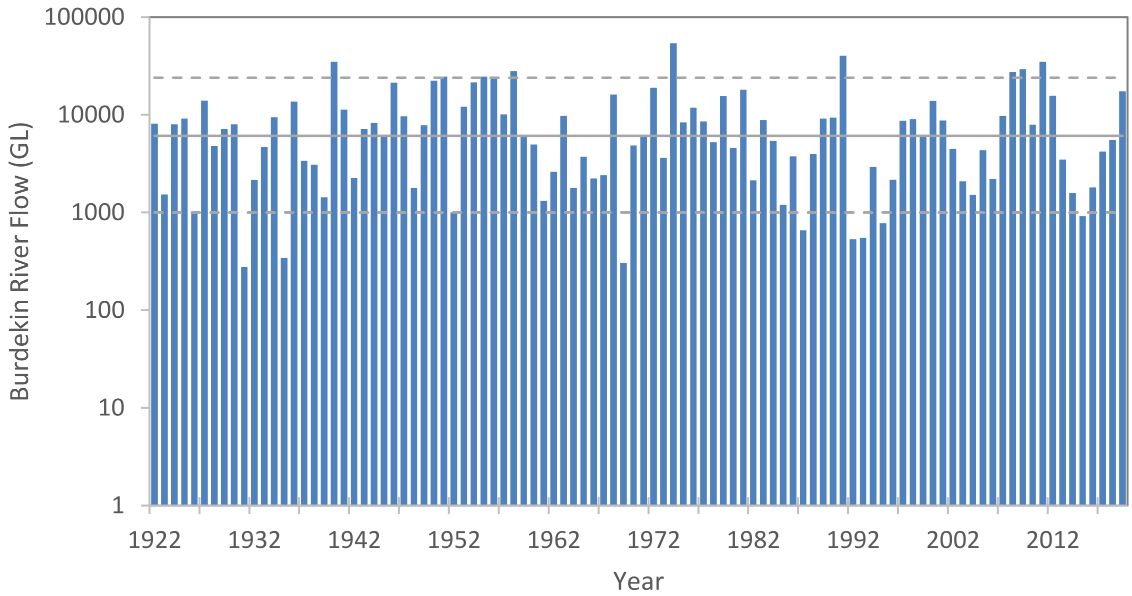


Figure 5. Annual water year flow (GL) for the Burdekin River (1 October 1922 - 30 September 2019, inclusive) and long-term median flow (grey line) and 90th and 10th percentiles (dashed grey lines). Source: Queensland Government Department of Natural Resources, Mines and Energy, 2019.

The Burdekin catchment includes five major sub-catchments, four of which drain into Lake Dalrymple — an artificial lake impounded behind the Burdekin Falls Dam. Due to enormous run-off from this large catchment, the dam has overflowed every wet season but two since its construction was completed in 1987 despite the highly variable rainfall and river flow (Faithful and Griffiths 2000, Bainbridge et al. 2016). The fifth major sub-catchment, the Bowen River discharges directly into the Burdekin River downstream of the dam and comprises ~50% of this below dam area. There are five additional basins that discharge into and affect Cleveland Bay that are therefore relevant to the objectives of this report. They are: Haughton River, Ross River, Stuart Creek, Alligator Creek and Crocodile Creek (Figure 4).

Annual sediment export is five to eight times higher than pre-development loads based on historical records of coral cores influenced by Burdekin River and catchment modelling (McCulloch et al. 2003, Kroon et al. 2012). Discharge regimes and sediment yields from the different sub-catchments of the Burdekin River are affected by rainfall, topography, geology and stream transport efficiency (Bainbridge et al. 2014). The Upper Burdekin sub-catchment has the highest suspended sediment yields and is the major source of both discharge and sediment to both the Burdekin Falls dam and the major source of discharge at the end-of-river (Bainbridge et al. 2014). The dam traps sediment from the upper catchment, and has reduced the suspended sediment load from the upstream catchment area (88% of the entire catchment) to end-of-river export (Lewis et al. 2013). The sediment-size fractions transported from the upstream catchment area to the end-of-river have also been altered by the dam, with the finer clay fraction now dominating all sediment exported over the dam spillway to the river mouth and adjacent GBR lagoon. As the Bowen River sub-catchment has the highest sediment yield/unit area (Bainbridge et al. 2014, Bartley et al. 2015) and a high delivery ratio being downstream of the dam and within close proximity to the Burdekin River mouth, this sub-catchment has become the focus of current management efforts to reduce Burdekin River sediment export.

The Burdekin River catchment includes areas of high nutrient hazards (Waterhouse et al. 2017) and is second and third largest region contributing dissolved inorganic and particulate nitrogen loads, respectively, to the GBR lagoon (Bartley et al. 2017). Furthermore, DIN generation from plume sediments can account for at least 12-38% of the DIN catchment load such that sediment loads in plumes affect nutrient export to the GBR lagoon (Lewis et al. 2018). Elevated nutrients contribute to increases in phytoplankton concentration in the GBR lagoon, and the long-distant transport of nutrients is facilitated by the cycles of growth, decay and remineralization of plankton (Schaffelke et al. 2017). This cycle contributes — along with terrestrial and marine-derived organic matter — to suspended particulate matter (flocs), and water clarity in the lagoon (Bainbridge et al. 2018). Unravelling the complex pathways influencing flocs in the Burdekin region is an active area of research (Lewis et al. 2018), and data availability for use in modelling projects such as this is scant. Therefore, we were unable to account for these processes in this study, but strongly recommend that future catchment to reef modelling and ERT analysis addresses these if and when data is available.

Pesticides, in particular PS-II herbicides and metal pollutants are also of concern within the lower Burdekin catchment and sub-basins with the Burdekin NRM (Bartley et al. 2017), and present a very low to moderate risk depending on the year and method for calculating risk (Gallen et al. 2019). As for nutrients, there is insufficient data available to model their influence at the time of this analysis, but they are also ranked of lower concern for the region compared to sediments and nutrients.

1.4 Seagrasses of the Great Barrier Reef

1.4.1 Seagrass diversity and ecological function

Seagrasses are a functional grouping of marine plants that share common features: namely they are angiosperms, or flowering plants that occupy shallow (down to 60m) coastal areas including estuaries and reefs (Waycott et al. 2004, Coles et al. 2015). They form part of highly connected coastal and reef habitat that have multiple functional roles in supporting ecosystems and human livelihoods (Nordlund et al. 2016). The tropical seagrasses of the GBR are especially valued for their cultural significance (both Traditional Owners and non-Traditional Owners) in supporting dugong and green turtle, commercial and recreational fisheries production through provision of habitat to juvenile fish and prawns, and for their role in filtering water by recycling nutrients, enhancing sediment settlement and removal of pathogens.

The GBR is a diversity hotspot, hosting 15 of the world's 72 seagrass species. Therefore, many of the shallow seagrass meadows (<10m deep) form multi-species meadows. This diversity enhances their ecological values, as each of the seagrass genera have unique benefits to ecological services (Nordlund et al. 2016) and unique levels of vulnerability to disturbances. Seven species of seagrass are common in Cleveland Bay, and these form in multi-species meadows, the composition of which are affected by benthic light, exposure to air and wind/waves and sediment type. The elements affecting community composition is one of the outcomes of classifying communities for describing seagrass desired state (Chapter 2).

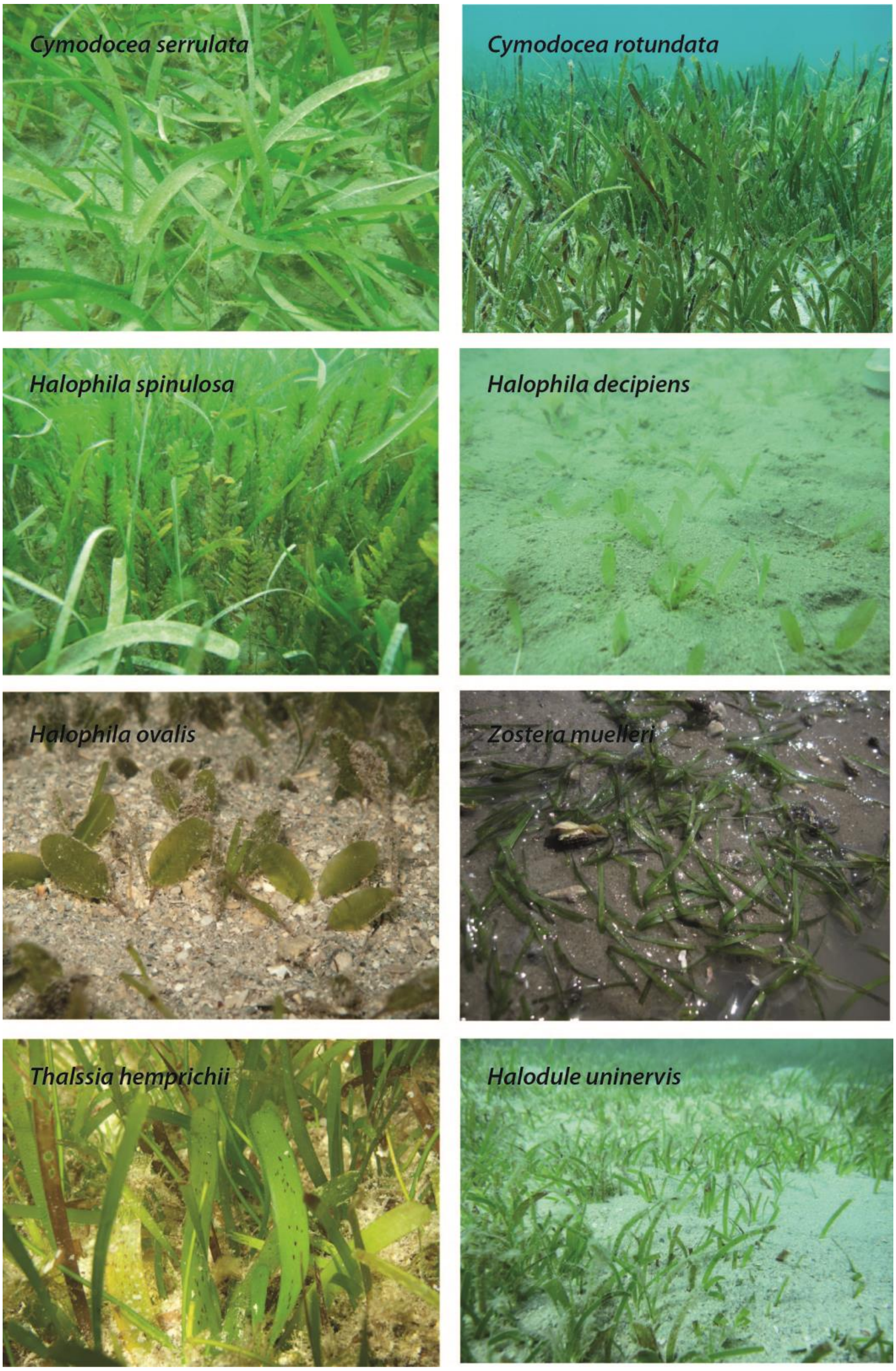


Figure 6. Eight of the seagrass species commonly occurring in the GBR and the study area.

Traditional owner values of seagrass habitat

Ecological value can be considered from many perspectives and can influence what is considered desired state. As a component of this project, we discussed with Rangers why seagrasses are important in their communities, Seagrass-Watch provides training to Rangers in how to monitor seagrass meadows. As an add-on module to that training, we discussed monitoring in their local communities, and why they were interested in monitoring. All respondents identified the importance of seagrasses to dugong and turtle, while a few also mentioned sea life, in particular fish and prawns. Their value in preventing sediment erosion was also identified. This highlights the need for us to discuss the management of seagrass with Traditional Owners in the context of the values that are important to them, while also continuing to communicate about the many other benefits that seagrass meadows provide. As a part of NESP TWQ 5.4, we will follow up with Rangers who undertook the Seagrass-watch training.

1.4.2 Seagrasses are sensitive to water clarity

Seagrasses have relatively high light requirements compared to other submersed marine plants, specifically compared to most algae (Dennison et al., 1993), making them at high risk of suspended sediments because of the resultant effects on water clarity and sunlight available for photosynthesis. Seagrass resilience to low light can be described as a function of resistance to light deprivation, and recovery following loss (O'Brien et al. 2017). Their response can be described according to their growth strategy as colonizing, opportunistic and persistent (Kilminster et al. 2015). Colonising species, including Halophila species, adopt a recovery strategy to disturbances. They grow rapidly and have a large investment in sexual reproduction and persistent seed production (Kilminster et al. 2015). They have low physiological resistance to periods of light below their light requirements and suffer mortality within days to weeks (Longstaff et al. 1999, Collier et al. 2016, Collier et al. 2016, Chartrand et al. 2018), relying on recovery from the persistent seed bank for overall survival (Kenworthy 1999, Kilminster et al. 2015). Persistent species adopt a resistance strategy (O'Brien et al. 2018). They grow slowly and have a large investment into persistent carbohydrate storage tissues – the rhizomes. This enables them to tolerate periods of light below light requirements by drawing on reserves and making other structural modifications (Collier et al. 2009). Sexual reproduction is important for maintaining genetic diversity and recovery from seed banks also occurs in persistent species (Waycott et al. 2004), but tolerance to low light is critical to their overall survival in variable light conditions. Opportunistic species adopt elements of both (Kilminster et al. 2015). Therefore, the species composition, or community type, fundamentally affects the way a seagrass meadow responds to periods of elevated suspended sediments and low light.

Benthic light levels within seagrass habitat of the GBR follow clear seasonal cycles (McKenzie et al. 2019), but with interannual variability particularly associated with periods of high river discharge. Benthic light is affected by water clarity, water depth and incoming solar radiation (Kirk 2011). In general, light levels decline in January or February, depending on the timing of onset of the wet season and persist through winter until solar insolation increases in spring and in the dry season (McKenzie et al. 2019). Annual seagrass surveys are typically undertaken after light levels have returned and when seagrass biomass and extent reach their annual maximum, and the legacy effects of the previous wet season is expected to be fully realized. The effect of river run-off and sediment loads on photic depth (the depth in which light levels reach 10% of surface light) has been assessed through statistical models that can account for wave (resuspension) and tide effects (Fabricius et al. 2014). In wet years, photic depth was reduced for 156 days following rainfall and run-off, compared to 9 days in drier years in the central GBR, including the Burdekin region (Fabricius et al. 2014). The relationship between photic depth and run-off was not as strong in chronically turbid coastal areas, such as Cleveland Bay (Fabricius et al. 2014). Seagrasses in the Burdekin region were the most at risk from suspended sediments, compared to other regions because it had the largest area of seagrass (363 km^2) falling into the highest likelihood of exposure to sediment discharge (Waterhouse et al. 2017).

There has been considerable research into seagrass light requirements, with a focus on short-term (weeks-months) light requirements that resemble typical durations of dredging within ports for channel maintenance and periods of elevated suspended sediment/low light from wet season run-off (Table 1). The light requirements also vary among species and were summarized in Collier et al. (2016). Light requirements for the most common species occurring in areas of high risk were used to model sediment load reduction targets for the Reef 2050 WQIP (Brodie et al. 2017). Longer-term light requirements (annual-multiannual timescales), are a function of physiological capacity to tolerate low and variable light conditions requiring both resistance and recovery strategies such as opportunistically growing from shoots or seeds under favorable light levels (O'Brien et al. 2018). As light availability is the primary limiting factor in coastal waters, the spatial and temporal variation in light levels influences seagrass distribution, including the distribution of species with different light requirements (Collier and Waycott 2009). Despite that, the long-term light requirements in absolute values, are largely unknown for the seagrass species occurring in the GBR. It is a subject of research within this project, the extension project 5.4 and complimentary research on remote-sensing benthic light in project 2.3.1 (Robson et al. 2019).

There are extensive areas of intertidal seagrass throughout the GBR, including in Cleveland Bay, which can receive periods of high light during low tide (Petrou et al. 2013). However, they are unable to use these high light levels proportionally, because photosynthetic rates plateau beyond certain light levels (i.e. Pmax (Beer et al. 2001, Ralph and Gademann 2005, Collier et al. 2018), and air exposure limits dissolved inorganic carbon acquisition needed for photosynthesis (Petrou et al. 2013). Furthermore, depending on the height of exposure, many areas classified as intertidal are not exposed very often, and even less so during daylight hours over the wet season due to astronomical conditions, and this is the time when water becomes the most turbid and light limitation presents the greatest risk. Therefore, even intertidal meadows can suffer declines under extreme conditions that reduce benthic light levels, though sometimes to a lesser extent than subtidal areas (Petus et al. 2014). Sensitivity to decline (Collier et al. 2012, Collier et al. 2016, Collier et al. 2016) and recovery following low light periods also depends on life history strategies (Rasheed et al. 2014).

The effects of water quality on seagrasses in broader terms, has been summarized elsewhere including: nutrients, herbicides and salinity (Flores et al. 2013, Collier et al. 2014, Collier et al. 2014, Negri et al. 2015, Wilkinson et al. 2015, Wilkinson et al. 2015, Wilkinson et al. 2017). The relevance of these, and other environmental stressors such as water temperature, are addressed throughout as relevant, but they are not the focus of this report.

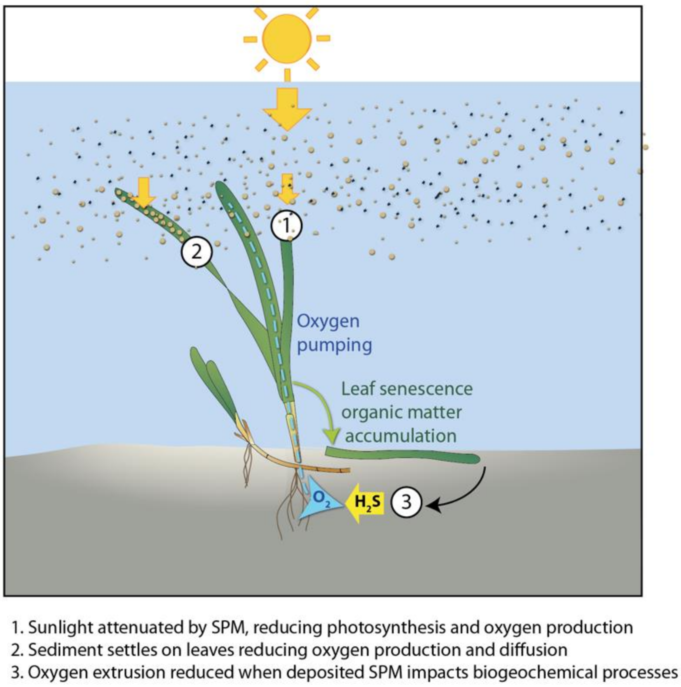


Figure 7. The effects of suspended sediment on seagrasses. Adapted from Bainbridge et al 2018

2.0 AN EVIDENCE-BASED APPROACH FOR SETTING DESIRED STATE IN A COMPLEX GREAT BARRIER REEF SEAGRASS ECOSYSTEM: A CASE STUDY FROM CLEVELAND BAY

This section is based on the following article:
Collier, C.J., A.B. Carter, M. Rasheed, L. McKenzie, J. Udy, R. Coles, J. Brodie, M. Waycott, K. O'Brien, M. Saunders, M. Adams, K. Martin, C. Honchin, C. Petus, and E. Lawrence, 2020, *An evidence-based approach for setting desired state in a complex Great Barrier Reef seagrass ecosystem: a case study from Cleveland Bay*. Environmental and Sustainability Indicators. Vol 7. 100042

2.1 Pre-amble

Adaptive management of the GBR requires knowing the desired ecological outcome of management activities, which has led to the inclusion of a priority action in the GBR Long-term Sustainability Plan being to determine desired state (e.g. EHA6 Great Barrier Reef Marine Park Authority and Queensland Government 2015). Desired state is an aspirational target for reporting on ecological health and for guiding management decisions. The inshore Great Barrier Reef is dynamic (e.g. York et al 2015, McKenzie et al 2019, Collier et al 2012, Fabricius et al 2013). The ecosystems undergo periods of impact and recovery, some of which are driven by 'natural' causes not related to manageable anthropogenic pressures, though these can be complicated to separate (see previous section). But irrespective of the cause, when habitat is in a poor condition, this is undesirable for the ecosystems that they support (Scott et al 2018, Preen 1995). Therefore, desired state does not allow for 'naturally' low periods of biomass and extent in this study. 'Desired state' can be used in analysis of pressures and to set environmental targets, including ecologically relevent sediment load targets (ERTs). Considerations for using desired state to set environmental targets include appropriate space-time scales of both the pressure and the ecological response to it, and selecting appropriate and sensitive communities for the pressure (e.g. chapter 3).

In the first stage of this project, we explored an evidence-based approach for setting desired state of seagrasses based on species composition, biomass and extent in Cleveland Bay as a case study. As a result of this case study and building on a seagrass community classification framework developed for the GBR in this project (Carter et al. 2018) desired state will be determined for the entire GBR seagrass data set in NESP TWQ project 5.4 (https://nesptropical.edu.au/index.php/round-5-projects/project-5-4/). This case study is a demonstration of how to overcome multiple challenges in setting quantitative targets but is not a definitive method. The method will be adapted to these other regions to accommodate regional conditions and habitat characteristics. At the same time, resilience and trajectory metrics should be explored so that desired state can account for previous changes in state, and predict future changes.

2.2 Executive summary

Implementing management actions to achieve environmental outcomes requires defining and quantifying ecological targets, but this is a complex challenge, and there are few examples of how to quantitatively set them in complex dynamic marine ecosystems. Here we develop a methodology to devise ‘desired state’ for tropical seagrasses in Cleveland Bay, northern Australia, in the Great Barrier Reef World Heritage Area. Analysis of diverse species assemblages was used to define seagrass communities as indicators of the region’s ecological value. Multivariate regression trees assigned 8000 observations of species presence/absence and habitat characteristics from 2007 to 2017 into seven community types. Generalised Linear Models were used to assess annual variation in above-ground biomass of each seagrass community. Reference subsets of the data expressing high biomass and spatial extent were identified, and desired state was defined as the mean and 95% confidence intervals. This approach rests on the assumption that seagrass resilience and its ecosystem services are met when the diverse seagrass communities reach desired state. This method required a data set that spanned a range in seagrass conditions, but which may have been compromised by a history of pressures. Our method for defining desired state provides evidence-based targets that can be used within an adaptive management framework that prioritises and implements management actions.

2.3 Introduction

Degradation of ecosystems and associated ecosystem services is a pressing issue for humanity (MEA 2005, Steffen et al. 2015). Managing natural resources more sustainably has challenges: urbanization, climate change, coastal development, consumption, and the complexity and uncertainty created by multiple pressures (Grech et al. 2011, Walker and Salt 2012, Head 2014). Adaptive management provides a best practice approach to managing natural resources by linking management objectives and actions to ecosystem health through appropriate indicators (Hallett et al. 2016). A fundamental challenge is defining success (Borja et al. 2013): what is the desired state of an ecosystem that we are aiming to achieve? This ought to be the specific outcome of management actions, and a target for success when considered in context of natural disturbances.

‘Desired state’ is defined in this study as an aspirational target for guiding management decisions. Defining desired state has been identified as a priority information need for management of the Great Barrier Reef World Heritage Area (GBRWHA) because of an importance in standardizing the evaluation of success and for prioritizing remediation (Great Barrier Reef Marine Park Authority and Queensland Government 2015). Desired state for seagrass habitats ideally would be that which maintains ecosystem services (Madden et al. 2009). Seagrass ecosystems are of global significance because they provide a range of ecological functions such as food for dugongs and turtles, feed a large proportion of the world’s population by providing nursery grounds for fisheries species, sequester vast amounts of carbon, and provide shoreline protection by stabilising sediments (Cullen-Unsworth and Unsworth 2013, Nordlund et al. 2016, Unsworth et al. 2018). In some cases, these ecosystem services are used to define management objectives (Borja et al. 2012, Samhouri et al. 2012). However, quantifying every aspect of ecosystem services is a challenging task, especially when the relationship between services, functions and underlying biodiversity remains poorly understood (Kremen 2005, Barbier 2014). Not all ecosystem services have been defined, previously unknown seagrass ecosystem services continue to emerge, such as reducing disease-causing pathogens (e.g. Lamb et al. 2017), and trade-offs in seagrass ecosystem services exist (Butler et al. 2013, Scott et al. 2018). The services also vary among seagrass genera and among community types, adding complexity to basing targets on ecosystem services in multi-specific seagrass habitat (Cullen-Unsworth et al. 2014, Nordlund et al. 2016).

Two of the challenges for defining desired state of complex, dynamic ecological systems are: 1. choosing the right indicator/s and metrics for the ecosystem; and, 2. quantitatively defining the desired values of metrics for the indicator (Wicks et al. 2010). We define ‘indicator’ as seagrass communities which have unique assemblages, ecological value and sensitivity to pressures and ‘metric’ as a measurable quality of the seagrass community (sensu. Daan 2005). Seagrass habitat has properties of condition and resilience (O'Brien et al. 2017). We define ‘condition’ as relative quantities of characteristics of the seagrass that can provide ecological services at the time of assessment. ‘State’ is synonymous with ‘condition’, but the term state is reserved for use in ‘desired state’ for clarity. ‘Resilience’ is the capacity to provide those services in the future, based on being able to retain condition and function in the face of disturbances (O'Brien et al. 2017, Connolly et al. 2018). Ideally, desired state would encapsulate both condition and resilience, and while the metrics used to quantify these can overlap (Unsworth et al. 2015), simple metrics of condition are generally easier to measure and report against than resilience metrics (Marbà et al. 2013, Tett et al. 2013).

Spatial extent is one indicator of seagrass habitat availability and the provision of ecosystem services that it provides, so knowledge of extent is required before implementation of management strategies to protect these services (Unsworth et al. 2019). Extent can fluctuate for multiple reasons, including from pressures that arise from human activities. For example: it can fluctuate at the deepest limit due to declining water quality and light limitation (Dennison et al. 1993); in shallow water due to thermal anomalies and tidal variability (Massa et al. 2009, Rasheed and Unsworth 2011, Thomson et al. 2015), which may become more frequent and extreme in the future (Hoegh-Guldberg et al. 2014); and, from increasing patchiness associated with disturbances (Kendrick et al. 1999, Cunha et al. 2005). Extent can also fluctuate naturally, including due to seasonality in annual (York et al. 2015) and perennial species (O’Hara et al. 2002). Seagrass extent can be easily integrated among studies to assess broad-scale change in seagrass habitat, including in global assessments (Waycott et al. 2009). Seagrass presence/absence, species composition, and abundance are other common and simple population-level metrics of seagrass condition and resilience; they encapsulate the effects of multiple human-induced pressures (Martinez-Crego et al. 2008, Madden et al. 2009, Marbá and Duarte 2010), and may fluctuate independently of extent (Rasheed and Unsworth 2011). These metrics form the basis of most robust studies investigating the condition and resilience of seagrass meadows (e.g. Madden et al. 2009, Personnic et al. 2014) and are applied in monitoring and assessment programs within the Great Barrier Reef (e.g. Bryant and Rasheed 2018, McKenzie et al. 2019).

Determining the desired state of metrics for an indicator is not trivial (Hallett et al. 2016). This is further exacerbated in systems where there is large seasonal and/or inter-annual variability, particularly for biotic indicators with no long-term data sets that encapsulate each metric’s variability. Desired state should be ambitious yet realistic, (Perrings et al. 2011, Samhouri et al. 2012) and can be based on understanding the functional cause-effect with environmental conditions (Steward et al. 2005, Steward and Green 2007, Samhouri and Levin 2012, Choice et al. 2014, Saunders et al. 2017), which likely requires complex analysis specific to the local system. In many cases, targets have been based on historical status or on the maximum value in the region (Borja et al. 2012), providing reference points for management activities, without being specific to one pressure. Irrespective of the approach, setting targets requires supporting data.

The objective of this study was to develop a methodology for defining desired state by selecting indicators and metrics and then defining desired state of each metric. Our paper describes a case study from Cleveland Bay in the GBRWHA where the seagrass habitats are complex because they are dynamic and diverse, but the approach can be applied to habitats with different ecological attributes and adapted to a range of spatial scales. Desired state can be used as a reference point against which to quantitatively assess the influence of human pressures and 'natural' variation thereby enabling the implementation of remediation strategies.

2.4 Methods

2.4.1 Study area and management objectives

We chose Cleveland Bay as an appropriate study area for implementing a model of adaptive management because of its highly valued ecological attributes and the well-understood risks to those ecosystem services. Cleveland Bay lies within a region of international significance — the GBRWHA — where the over-arching management objective for biodiversity is "The reef maintains its diversity of species and ecological habitats in at least a good condition with a stable to improving trend" (Great Barrier Reef Marine Park Authority and Queensland Government 2015). The GBRWHA protects up to 10% of the world's coral reef ecosystems, but they only cover about 7% of its area. Seagrasses are another of the key ecological attributes of the GBRWHA by virtue of their extensive area and the ecosystem services they provide (Great Barrier Reef Marine Park Authority and Queensland Government 2015), including supporting dugong and green turtle populations (Marsh et al. 2011, Tol et al. 2016, Scott et al. 2018).

Seagrass grows throughout most of the bay, from intertidal banks to deeper subtidal waters (Bryant and Rasheed 2018). There are seven species of seagrass in Cleveland Bay: *Cymodocea serrulata, Halophila decipiens, Halodule uninervis, Halophila ovalis, Halophila spinulosa, Thalassia hemprichii* and *Zostera muelleri* subsp. *capricorni* and the meadows they form here are a connectivity hotspot in the central GBR (Grech et al. 2018). Cleveland Bay is affected by discharge from the Burdekin River — the second largest river basin on Australia's east coast — as well as several smaller rivers. These rivers discharge fine sediment, nutrients and particulate organic matter during the wet season (October to April), the loads of which have increased in association with agricultural developments (largely beef grazing and sugarcane cultivation) in the catchments (Bainbridge et al. 2012, Kroon et al. 2012, Fabricius et al. 2014, Bainbridge et al. 2018). Discharge from the river has high inter-annual variability in volume of discharge, sediment and nutrient loads, and the direction of plume flow depending on prevailing winds(Fabricius et al. 2014, Lewis et al. 2018). These influence water clarity (Fabricius et al. 2014), and contribute to changes in seagrass extent and biomass (Collier et al. 2012, Petus et al. 2014, Rasheed et al. 2014). Cleveland Bay is also located adjacent to the city of Townsville presenting multiple threats to seagrass distribution and abundance in the region, including urban and port developments (Grech et al. 2011). The region is exposed to large-scale disturbances from tropical cyclones, and to increasing risk from heat waves (Hughes et al. 2017, Lough et al. 2018).

We use biomass and extent from observations spanning over a decade to quantify desired state, which results in desired states that are ambitious, yet realistic. In general, targets could be based on reference sites or on a reference period of time (Samhouri et al. 2012), such as the designation of the Great Barrier Reef Marine Park in 1981, or on pre-industrial times. However, reliable historical information on the condition of seagrasses in the region is available only from 2007, and developing targets for any time prior to that would be based on scant evidence and require a considerable number of assumptions. Furthermore, the historical predictions could not be validated. Environmental managers responsible for the GBRWHA report on the condition and trend of ecological health and prioritise and implement actions to achieve management objectives in an adaptive management process (Great Barrier Reef Marine Park Authority 2019). We developed desired state for all communities without being specific to a management action, but our intention is to apply or adapt them to provide an evidence-base for management decisions. The implications of this approach are discussed throughout.

2.4.2 Define indicators: community types based on species composition and habitat

Setting seagrass desired state in this region required an approach that accommodates the relatively high species diversity and dynamic nature of the seagrass meadows. Therefore, we define the indicators in this study as not just seagrass, but as different community types of seagrass. As the community types were then used as the basis to establish desired states for biomass and spatial extent, it was necessary to exclude data from years when the species assemblages were altered due to the impacts of large events as described below.

Available data

Seagrass biomass and species composition were assessed as part of routine monitoring of benthic habitats for the Port of Townsville. Seagrass biomass and species composition was visually assessed at least annually between 2007 and 2017 (Bryant and Rasheed 2018). The data is made up of 8122 observations (518 – 1209 sites/year, median = 626). Sampling was stratified into discrete seagrass meadows and non-seagrass areas in the bay, and the distribution of sites covered most of Cleveland Bay during broad-scale surveys in 2007, 2013, and 2016. A subset of discrete seagrass monitoring meadows was surveyed in the other years. Sites (an area of 5m radius) were haphazardly allocated within each stratified area to ensure good spatial coverage. This method ensured all seagrass monitoring meadows were assessed each year regardless of the annual spatial change. The number of sites needed to represent the variability and patchiness of the communities and detect change in biomass in the original monitoring program was determined by power analysis. Above-ground biomass was visually assessed within three replicate quadrats (50 $\times$ 50 cm) randomly placed within each site. Visually estimated above-ground biomass is a widely-used non-destructive method that has been applied in high-precision time-series analysis (Rasheed 1999, Aragones and Marsh 2000, Rasheed 2004) and meadow scale change assessments (Rasheed and Unsworth 2011, McKenna et al. 2015). The visual assessment is calibrated for each individual observer against harvested biomass samples at each time of sampling. Biomass for the site was calculated from an average of the three quadrats and scaled up to grams dry weight m^{-2} (g DW m^{-2}). Species composition was the percent contribution of each species to mean biomass within the three quadrats. When defining community types species data was simplified to presence/absence (Table 1).

Habitat requirements including depth range, sensitivity to changing water quality, the benthic substrate suitable for growth, and the frequency of exposure to air at low tide for intertidal communities vary among species (Waycott et al. 2004, Erftemeijer and Robin Lewis III 2006, Lee et al. 2007, Shafer et al. 2007, Collier et al. 2016), and lead to differences in species distributional patterns (Waycott et al. 2004, Waycott et al. 2005, Coles et al. 2009). Amongst water quality stressors, light limitation is regarded as the primary cause of seagrass loss in the region, and exposure to turbid flood water and subsequent resuspension of sediments has been linked to declines in seagrass meadow area and biomass in the GBRWHA and Cleveland Bay (Collier et al. 2012, Petus et al. 2014, Petus et al. 2016). Habitat requirements may also overlap among species, resulting in multi-species meadows such as those found in Cleveland Bay (Bryant and Rasheed 2018). Habitat characteristics, such as sediment type, tidal exposure, water quality measured as the clarity of water and/or depth, were therefore used to classify seagrass species assemblages into community types, with separate analyses for intertidal and subtidal sites.

Benthic sediment type at each site was visually assessed and defined according to broad categories (e.g. mud, sand) and listed from most to least dominant; dominant sediment (Sed_{dom}) was defined as the most dominant of these categories at a site (Table 1). Water clarity at each site was defined by a Water Clarity Index (WCI) and calculated as the frequency (number of weeks) of exposure to turbid water during the previous wet season which spans 22 weeks from December to April in each ‘water year’. Turbid water was identified from water colour as brownish to brownish-green waters in MODIS true colour satellite images and processed according to Álvarez-Romero et al. (2013) and Petus et al. (2019) as part of routine annual water quality monitoring for the GBRWHA (Waterhouse et al. 2018). Sites were defined as intertidal or subtidal using the habitat classification of Carter et al. (Carter et al. 2018). Depth below mean sea level was included as a predictor in the subtidal analysis only. The relative frequency of intertidal exposure was included as a predictor in the intertidal analysis only (Table 1).

Table 1. Seagrass species and habitat data used to determine desired state, including collection method, units, data source, resolution, and whether the data was used as a predictor or response variable.

Label	Description	Methods	Units	Source	Data resolution	Predictor/ response
Seagrass species presence/absence data						
P/A	Seagrass species presence/absence	Assessed in three 50 x 50 cm quadrats per 'site' deployed from helicopter, camera drops, or free diving depending on water depth and sea conditions.	0/1	Summarised in Bryant and Rasheed (2018)	Annual data 518 – 1209 sites/year, median = 626	Response (to habitat predictors)
Habitat data						
Sed_{dom}	Dominant sediment type	Recorded in the field and aggregated into broad categories for this analysis based on the dominant sediment type. Coarse Sand, Mud, Reef, Rock, Rubble, Sand.	n.a.	Bryant and Rasheed (2018)	Annual data 424 – 1101 sites/year, median = 592	Predictor
WCI	Water clarity index	Remote sensing imagery was used to derive a categorical index of water clarity, ranging from 1 (lowest) to 7 (highest). Categories 1-4 represent water that has high levels of total suspended solids, chlorophyll *a* and coloured dissolved organic matter, leading to high light attenuation coefficients, and low clarity	# weeks	Petus et al. (2016)	Annual data. Number of weeks (out of 22 weeks) in the previous wet-season (from December to April) that were category 1-4	Predictor
Depth class	Depth class	Habitat classification developed in Carter et al. (Carter et al. 2018), a spatially-explicit habitat classification scheme developed for the entire GBR based on water depth and water clarity (using the techniques described for WCI). Only depth categories were relevant to Cleveland Bay analysis: Coastal intertidal and Coastal subtidal (shallow and deep combined).	n.a.	Carter et al. (2018)	Single polygon file	Neither. Used to allocate sites for analysis in subtidal or intertidal models

RelExp	Relative tidal exposure index	Extracted from the intertidal extents model raster (ITEM v1.0), where 0 is never exposed, and 1-9 is exposed at increasing amounts of time where 1 = exposed at the lowest 0-10% and 9 = exposed at highest 80-100% of observed tidal range.	Relative scale	Geoscience Australia (2017) and Carter et al. (2018)	Single raster file. Uses all Landsat observations (5, 7, 8) for Australian coastal regions, 1987-2015	Predictor (intertidal analysis only)
Depth	Colonisation depth	Depth of the sampling site as determined from Beaman (2010) supplemented by other sources as summarised in (Carter et al. 2018).	m (metres below mean sea level)	Carter et al. (2018)	Single raster file Beaman (2010) and polygon shapefile Carter et al. (2018)	Predictor (subtidal analysis only)
Define metrics						
Biomass	Above-ground biomass	Estimated using a calibrated visual estimation technique during the peak growing season (September to November) for each species at each site.	g DW m^{-2}	Summarised in Bryant and Rasheed (2018)	Annual data 424 – 1101 sites/year, median = 592	Response (to year)
Spatial Extent	Area of seagrass habitats	Determined by GIS spatial extent analysis of site data for each seagrass community type collected during the peak growing season (September to December).	Ha	Derived from habitat assessment sites in Bryant and Rasheed (2018)	Annual data	Response (to year)
Identify desired state						
Year	Survey year		Factor	Bryant and Rasheed (2018)	Annual data	Predictor

2.2b Define community types

Seagrass species presence/absence (P/A) was used as a response variable to assign the seagrass at each site into a community type with unique species assemblages using multivariate regression trees (). While there are several other methods for defining species assemblages, multivariate regression trees result in discrete site groups (with distinct environmental affinities) allowing prediction and inference about sites where there is environmental data but no seagrass data. We used presence/absence from each site rather than biomass, which resulted in the community type being defined based on the frequency of occurrence of each species. Regression trees (Breiman et al. 1984, Clark and Pregibon 1992) are a machine-learning method for constructing prediction models and do not include *a priori* assumptions about the relationships between the response and predictor variables. Multivariate Regression Trees (MRTs; (De’ath 2004)) can be used to describe and predict relationships between multiple species and habitat characteristics (De'ath 2002). The parameters leading to the splits in the MRTs are interpreted by stepping down the tree. Once the tree has finished splitting the data, the bottom 'leaves' of the tree are nodes that we refer to as community types. As the aim was to cluster the sites spatially (not predict the abundance at a site at a point in time), we did not include 'year' as a factor in the model. Instead we aimed to categorise where each seagrass species is found, on average, through time.

To define seagrass community types, the MRT was fitted to data for all years excluding 2009 to 2012. These data were removed from the analysis because our aim was to identify community types that could be used to set seagrass desired state. There was loss of seagrass area and biomass in this period from most likely significant rainfall and the subsequent discharge of sediment and nutrients, which led to low water clarity and low benthic light levels (Petus et al. 2014, Bryant and Rasheed 2018). We removed these years from the analysis to avoid defining seagrass community types based on data that overwhelmingly represented a significant environmental impact, rather than more nuanced habitat conditions (e.g. sediment type, water quality) likely to drive community types in relatively normal years and desired state years. To check the effect of this decision, the MRTs were run on the data from years 2009 to 2012 separately. The species assemblages in those years were disproportionally dominated by colonising species indicative of a disturbance event, *Halophila ovalis* at intertidal and *Halophila decipiens* at subtidal sites, leading to an overly simple community classification that was not appropriate for setting desired state. The MRTs were fitted to the intertidal and subtidal sites separately. This analysis identified nine potential seagrass community types, which have been numbered one to nine and the characteristics of these communities are defined in the results.

The models were fitted using the *mvpart* package (De'ath 2004) in R (available in archive form on CRAN, https://cran.r-project.org). Exploratory analyses and sensitivity testing of the MRTs included: MRTs on biomass, which revealed a similar classification to the seagrass species presence/absence classification (Appendix A); Separate MRTs for each year to test the sensitivity of the community classifications to "good" and "bad" years (i.e. when there were significant rainfall events leading to poor water clarity and low benthic light) years; MRTs for all years combined and not just the "good" years; and, single regression trees for individual species.

The data from 2007 – 2008 and 2013 – 2016 was used in the initial analysis to define communities, while the 2017 data was included as it became available. This provided an opportunity to demonstrate how the fitted model can predict membership to a community type for additional data.

Determine spatial extent of each community

The spatial extent of each of the nine community types was assessed annually from 2007 to 2017. The data set is for observations collected from September through to December as this is the peak growing season for seagrasses in the region, and the time-period in which most of the surveys were conducted. Spatial analysis was also restricted to the smaller survey extent of meadows monitored annually, so the results were not biased in years which included the bay-wide surveys and increased sampling effort. (2007, 2013 and 2016). This means that spatial extent desired state could not be determined for deep subtidal community 1 as determined by the MRT classification. Survey extent was calculated from the concave hull (polygon enveloped) of all points based on spatial density in six different sub-regions in the Bay in each year (Geoffrey Bay, Nelly Bay, Cockle Bay, Shelly Beach, Rowes Bay/The Strand, and South Cleveland Bay, which are shown in the results in Figure 5). The sub-regions were separated by parts of the bay having no seagrass, or not surveyed. Thiessen polygons were created from site data to geostatistically define the area of seagrass in each sub-region for each year using seagrass presence/absence (0/1 data), clipping the polygons to each sub-region's survey extent, then removing polygons where seagrass was absent.

The area of each seagrass community type was determined by calculating the area of the remaining Thiessen polygons (in hectares) then summing these according to community type, sub-region and year. Survey extent (concave hull) analysis was conducted in QGIS v. 3.4.0 (QGIS Development Team 2018); all other spatial analyses were conducted in ArcMap v.10.4.1 (ESRI, Redlands, CA).

Re-assess community types

There were nine communities identified; however, the species composition and biomass of communities 6 and 7, and of communities 8 and 9 were very similar, varying in their classification between years based only on dominant sediment type or the water quality index, respectively. This led to an inter-annual switch in the occurrence of these community types between years, and was associated with inter-annual fluctuations in the biomass of each community type. Therefore, these community types were re-classified into community 6/7 combined and community 8/9 combined, resulting in seven seagrass communities identified in Cleveland Bay. Combining these very similar communities also meant we could do a more robust analysis on desired state biomass because the number of samples was increased.

2.4.3 Select metrics

Above ground biomass and geostatistical spatial extent were selected as metrics for setting seagrass desired state because there is substantial evidence that these are ecologically-important attributes of seagrass condition, and are sensitive to environmental change over the spatial-temporal scale of this study, including to the pressures occurring in the region (Marbà et al. 2013, McMahon et al. 2013, Petus et al. 2014, Rasheed et al. 2014, Bryant and Rasheed 2018). They are also measured in many monitoring programs, enabling this method to be applied in other regions.

2.4.4 Identify desired state

Desired state of above-ground biomass

Once the species assemblages were defined using the MRTs, temporal trends in above-ground biomass were examined. Generalized Linear Models (GLMs) were fitted using Tweedie models (Tweedie 1984). The Tweedie models were compared to Hurdle models (Mullahy 1986), which performed similarly. Uncertainty was estimated by calculating the 95% confidence interval (CI) of model predictions for each year.

For the determination of above-ground biomass desired state within each community, years with low sample size (number of sites<15) were excluded due to the high variability in biomass estimates for these years. We aimed to set ambitious targets, and acknowledged that the ecological integrity of the bay over the period of time in which data was available was likely to be somewhat compromised relative to a non-impacted baseline. Therefore, a reference data set was compiled for each community from years when biomass was highest. Specifically, the reference data was biomass in the year where maximum seagrass biomass was present, plus those years where biomass was not significantly different from the maximum year using Wald post hoc comparisons. In three of the communities (3, 4 and 5), the reference data set was compiled from three to four years of data for each community. In the remaining four communities (1, 2, 6/7 and 8/9), maximum biomass occurred in 2007, and this was significantly different from all other years. Where this occurred, 2007 was considered an outlier year that was unlikely to represent an achievable desired state, and the reference data set was therefore based on the mean of 2007 and the second and third greatest biomass years. Desired state was determined as average above-ground biomass of the reference data for each community, bounded by the 95% confidence intervals. All plots were created using the *ggplot* package in R (Wickham 2016).

Desired state of spatial extent

Spatial extent desired state was defined as the mean total seagrass spatial extent (i.e. all communities combined) based on the three years where extent was at its maximum. This was calculated separately for each sub-region because the large range in spatial extent among sub-regions, from tens to thousands of hectares, meant results from the largest meadows, e.g. South Cleveland Bay, masked trends in the sub-regions with small meadows. Desired state mean total extent (hectares) and 95% CI for those three best years, plus the contribution of each community to area desired state for those years, were calculated using the bias-corrected accelerated bootstrap method (repeated 10,000 times) with the *boot* package in R (Davison and Hinkley 1997, Canty and Ripley 2017). This approach ensures that the spatial coverage of community types, not just total extent, contributes to desired state.

We could not calculate a desired state of extent for subtidal community 1, as sampling only ever occurred during the broad-scale surveys. Shelly Beach was removed from the calculation of desired state for both subtidal communities, as even very shallow subtidal sites were only surveyed during broad-scale surveys.

2.5 Results

2.5.1 Seagrass communities

Intertidal areas within the Bay supported a greater number of seagrass community types, and the habitat conditions associated with these was more complex. This demonstrates that the common grouping of seagrass habitat as “intertidal” likely underestimates the complexity of conditions and community types in the intertidal zone. The species presence/absence MRTs identified two subtidal communities (communities 1 and 2) and seven intertidal communities (communities 3 – 9) (Figure 8). All four habitat characteristics were used by the MRTs to determine the different communities: Sed, RelExp, WQ and Depth. *C. serrulata*, *H. ovalis*, and *H. uninervis* occurred in all seagrass communities with varying levels of frequency. The most common species were: *Z. muelleri* in communities 4 and 9, *H. ovalis* in community 5, *H. spinulosa* in community 1, and *H. uninervis* in communities 2, 3, 6, 7, and 8 (Table 2). *T. hemprichii* was absent in the two subtidal communities and in the two *Z. muelleri*-dominated intertidal communities, and occurred at low frequency in the remaining intertidal communities. Both *Z. muelleri* and *T. hemprichii* occurred almost exclusively in the intertidal habitats in Cleveland Bay and did not overlap with *H. spinulosa* and *H. decipiens* which were more dominant in the deepest community. For subtidal seagrass, Depth was the only explanatory variable dividing communities (Figure 8). In water shallower than 3.5m the community was more diverse and dominated by *H. uninervis*, while the community deeper than 3.5m was dominated by *H. spinulosa*.

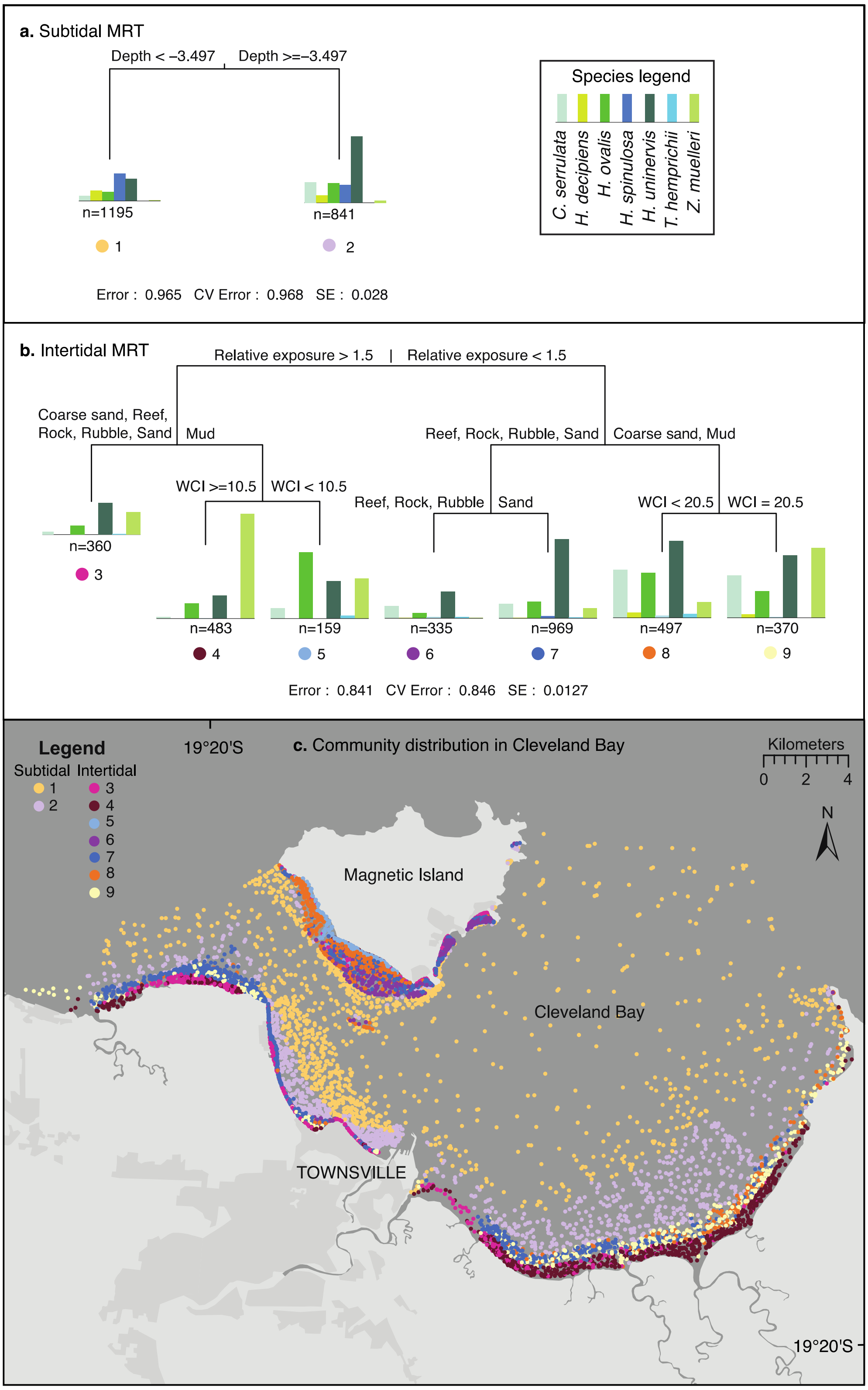


Figure 8. Multivariate regression tree (MRT) and seagrass communities classified using presence/absence data for a. subtidal sites, b. intertidal sites and c. the spatial distribution of communities in Cleveland Bay, 2007, 2008, 2013-2016. The number below each community is the count of observations that fall into that community. The histogram shows the frequency of occurrence for each species in that community with the height of the bar representing the frequency that each species was observed in that assemblage. The coloured dots represent unique communities one to nine (later grouped into seven communities with 6/7 and 8/9 combined). The CV Error is the cross-validated relative error and is the best indication of the error here.

Table 2. Frequency of occurrence of each species within the nine community types (Com.) identified using multivariate regression tree analysis on site data. Bold type indicates most common species

Com.	*C. serrulata*	*H. decipiens*	*H. ovalis*	*H. spinuolsa*	*H. uninervis*	*T. hemprichii*	*Z. muelleri*
1	*0.07*	*0.14*	*0.12*	***0.37***	*0.30*	*0.00*	*0.01*
2	*0.15*	*0.05*	*0.15*	*0.13*	***0.49***	*0.00*	*0.02*
3	*0.06*	*0.00*	*0.13*	*0.00*	***0.47***	*0.01*	*0.33*
4	*0.01*	*0.00*	*0.10*	*0.00*	*0.16*	*0.00*	***0.72***
5	*0.07*	*0.00*	***0.42***	*0.00*	*0.24*	*0.02*	*0.26*
6	*0.26*	*0.01*	*0.11*	*0.03*	***0.56***	*0.03*	*0.01*
7	*0.12*	*0.00*	*0.13*	*0.02*	***0.64***	*0.01*	*0.08*
8	*0.24*	*0.03*	*0.23*	*0.01*	***0.39***	*0.02*	*0.08*
9	*0.21*	*0.02*	*0.13*	*0.00*	*0.30*	*0.00*	***0.34***

For intertidal seagrass, the first split in the MRT was relative exposure with communities 3 – 5 exposed relatively more (>1.5 out of 9) than communities 6 – 9 (<1.5 out of 9) (Figure 8). Sediment was the next split, with communities defined predominantly on whether they grew in mud compared with all other sediment types (Figure 8). Mud communities were dominated by *Z. muelleri* (communities 4 and 9), *H. ovalis* (community 5), and *H. uninervis* (community 8), while *H. uninervis* was always the dominant species in the three non-mud communities (3, 6, and 7). Mud communities were further defined according to the WCI (Figure 8). On the right hand side, there is a second split based on sediment where habitat that has sand substrate separates from habitat that is reef, rock or rubble. Both of these are mixed communities dominated by *H. uninervis*. On the far right, the mud/coarse sand sites were further split based on the WCI (Figure 8).

The MRT was repeated with above-ground biomass (square root transformed) as the response variable instead of presence/absence (see supplementary material, Figure S1, Table S1). The splits in the tree were almost exactly the same as the presence/absence MRT therefore, the results appear to be quite robust to changes in the choice of response variable. The only small differences were that in subtidal habitat, the depth leading to the split is 3.3m compared to 3.5m. At intertidal sites community 6 was combined with community 7, as the final split based on sediment was not important when using the biomass data.

The presence/absence MRT was then applied to the 2017 data, demonstrating that the model can be used to predict community types and the distribution of community types is similar to the preceding years (Supplement, Figure S2).

2.5.2 Above-ground biomass desired state

Above-ground biomass desired state in the shallow subtidal community 2 (10 gDW m^{-2}), which was dominated by *H. uninervis,* was double that of deep subtidal community 1, which has a greater dominance of *Halophila* species (Figure 9, Table 3). For intertidal communities, above-ground biomass desired state was lowest for community 5 (~6 gDW m^{-2}), the high exposure intertidal *H. ovalis* dominated community at Magnetic Island. Intertidal community desired state biomass was greatest for the high exposure *Z. muelleri* dominated community 4 along the mainland coast (~34 gDW m^{-2}), and the low exposure communities 8 (*H. uninervis* with *C. serrulata*) and 9 (*Z. muelleri* with *C. serrulata*) (~33 gDW m^{-2}) (Figure 9, Table 3).

Above-ground biomass of all communities significantly varied among years. The highest biomass was observed in 2007 or 2008 in all communities, while biomass reached high levels also in 2017 or 2014 (Figure 9). The lowest biomass was observed in 2011, but very low biomass was observed from 2009 to 2012. The largest variation in biomass occurred in the communities that also reached the highest biomass. These were community 2 (shallow subtidal *H. uninervis* dominated), community 4 (high exposure intertidal, predominantly *Z. muelleri* community) and community 8/9 (low exposure intertidal, mixed species). The lowest variation in biomass occurred in high exposure intertidal communities 3 and 5 (Figure 9).

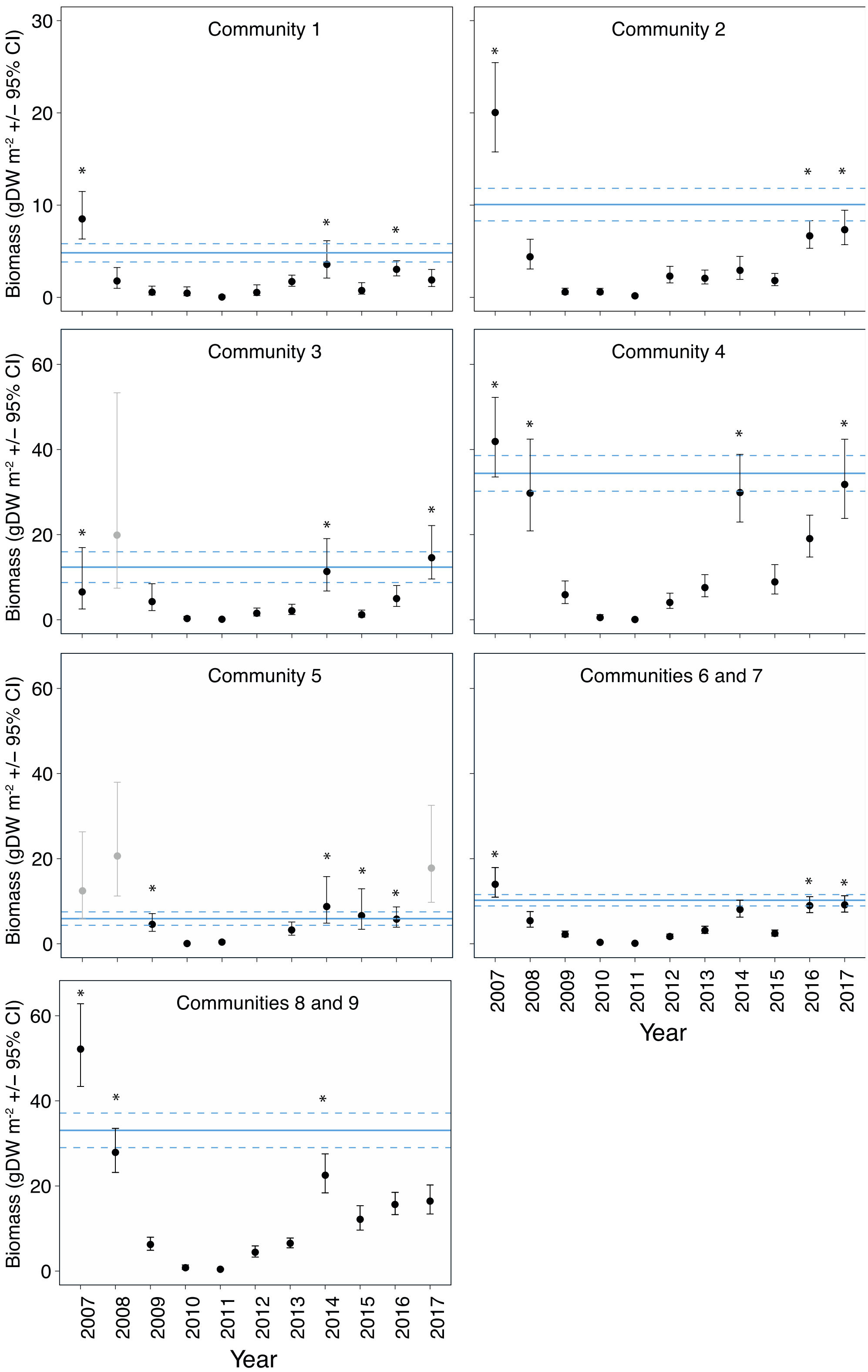


Figure 9. Annual mean above-ground biomass (+ 95% CI) for Cleveland Bay seagrass communities, 2007–2017. Greyed values were not included in Tweedie GLM statistical analyses due to low sample size for that year. Seagrass above-ground biomass desired state (solid blue line) with upper and lower 95% CIs (dashed blue lines). Asterisks indicate years used to form the reference data for setting desired state.

Table 3. Seagrass community, dominant habitat requirement (first split in the tree is either depth or tidal exposure), dominant species (most frequently recorded, see Figure 8), and above-ground biomass desired state (mean with 95% confidence intervals)

Depth	Community	Depth/exposure	Dominant species	Desired state biomass ($gDW\ m^{-2}$)	
				Mean	95% CI
Subtidal	1	Deep (>3.5m)	*H. spinulosa*	4.8	3.8, 5.8
	2	Shallow (≤3.5m)	*H. uninervis*	10.1	8.3, 11.8
Intertidal	3	High exposure (>1.5)	*H. uninervis*	12.4	8.7, 16.0
	4	High exposure (>1.5)	*Z. muelleri*	34.4	30.2, 38.6
	5	High exposure (>1.5)	*H. ovalis*	5.9	4.4, 7.5
	6/7	Low exposure (<1.5)	*H. uninervis*	10.2	8.9, 11.6
	8/9	Low exposure (<1.5)	*H. uninervis*	33.1	29.0, 37.1

2.5.3 Spatial extent desired state

The years used to form the reference data set for extent differed among sub-regions, but most frequently included the years 2007, 2014, 2016 and/or 2017 (Figure 9). The years 2010–2013 were not used to define extent desired state for any sub-region, with extent particularly low in 2011 (Figure 10, Figure 11). Extent desired state varied greatly among sub-regions, ranging from 4323 ha in the large South Cleveland Bay meadow, to 7.7 ha in the small Nelly Bay meadow (Figure 10). The maximum seagrass extent was limited largely by local topography, such as the reef-top meadow at Cockle Bay. Extent desired state was greatest for South Cleveland Bay where shallow subtidal community 2 was a dominant contributor to seagrass extent (Figure 10, Figure 11).

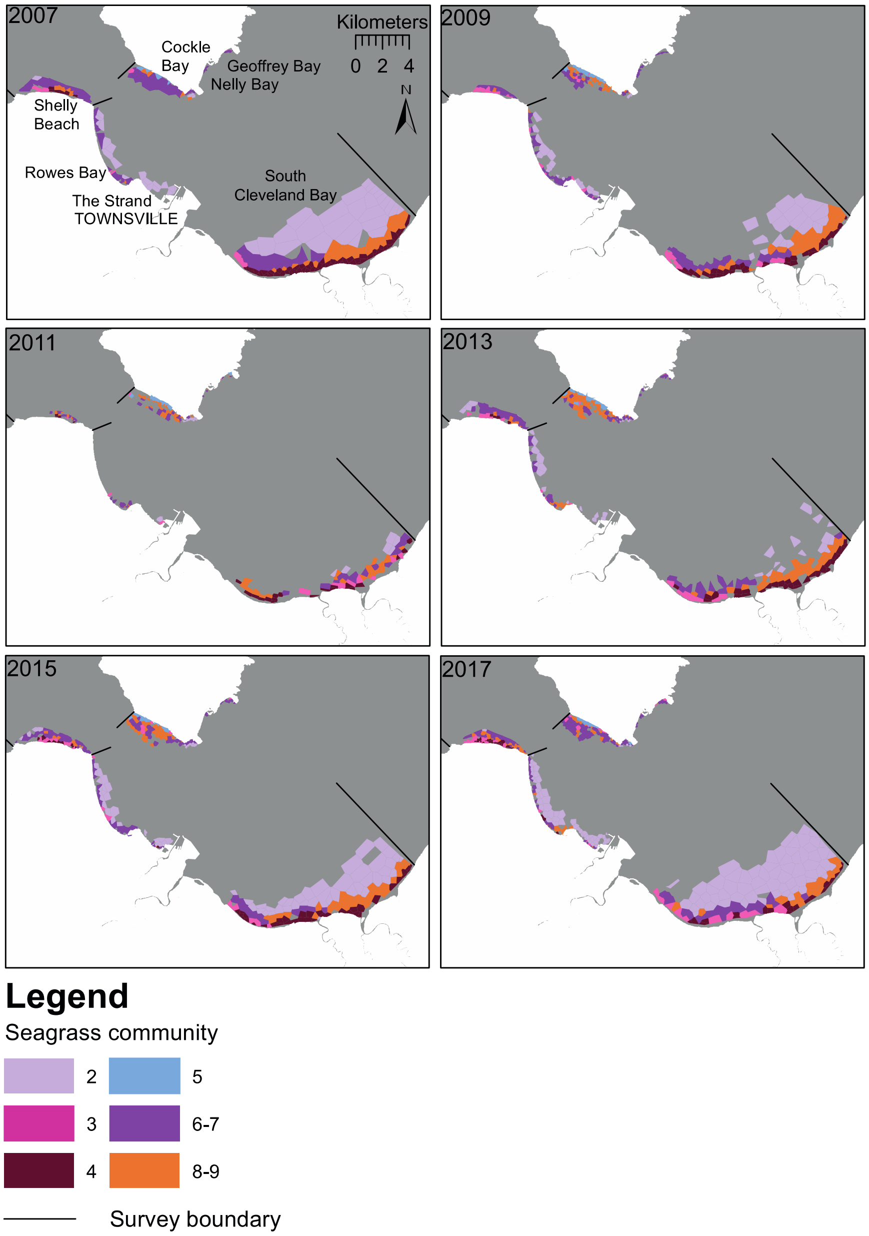


Figure 10. Temporal change in spatial extent of Cleveland Bay seagrass communities 2, 3, 4, 5, 6/7 and 8/9. Community 1 (deep subtidal) excluded, as sampling only ever occurred during broad-scale surveys. Extent shown for every second year to demonstrate change overtime.

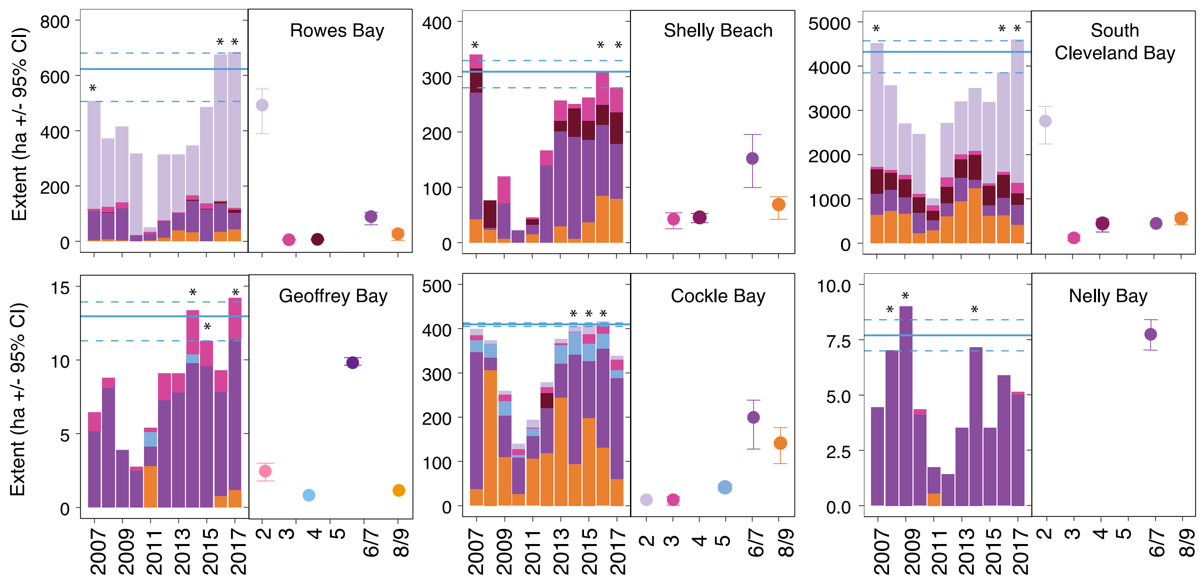


Figure 11. Annual extent (hectares) for Cleveland Bay seagrass communities in each sub-region, 2007–2017. For each sub-region, bar plots (left) show seagrass extent desired state (solid blue line) with upper and lower 95% CIs (dashed blue lines); dot plots (right) show expected contribution of each seagrass community to extent desired state (± 95% CIs). Colour coding of community types match those presented in Figure 8.

Each of the sub-regions had a unique combination of seagrass community types. Community 6/7 was present in every sub-region, and was the most extensive community in Geoffrey Bay, Nelly Bay, Shelly Beach, and the intertidal component of Rowes Bay. Communities 8 and 9 contributed most to extent desired state at Cockle and South Cleveland Bays. Intertidal communities with high intertidal exposure were restricted to a narrow band along the shoreline so contributed least to extent desired state. Community 4 contributed to extent desired state only on the mainland (Rowes Bay, Shelly Beach, and South Cleveland Bay), while community 5 was only recorded in Cockle and Geoffrey Bays at Magnetic Island. Community 3 occurred in all sub-regions but was always a minor contributor to seagrass extent (Figure 10, Figure 11).

2.6 Discussion

Using two metrics of seagrass condition measured over more than a decade we present an approach to setting desired state for seagrass communities in a complex and dynamic tropical habitat. Setting targets is one of the most critical, yet challenging aspects of assessing ecological status (Samhouri et al. 2012) but they are needed to assess the progress towards meeting management objectives when considered in context of natural disturbances. We discuss the benefits and limitations of this approach, and considerations for broader assessment of seagrass desired state.

2.6.1 Setting desired state

There are many attributes that determine whether seagrass habitat has reached a desired state, including both its condition and resilience. However, environmental managers often require simple indicators and metrics that can provide information on both. Simple condition metrics such as above-ground biomass and extent are important criteria because they are the sum effect of multiple processes (Daan 2005, Roca et al. 2016), and can be proportional to provisioning of ecosystem services (Scott et al. 2018). They also overlap with some of the metrics recommended for assessment of resilience, which would also require additional metrics not included in our study (Unsworth et al. 2015, O'Brien et al. 2017). They respond to a diverse range of environmental pressures including light availability, water temperature, and toxicant concentrations (Collier et al. 2012, Negri et al. 2015, Chartrand et al. 2016), plus biological processes and pressures (Scott et al. 2018). By contrast, when screening for a specific stress other metrics such as physiological measures can be used (McMahon et al. 2013, Schliep et al. 2015, Roca et al. 2016, Collier et al. 2017), but these are not as relevant to the time-scales considered here. Seagrass communities provide many ecosystem services but different species and community types vary in their contribution to each of the services because of features such as biomass and other structural characteristics (Nordlund et al. 2016). Attempting to define desired state for each of those functions would require substantial quantitative information on ecosystem services that is not available. Hence we need to adopt the assumption that resilience and ecosystem function of the habitat will be preserved if desired state of biomass and extent is met in all community types (Tett et al. 2013), which is acknowledged as unsatisfactory if maintaining resilience is the overarching management objective. We therefore recommend inclusion of complimentary resilience metrics such as population structure and measures of sexual reproduction – an inclusion that is not possible at this stage owing to a lack of data.

Pollutant discharge into the GBRWHA has increased following mining and agricultural development that commenced in the 1850s (Bainbridge et al. 2018); the effect of these activities on seagrass communities in Cleveland Bay is not directly known. The earliest comprehensive seagrass surveys conducted within the area were in the 1980s (summarised in Coles et al. 2015), but these were snap-shot surveys and cannot be used to gauge trends in seagrass condition since then. However, it is in the opinion of authors engaged in those early surveys that the maximum level of the metrics observed in the 11-year data set (i.e. desired state), is not dissimilar to observations from the 1980s, but the amount of variability at that time is not known (R. Coles pers com.). In the absence of longer-term historical information on seagrass habitat condition, we have used available data from the previous 11 years. During this period, there was extensive declines in biomass and extent associated with multiple impacts, including flooding and cyclones (Petus et al. 2014, Bryant and Rasheed 2018, McKenzie et al. 2019). Therefore, the highest levels of biomass and areal extent was used as a reference data set to define desired state, which has resulted in targets that are realistic, but also ambitious.

The region is affected by multiple threats, and targets that are linked to any one anthropogenic pressure (e.g. river discharge), may not be relevant for another pressure (e.g. thermal stress). River discharge can affect water clarity (Fabricius et al. 2014) in which case targets for discharge may be focussed on subtidal or deepwater seagrass communities growing near the edge of light requirements (Choice et al. 2014) and/or against other habitats that are sensitive to turbidity including coral reefs. The time-scales over which these environmental pressures affect seagrass condition can range from weeks and months (Collier et al. 2012, Chartrand et al. 2016) to annual or multi-annual (Lambert et al. 2019), which influences how targets are used or interpreted for management actions. Therefore, community (indicators) and metrics needed to meet sensitivity, responsiveness, and specifity requirements to pressures must be considered (Rice and Rochet 2005, Lambert et al. 2019). There may be a need to adapt, or even develop complimentary targets that are specific to these time and space-scales for example, defining levels of change (loss or gain) by gradients in pressure (Collier et al. 2012, Collier et al. 2016, Lambert et al. 2019).

Pressure-response models can be used to prioritise investment into management strategies to protect seagrass condition (Choice et al. 2014, Adams et al. 2015, Saunders et al. 2017) and to identify the cause of any failure to meet desired state. Also needed is the capacity to forecast the trajectories of ecosystems subject to multiple simultaneous pressures and changes. Ecological thresholds and environmental condition boundaries should be identified, and the consequences of crossing them identified as far as possible (Strange 2007, Collier et al. 2016). However, pressure-response models require locally-specific data on pressures at a scale that is complimentary to the scale of information on seagrass condition and response to the pressures (Wicks et al. 2010, Adams et al. 2015). We have tested an approach to setting desired state that is not constrained by these modelling needs, but which nonetheless can be used for testing management scenarios.

Our study highlights some limitations and considerations when applying this approach in other areas:

1. *Historical data required.* This approach requires a relatively large historical seagrass data set that captures decadal-scale change. In Cleveland Bay, there was large variability in the biomass and extent metrics that enabled us to develop a reference dataset based on years when biomass and extent were high, and significantly different from other years. An independent test of the targets can occur within an adaptive management cycle as more data is collected in annual surveys. In less or more dynamic regions, it may be more difficult to identify an appropriate reference data set or the need to exclude 'bad years' for community analysis, and so adjustment to the decision rules may be required.
2. *Decision rules were required*. Setting desired state required informed choices to made by authors most familiar with the data and the study region in conjunction with exploratory analysis e.g. removal of 'bad years' for classifying the communities. These decision rules are detailed throughout the methods, and may have been slightly different if this analysis was undertaken by others.
3. *Matching monitoring scale to desired state scale.* Biomass desired state was developed for each community type across a relatively broad area (Cleveland Bay), and extent targets for the sub-region. When bay-wide targets were tested against individual meadows at the sub-region scale, the bay-wide biomass desired state for each community was not applicable for some individual meadows meaning that desired state may never be achieved at some locations. This is likely due to local features that our current model used to define seagrass communities is not able to resolve, such as wave and wind exposure, sediment nutrient concentration, and grazing pressure by green sea turtles (*Chelonia mydas*) and dugong (*Dugong dugon*) that will influence biomass but is less likely to affect extent (Scott et al. 2018). If the reporting and monitoring is matched to the desired state scale (i.e. Cleveland Bay), then small-scale disturbances can occur and the target for that community still be met. These small-scale disturbances and variation in local conditions occurred from 2007 to 2017, and were an inherent component of the data set used to set the reference points. Desired state can be refined to increase the spatial resolution of the targets to investigate small-scale processes and pressures, but doing this could also make the desired state less useful as it would result in a greater number of targets, increase complexity, and complicate procedures for tracking progress against targets.

Cleveland Bay is affected by tropical cyclones, extreme rainfall and river discharge events (Cook et al. 2016, Bryant and Rasheed 2018, McKenzie et al. 2019), and heat waves that have devastated vast swathes of coral reefs in the broader region (Hughes et al. 2018, Lough et al. 2018). Our data confirms that large, event-driven changes in the biomass and extent of seagrass in Cleveland Bay have occurred, as observed in other locations in the GBRWHA (Rasheed et al. 2014, McKenna et al. 2015) and more extreme conditions are projected in the future (Lough and Hobday 2011). Excursions below desired state will continue in response to events such as cyclones with frequent occurrence. Under these circumstances, it is the ability for the seagrass communities to rapidly return to the prescribed desired state levels that will be of interest. While it may appear that single targets could make these changes difficult to reach, reporting procedures can be implemented to track trends relative to targets.

While returning ecosystems to a particular historic state is a useful goal, it may not be achievable. For example, reduced nutrient loading from rivers may be ineffective in the presence of other major stressors such as climate change – the Return to Neverland conundrum (Duarte et al. 2009). Adaptive management frameworks (e.g. Hallett et al. (Hallett et al. 2016)) include a need to revise steps within the cycle, however once set, changes to targets should be adopted cautiously and infrequently. It may be necessary to refine the targets to accommodate the resilience needed to withstand changing pressures (Cook et al. 2016). On the other hand, if management actions are effective and there is an increase in the frequency in which targets are reached, then it may be necessary to refine them to a higher level to maintain the ability to understand the conditions associated with when they are met and when they are not. Alternatively, proxies for resilience such as connectivity among seagrass meadows (Grech et al. 2016), could be added to the definition of desired state and used to track progress towards management goals in the face of increasing pressures or improved management strategies.

2.6.2 Reporting against desired state

Our definition of desired state provides a benchmark against which to assess future annual growing season (September – December) condition, where:

- *Desired state is met* with a high level of confidence placed in that assessment if the mean biomass or spatial extent exceeds desired state and its upper CI (Figure 12a).
- *Desired state is not met* with a high level of confidence if the mean biomass or spatial extent is lower than the lower CI (Figure 12b).
- *Desired state is met with a reduced level of confidence* when: 1. the mean biomass of a community is above the upper CI of desired state but the CI overlaps with desired state range; or 2. when the mean biomass of a community or spatial extent is within the desired state range (Figure 12c).
- *Desired state is not met with a reduced level of confidence* when the mean biomass is lower than the desired state range, but the upper biomass CI falls within the desired state range (Figure 12d).

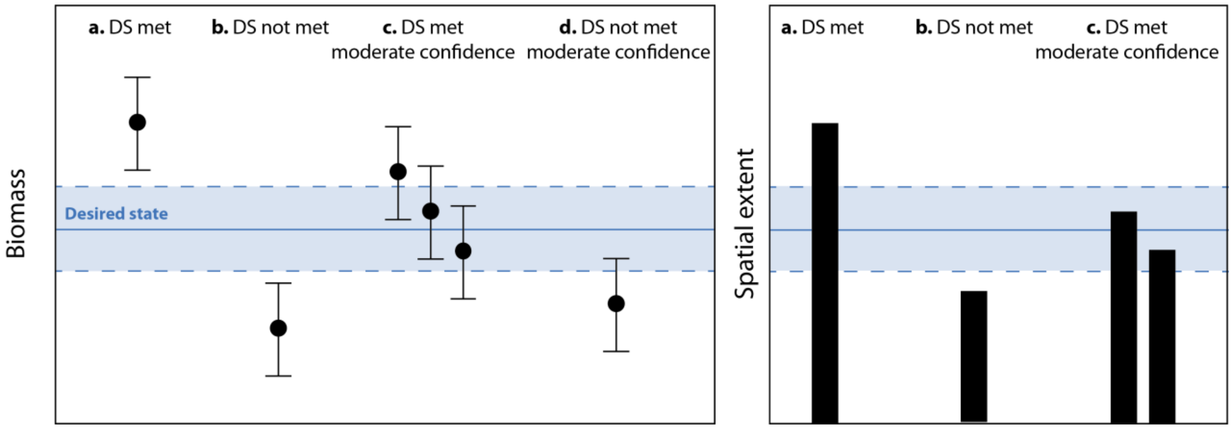


Figure 12 Interpretation of whether desired state (DS) is met for above-ground biomass (mean ± 95% confidence intervals (left); and spatial extent (right).

The considerations for reporting against desired state will be affected by the monitoring and reporting needs of specific programs, all of which are possible with small adaptations to the framework presented here. These include scaling community types based on dominance or sensitivity, or impacted versus pristine areas. Trends in ecological condition can also be accommodated by applying the biomass models to new annual monitoring data and a statistically significant increase or decrease in biomass can be determined. A failure to meet desired state doesn't necessarily mean that management actions have failed where there is an improving trend, or if there have been disturbances that are outside of management control. The timeframe over which reporting against desired state occurs will be important in these dynamic habitats with significant interannual variation. Alternatively, consideration can be given to designing management around a relative desired state with better values than currently (i.e. improving trend), but not an absolute desired state. Given the long time lags inherent in improving water quality such as reduction in sediment loads from the Burdekin River, trends in seagrass condition due to management actions will take many years to become evident (Bartley et al. 2014).

2.6.3 Conclusions

Setting targets is essential for the management of marine ecosystems, but doing so presents multiple challenges, and there are few quantitative examples for benthic habitats. We present an approach to setting seagrass desired state in complex habitat that is both dynamic and diverse. The framework we developed enables flexibility to locally-optimize the analysis to other locations. The process used for setting desired state was tailored towards the system of Cleveland Bay, but could be modified for application in other regions with particular environmental contexts, data availability, and management needs. The study site used herein may be somewhat unusual in having a relatively long decadal scale historical data set with distinct differences among years that could be used to set a reference data set. However, the approach presented herein may be useful in other jurisdictions to adopt this methodology according to data availability, or to assess how current data collection strategies could be modified to allow for desired state estimates in future. The confidence intervals around target state can be used for reporting on whether the desired state has been met for future data collections. It is important that the scale of reporting is consistent with the scale over which the reference points were set, and these desired states could be re-scaled as needed. Future research could assess how desired state could be used to test management scenarios likely to return seagrass communities to an improving trend.

2.7 Supplementary information

Table 1S. Mean visually-estimated square-root transformed above-ground biomass (gDW m^{-2}) of each seagrass species within the eight community types identified by regression tree analysis on site data from 2007 to 2016. Note that community 6, which was identified from the presence/absence data was not produced using biomass, but community 6 was later grouped as community 6/7 for desired state assessment.

Com.	*C. serrulata*	*H. decipiens*	*H. ovalis*	*H. spinulosa*	*H. uninervis*	*T. hemprichii*	*Z. muelleri*
1	170.44	100.76	74.78	433.68	382.78	0.00	14.57
2	351.14	31.55	96.97	130.55	573.12	0.00	40.44
3	35.84	0.00	29.16	0.00	161.22	1.73	230.39
4	15.45	0.00	64.91	2.65	150.90	0.00	1654.34
5	37.25	0.00	109.00	0.00	68.11	11.08	144.57
7	569.02	4.73	166.09	59.46	1339.44	31.59	190.54
8	646.16	22.85	228.68	17.76	655.41	45.12	216.94
9	371.63	11.00	95.35	3.97	345.30	0.00	731.83

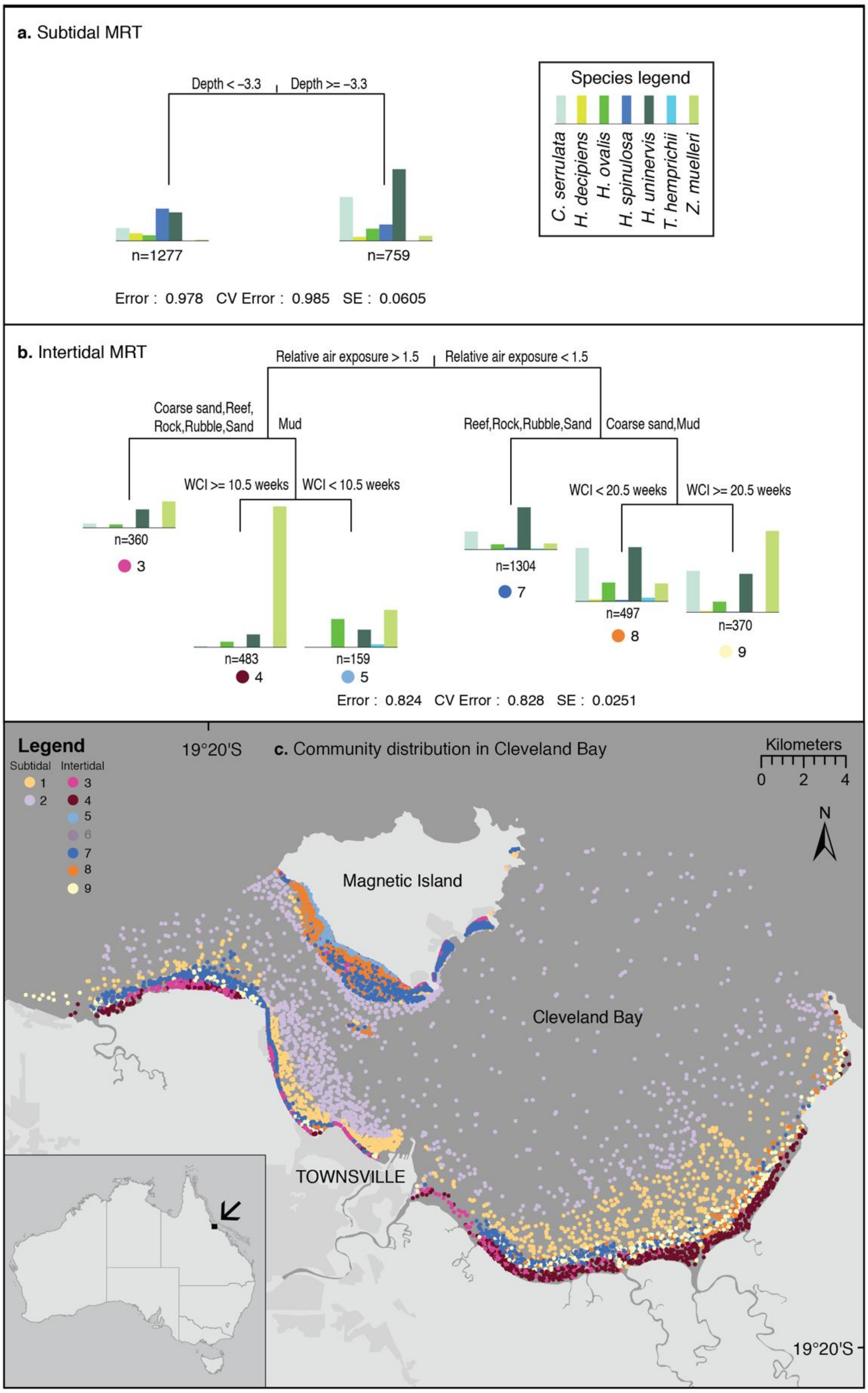


Figure S1. Multivariate regression tree (MRT) and seagrass community types as classified using visually estimated above-ground biomass data for a. subtidal sites, b. intertidal sites and c. the spatial distribution of these communities in Cleveland Bay, 2007 – 2016. Excludes the years 2009 – 2012. The number below is the number of observations that fall into that node. The histogram shows the square root transformed biomass of each species in that node. The CV Error is the cross-validated relative error and is the best indication of the error here.

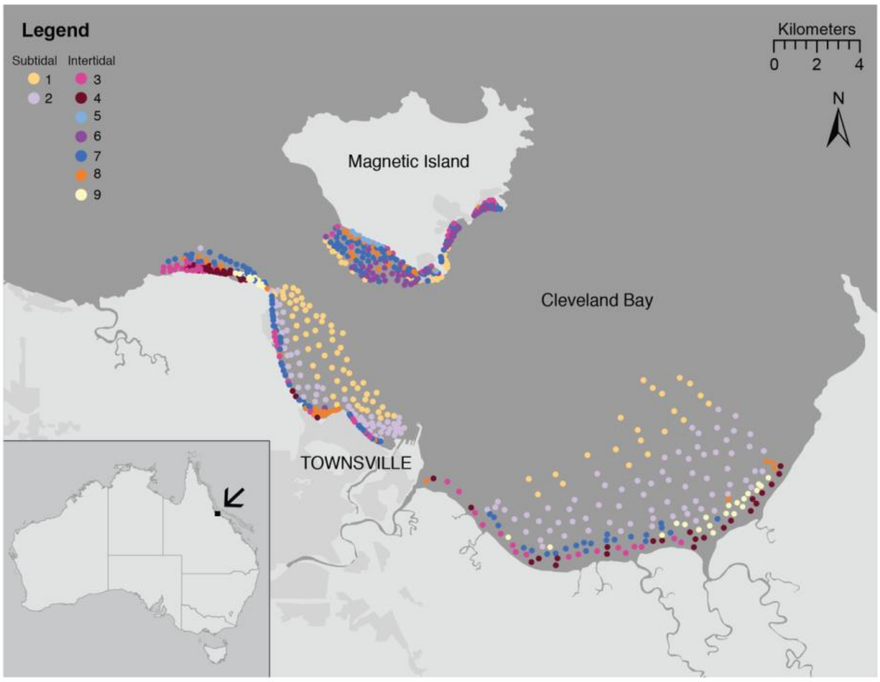


Figure S2. Seagrass community types predicted from the presence/absence multivariate regression tree (MRT) in Cleveland Bay in 2017.

3.0 CONNECTING SEDIMENT LOAD TARGETS TO ECOLOGICAL OUTCOMES FOR SEAGRASS

This section is based on an article in preparation for Marine Pollution Bulletin:
"Connecting sediment load targets to ecological outcomes for seagrass" by Victoria Lambert, Zoe Bainbridge, Stephen Lewis, Matthew P. Adams, Catherine Collier, Alex Carter, Megan Saunders, Jon Brodie, Ryan Turner, Michael Rasheed, and Katherine R. O'Brien.

3.1 Pre-amble

Fine sediment targets within the 2018 WQIP are based on a required level of load reduction to achieve an acceptable light climate for seagrass of 6 mol/m^2/d according the CSIRO Environmental Modelling Suite (eReefs) (Table 4). The 'anthropogenic' fine sediment load reduction needed to meet this light level in receiving waters of the Burdekin River was 836 (kt) by 2025, which is equivalent to a 30% fine sediment target reduction (Table 5) (Brodie et al. 2017, State of Queensland 2018). In this study, we applied a different approach to identify ERTs by comparing condition of seagrass (area and biomass) in Cleveland Bay, to Burdekin River (and the smaller basins influencing Cleveland Bay) river flow and associated sediment loads. From these, "sediment load thresholds", above which seagrass was predicted to decline or fail to meet desired state (Chapter 2) were identified. These multiple lines of evidence create an ensemble approach to increase confidence in load targets.

Table 4. Summary of analysis criteria used to set existing targets for reduction of suspended sediment from rivers according to Brodie et al., (2017). Acute refers to unfavourable condition over a shorter period. While the acute and chronic limits are the same, the acute ensures that the conditions are favourable in the summer growing season. In the final analysis, only the chronic case was used to set targets. The interaction of chronic and acute stress was recommended to be explored further in the future. From Brodie et al., (2017).

Criteria	*Relevant time period*	*Depth*	*Threshold*	*Reference*
Seagrass health (acute)	Dec–Mar	<10 m	Running monthly mean >6 mol photon m^{-2} d^{-1}	Collier et al. (2012a, 2012b), Collier et al. (2016a, 2016b), Chartrand et al. (2016)
Seagrass health (chronic)	Full modelling period	<10 m	Running monthly mean >6 mol photon m^{-2} d^{-1}	Collier et al. (2012a, 2012b), Collier et al. (2016a, 2016b), Chartrand et al. (2016)

Table 5. Burdekin region sediment load reduction targets. From Brodie et al. (2017).

Basin	*Fine sediment total baseline load (2012-2013) (kt/yr)*	*Fine sediment anth. baseline (2012-2013) (kt/yr)*	*Proposed anth. fine sediment target reduction (%)*	*Fine sediment load reduction (from anth. Baseline) (kt)*	*Fine sediment target anth. load (kt/yr) by 2025*	*Fine sediment target total load (kt/yr) by 2025*
Black	62	34	ND	0	34	**62**
Ross	62	49	ND	0	49	**62**
Haughton	183	157	0%	0	157	**183**
Burdekin	3260	2786	30%	836	1950	**2425**
Don	213	183	30%	55	128	**158**
REGIONAL TOTAL	3781	3209	28%	891	2319	**2890**

3.2 Abstract

Catchment activities, such as logging, grazing, agriculture and urbanization, generate elevated sediment loads which impact downstream water quality and coastal ecosystems. Quantifying the complex link between catchment sediment sources and downstream ecosystems is challenging but important for the development of reliable land-based ecologically relevant load targets. With this goal in mind, we compared condition of seagrass (area and biomass) in Cleveland Bay, northeast Australia, to river discharge and associated sediment loads, fitting linear models to 12 years of routine monitoring data. The data demonstrate that the Burdekin catchment dominates sediment delivery to Cleveland Bay. Annual changes in the area and biomass of shallow subtidal seagrass were significantly correlated with annual total suspended solid (TSS) loads from the Burdekin River (and to flow, in the case of area). However annual TSS loads were not good predictors of change in area and biomass across all seagrass communities. Neither area nor biomass was significantly correlated to annual sediment (i.e. TSS and fine sediment) loads for both the shallow subtidal community, and all communities combined, but area was significantly correlated to 4-year antecedent TSS and fine sediment loads. The results demonstrate that the trajectory of decline and recovery differed between biomass and area, and suggest that processes occurring on annual timescales drive year-to-year variation, but that seagrass state is affected by conditions accumulating over longer time periods. The findings also highlight different responses of subtidal and intertidal seagrasses to TSS loads. Fine sediment (particle size <20 μm) loads are thought to be of particular concern for ecological impacts, but differentiating between fine sediment and TSS loads did not improve correlation with seagrass metrics. The three strongest relationships between TSS loads and Cleveland Bay seagrass condition (R^2>0.55, p<0.01) were used to estimate "sediment load thresholds", above which seagrass was predicted to decline or fail to meet desired state. These threshold loads were equivalent to a reduction of the anthropogenic fine sediment load in the Burdekin River by 38-49%. Allowing for uncertainty, our estimate of sediment load reductions is comparable to those in the WQIP 2018. Achieving these load reductions would not guarantee that seagrass in Cleveland Bay achieves the desired state, but similarity between estimates generated from independent approaches strengthens confidence in these targets, while highlighting the challenges in quantifying the effect of terrestrial activities on downstream ecosystems. Flow was a better predictor of seagrass than TSS load, indicating that catchment inputs on seagrass are not restricted to sediment loads and reflecting the fact that events linked to high discharge can independently impact seagrass state (e.g. direct damage or sediment resuspension associated with storms or cyclones). The interaction of natural and anthropogenic processes over a large range of spatial and temporal scales makes it hard to assign causality in systems such as these, but since catchments do clearly impact ecosystems downstream, efforts to quantify these connections are important, to protect ecosystems and their capacity to deliver ecosystem services.

3.3 Introduction

Coastal ecosystems are threatened by activities occurring both within and adjacent to the coastal zone, which can be broadly summarized as coastal development, trawling, and urban, industrial and agricultural run-off (Grech et al. 2012). Global scale declines in coastal habitat and ecosystem function (Orth et al. 2006, Waycott et al. 2009) suggest the need to enhance conservation by improving legislation, policies and planning frameworks to tackle cumulative pressures including climate change, on ecosystems (Griffiths et al. 2019, Unsworth et al. 2019).

This is a pressing matter for the many people whose livelihoods and lifestyles depend on healthy coastal habitats for food resources as well as economic (i.e. fisheries), social and cultural activities (Unsworth et al. 2014, Nordlund et al. 2017).

Defining management targets that correspond to meaningful ecological outcomes is one of the fundamental challenges in implementing policy frameworks (Samhouri et al. 2012). Once defined, management targets can help to focus remediation effort for the best ecological outcomes (De'ath and Fabricius 2010). Ecologically Relevant Targets (ERTs) for pressures affecting water quality, such as agricultural run-off, need to be established in the context of desired ecological outcomes (Brodie et al. 2017). However, there are two major challenges to define ERTs. Firstly, there is the challenge of defining the desired state of the target ecosystem: it is difficult to capture the important aspects of any ecosystem in a single indicator, and then there is the challenge of defining desired state of that indicator (Collier et al. 2020). Secondly, it is very difficult to predict how the ‘desired state’ of the indicator will respond to external pressures, because ecosystem state is affected by numerous natural and anthropogenic processes acting and interacting across a range of spatial and temporal scales, buffered or enhanced by various feedbacks (O'Brien et al. 2017).

Seagrasses are a functional grouping of marine plants that form coastal habitat in the tropics together with mangroves and coral reefs (Barbier et al. 2011, Saunders et al. 2014). Seagrass habitat supports commercial and recreational fisheries, dugong and green turtles, stabilizes benthic sediments and filters water (Barbier et al. 2011). The Great Barrier Reef contains extensive seagrass meadows that are highly sensitive to water quality, in particular turbidity and light availability, and therefore the distribution, density and diversity of seagrasses vary according to gradients and changes in water quality (Collier and Waycott 2009, Waterhouse et al. 2017). Following extreme weather events, seagrass habitat can suffer large declines due to direct damage and light deprivation associated with flood plumes (Preen et al. 1995, Collier et al. 2012, Petus et al. 2014, Rasheed et al. 2014, McKenna et al. 2015). Large-scale seagrass declines can in turn have negative consequences for the fauna and industries dependent on seagrass ecosystems (Barbier et al. 2011, Scott et al. 2018, Unsworth et al. 2018).

Land-based activities such as logging/land clearing, agriculture and grazing have resulted in heavy catchment modification, and have increased sediment export into coastal waters (Lewis et al. 2007, Kroon et al. 2012, Lewis et al. 2014). Sediments delivered by river plumes increase inshore turbidity, during both initial flood events and in the subsequent resuspension events that occur over following months (Fabricius et al. 2014, Fabricius et al. 2016). Terrigenous fine sediments (<20 µm) and associated nutrients are quickly transformed into organic-rich flocs within the marine environment, which are easily resuspended due to their low density and have a disproportional influence on light attenuation (Waterhouse et al. 2017, Bainbridge et al. 2018). The Burdekin River catchment, discharges into the Central Great Barrier Reef (GBR) and has the largest sediment load of all catchments entering the GBR lagoon. The current annual average Burdekin sediment load (3.2 – 4.0 Mt) is estimated to be six to eight times higher than in pre-development times (Kroon et al. 2012, McCloskey et al. 2017). The transport and mixing processes leading to the delivery of sediment in the marine environment are complex, and thus the effects of these processes on downstream habitats are also complex (O'Brien et al. 2017, Bainbridge et al. 2018). Regardless of this complexity, there is a need to take action and implement activities to achieve management objectives of reducing loads (State of Queensland 2018). Coupling scientific data into fit-for-purpose models is a proposed methodology for informing such management objectives, although a first-pass approach is to examine the various data available for the catchment and downstream coastal communities to identify how these data may or may not be correlated. We take the latter approach in this paper.

This study applies an understanding of the links between sediment, seagrass and benthic light and turbidity to examine the relationships between sediment loads and seagrass state. The objective of this study is to investigate how changes in the area and biomass of seagrass in Cleveland Bay, a coastal zone which is located within the GBR, compare with river flows and sediment loads over the same period. Linear models are used to assess how river flow and sediment load correspond to current condition and annual change in seagrass condition, and the results of these models are compared to existing estimates of ecologically-relevant sediment load targets.

3.4 Methods

Annual river discharge volumes and calculated fine sediment (<20 µm) and total suspended solid (TSS) loads were quantitatively compared to observed changes in seagrass area and biomass in Cleveland Bay, from 2007-2018. Annual river discharge data are reported for 'water years' from October to September (2002-2019), to enable comparison with seagrass data, which was collected in September-November each year.

3.4.1 Study site

The Burdekin basin has a large catchment (~130,000 km^2) located in tropical north Queensland (Figure 13a), and is impacted by tropical cyclones, rain depressions and monsoonal rains that cause sediment laden discharges (Figure 13b). The Burdekin River mouth is located in Upstart Bay, and discharges after large flood events extend far into the GBR, typically flowing northwards along the coastline into Bowling Green Bay and Cleveland Bay. Cleveland Bay is home to large areas of seagrass meadows. There are also local rivers and creeks, including the Ross River, Alligator Creek and Stuart Creek, which flow directly into Cleveland Bay. The Haughton River discharges into Bowling Green Bay, which is adjacent to Cleveland Bay (Figure 13b). Figure 13a shows the extent of the Burdekin River catchment compared to other local streams.

Cleveland Bay also hosts a port for the city of Townsville. Regular annual maintenance dredging is required in Cleveland Bay, which occurs over short durations (typically around 2-4 weeks) with relatively similar volumes dredged each year (McCook et al. 2015). The dredge plumes generated are typically localised around the channel and studies show that the majority of seagrasses can cope with reduced light below their thresholds for 2 for 4 weeks before physical losses are recorded (Collier et al. 2016). As maintenance dredging is relatively consistent between years and plumes are minor or localised to the channel area we have not accounted for dredging impacts in our study.

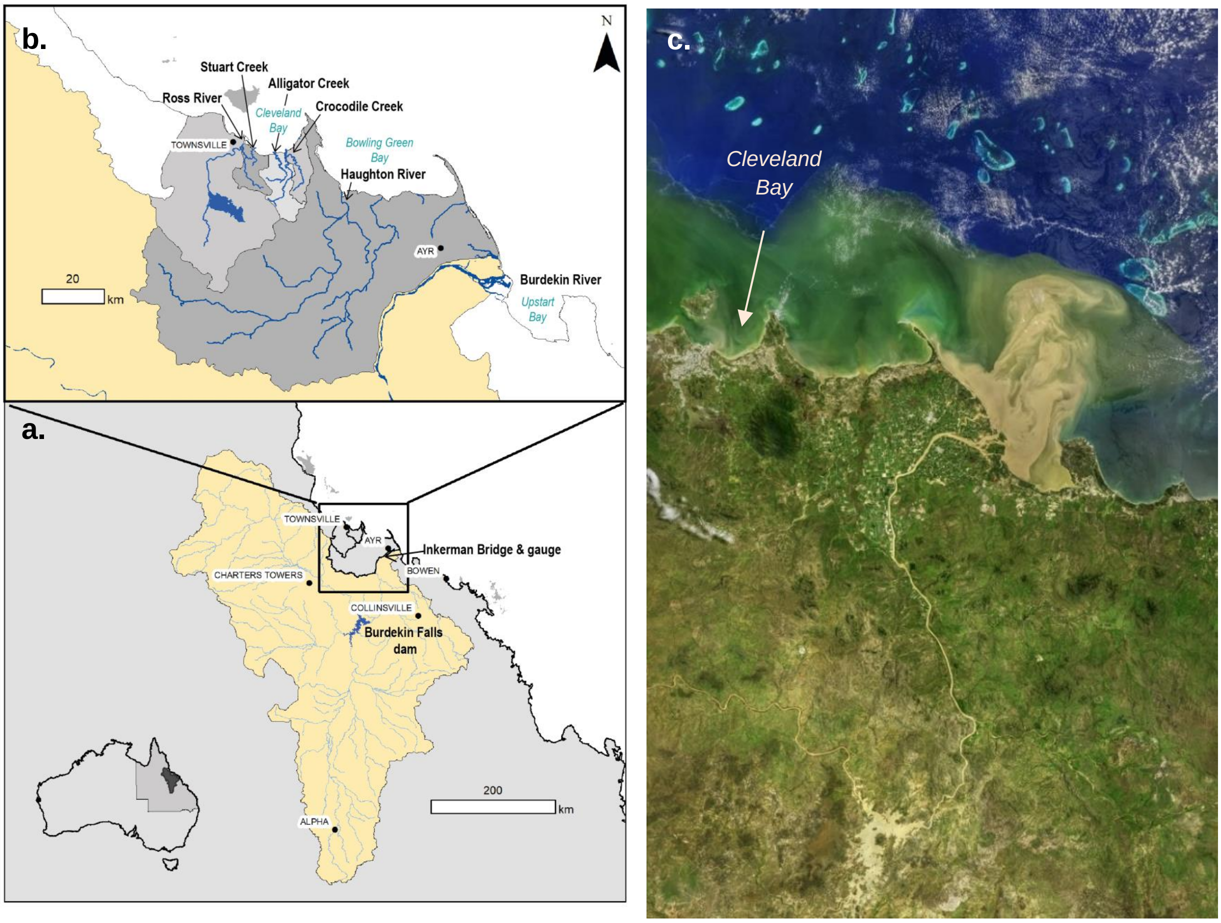


Figure 13. Clockwise from bottom left a) location map showing the Burdekin River catchment (yellow), b) other local rivers and creeks, and the relative location of Cleveland Bay, Bowling Green Bay and Upstart Bay; c) Satellite image showing sediment discharge on 11 February 2019. Source: NASA Ocean colour webmaster https://oceancolor.gsfc.nasa.gov/gallery/620/

3.4.2 Data Sources

For this study, measured data for seagrass condition (area and biomass), river discharge, TSS load and particle size distribution data to calculate fine sediment load were compiled from multiple sources (Table 6).

Table 6. Summary of data sources used to calculate metrics for seagrass state (area and biomass), discharge and sediment loads.

Metric	Data source	Location	Reference
Seagrass Area (ha)	Spatial extent calculated site from survey	Cleveland Bay annual seagrass monitoring 2007 – 2018	TropWATER (JCU)/ Port of Townsville (Bryant et al. 2019) with extent calculations and desired state based on Collier et al. (In press, Chapter 2)
Seagrass Biomass per unit area (g Dry Weight (DW)/m²)	Biomass, visually-estimated and calibrated against harvested cores	Cleveland Bay annual seagrass monitoring 2007 – 2018	TropWATER (JCU)/ Port of Townsville (Bryant et al. 2019) with extent calculations and desired state based on Collier et al. (In review)
Annual discharge (Water year: 1st Oct – 30th Sept) (GL)	Stream gauge measured discharge (ML/day)	Burdekin River at Clare (120006B) Haughton River at Powerline (119003A) Alligator Creek at Allendale (118106A)	Queensland Government Department of Natural Resources, Mines and Energy, 2019
	Discharge calculated from water height (m) at weir	Ross River at Aplin's Weir (532029)	Bureau of Meteorology, 2019 Discharge calculated using an established relationship between discharge and water height at weir (Queensland Government Department of Natural Resources, Mines and Energy, 2019)
Annual TSS loads (Mt)	Measured total suspended solid (TSS) concentration data (mg/L), in combination with discharge (above)	Burdekin River at Home Hill (120001A)	2002/03 to 2009/10: Annual TSS loads calculated by Kuhnert et al. (2012) using a statistical tool drawing on 24-years of measured TSS data collected by research and government providers at this site. 2010/11 to 2017/18: Annual TSS loads reported by GBR Catchment Loads Monitoring Program (Queensland Government Department of Environment and Science, 2017)
		Haughton River at Powerline (119003A)	2004/05 to 2008/09: Annual TSS loads reported by TropWATER (JCU)/North Queensland Dry Tropics (Bainbridge et al. 2008). 2013/14 to 2017/18: Annual TSS loads reported by GBR Catchment Loads Monitoring Program (Queensland Government Department of Environment and Science, 2017)
		Ross River at Aplin's Weir (532029)	2006/07 to 2007/08: Annual TSS loads reported by TropWATER (JCU) for the Coastal Catchments Initiative (Lewis et al. 2008). All other years: Annual TSS loads were estimated using an annual mean concentration (AMC) of 75 mg/L (from Lewis et al. 2008) coupled with discharge (above). A higher AMC (100 mg/L) was applied to the 2018/19 wet season, based on measured data collected during the extreme Feb 2019 flood event (Z. Bainbridge, unpublished data).

		Alligator Creek sub-basin	2006/07: Annual TSS load reported by TropWATER (JCU) for the Coastal Catchments Initiative (Lewis et al. 2008). All other years: Annual TSS loads were estimated using an AMC of 35 mg/L from Lewis et al. 2008 coupled with discharge (above).
		Stuart Creek sub-basin	All years: Annual TSS loads were estimated using an AMC of 300 mg/L based on previous monitoring data coupled with discharge (above).
Fine Sediment loads (<20 µm) ***(Mt)***	Sediment particle size classes (in µm) for measured TSS, in combination with TSS load data (above)	Burdekin River at Home Hill (120001A)	Data provided for samples collected in the 2005/06, 2010/11, 2011/12, and 2015/16 - 2017/18 wet seasons by the GBR Catchment Loads Monitoring Program (Queensland Government Department of Environment and Science, 2017) The 16 µm fraction is used in this study as the best available data representation of the fine sediment fraction (<20 µm) used in the Source Catchments model and for the Brodie et al. (2017) targets.

3.4.3 Seagrass

Seagrass biomass and seagrass species presence/absence data from 2007-2018 were sourced from routine annual monitoring data collected for the Port of Townsville as detailed in Bryant et al. (2019). The dataset spanned the time period 2007 to 2018, and consisted of more than 8000 observations (between 518 and 1209 sites/year, median = 626) The multi-species seagrass habitats occurring within Cleveland Bay were classified into seven seagrass community types, based on depth, substrate, tidal exposure and water clarity as outlined in Collier et al. (in press). The distribution of sites covered most of Cleveland Bay during broad-scale surveys in 2007, 2013, and 2016, and a subset that included defined monitoring meadows in the remaining years. Above-ground biomass (g Dry Weight (DW)/m^2) for each community type was averaged across all sites meeting the criteria for that community. Biomass was originally visually assessed at each site within three replicate quadrats (50 $\times$ 50 cm) haphazardly placed within each site (Bryant et al. 2019). The area occupied by each community was then estimated using geospatial tools, as per Collier et al. (in press).

The analysis here considered seagrass data from (i) only the shallow subtidal seagrass (community 2 from chapter 2), which occupied 46 % of total seagrass area on average over the study period; and, (ii) total seagrass. Intertidal communities are ecologically significant in Cleveland Bay, and are affected by sediment loads and turbidity (Petus et al. 2014, Rasheed et al. 2014). However, the environmental conditions within the intertidal zone are complex, and the analysis identified five different intertidal communities (Collier et al. 2020, Chapter 2). For simplicity, area and biomass of these intertidal communities were considered in this analysis only as a component of total seagrass. ‘Desired state’ of biomass and area was based on data from reference years that expressed high levels (Collier et al. 2020, Chapter 2). Desired state of biomass for the total community was calculated as the mean desired state across all community types. Desired state of area for all communities was determined by summing the desired state for each bay together. Note this did not include deep subtidal community S1 as extent for this community is not regularly surveyed. Desired state is presented as a mean value with 95% confidence intervals across all of Cleveland Bay (i.e. summation of desired state for extent across all bays), calculated either for one community type (e.g. shallow subtidal community) or for all seagrass communities. Year-to-year change in seagrass area and biomass of the subtidal and total seagrass communities were also analysed, with the ecological target defined as no net decline.

3.4.4 River discharge

End-of-river annual water year discharge (in GL) for the Burdekin and Haughton Rivers were calculated from the Queensland Government Clare and Powerline gauging stations, respectively (Table 6). To capture the influence of smaller local rivers that discharge directly into Cleveland Bay during the study period, estimates of annual discharge for the Ross River catchment, and Alligator and Stuart Creek sub-basins (see Gunn and Manning, 2010) were also calculated. These estimates of annual discharge rely on a number of assumptions as outlined below, and therefore have greater uncertainty than the discharge and sediment loads reported for the long-term gauged and well-monitored Burdekin and Haughton Rivers. Briefly, Ross River discharge was calculated using an established relationship between discharge and water height over the Aplin's Weir. Discharge for Alligator Creek (Allendale gauge) was up-scaled (with respect to area) to represent an approximate annual discharge for the entire Alligator Creek sub-basin, including Coco and Crocodile Creeks. Finally, approximate discharge for the ungauged Stuart Creek sub-basin area was calculated using annual discharge per unit area from the neighbouring Alligator Creek at Allendale gauge. Annual discharge flows are collated in Table 10 (see Supplementary Information).

3.4.5 Sediment characteristics

It first is important to consider and define the key differences in the reporting of sediment loads across the monitoring and modelling platforms that are relevant to this study. The monitored loads apply the TSS method and hence are referred to in this report as 'TSS loads'. These monitored loads provide a measure of the 'bulk' suspended sediment load based on sampling from the surface of the water column which predominately captures particles <63 µm. The Source Catchment modelling provides 'fine sediment' loads based on the <20 µm fraction which also applies to the 'anthropogenic fine sediment load' and catchment sediment targets. Indeed, when these differences are taken into account the average measured TSS load (4.0 Mt) for the Burdekin River reported by Kroon et al. (2012) is identical to the modelled fine sediment load (3.2 Mt) reported by McCloskey et al. (2017) as particle size data show that 80% of the TSS load is <20 µm (Bainbridge et al., 2014; section 3.4.5.2 of this study).

3.4.5.1 Measured TSS loads

Reported TSS loads for the Burdekin (2002/03 to 2017/18) and Haughton (2004/05 to 2008/09 and 2013/14 to 2017/18) rivers were compiled where available from various sources, and summarised in Table 6. These TSS loads are annually reported, with each annual load based on extensive monitoring of TSS concentration data collected from multiple event flow hydrographs over each water year. At the time of this study, load data for the 2018/19 water year had not been reported for the Burdekin and Haughton Rivers. Using the existing TSS load data we calculated long-term annual mean concentrations (AMCs) of TSS for each river, and coupled with the corresponding measured discharge these data were used to estimate TSS loads for water years within the study period where monitoring data and associated loads were not available. For both the Burdekin and Haughton Rivers this included 2018/19, while for the

Haughton River this also included water years 2002/03 to 2003/04 and 2009/10 to 2012/13. Sediment loads are compiled in Table 11 (see supplementary information).

3.4.5.2 Fine sediment loads (<20 μm)

Terrigenous fine sediments (<20 μm) are of greatest concern to marine ecosystems as they remain in suspension and can be carried in flood plumes and currents over long distances (Bainbridge et al., 2012, 2018). These finer sediments have greater potential impact on benthic light, due to their higher surface area per unit volume, lower settling rates and their potential to transform into organic-rich flocs which are more difficult to remove by marine organisms (i.e. coral tissue, seagrass leaves) as well as being more easily resuspended following initial settling (Bainbridge et al. 2018). Hence it is this fraction that is the focus of the current WQIP targets and the Source Catchment model outputs. The particle size measurements used in this study from the TSS samples report particles <16 μm (Turner, R. 2019) which we have applied as the closest approximation to the fine sediment (i.e. <20 μm) loads. This fraction will hereafter be referred to as “fine sediment (<20 μm)” for consistency.

Therefore in relating seagrass condition to sediment loads, we considered loads of both bulk TSS and fine sediment, which required accounting for the variation of particle size with flow. While high flows typically generate greater TSS loads (all else being equal), those high loads are likely to contain a higher fraction of coarser particles due to the associated increase in hydraulic power. For this reason, the proportion of fine sediment declines as the total TSS loads increase in the Burdekin River (Figure 14). Thus, while fine sediment loads will be correlated to TSS loads, it was worth exploring these loads separately to examine the relationship with seagrass state in Cleveland Bay.

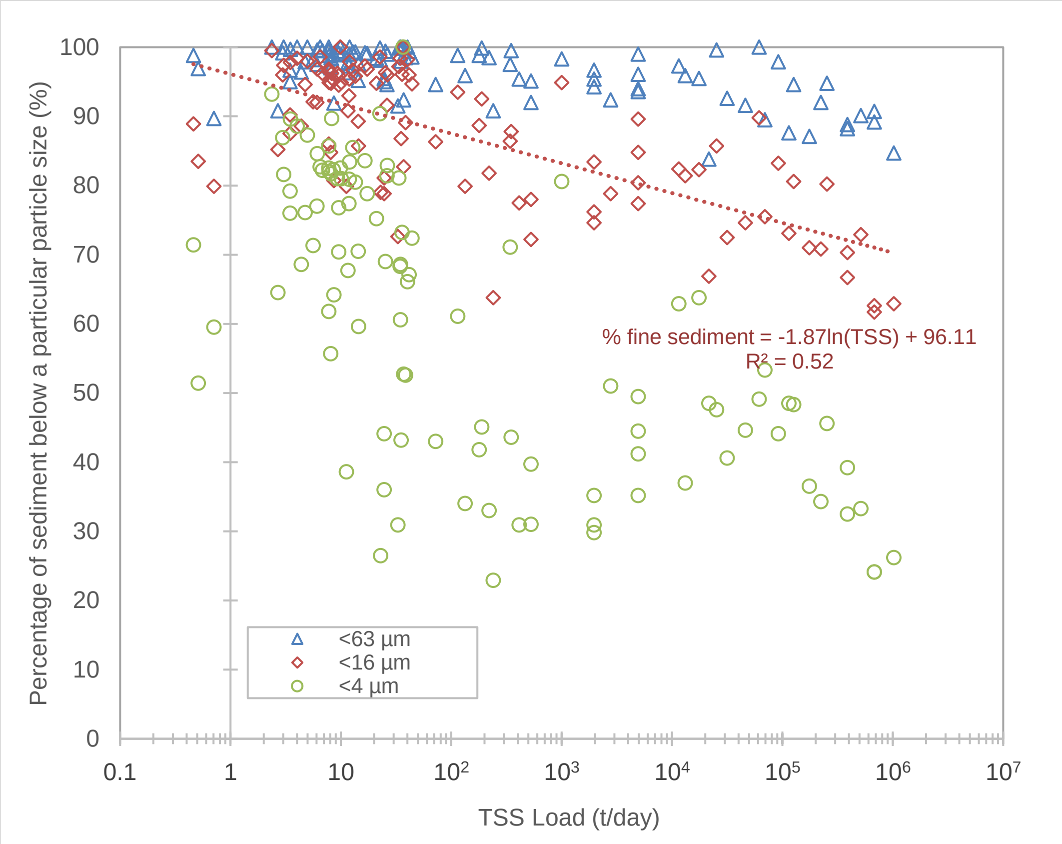


Figure 14. Sediment particle size variation with Burdekin River TSS load (t/day) based on event sampling data at Home Hill, including all silt and clay fractions (<63µm), fine sediment (<16 µm) and clay (<4 µm) fractions. Note that the x-axis scale is logarithmic. Contains data provided by the State of Queensland (Department of Environment and Science) 2017.

Annual Burdekin fine sediment loads were calculated from the TSS load, based on the following equation:

PFS=Pmax- alpha ln (TSS load) (1)

Where PFS (percentage fine sediment) is the mass percentage of TSS with particle size <20 µm; Pmax = 96 is the maximum proportion of fine sediment, alpha = 1.87 is the rate of change, and TSS load is in t/day. From Eqn (1), it can be seen that each factor of 10 increase in sediment corresponds to a 4-percentage-point decline in the proportion of the TSS load which is fine sediment. This relationship is more reliable for high TSS loads with less variability, as shown in Figure 14 and through analysis of residuals in Supplementary Information (Figure 20).

Over the 17-year study period this fine sediment annual load accounted for an average of 80 (±2) % of the total annual TSS load (see Table 13 in Supplementary material), in agreement with other studies (Bainbridge et al., 2014). This could represent a simplified approximation for converting between Burdekin River TSS and fine sediment loads. Fine sediment (<20 µm) loads for both the Haughton and Ross Rivers were estimated to account for 65% of total loads based on particle size measurements of samples collected during or shortly after peak flows in the 2018/19 wet season from both rivers (Z. Bainbridge, unpublished data). Given the low sediment concentrations of monitored waters draining the Alligator Creek sub-basin, fine sediment loads were assumed to be equal to the total loads for this sub-basin. Fine sediment annual loads for the Stuart Creek sub-basin were estimated to account for 50% of the total loads as the autosampler collected both suspended and bed load samples throughout the monitored wet season (Liessmann et al., 2007). Estimates are contained in Table 12 (see supplementary material).

3.4.5.3 TSS load "delivered into Cleveland Bay"

The amount of suspended sediment delivered to Cleveland Bay from the Burdekin and Haughton Rivers is governed by (i) the peak and total discharge volume of the rivers; (ii) the TSS load (in particular fine sediment) exported from the rivers; and (iii) the movement of the plume waters in the marine environment, particularly coinciding with peak/elevated flows. We have applied the calculations for points (i) and (ii) coupled with observations from plume monitoring, satellite time series imagery and modelling simulations for the plume movements (iii) to estimate the annual TSS load "delivered to Cleveland Bay" (see Supplementary information, Table 13). Monitoring and modelling have shown that approximately 10-15% of the TSS load from the Burdekin River moves beyond the vicinity of the river mouth (Bainbridge et al., 2012; Delandmeter et al., 2015); hence when the Burdekin plume flows exclusively to the north then most of this sediment will pass through (or into) Cleveland Bay. While the amount of TSS load from the Burdekin River deposited in Cleveland Bay is still uncertain (see Lambrechts et al., 2010; Lewis et al., 2014; Delandmeter et al., 2015), using the above we have applied the following best estimates of the proportion of Burdekin TSS load "delivered to Cleveland Bay":

- 15% in years when the plume has predominantly moved northward during peak flows (2006/07-2008/09, 2010/11-2011/12, 2017/18);
- 10% in years when the plume moved to the north occasionally during elevated flows (2002/03, 2004/05-2005/06, 2009/10, 2012/13, 2018/19);
- 5% in very low flows (and loads) meant that very little sediment exported from the Burdekin River had opportunity to reach Cleveland (2003/04, 2013/14- 2015/16); and,
- 0% when the plume did not move northwards into Cleveland Bay (2016/17).

All of the TSS loads from the streams in the local region were assumed to reach Cleveland Bay. As the Haughton River discharges in closer proximity to Cleveland Bay than the Burdekin River, we estimated that 15% of the sediment load may potentially reach Cleveland Bay in all years. These load proportions were added to calculate annual combined TSS loads "delivered to Cleveland Bay". The "total" combined TSS load – the addition of all river TSS loads with no discounting factor – was also calculated.

3.4.5.4 Ecologically Relevant Targets: relating seagrass state to sediment loads and river discharge

Seagrass area and biomass for shallow subtidal seagrass, and all seagrass communities combined, were compared with a range of metrics of river flow and sediment loads to explore relationships between seagrass state in Cleveland Bay, and discharge and sediment loads from rivers in the region. Annual and multi-annual discharges (two, three and four-year flow) were investigated, to account for impacts of sequential years of high flows on seagrass condition. We also explored the impact of the prior state of seagrass, by examining the relationships between annual flow and load, and year-to-year annual change in seagrass area and biomass.

Linear models were used to relate the indicators of seagrass condition to a range of flow and load metrics, as outlined above. Non-linear models were also fitted to the indicators and metrics and are presented in the supplement. The linear models with significance $p<0.01$ were then used to estimate the sediment load thresholds (ERTs) which corresponded to maximum loads under which seagrass was predicted to meet desired state, or not decline. The non-linear models were similar (similar R^2) or only marginally better than linear models, but — being based on 12 data points (years) of annual mean biomass or area for the communities — were also sensitive to individual data points, and the amount of data was considered insufficient for these more complex models (see supplementary material). Therefore, these were not used for ERTs. Where multiple similar metrics met this significance criteria and produced similar R^2 values, the metric constructed from data with the lowest uncertainty was chosen. For example, TSS load would be chosen over fine sediment load, because the latter involves application of an additional empirical equation (Eqn 1). Similarly, flow and TSS loads from the Burdekin have higher confidence than flow and TSS loads "delivered to Cleveland Bay", because the latter are derived from the former via a series of assumptions.

Sediment load thresholds were compared to the current Reef 2050 WQIP sediment load reduction target for the Burdekin Basin (30% reduction in anthropogenic load) (State of Queensland, 2018). With the data available, it was not possible to establish causality, i.e. to verify that the sediment loads were the primary cause of the seagrass decline. Significant correlations could reflect that both variables were driven by the same external force: for example, a major cyclone event could impact seagrass area and biomass through direct disturbance, and simultaneously increase river flow and sediment loads. For this reason, we also explore the relationship between flow and seagrass indicators, as well as sediment loads.

3.5 Results

3.5.1 Annual variability is high for seagrass condition and river inputs

Seagrass area and biomass varied across the study period, declining in years of high discharge and sediment load. Decline and recovery trajectories varied between the different seagrass metrics. Seagrass area (Figure 15a) retracted consistently after periods of high flow (2008, 2009 and 2011), but recovered from the 2011 minimum to half of its original 2007 extent within a year (by 2012) and returned to its 2006/07 state within the decade. Seagrass biomass (Figure 15b) fell steeply during 2008 and 2009, coinciding with periods when sediment loads delivered to Cleveland Bay were high, and has yet to return to its 2006/07 state. Not all declines were observed in high flow years: biomass declined in 2015 despite riverine flow and sediment loads being below average, although this effect was not observed in seagrass area.

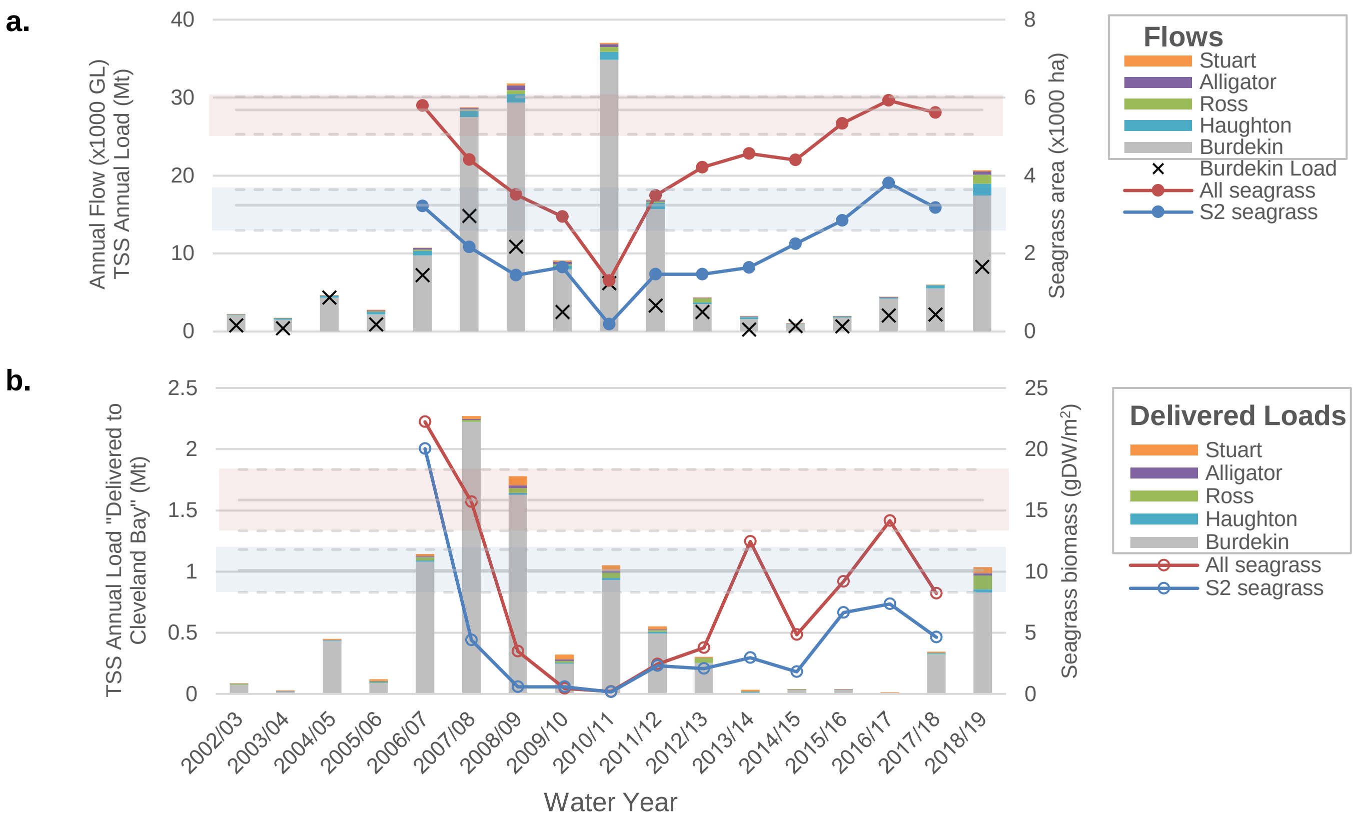


Figure 15. Time series with bars showing a) annual flows and Burdekin TSS load; and b) annual TSS loads "delivered to Cleveland Bay" from the Burdekin and other local rivers and creeks over a water year (October to September); and lines indicating seagrass a) area and b) biomass for the shallow subtidal seagrass community (denoted as S2) and all seagrass communities combined at the end of the water year. For context, the discharged Burdekin River sediment load is also indicated in a). Desired state range is shaded (shallow subtidal seagrass in blue, all seagrass communities in red) with mean (grey line) and 95% confidence intervals (dashed grey lines) also indicated.

Between 2003 and 2019, Burdekin River annual discharge varied by a factor of 40, up to 35 GL/yr (Figure 15). Burdekin River discharges over this 17-year period were at least an order of magnitude greater than other local streams (Figure 15a). Over the same period, peak discharges from the Haughton and Ross Rivers were 1.5 GL/yr and 1.1 GL/yr respectively, while maximum flows from Alligator and Stuart Creeks were less than 1 GL/yr. Several large flooding and disturbance events occurred during the study period associated with monsoonal rain events, tropical rainfall depressions/weak tropical cyclones (i.e. 2007/08, 2008/09, 2010/11, 2011/12 and 2018/19) and severe Tropical Cyclone Yasi (2010/11). Indeed, this study period captured three of the four largest discharge years for the Burdekin since 1987 (Figure 15).

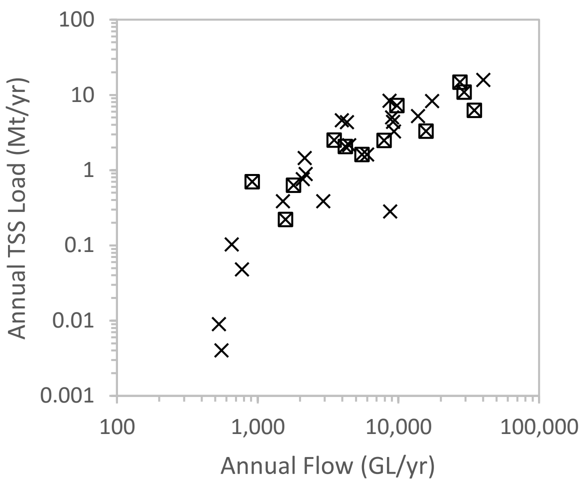


Figure 16. TSS load from the Burdekin River generally increases with flow (historical data 1987-2019). Boxes indicate data included in this study for correlations with seagrass state (2007-2018).

TSS loads were also highly variable between years, ranging from 0.22 - 14.8 Mt/yr for the Burdekin River alone (Figure 15b, Figure 16). Estimates of annual Burdekin TSS loads delivered to Cleveland Bay were lower by definition than total Burdekin TSS loads (up to 2.2 Mt/yr, in 2007/08), but still at least an order of magnitude higher than the maximum loads from local creeks and rivers, which were estimated to be 0.025 to 0.16 Mt/yr. Typically, the more runoff (i.e. flow) that is generated, the more erosion (i.e. sediment load) that occurs, and hence TSS loads on average increase with flow (Figure 16). However, the years with the highest flows do not necessarily correspond to the highest loads, and the relationship between flow and load can differ between high and low flow, as shown in Figure 16. Fine sediment followed the same pattern, since this was strongly correlated to TSS loads.

3.5.2 Annual change in subtidal seagrass biomass is strongly correlated to Burdekin sediment loads

Annual flow, TSS load and fine sediment load did not correlate to subtidal or total seagrass area or biomass (Table 8). However *annual change* in these two indicators for subtidal seagrass was significantly ($p<0.05$) correlated to TSS load and fine sediment loads from all river sources that included the Burdekin: i.e. Burdekin loads, combined "total" loads and combined loads "delivered to Cleveland Bay" (Table 7). Even accounting for the fact that only a small fraction of this sediment is delivered to Cleveland Bay, the Burdekin River still dominates the delivery of new sediment flux within Cleveland Bay (Figure 15), which may explain why the Burdekin featured in 15 out of the 16 statistically significant ($p<0.05$) correlations found between year-to-year change in seagrass condition and flow or sediment loads metrics in Figure 7, along with all correlations with $R^2>0.4$. For all significant correlations between year-to-year change in seagrass condition and river inputs, the R^2 for the Burdekin River values was similar to, or higher than, R^2 values for the same combined "total" load or combined "delivered" load values of the same metrics (Figure 7), reflecting the dominance of the Burdekin in both water volume and sediment loads entering Cleveland Bay (Figure 15).

Table 7. Results for linear regression (R^2) between year-to-year change in subtidal seagrass area and biomass in Cleveland Bay, and river inputs: flow, TSS load and fine sediment load. Significance indicated by * p<0.05; ** p<0.01. Grey shading indicates correlations subsequently used to predict thresholds for seagrass decline

River Source	*Metric*	*Annual change in Seagrass Area*			*Annual change in Seagrass Biomass*		
		Flow	TSS Load	Fine sediment	Flow	TSS Load	Fine sediment
Combined Rivers	Total	0.48*	0.42*	0.42*	0.25	0.71**	0.70**
	Delivered	0.48*	0.44*	0.44*	0.20	0.66**	0.67**
Burdekin	Total	0.48*	0.42*	0.42*	0.26	0.72**	0.71**
Haughton	Total	0.37*	0.20	0.20	0.17	0.00	0.00
Ross	Total	0.37	0.35	0.35	0.02	0.02	0.02
Alligator	Total	0.24	0.24	0.24	0.05	0.05	0.05
Stuart	Total	0.24	0.24	0.24	0.05	0.05	0.05

For the year-to-year change in area, Burdekin River-only flow and loads had the same significance as combined river "total" and "delivered" flows and loads with year-to-year change in seagrass area. These river metrics all had significant ($p<0.05$) correlations with annual change in seagrass area, with flow having the highest R^2 value (Table 7). No load thresholds were determined from the year-to-year change in seagrass area, because none of the relationships met the criteria of significance $p<0.01$. Large declines were observed in seagrass area in 2010/11, but not in biomass, which may reflect the fact that biomass was already close to zero (Figure 15). The year was also notable in that TSS loads were low relative to total flow (Figure 15a). In that year, the region was hit by category 5 Tropical Cyclone Yasi.

Annual change in seagrass biomass was strongly correlated to TSS load and fine sediment, with very similar correlations. Therefore, based on the criteria outlined in the methods, the model of change in seagrass biomass as a function of Burdekin River TSS load (indicated with grey shading) was the only relationship from Table 7 used to quantify sediment load thresholds. As outlined in the methods, the correlations in Table 7 do not necessarily indicate causality, i.e. that changes in the predictor variable drove the changes in seagrass response, and the implications of this approach are discussed further later in the paper.

Table 7 show results for subtidal seagrass only. The effect of flow and load on annual change in seagrass was not significant when all seagrass communities were combined (Table 14, see Supplementary Information). Only a weak correlation ($R^2 = 0.37$, $p = 0.048$) was found between year-to-year change in total seagrass area and the combined "delivered" TSS and fine sediment loads.

3.5.3 Seagrass area contracts with increasing multiannual flows

Annual flow and sediment loads were not good predictors of seagrass area or biomass: none of these relationships were significant, except a low correlation between total seagrass area and annual flow (R^2 = 0.37, p<0.05, Table 8). However multi-annual flows and loads were found to correlate significantly with the area of both shallow subtidal seagrass and all seagrass communities combined, depending on the number of years considered (Table 8). Four years of antecedent flow gave the strongest correlation results for both shallow subtidal (R^2 = 0.86) and all seagrass communities combined for area (R^2 = 0.82), and significant correlations with biomass (R^2=0.35, 0.43, p<0.05). TSS loads over the preceding four years were also strong predictors of seagrass area: R^2 = 0.56 for shallow subtidal seagrass, and R^2 = 0.69 across all communities. Correlations between biomass and multi-year flow were significant but weak (R^2 = 0.35 to 0.43) (Table 8, also see Supplementary Information Figure 22).

Table 8. Multiyear results of linear models (R^2) for seagrass area and biomass as a function of Burdekin River cumulative flow, TSS load, fine sediment load and TSS load "delivered to Cleveland Bay" over 1-4 years. Significance indicated by * p<0.05; ** p<0.01; *** p<0.001; grey shading indicates models used to quantify sediment load thresholds

Burdekin River	*Sum of Prior Years*	*Shallow Subtidal Seagrass*		*All Seagrass*	
		Area	Biomass	Area	Biomass
Flow	1yr	0.32	0.06	0.37*	0.05
	2yr	0.43*	0.18	0.48**	0.24
	3yr	0.69***	0.28	0.71***	0.41*
	4yr	0.86***	0.35*	0.82***	0.43*
TSS load	1yr	0.03	0.01	0.04	0.05
	2yr	0.12	0.04	0.15	0.01
	3yr	0.30	0.09	0.39*	0.10
	4yr	0.56**	0.19	0.69***	0.23
Fine sediment load (<20µm)	1yr	0.03	0.01	0.04	0.05
	2yr	0.12	0.04	0.15	0.01
	3yr	0.30	0.09	0.39*	0.10
	4yr	0.56**	0.19	0.70***	0.23
Burdekin River TSS load delivered to Cleveland Bay	1yr	0.05	0.01	0.05	0.04
	2yr	0.14	0.04	0.16	0.01
	3yr	0.33	0.10	0.40*	0.11
	4yr	0.59**	0.20	0.71***	0.24

The results in Table 8 have a number of important implications: the higher correlation between river flow and seagrass in Cleveland Bay is not just due to sediment loads, but from other causes as well. Possible causes include low light conditions associated with clouds and rainfall, cyclone damage, sediment resuspension, effects of salinity and temperature, or other terrestrial contaminants, as outlined in the Discussion, although the mechanisms cannot be determined from the data available here. The important point is that the sediment load thresholds determined from these data give only a partial picture of the impact of local catchments on seagrass state. In any case, the delivery of new sediment into Cleveland Bay explained a high proportion of the variance for both seagrass area and biomass and hence justifies our approach to develop sediment load thresholds.

Based on the information in Table 8, sediment load thresholds were estimated from the correlation between area of shallow subtidal seagrass and all seagrass with Burdekin River TSS loads. Whilst the R^2 values for the correlation with seagrass area are slightly higher for Burdekin TSS loads “delivered to Cleveland Bay” and also fine sediment loads, as outlined earlier, the uncertainty in the estimates of the “delivered” and fine sediment loads are higher than for the TSS loads, and the difference in R^2 is too small to justify using less accurate inputs to the thresholds. However, as the current load targets and modelling are based on the fine sediment load (i.e. <20 μm) we have adjusted the TSS loads so that they are directly comparable as outlined below.

3.5.4 Burdekin River sediment load thresholds from seagrass state in Cleveland Bay: ecologically relevant targets

Three key relationships between Cleveland Bay seagrass metrics and Burdekin River TSS loads were determined from the process outlined above, and highlighted in grey in Table 8 and Table 9. The relationships are as follows, and are plotted against the monitoring data in Figure 17:

$$\Delta Biomass_{subtidal} = A1 - B1 \times BSL_{1yr} \quad (2)$$

$$Area_{subtidal} = A2 - B2 \times BSL_{4yr} \quad (3)$$

$$Area_{total} = A3 - B3 \times BSL_{4yr} \quad (4)$$

Where $\Delta Biomass_{subtidal}$ is annual change in shallow subtidal biomass (g DWm^{-2}), $Area_{subtidal}$ is are of shallow subtidal seagrass (ha), $Area_{total}$ is total seagrass area (ha), BSL_{1yr} is annual Burdekin River TSS load (Mt), BSL_{4yr} is Burdekin River TSS load over the 4 antecedent years (Mt), and the coefficients are as follows: A1 =2.58 (+/-1.22) g DW m^{-2}, B1 =0.95 (+/-0.20) g DW m^{-2} Mt^{-1}, A2 =3194 (+/-365) ha, B2 =-61 (+/-17) ha Mt^{-1}, A3=5900 (+/-406) ha, B3 =-90.6 (+/-19) ha Mt^{-1}.

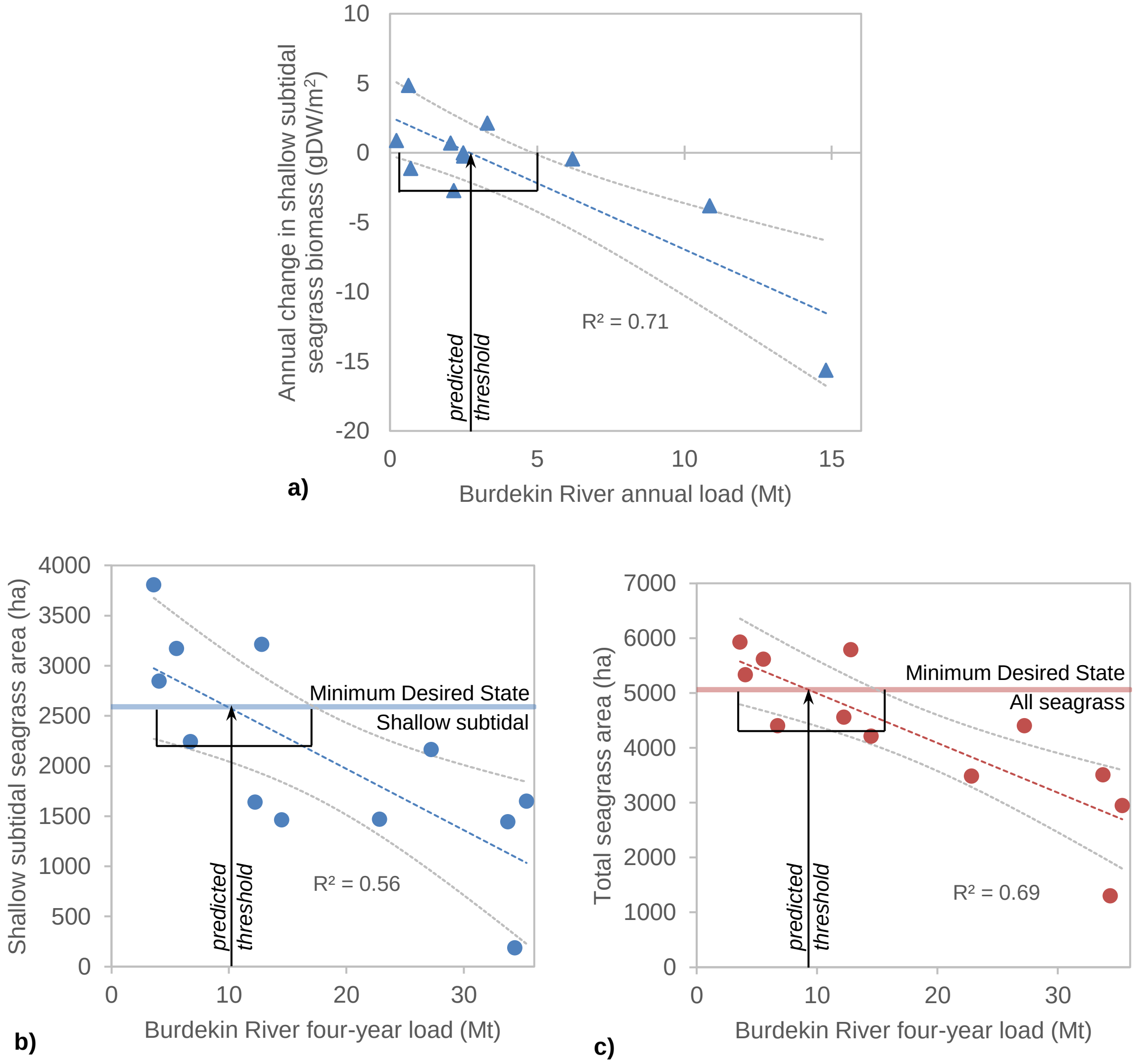


Figure 17. Predicted load thresholds based on a) Annual Burdekin TSS load corresponding to no decline in biomass of shallow subtidal seagrass (S2); b) 4 year Burdekin TSS load corresponding to area of shallow subtidal seagrass (S2) meeting desired state; c) 4 year Burdekin TSS load corresponding to total seagrass area meeting desired state. 95% confidence intervals are shown as grey dashed lines.

From Equations 2-4, three different sediment load thresholds were determined.

Maximum annual Burdekin River sediment load for which annual change in shallow subtidal biomass is predicted to be greater than zero:

BSL_{1yr} for positive $\Delta Biomass_{subtidal}$ $=A1/B1$ (5)

Maximum four-year antecedent Burdekin River TSS load for which shallow subtidal seagrass area is predicted to exceed minimum desired state ($DS_{subtidal}$):

BSL_{4yr} for subtidal area desired state$= (A2 - DS_{subtidal})/B2$ (6)

Maximum four-year antecedent Burdekin River TSS load for which total seagrass area is predicted to exceed minimum desired state (DS_{total})

BSL_{4yr} for total area desired state $= (A3 – DS_{total})/B3$ (7)

The predicted Burdekin River TSS loads corresponding to the ecologically relevant targets of seagrass state in Cleveland Bay (calculated from Equations 5-7) are summarized in Table 10. For the multi-year load thresholds (Equations 6-7), the total load was divided by the number of years to calculate an average annual load. Annual TSS load thresholds were converted to fine sediment thresholds by applying the 80 (±2) % average derived from the logarithmic relationship in section 3.4.5.2 as a scale factor. This simple approximation could also be applied to future TSS loads to enable direct comparison with fine sediment load targets.

The predicted fine sediment load thresholds range from 1.9 to 2.2 Mt/yr, and are slightly lower than the WQIP Burdekin Catchment Target of 2.4 Mt/yr (State of Queensland, 2018), also shown in Table 9. Another way to express these targets is as a percentage reduction in “anthropogenic load”. Brodie et al. 2017 estimated the typical Burdekin load at 3.26 Mt/yr, of which 2.79 Mt was attributed to anthropogenic activity. The sediment load thresholds of 1.9-2.2 Mt/yr year would therefore correspond to a load reduction of 1.06-1.36 Mt/yr, i.e. 38-49 % of the anthropogenic load. The official WQIP target for the Burdekin River catchment is 30% reduction in anthropogenic fine sediment load, or 0.84 Mt/yr reduction by 2025 (State of Queensland, 2018), i.e. a total fine sediment load from the Burdekin River of 2.4 Mt/yr.

Table 9. Predicted thresholds for Burdekin River TSS load calculated from Equations 5-7, and equivalent load reduction compared with WQIP targets.

Burdekin River metric	***Seagrass indicator***	***Source equation***	***TSS threshold (Mt)***	***Fine sediment (<20 μm) load threshold (Mt)***	***R^2***	***p-value***	***Annual fine-sediment load (Mt/yr)***	***Fine sediment load reduction[1] (Mt/yr)***	***Fine sediment load reduction (% anthropogenic[2])***
1-year load	$\Delta Biomass_{subtidal} > 0$	5	2.7	2.2	0.71	0.001	**2.2**	1.06	38%
4-year load	$Area_{subtidal} \geq DS_{subtidal}$[3]	6	9.9	7.9	0.56	0.005	**2.0**	1.26	45%
4-year load	$Area_{totall} \geq DS_{total}$	7	9.3	7.4	0.69	0.0008	**1.9**	1.36	49%
	WQIP Burdekin Catchment Target[4]						**2.4**	**0.84**	**30%**

[1] Load reduction based on the 2012-2013 fine sediment total baseline load of 3.26 Mt/yr for the Burdekin River (Brodie et al. 2017)
[2] Load reduction (% anthropogenic) is based on 2012-2013 fine sediment total anthropogenic load of 2.786 Mt/yr (Brodie et al. 2017)
[3] DS = minimum Desired State
[4] State of Queensland (2018)

Sediment thresholds calculated here based on seagrass state in Cleveland Bay, are higher than those calculated by Brodie et al. 2017 (using seagrass light requirements applied within the eReefs hydrobiogeochemical model of the region). However, it is important to use caution in applying the figures in Table 10. From Tables 7-8, it is clear that the observed correlation between seagrass and sediment loads is driven at least in part by negative effects of high annual river discharge which are unrelated to sediment loads: correlation is not the same as causation. While there is evidence that sediment from the Burdekin River does affect light attenuation in Cleveland Bay (Fabricius et al., 2013, 2014) and that seagrass in Cleveland Bay is affected by low benthic light (Collier et al., 2012, Collier et al 2016), it seems likely that years of high annual river discharge bring other stressors to seagrass. From the data available, we can't determine what those additional stressors are, but they could include direct damage (e.g. from cyclones), sediment resuspension caused by rough weather events (i.e. when the sediment bed is remobilised as opposed to the increased turbidity generated from the resuspension of newly delivered sediment), salinity or temperature effects, or other catchment contaminants.

3.5.5 Seagrass decline and growth trajectories are different

From Figure 15 and Tables 7-8, it is clear that area and biomass of different seagrass communities exhibit different relationships with both river discharge and sediment load, and respond on different timescales. In order to further explore these relationships and timescales, the trajectories of seagrass area and biomass for shallow subtidal and all seagrass communities in Cleveland Bay are plotted in (Figure 18). Both seagrass area and biomass were high at the start of the study period (2007). The trajectory plots show the decline of seagrass after sequential high flows and loads from the Burdekin and local catchments between 2008 and 2010, followed by slow recovery. The non-linear shape of the trajectory plot indicates that the condition of seagrass is affected by both current and preceding conditions. This time delay occurs because changes in growth or decline of seagrass in response to the external environment can take months or years for their cumulative effects to be seen (O'Brien et al. 2018). Area of seagrass gradually declines over the study period, through the periods of high flow and large sediment loads. Once those loads and flows reduce, the area gradually recovers. The shape of the biomass trajectory is quite different, suggesting (as do the correlations in Tables 7-8) that that relationship between biomass and years with high flow/sediment load is much less clear.

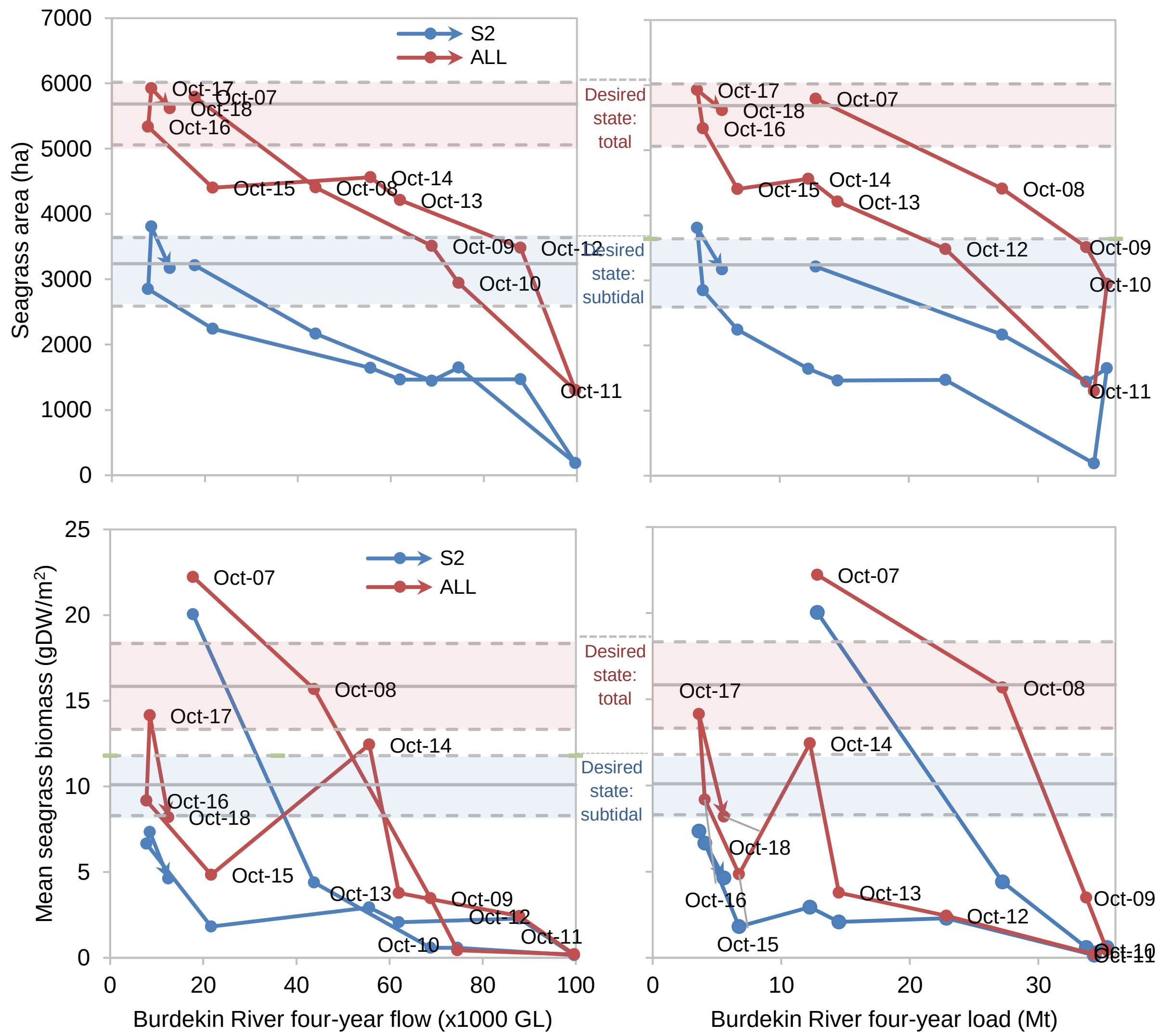


Figure 18 Area (top) and biomass (bottom) trajectory plots for shallow subtidal seagrass (blue) and total seagrass (red) showing different decline and recovery pathways from and back to desired state for 4-year antecedent Burdekin River flow (left) and TSS load (right). Desired state range is shaded with mean (grey line) and 95% confidence intervals (dashed grey lines) also indicated.

3.6 Discussion

Defining ecologically-relevant targets (ERTs) is a critical aspect of implementing evidence-based management, because objectives must be quantified in order to identify how they can be met, and when they are achieved (Samhouri et al. 2011, Brodie et al. 2017). However, defining ERTs is a major challenge, because most environmental systems are impacted by multiple stressors acting across a range of spatial and temporal scales. This poses two major challenges: first, establishing a causal link between any one stressor and the ecosystem response; secondly, even if the ERT for one stressor is met, other stressors may still pose a threat. Here we employed a number of the best-practice approaches for setting ERTs including: establishment of functional relationships between environmental conditions (sediment loads and flow) and ecological outcomes (seagrass condition); identifying ecological reference points (seagrass desired state); and, using time-series data to develop internal reference points (seagrass monitoring data, sediment loads, and river flow monitoring)

(Samhouri et al. 2012). We used multiple seagrass condition metrics and targets, including seagrass desired state (Collier et al. 2020), explored different sediment fractions, and quantified all likely sources of riverine sediment input, including “delivered” sediment load based on long-term and rigorous monitoring programs (Bryant and Rasheed 2018) (Queensland Government Department of Environment and Science, 2017). As an outcome, we identified sediment loads that are associated with seagrass in the study site meeting condition targets. There is abundant evidence of the functional relationships between riverine discharge and turbidity (Fabricius et al. 2014, Fabricius et al. 2016) and turbidity, light attenuation and photosynthesis of benthic habitats (Erftemeijer and Robin Lewis III 2006, Collier et al. 2012, Choice et al. 2014, Collier et al. 2016, Fernandes et al. 2018), but associations or correlations are still inadequate to establish causation in this data. This study, in conjunction with alternative approaches to setting ERTs (Brodie et al. 2017, State of Queensland 2018) provides further evidence in an ensemble approach that can frame ERTs.

The physical basis of a correlation between sediment load and seagrass biomass and area are relatively clear. Sediment discharged from the Burdekin River mouth is predominately transported northwards up along the coast into Cleveland Bay, and in the process is transformed into organic-rich sediment flocs due to associated nutrients and resulting plankton blooms (Bainbridge et al. 2012). This suspended particulate matter reduces benthic light within the Bay during the plume event (Fabricius et al. 2014, Fabricius et al. 2016), and hence has the potential to reduce seagrass growth. The link between water quality, turbidity, benthic light and seagrass condition is very well established (Erftemeijer and Robin Lewis III 2006, Lee et al. 2007, Petus et al. 2014, Chartrand et al. 2016), yet quantifying critical light thresholds remains challenging for multiple reasons. Following a discharge event, the sediment “delivered” to Cleveland Bay can be resuspended during periods of high winds and hence also reduce benthic light for many months afterwards, until the recently delivered sediment is dispersed out of the Bay or consolidated (e.g. Lambrechts et al. 2010, Lewis et al. 2014, Fabricius et al. 2016). Thus, the period of reduced light after a significant river discharge event may persist for four to nine months following initial flood plume delivery (Fabricius et al. 2013, Fabricius et al. 2014, Fabricius et al. 2016). While further investigation is required to strengthen these links by acquiring additional empirical data and improving modelled relationships, we contend there is enough evidence to proceed with comparing the sediment thresholds identified here to current targets (State of Queensland 2018).

Meeting targets will not necessarily ensure seagrass will be at its defined desired state in Cleveland Bay, for a number of reasons. As outlined in the results section, the threshold loads calculated here are from coarse empirical relationships, where correlation does not prove causality. Seagrass are affected by a range of other pressures in addition to turbidity, and these could be exacerbated by climatic conditions that cause elevated rainfall, river discharge and sediment loads. For example, increased cloud cover during rain periods, reduces incoming solar radiation and compounds the effects of turbidity on benthic light levels. Other compounding influences could include direct damage (e.g. from cyclones), sediment resuspension caused by rough weather events (i.e. when the sediment bed is remobilised as opposed to the increased turbidity generated from the resuspension of newly delivered sediment), salinity or temperature effects, or other catchment contaminants. Many seagrass systems around the world have shown evidence of hysteresis in decline, such that improvements in water quality do not necessarily correspond to expected improvements in seagrass condition, due to the presence of feedbacks (Maxwell et al. 2017, O'Brien et al. 2018).

Nevertheless, the observed strong correlation between seagrass area and biomass in Cleveland Bay with terrestrial runoff, particularly large discharge events from the Burdekin measured in this study is supported by our current conceptual understanding of the influence of new sediment on turbidity regimes in the inshore GBR (Fabricius et al., 2016, Bainbridge et al., 2018). Such land-sea connections have been demonstrated in cases the world over (e.g. Fabricius 2005, Saunders et al. 2017); but local evidence for the influence of rivers on seagrasses is needed to justify management investment.

The greater correlation between flow and seagrass condition than between sediment load and seagrass condition has important implications: it indicates that the riverine discharge has other physico-chemical properties that could affect seagrass area and biomass, or it may also indicate that flow is a better proxy for the range of environmental conditions that affect seagrass. Low salinity in river plume water is unlikely to be the cause of Burdekin River influence on seagrass biomass and extent because the salinity in plumes (26 at Orchard Rocks – Bainbridge et al. (2012)), only lasts a few weeks with the lowest salinities generally concentrated within the upper ~ 5 m of the water column. This brief level of lowered salinity will have no detectable effect on seagrass (Kerr and Strother 1985, Ralph 1998, Ralph 1999, Collier et al. 2014). However, the Burdekin River carries nutrients and floc aggregates containing organic matter with fine sediments (Bainbridge et al., 2012) and these cannot be accounted for in our models as there is no long-term information on these fractions. This may influence the differences in response of seagrass indicators to flow or to loads, which only account for the mineral fraction. Flocs may affect light attenuation, but they can also affect nutrient availability and the effect on the sediment when deposited. The combined effects of multiple stressors, including nutrients, organic matter and sediments, are complicated and rarely studied (Govers et al. 2014), and feedbacks could make seagrasses liable to sudden and unpredictable transitions that do not link to an individual stressor, such as sediment loads (Duarte 1995, Munkes 2005, Van der Heide et al. 2008, van der Heide et al. 2010).

The range of pressures on the system do not just affect the correlations between sediment load and seagrass state, but also influence ERTs. For example, pressures will vary between intertidal and subtidal seagrass and spatially around Cleveland Bay. Light deprivation is likely to be a greater issue for subtidal compared to intertidal seagrass and this is reflected in our results. Our estimate of 38 – 49% of anthropogenic load reduction may be influenced by these interacting factors, some of which are an inherent component of the data which is based on long-term monitoring. Allowing for uncertainty, our estimate of sediment load reductions is comparable to those in the WQIP 2018.

Spatial and temporal variability in both terrestrial runoff predictors and seagrass response variables are another major challenge in setting ERTs which connect catchment inputs to ecosystem response. Assessing and managing catchment loads for coastal ecosystem health must consider rainfall events and the spatial-temporal scales of catchment processes. For example, groundcover can be very low in periods of drought, with sediment loads a function of discharge volume, intensity and distribution of rainfall, and antecedent catchment conditions. The intense rainfall and discharge in the 2007/08 water year occurred after a prolonged drought, and therefore contained a larger sediment load than in subsequent water years (2008/09 and 2010/11) which had higher river discharge as seen in Figure 15 (Bainbridge et al. 2014). Understanding these catchment processes and the associated time lags in sediment transport through, and export from, the catchment is essential for management of the downstream environment and will influence the timescales required to identify the influence of catchment remediation on inshore water quality and ecosystem health. Hence, the better performance of the multi-annual correlations may well reflect this variability in catchment time lags and associated ecological response.

Our results demonstrate different timescales of both decline and recovery between biomass and area The biomass of shallow subtidal seagrass was highly sensitive to load, declining by 74 - 87% when there were high flows and loads in 2007/08, 2008/09 and 2010/11, and as such, load targets based on biomass were more robust (higher R-squared) when based on annual change in biomass. By contrast, seagrass area declined successively over multiple years, and therefore targets using seagrass area as an indicator were more robust when loads over the previous 3 or 4 years were considered. The reason for this lag likely lies in the mechanisms of resilience for the shallow seagrass species that made up the meadows in this study: a combination of resistance and recovery (O'Brien et al. 2017). The initial impacts of reduced light can cause decline in seagrass shoot size and density (hence biomass) as the plants increasingly rely on stored energy reserves to persist. While they may initially decline in biomass, they are able to maintain a presence across their previous extent until such a point that their reserves are depleted and they are no longer able to produce new above ground material. The fact that area recovered more quickly than biomass is likely to reflect the rapid colonization by small, fast growing species such as *Halophila*, which are gradually replaced by opportunistic and persistent seagrass (McKenzie et al. 2016). It is worth noting that deeper communities (subtidal community 1 from Chapter 2) of Cleveland Bay, dominated by *Halophila spinulosa* and *Halophila decipiens*, were not included in this analysis owing to a lack of data, but they vary over space and time differently to shallow communities (York et al. 2015) and may require different methods for setting targets.

Trajectories shown in Figure 19 express a hysteretic pattern – such patterns are seen when a measure of ecological state varies in response to an environmental input, but with a time delay in its response (Rheuban et al. 2014, Adams et al. 2016). In the present study, the observed hysteretic patterns occur because seagrass area and biomass (measures of ecological state) appear to respond to changes in sediment flows or loads (the environmental input) with a time delay. This time delay occurs because changes in growth or decline of seagrass in response to the external environment can take months or years for their cumulative effects to be seen on seagrass morphology (O'Brien et al. 2018); hence in our case the seagrass biomass and area are indicators of system state that are accounting for the cumulative impacts of sediment flows or loads over several previous years. Other studies in the GBR have shown that large scale seagrass losses are generally the result of multiple events over a number of years rather than a single weather or river flow event (McKenna et al. 2015). There are exceptions however, when cyclones result in major physical disturbance or where the seagrass meadows are dominated by highly ephemeral species with a very low capacity to resist low light conditions (Rasheed et al. 2014, York et al. 2015, Chartrand et al. 2018). Our observations show that seagrass area and biomass had already considerably declined prior to the major disturbance event of TC Yasi in 2011. Importantly, the seagrass meadow area appeared to contract in the deeper sections of the sub-tidal zone (Petus et al. 2014) consistent with what would be expected via reduced light limitations. There did not appear to be any major physical high energy wave events over this period that would have caused this reduction, in particular to the deeper areas (i.e. a physical disturbance would have more likely disturbed shallow zones). These ecological response trajectories are therefore important for understanding how to implement ERTs that consider ecologically-relevant time-scales, and they have important implications for ecosystem services (Tol et al. 2016, Scott et al. 2018).

It is important to focus on the finer fraction of sediment in river loads as it is known to travel furthest in flood plumes and reach Cleveland Bay and sensitive habitats (Bainbridge et al. 2012, Lewis et al. 2014). Indeed, a more targeted modelling approach (e.g. SLIM, eReefs) could more accurately quantify the Burdekin discharged sediment reaching Cleveland Bay each year (Delandmeter et al. 2015, Margvelashvili et al. 2018). Moreover, if this fine sediment fraction that travels the furthest in the marine environment can be better characterised to a finer particle size (e.g. <4 μm) or a clay mineral type, then ERTs can be developed to specifically target this most damaging sediment. For example, an ERT based on the reduction of the 15% of the Burdekin load that travels furthest in the marine environment may appear much less daunting (and more achievable) to a manager (i.e. 140,000 tonnes of 480,000 tonnes) than the current ERT of 840,000 tonnes (i.e. 30% of the 2012-2013 anthropogenic load of 2.8 Mt).

Extreme flow events are predicted to increase in Queensland, and many other parts of the world: catchment practices which offset the impact of these flows on receiving waters will be in greater demand over time. Based on current data, it is not possible to quantify all the processes by which high river flows impact the health of seagrass in Cleveland Bay, a data-rich system by world standards. How then can ERTs be defined in the many environments which have even less data? One way is to take a different approach: rather than quantifying the impact of specific contaminants or threats, it may be worth focusing on the methods which reduce those threats. For example, establishing industry-recognised best management practices to reduce sediment runoff within key industries in the catchment, revegetating catchments to reduce sediment runoff, or revegetating coastal wetlands to trap those sediments, are all possible and could contribute towards improved seagrass (and coral) habitat, while also addressing other less well-quantified pressures, such as nutrient inputs. This would involve a fundamental shift in direction, from minimizing specific threats below a threshold, to maximizing conditions which mitigate those threats. This may well be a sensible approach when the cost of quantifying ERTs is particularly high, or where the data are simply unavailable.

3.6.1 Conclusions

Our results highlight the importance, and difficulty, in estimating ERTs for aquatic ecosystems based on terrestrial inputs. Some of the key challenges are: the impact of cumulative pressures; the challenges of identifying causality; and the multiple spatial and temporal scales which need to be considered in both pressures and ecological responses. Given this complexity and uncertainty, it is important that ERTs are estimated using a range of methods, in order to provide some indication of uncertainty, as we have done here. Future work on this topic should refine the ERTs through considering other important mechanisms by which terrestrial runoff can affect ecosystems downstream. It is also worth noting that in many systems, there is insufficient data to quantify desired ecological state, let alone targets of the pressures impacting on that state. Therefore, in tandem with exploring how to set ERTs, it's also worth considering whether in data-poor systems, it might be more useful to shift the focus, from quantifying the threats posed by specific catchment pressures (such as sediment runoff) to practices which mitigate simultaneously against multiple pressures, such as catchment revegetation.

3.7 Supplementary Information

Table 10. Annual Discharge (ML) of the waterways discharging into, or affecting Cleveland Bay

Water Year[1]	Burdekin River	Haughton River	Ross River	Alligator Ck	Stuart Ck
Location	End of River	Powerline	Aplins		
2002/2003	2,092,792	80,651	22,397	19,014	7,454
2003/2004	1,516,142	172,479	38	39,723	15,571
2004/2005	4,328,246	248,110	1,095	62,583	24,533
2005/2006	2,199,734	287,000	107,289	119,232	46,739
2006/2007	9,768,966	584,063	164,786	167,561	65,684
2007/2008	27,502,703	805,802	185,218	195,934	76,806
2008/2009	29,352,242	1,113,845	496,970	613,149	240,354
2009/2010	7,946,687	499,519	160,134	345,010	135,244
2010/2011	34,834,316	1,050,330	595,992	377,287	147,896
2011/2012	15,721,641	763,353	158,734	198,988	78,003
2012/2013	3,499,875	224,813	540,992	57,738	22,633
2013/2014	1,579,528	249,555	52,137	90,579	35,507
2014/2015	918,637	52,467	6,671	18,930	7,420
2015/2016	1,804,490	116,516	8,453	33,025	12,946
2016/2017	4,208,655	147,063	4,075	67,583	26,493
2017/2018	5,539,676	359,523	25,092	71,633	28,080
2018/2019	17,451,417	1,506,168	1,134,223	437,689	171,574

[1] Water year goes from 1 October to 30 September the following calendar year.

Table 11. Annual TSS Load (kt) of the waterways discharging into, or affecting Cleveland Bay

Water Year[1]	Burdekin River	Haughton River	Ross River	Alligator Ck	Stuart Ck
Location	End of River	Powerline	Aplins		
2002/2003	755	9	1.68	0.8	2.2
2003/2004	384	19	0.00	1.6	4.7
2004/2005	4,338	38	0.08	2.5	7.4
2005/2006	884	35	8.0	4.8	14.0
2006/2007	7,195	79	26.5	6.7	19.7
2007/2008	14,806	22	14.5	7.8	23.0
2008/2009	10,855	105	37.3	24.5	72.1
2009/2010	2,485	54	12.0	13.8	40.6
2010/2011	6,200	114	44.7	15.1	44.4
2011/2012	3,300	83	11.9	8.0	23.4
2012/2013	2,500	24	40.6	2.3	6.8
2013/2014	220	32	3.9	3.6	10.7
2014/2015	700	0.62	0.50	0.8	2.2
2015/2016	630	14	0.63	1.3	3.9
2016/2017	2,054	21	0.31	2.7	7.9
2017/2018	2,159	54	1.9	2.9	8.4
2018/2019	8,300	164	113	17.5	51.5

[1] Water year goes from 1 October to 30 September the following calendar year.

Table 12. Estimated annual fine sediment load (<20 µm) (kt)

Water Year[1]	Burdekin River	Burdekin River	Haughton River	Ross River	Alligator Ck	Stuart Ck
Location	End of River	% of TSS[2]	Powerline	Aplins		
2002/2003	618	82%	6	1.09	0.8	1.1
2003/2004	319	83%	12	0.00	1.6	2.3
2004/2005	3,408	79%	25	0.05	2.5	3.7
2005/2006	721	82%	23	5.2	4.8	7.0
2006/2007	5,585	78%	51	17.2	6.7	9.9
2007/2008	11,292	76%	14	9.4	7.8	11.5
2008/2009	8,342	77%	68	24.2	24.5	36.1
2009/2010	1,978	80%	35	7.8	13.8	20.3
2010/2011	4,830	78%	74	29.1	15.1	22.2
2011/2012	2,609	79%	54	7.7	8.0	11.7
2012/2013	1,990	80%	16	26.4	2.3	3.4
2013/2014	185	84%	21	2.5	3.6	5.3
2014/2015	574	82%	0.40	0.33	0.8	1.1
2015/2016	518	82%	9	0.41	1.3	1.9
2016/2017	1,642	80%	14	0.20	2.7	4.0
2017/2018	1,724	80%	35	1.2	2.9	4.2
2018/2019	6,420	77%	106	73.5	17.5	25.7

[1] Water year goes from 1 October to 30 September the following calendar year.

[2] Average Burdekin River annual fine sediment load is 80 (±2) % of annual TSS load.

Table 13. Estimated annual TSS load (kt) delivered to Cleveland Bay

Water Year[1]	Burdekin River	Burdekin River	Haughton River	Ross River	Alligator Ck	Stuart Ck
Location	Estimated % reached Cleveland Bay	Cleveland Bay = % x end of River	15% x Powerline	Aplins		
2002/2003	10%	76	1.32	1.68	0.8	2.2
2003/2004	5%	19	2.85	0.00	1.6	4.7
2004/2005	10%	434	5.7	0.08	2.5	7.4
2005/2006	10%	88	5.28	8.0	4.8	14.0
2006/2007	15%	1079	11.85	26.5	6.7	19.7
2007/2008	15%	2221	3.3	14.5	7.8	23.0
2008/2009	15%	1628	15.77	37.3	24.5	72.1
2009/2010	10%	249	8.14	12.0	13.8	40.6
2010/2011	15%	930	17.11	44.7	15.1	44.4
2011/2012	15%	495	12.43	11.9	8.0	23.4
2012/2013	10%	250	3.66	40.6	2.3	6.8
2013/2014	5%	11	4.8	3.9	3.6	10.7
2014/2015	5%	35	0.09	0.50	0.8	2.2
2015/2016	5%	32	2.1	0.63	1.3	3.9
2016/2017	0%	0	3.15	0.31	2.7	7.9
2017/2018	15%	324	8.1	1.9	2.9	8.4
2018/2019	10%	830	24.53	113	17.5	51.5

[1] Water year goes from 1 October to 30 September the following calendar year.

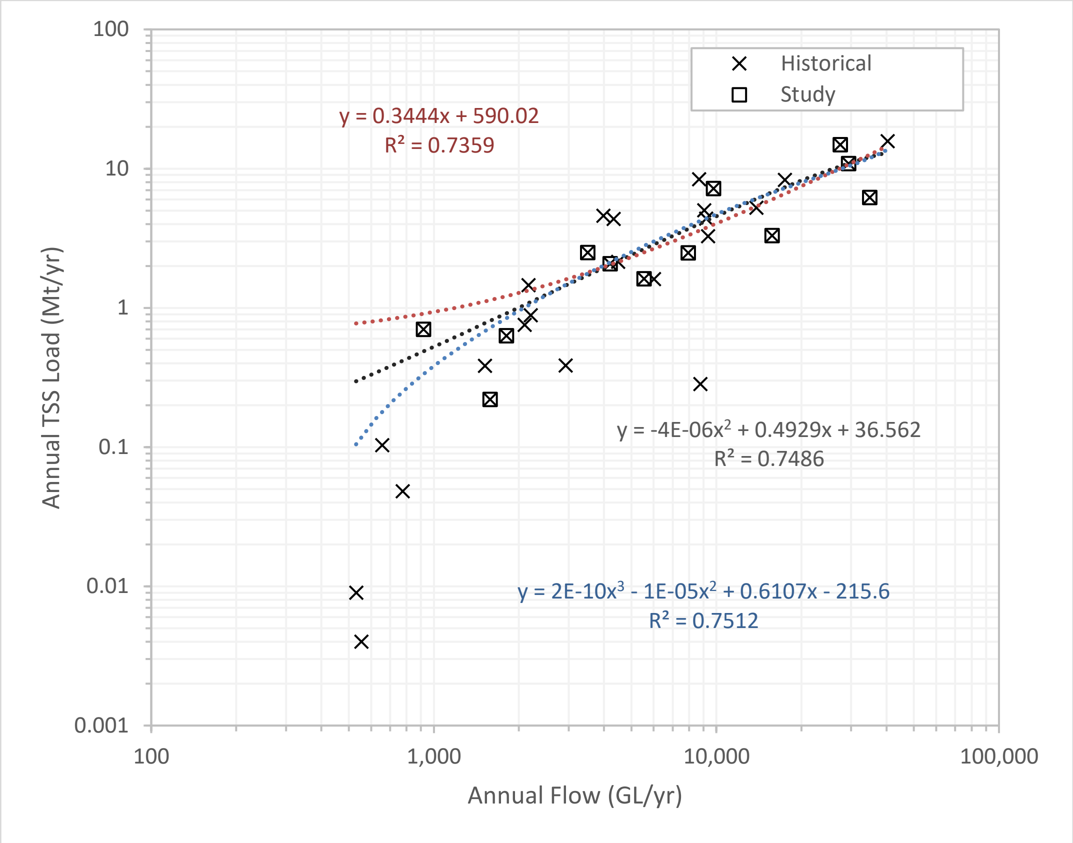


Figure 19. Linear (red) and polynomial (2nd order black and 3rd order blue) models showing how Burdekin River TSS load increases with flow (1987-2019). Boxes indicate data used in this study (2007-2018).

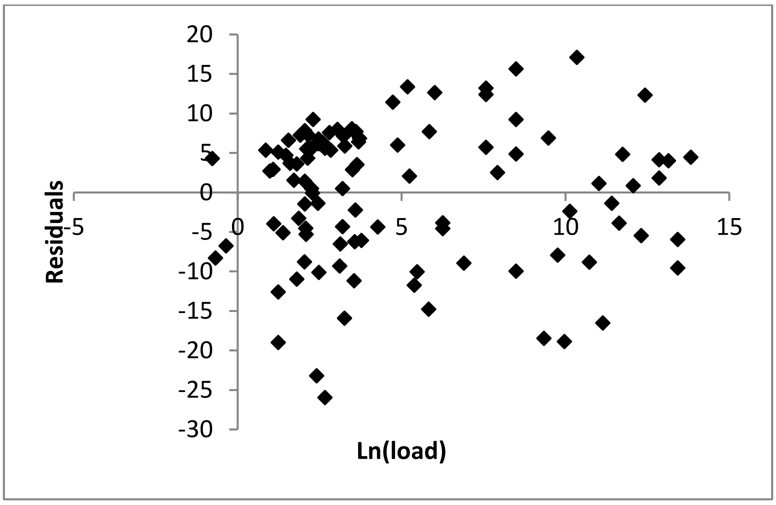


Figure 20. Residuals plot for Figure 18. Fine sediment vs the logarithm of the load (ln(load))

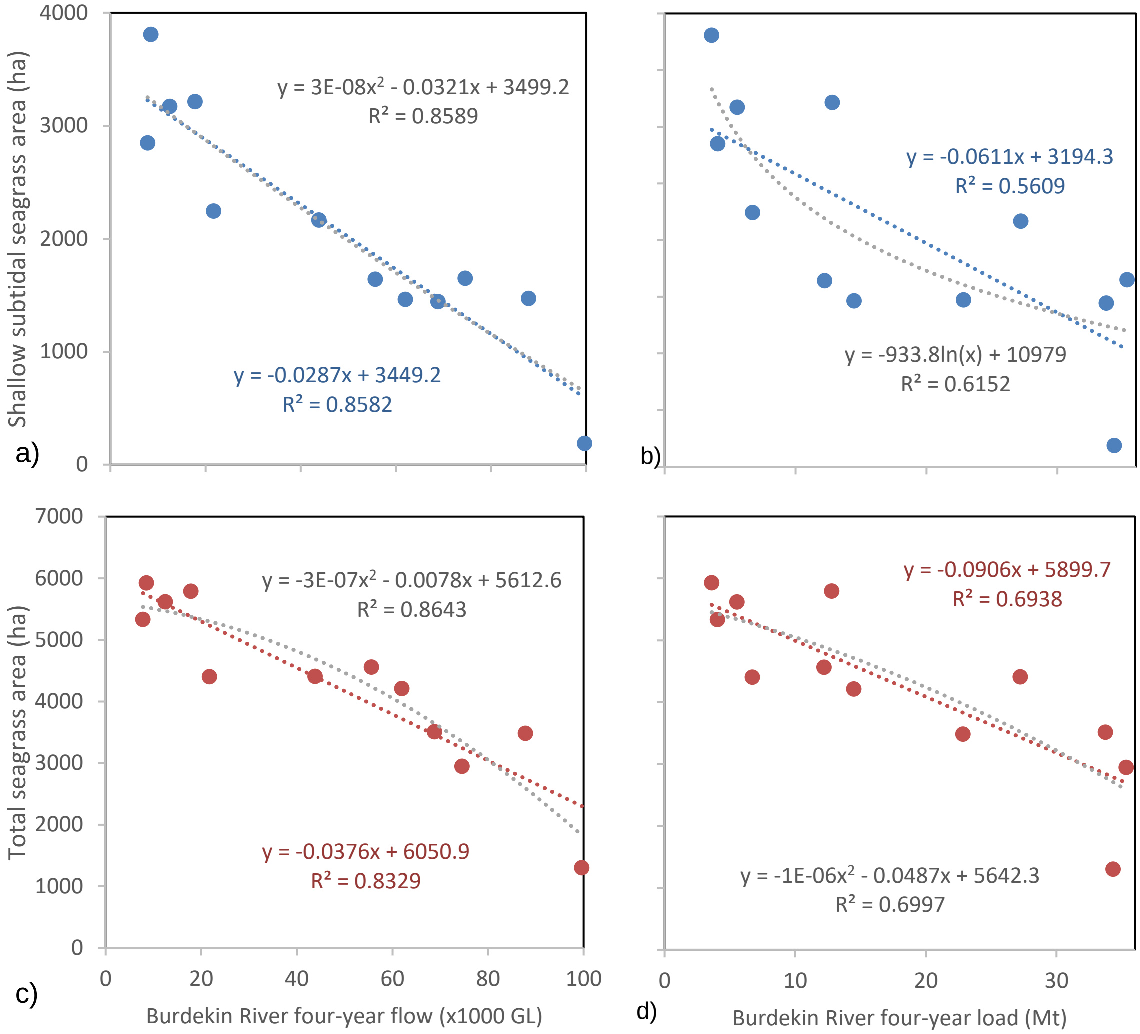


Figure 21. Impact of four-year antecedent Burdekin River flow (left) and TSS load (right) on Cleveland Bay seagrass area for shallow subtidal seagrass (top) and all seagrass communities (bottom). Linear (coloured) and non-linear (grey) models are shown. While non-linear models may exhibit a marginally better fit, there is insufficient data (12 datapoints) to warrant adopting these more complex models.

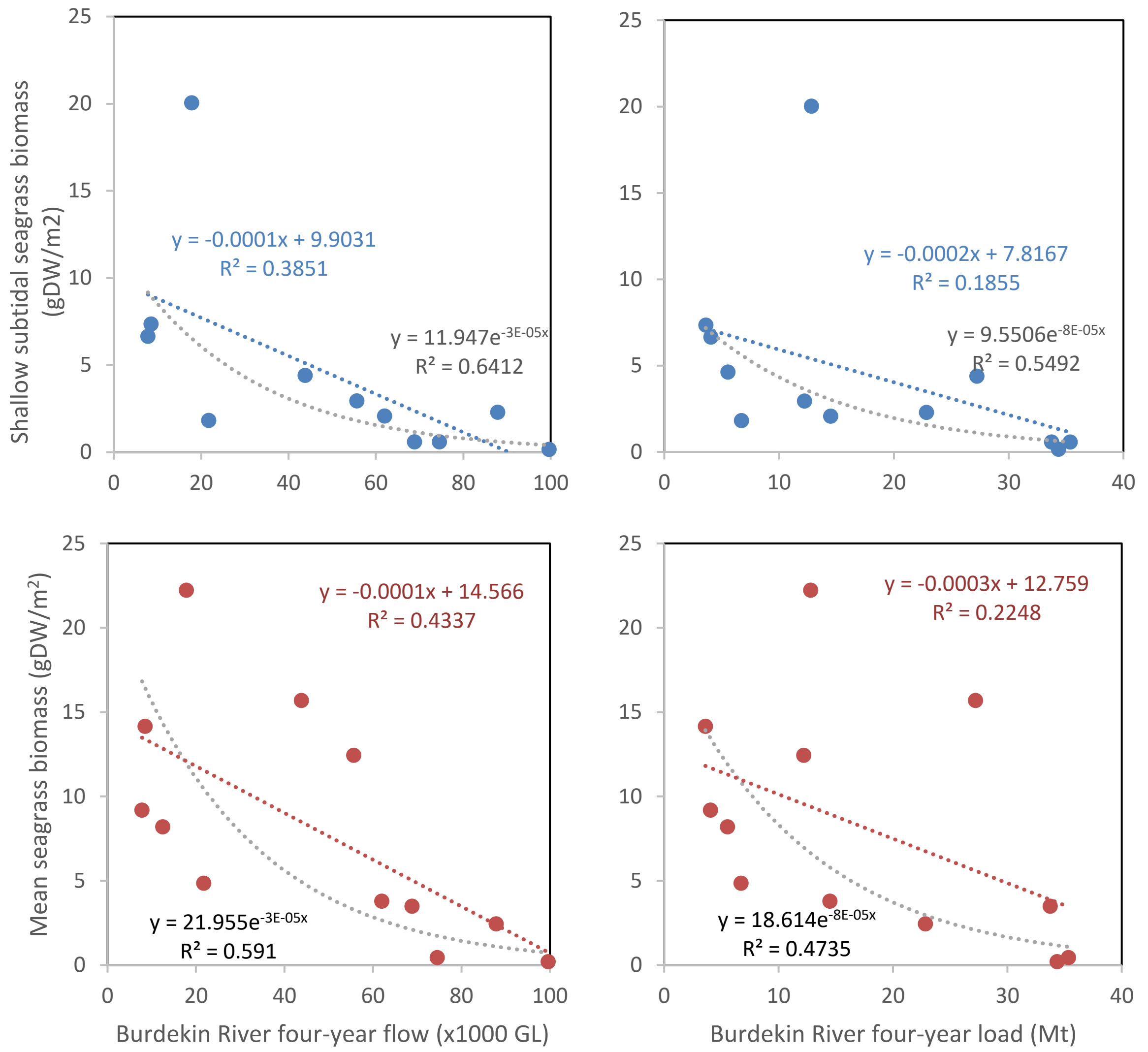


Figure 22. Linear (red) and exponential (grey) relationship correlations of shallow subtidal seagrass biomass (top) and the mean biomass of all seagrass communities (bottom) for four-year Burdekin River flow (left) and TSS load (right). Biomass was very high in October 2007, more than double all other observations. Linear correlations were therefore poor ($R^2 < 0.39$). Exponential models were a better fit, and correlations were significant. This could reflect exponential growth of seagrass biomass under favourable conditions, however there is insufficient data to warrant adopting this more complex model.

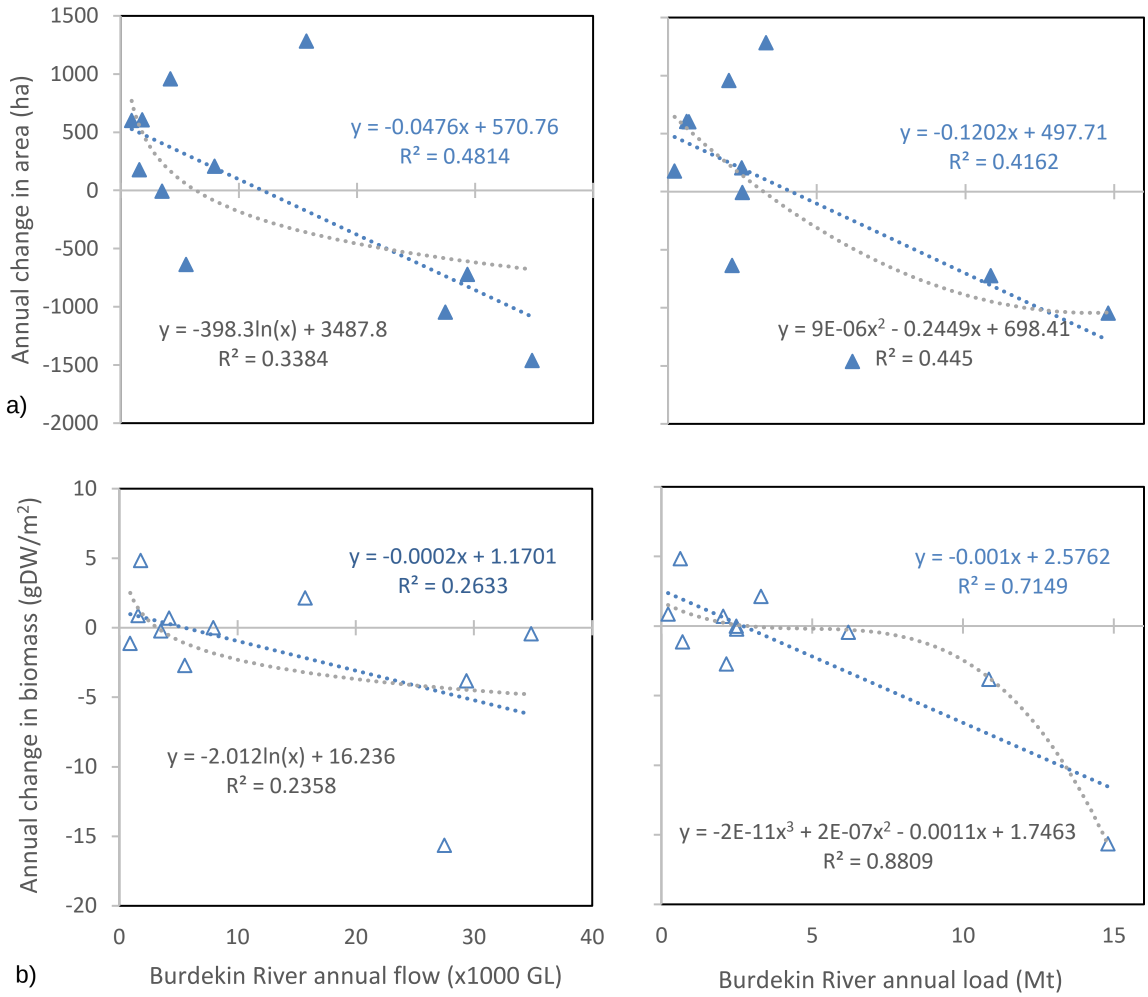


Figure 23. The effect of annual flow (left) and TSS load (right) from the Burdekin River on annual change in Cleveland Bay shallow subtidal seagrass: a) total area; and b) mean biomass. Linear (blue) and non-linear (grey) models are shown. While some non-linear models may exhibit a marginally better fit, there is insufficient data (12 datapoints) to warrant adopting these more complex models.

Table 14. All seagrass communities combined results for linear models (R^2) of different river source predictor variables (flow, TSS load and fine sediment load) and all Cleveland Bay seagrass communities (annual change in area and biomass). Correlations are poor and mostly insignificant. Significance indicated by * p<0.05; ** p<0.01; *** p<0.001.

River Source	*Metric*	*Annual change in Seagrass Area*			*Annual change in Seagrass Biomass*		
		Flow	TSS Load	Fine sediment	Flow	TSS Load	Fine sediment
Combined	Total	0.35	0.36	0.36	0.20	0.34	0.34
Delivered	Delivered	0.35	0.37*	0.37*	0.21	0.35	0.35
Burdekin	Total	0.36	0.35	0.35	0.20	0.34	0.34
Haughton	Total	0.23	0.07	0.07	0.20	0.07	0.07
Ross	Total	0.14	0.15	0.15	0.06	0.07	0.07
Alligator	Total	0.25	0.25	0.25	0.26	0.26	0.26
Stuart	Total	0.25	0.25	0.25	0.26	0.26	0.26

4.0 BENTHIC LIGHT AS A PREDICTOR OF SEAGRASS AREA

4.1 Executive summary

Benthic light levels are frequently identified as the primary factor limiting seagrass growth, and constraining distribution in the GBR. Acute light thresholds have been developed and are applied in the management of GBR seagrasses, such as dredge management, but the light levels associated with long-term survival of seagrass are not as well characterised. The objectives of this analysis were to examine long-term (annual, seasonal) light levels in relation to seagrass area and explore spatial benthic light data in analysis of Ecologically Relevant Targets. To do this, we made use of the recently developed satellite-derived, spatially-explicit benthic light product, bPAR. Potential seagrass habitat was calculated based on the area of Cleveland Bay that exceeded specific bPAR levels (ranging from 2-10 mol/m^2/d), and compared with measured area of seagrass. The seagrass area data were the same as those described in chapters 2 and 3 for the shallow subtidal seagrass and all seagrass combined. Root mean square error (RMSE) between observed seagrass area and predicted habitat based on annual average bPAR was minimized (i.e. best fit) for bPAR of 5.6 mol/m^2/d for all seagrass communities combined, and 7 mol/m^2/d for shallow subtidal seagrass. For the growing season, minimum RMSE corresponded to potential habitat with bPAR greater than 4.3 mol/m^2/d for all seagrass communities, and 5.4 mol/m^2/d for shallow subtidal seagrass. The model for benthic light (bPAR) overestimated benthic light in Cleveland Bay, and therefore, we did not apply it in the analysis of ERTS at this stage, and because of this, it could not be used in conjunction with, or as an alternative to measured *in-situ* benthic light. However, our analysis demonstrates that inter-annual variation in bPAR explains some of the inter-annual variation in seagrass area and should be further explored for future modelling of seagrass species and community distribution when tested and applied on the same bPAR data set.

4.2 Introduction

Seagrasses are dependent on light for photosynthetic carbon fixation, growth and biomass production (Alcoverro et al. 2001, Beer et al. 2002, Collier et al. 2009, Collier et al. 2011). Therefore, light availability affects the spatial distribution and depth range of seagrasses. Extreme weather events are associated with periods of elevated turbidity and low light due to the combined effects of river discharge, wind/resuspension, and cloudiness, which reduces overall solar radiation (Anthony et al. 2004, Fabricius et al. 2014, Fabricius et al. 2016). Light limitation can drive seagrass loss at levels worse than critical thresholds (Collier et al. 2012, Collier et al. 2012, Rasheed et al. 2014, Chartrand et al. 2016).

The current Reef Targets for Burdekin catchment loads are based on a load reduction scenario that causes the benthic light availability to exceed a running monthly mean of 6 mol/m^2/d for 90% of the time for areas under the Burdekin River influence (Brodie et al., 2017). This light threshold for seagrass viability was based on both field and experimental measurements in Gladstone Harbour (Chartrand et al., 2016) and Cleveland Bay (Collier et al., 2012), as well as evidence from laboratory experiments (Collier et al., 2016a), all of which tested for short-term (weeks to months) light requirements. It also meets or is better than the likely acute light requirements for most bladed seagrass species that occur in the region based on a recent synthesis for GBR seagrass species (Collier et al. 2016b), and is applied in the management of GBR, including to minimise the effects of dredging on seagrasses (Chartrand et al. 2012, Chartrand et al. 2016, Great Barrier Reef Marine Park Authority 2018).

Seagrass light requirements are frequently reported as minimum light requirements (annual) an indicator that is used to describe differences in light requirements amongst species, and to investigate changes in extent and depth ranges (Erftemeijer and Robin Lewis III 2006). Annual light levels can also potentially be related to the annual data sets (sediment loads, seagrass state) applied in the investigation of ERTs (Chapter 3). Long-term light requirements for seagrasses of the Great Barrier Reef have not yet been quantified. Estimates are in the range of 10 to 13 mol m^{-2} d^{-1}; however, this is based on very minimal experimental data (Collier et al. 2016), and there is ample evidence that they can occur in lower light conditions. For example, within Cleveland Bay at the Picnic Bay subtidal long-term seagrass marine monitoring site, the long-term (10 year) annual average light level is 5.7 mol m^{-2} d^{-1}, but 28-day rolling averages reach 10 mol m^{-2} d^{-1} during the growing season (McKenzie et al. 2019). Adjacent intertidal sites have much higher light levels (13.5-14.5 mol m^{-2} d^{-1} on average), but coastal intertidal sites in the region have low light levels (8.3 and 5.8 mol m^{-2} d^{-1} long-term annual average at Shelley Beach and Bushland Beach seagrass meadows just north of Townsville). The fact that site light levels are lower than estimated long-term requirements, indicates that: previous estimates of long-term light requirements were species/population specific; the limited previous evidence from experimental work is unable to capture the complexity that enables long-term survival in seagrass populations, including variable light levels; or benthic light at these sites are too low to support optimal seagrass area and biomass, even though seagrass can survive there on an on-going basis.

Spatially-explicit light data over the range of seagrass distributions have not previously been available, and so previously-defined seagrass light thresholds have been based on site level point measurements (Chartrand et al. 2016). As an outcome of NESP TWQ project 2.3, a light model provides benthic light (photosynthetically active radiation), or bPAR over the GBR (Magno-Canto et al. 2019, Robson et al. 2019), and this has provided an opportunity to explore how bPAR relates to changes in seagrass state over broad spatial scales. The eReefs coupled hydrodynamic-biogeochemical model, an application of the CSIRO Environmental Modelling Suite (EMS) was considered an ideal tool to undertake this task because it represents the hydrobiogeochemical processes that link sediment loads, to benthic light and seagrass distribution, as discussed in the following chapter.

The objectives of this work were to:

1. examine long-term (annual, seasonal) light levels that can be used to predict seagrass area in Cleveland Bay,
2. explore spatial benthic light data as a data set to contribute to Ecologically Relevant Targets.

4.3 Methods

4.3.1 Predicting seagrass area using bPAR

Spatial benthic light data, derived from satellite imagery (referred to here as bPAR), has been developed in NESP TWQ 2.3.1 as a data water quality product of the GBR that can be used for interpreting and predicting ecological changes (Magno-Canto et al. 2019, Robson et al.

2019). It is a spectrally-resolved model based on the Lambert-Beer's law of light transmission. The model typically agrees with radiative transfer values to within 10%, and performs better than chlorophyll-based or K_d-based models (Magno-Canto et al. 2019). The model performed well in optically shallow waters, but due to the complexity and temporal variability of the internal optical properties in coastal sites with stratified waters it did not perform as well at the coastal validation site (Yongala) (r^2 = 0.65) (Magno-Canto et al. 2019). It is one of only two spatially explicit benthic light products available (the other is eReefs – see next chapter), so we have applied and tested it in Cleveland Bay in this analysis (Figure 24).

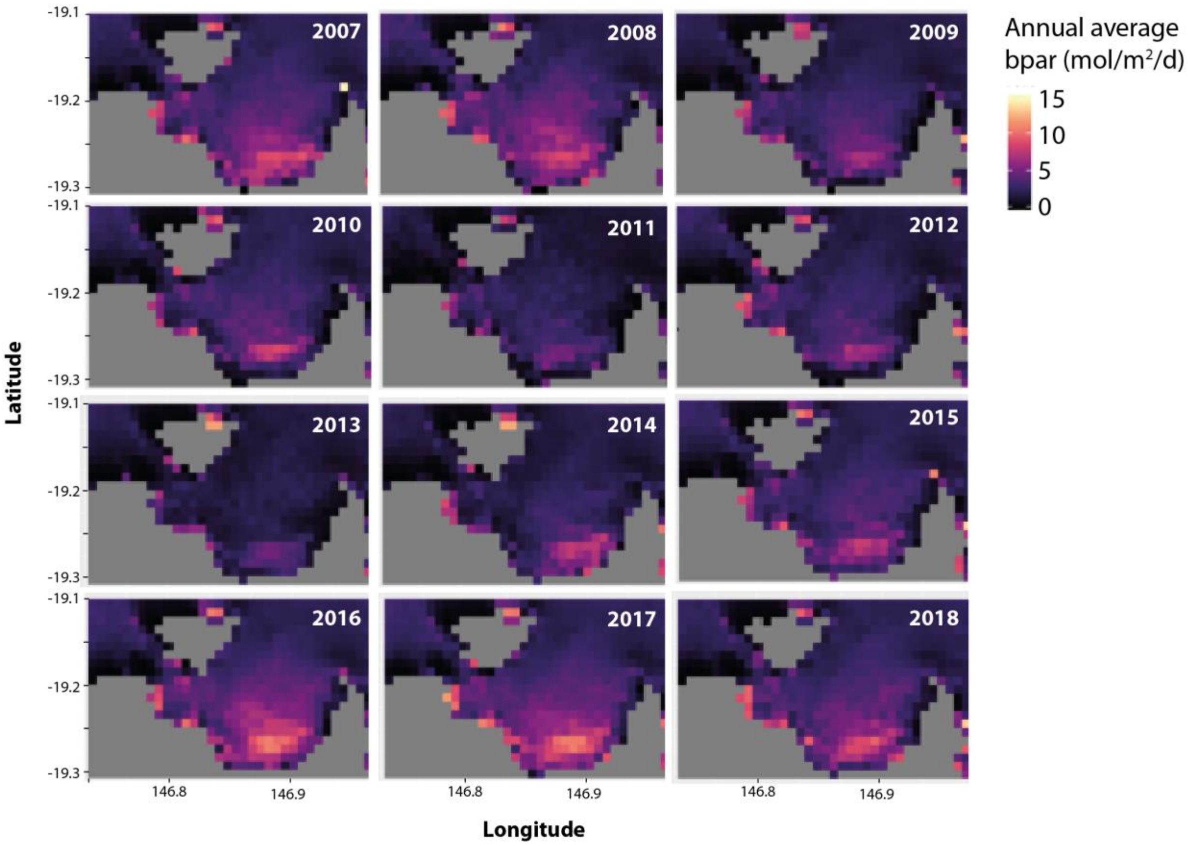


Figure 24. Annual average (October to September) bPAR [mol m^{-2} d^{-1}] from 2007 to 2018. Provided by the Australian Institute of Marine Sciences (T. Magno-Canto).

Monthly means of daily benthic photosynthetically active radiation (PAR) were extracted from the bPAR model database. These were used to calculate annual average bPAR (Figure 27) and seagrass growing season (June to October) average bPAR. Annual average bPAR was calculated for the year up to seagrass annual surveys (October to September), which also coincides with the water year used to calculate flow and loads (Chapter 3). Average annual benthic light encompasses the full range of the seagrass annual growth cycle including light limitation during the wet season and higher light levels during the growth season and therefore, remains a common indicator of seagrass habitat suitability often expressed as % surface irradiance (Erftemeijer and Robin Lewis III 2006), but is expressed as benthic light in the GBR because of its greater relevance to absolute light availability. Furthermore, seagrasses in Cleveland Bay that are included in this analysis persist over annual time-scales (i.e. they are not annual populations), and even respond to environmental pressures such as sediment loads over annual or multi-annual time-frames (see previous chapters). Therefore, annual bPAR is an appropriate starting point for exploring long-term light requirements. However, annual light levels are unable to distinguish variable light levels and light levels during the peak growing season and so we also summarised light levels for June to October when maximum seagrass growth and expansion occurs. It is also of interest to examine light levels during the wet season, when seagrass suffers wet season/senescent season decline (e.g. Collier et al. 2012); however, we didn't run a separate analysis on wet season light levels primarily because the seagrass survey data is from later in the year.

Previous work indicates that 6 mol/m^2/d is an acute light threshold of relevance for seagrass management for some of the higher light requiring species such as *Halodule uninervis* and *Z. muelleri*, with light levels below 6 mol/m^2/d leading to an increased risk of loss (Chartrand et al. 2016, Collier et al. 2016). It is worth noting here that other seagrass species require less light such as most *Halophila* species growing in deeper sub-tidal waters (Chartrand et al. 2018). We compared the area of Cleveland Bay with annual or growth season bPAR above 6 mol/m^2/d, with the area of seagrass detected in annual monitoring. The number of cells within each map that were above this bPAR level were counted and converted to an area and defined as the "potential seagrass habitat". We also investigated different bPAR levels ranging from 2-10 mol/m^2/d to determine the bPAR that yielded the best fit to the observed data (i.e. lowest root mean square error, RMSE). This analysis was undertaken on the shallow subtidal community (S2), and on all seagrass combined as per the previous chapter.

4.3.2 bPAR validation in Cleveland Bay

The original model used to estimate bPAR based on satellite imagery did not include depths shallower than 5m (mean sea level) (Magno-Canto et al., 2019), but the satellite remotely sensed and modelled benthic light and eReefs (section 4), are the only spatial light products available so we have applied it in shallow water in this analysis. Therefore, we undertook to evaluate its performance in shallow waters of Cleveland Bay. We compared the monthly mean bPAR values between the satellite data and *in situ* light logger data for sites around 5m depth (a map of locations is given in the following chapter, Figure 34).

4.4 Results

4.4.1 Predicting seagrass state from bPAR

The observed seagrass area is plotted against habitat area based on annual average and growing season bPAR above 6 mol/m^2/d in (Figure 25). When annual average light was used to predict potential habitat, bPAR > 6 mol/m^2/d tended to over-predict area of shallow subtidal seagrass, and underpredict area when all seagrass communities were combined. The same bPAR led to underprediction of both shallow subtidal and combined seagrass communities if the growing season bPAR were used to predict potential habitat. These results indicate that light requirements do differ between the communities.

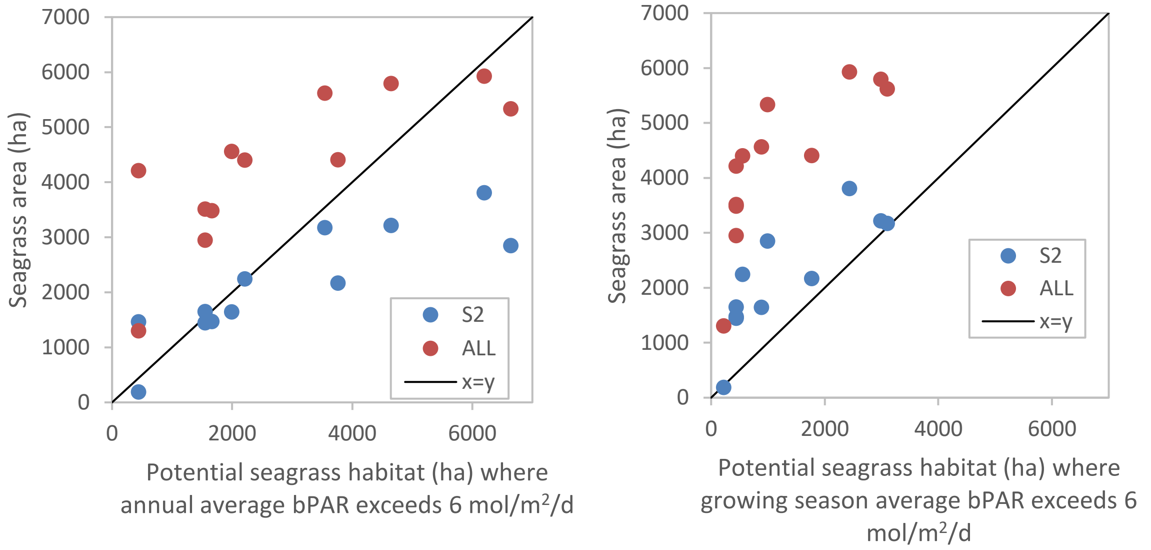


Figure 25. Observed seagrass area vs potential seagrass habitat where a) <u>annual average</u> bPAR exceeds 6 mol/m^2/d, and b) <u>growing season</u> average bPAR exceeds 6 mol/m^2/d.

For shallow subtidal seagrass area (S2), the minimum RMSE occurred when potential habitat was defined as area with annual average bPAR above 7 mol/m^2/d, and 5.4 mol/m^2/d when growing season average bPAR were used (Figure 26). When all seagrass communities were combined, the best agreement between potential habitat and observed seagrass area (i.e minimum RMSE) was for bPAR threshold of 5.6 mol/m^2/d and 4.3 mol/m^2/d, for annual average light and growing season bPAR respectively (Figure 26). In Figure 27, observed seagrass is plotted against potential habitat area for these "optimal" light thresholds.

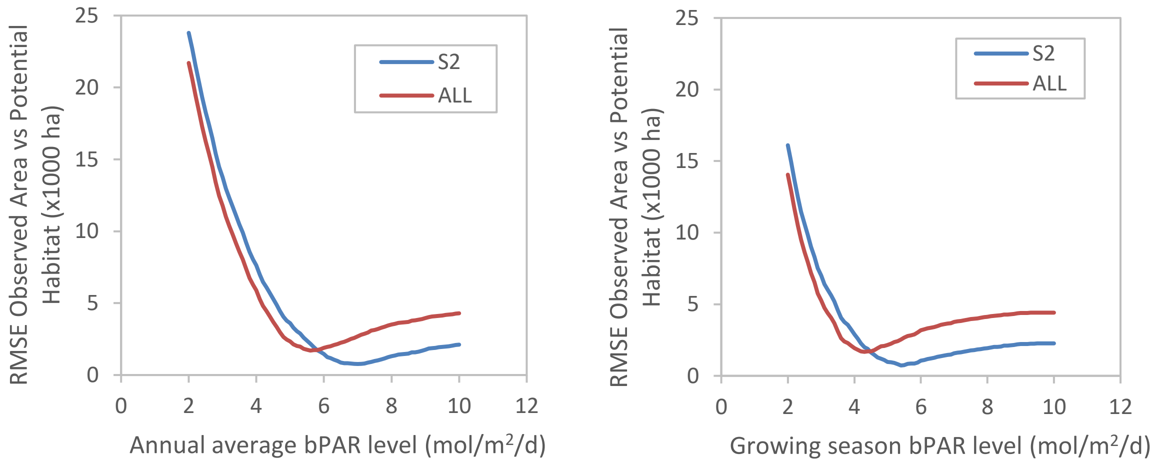


Figure 26. Root mean square error (RMSE) between observed seagrass area and potential habitat for a) annual average bPAR and b) growing season (Jun-Oct) average bPAR, for shallow subtidal (S2), and all (ALL) seagrass community types. For <u>annual average</u> bPAR, minimum RMSE for ALL seagrass communities occured at 5.6 mol/m^2/d, and 7 mol/m^2/d for shallow subtidal seagrass. For growth season, minimum RMSE for ALL seagrass communities occured at 4.3 mol/m^2/d, and 5.4 mol/m^2/d for shallow subtidal seagrass.

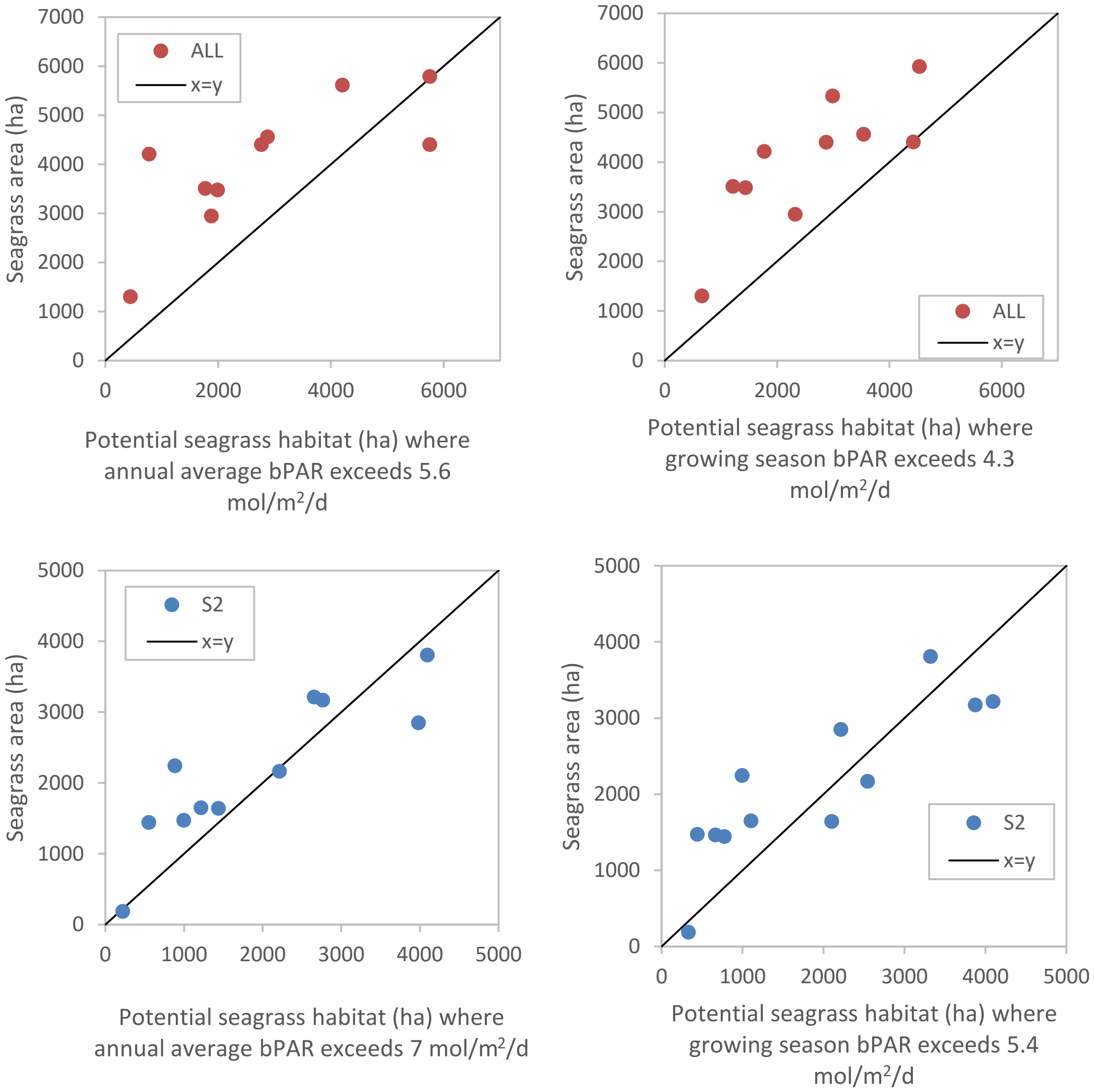


Figure 27. Observed seagrass area and potential habitat, based on bPAR threshold corresponding to minimum RMSE, for Top: ALL seagrass communities, Bottom: shallow subtidal (S2) seagrass. Left: Annual average. Right: Growing season average.

4.4.2 bPAR validation in Cleveland Bay

Light measurements from satellite data (bPAR) were often greater than those measured by *in situ* loggers (Figure 28 Figure 29). This may be affected by applying 1km resolution bPAR to logger data, which is deployed at a single point within a pixel that covers an area with sloping bathymetry and variable benthic light levels. However, if that was the only reason for the difference, we would expect that, on average, this would result in a spread around the 1:1 line with inclusion of multiple sites, but there is a bias towards over-prediction, that requires further exploration.

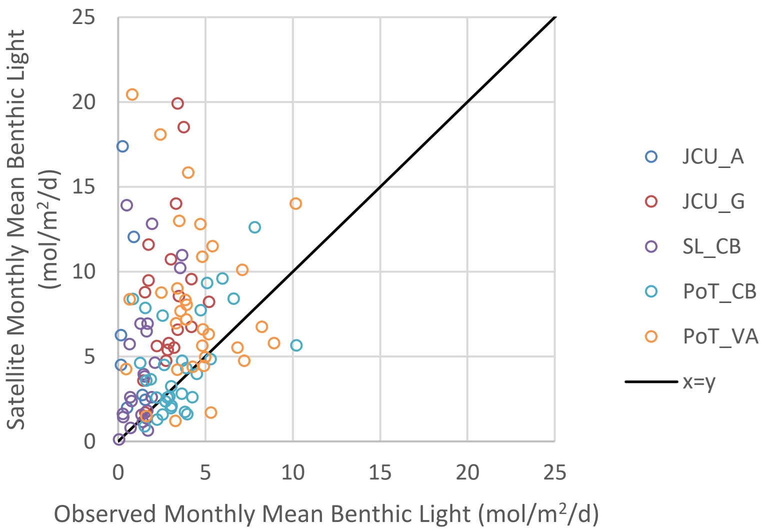


Figure 28. Satellite benthic light product validation against in-situ light logger data

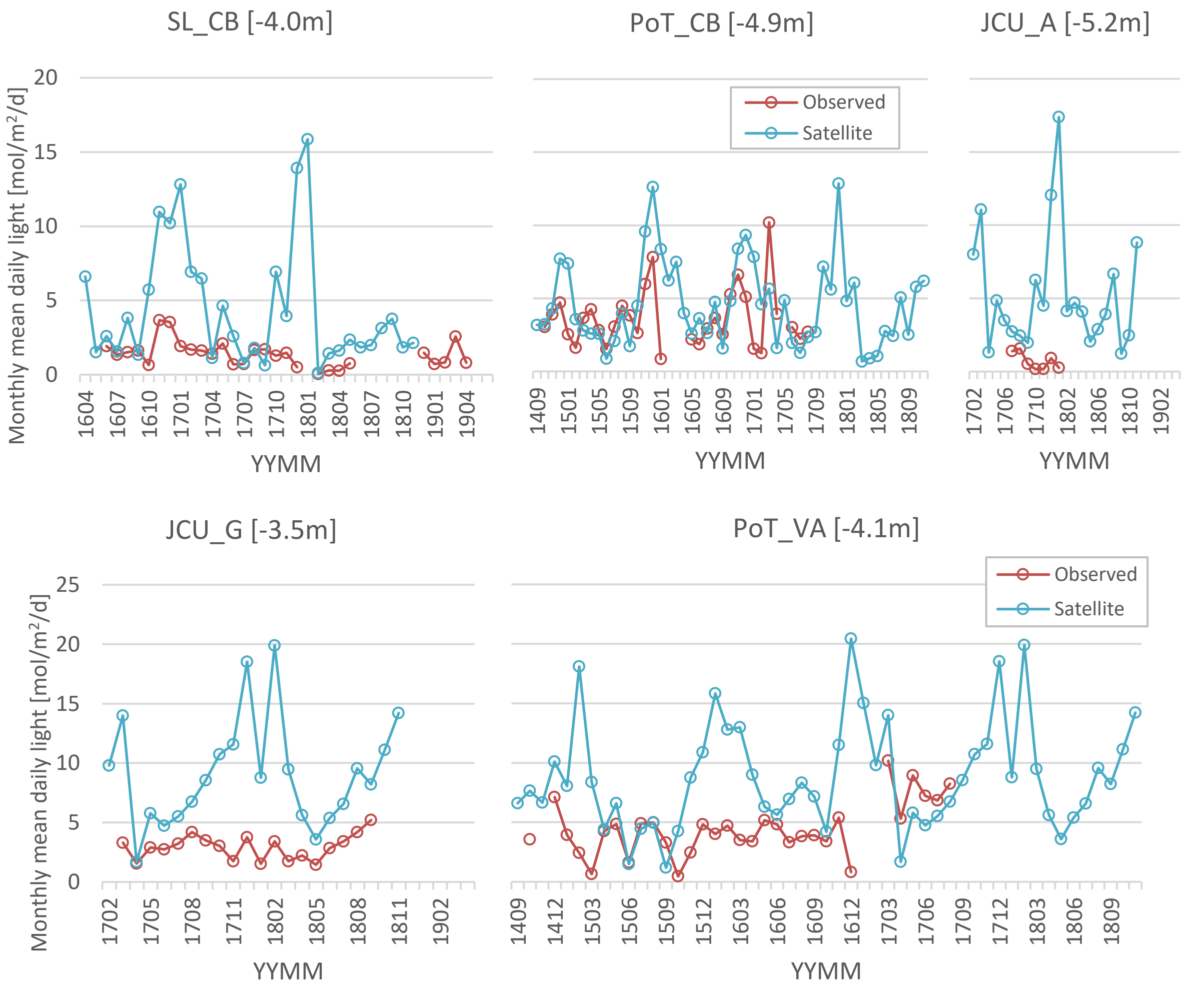


Figure 29. Monthly mean daily benthic light for satellite and in-situ light logger data. Observed light data are sourced from loggers deployed for this project (JCU), Port of Townsville and AIMS deployments (PoT), and from NESP project 2.1.5 from sites throughout Cleveland Bay (Figure 34)

4.5 Discussion

Spatial datasets such as bPAR, have potential application to seagrass distribution models, for assessing risk, setting thresholds and for development of a light-based metric for reporting on water quality (Robson et al. 2019). Here we investigate annual and semi-annual growth season bPAR levels used to predict potential seagrass distribution that most closely matches actual seagrass distribution (shallow subtidal population) and found this occurred at annual average bPAR of 4-7 mol/m^2/d. This simple approach could be used to predict where seagrass is expected to occur based on annual bPAR in Cleveland Bay.

The agreement between observed and predicted areas of seagrass (Figure 25 and Figure 27) was greatest for the shallow subtidal community compared to the seagrass community of all combined, which includes intertidal seagrass. The subtidal seagrass population is likely to be at greater risk of light limitation because it is permanently submerged compared to the intertidal community, which receives higher light levels during or around low tide. The high light levels at or around low tide do not necessarily translate to proportional increases in photosynthesis, growth and biomass, however, due to carbon limitation (and desiccation risk) (Shafer et al. 2007) when exposed to the air and saturation of photosynthetic rates (Petrou et al. 2013, Collier et al. 2018). Furthermore, the intertidal seagrass population is constrained in how much it can expand both at the lower and upper boundaries, so higher light levels do not necessarily allow greater expansion in either direction. There are also other factors that can impact intertidal seagrasses when exposed to air that may counter any benefit from high light levels. When tidal exposure occurs in the middle of the day seagrasses can suffer from desiccation stress with leaves “burning” resulting in seagrass loss (Unsworth et al. 2012). As previously described, intertidal populations are at risk of light limitation in turbid waters (Petus et al. 2014, Rasheed et al. 2014) especially at times when very low tides tend not to occur during the day (the wet season).

The subtidal population is also constrained at the upper boundary by definition (the boundary delimiting subtidal and intertidal populations), however, it can extend the deepest edge of its distribution into deeper waters as light levels increase across the habitat area, and there is greater area above certain light levels (Abal and Dennison 1996).

Seagrass distribution is also affected by a range of other environmental conditions, such as wind/wave exposure, benthic substrate, and nutrient availability to name a few and as discussed in previous chapters. It is also affected by biological processes, including grazing (Scott et al. 2018). Inclusion of these additional factors was beyond the scope of work in this study, but will be explored in NESP project 5.4 (where data is available), which is an extension of the project described here-in.

In the previous chapters, we identified that biomass varies over annual time-scales (chapter 2), and change in biomass responded the most strongly to sediment loads over annual time-scales, as opposed to multi-annual time-scales (chapter 3). Biomass can quickly respond to changes in light levels, by reducing leaf size, dropping leaves, and senescing shoots when light becomes limiting (McMahon et al. 2013), and increases in these morphological features as light levels increase during the growth season, leading to higher overall biomass. Therefore, further spatially-explicit analysis of bPAR or other light products should also consider biomass.

This initial bPAR data exploration was undertaken at a temporal scale (annual, and growing season) that is comparable to the temporal scale of the data sets used to identify ERTs (Chapter 3). However, the light environment is highly variable in both space and time (O'Brien et al. 2018) and the photoacclimatory response of benthic habitat to variable light levels is complex (DiPerna et al. 2018). For example, light use saturates above certain light levels, often denoted as the saturation constant (E_k) (Collier et al. 2018). Therefore, light requirements are sometimes referred to as the number of Hours of light saturating irradiance (H_{sat}) required for productivity and growth (Dennison and Alberte 1985, Collier et al. 2012). bPAR has been developed into a water quality index that also recognises that high light levels do not translate into higher productivity and growth above certain levels (Robson et al. 2019). As such, the index, which is based primarily on coral light requirements, reaches the maximum at 14 mol/m^2/d (with the range 0 to 14 mol/m^2/d scaled from 0 to 1). Further research investigating this index, and appropriate thresholds to be applied to seagrasses is the subject of on-going research (NESP TWQ 5.4, 3.2).

By comparing the bPAR model predictions to *in-situ* benthic light we identified that bPAR overestimates monthly light levels, and by extension over-estimated seasonal and annual bPAR used in the above analysis. Further exploration of the compatibility between bPAR and *in-situ* data is required, including finer scale temporal changes that cover different tidal ranges, levels of wind/resuspension etc could be undertaken to evaluate what processes influence the over-prediction. Due to these uncertainties, bPAR light thresholds were not used to develop seagrass distribution models or derive sediment load reduction targets in this project. Therefore, we also did not go to the next step of trying to understand what conditions were leading to a general over-prediction of benthic light based on bPAR in Cleveland Bay, and to compare the areas where seagrass habitat was predicted to the locations where seagrass was observed. However, even without these additional analyses, we demonstrate that bPAR may be useful to predict seagrass area in Cleveland Bay. This potential will likely be increased by consideration of a more nuanced understanding on the periodicity and intensity of light required to sustain seagrasses as well as other environmental factors influencing seagrass distribution and biomass.

5.0 AN EXPLORATION OF THE EREEFS MODEL FOR FINE-SCALE APPLICATION IN CLEVELAND BAY

5.1 Executive summary

The eReefs coupled hydrodynamic-biogeochemical model, an application of the CSIRO Environmental Modelling Suite was used by Brodie et al. (2017) to determine basin-specific water quality targets for the 35 basins discharging into the GBR, based on meeting seagrass light thresholds. The light thresholds (6 mol/m^2/d) were developed from short-term seagrass responses (biomass loss) to light reduction and it was assumed that light above this threshold would support long-term maintenance of seagrass biomass and extent without it being explicitly tested.

One of the key methods proposed for the NESP 3.2.1 project was to build on the work of Brodie et al. (2017) through using the eReefs model for setting and testing Ecologically Relevant Targets (ERTs) of catchment sediment loads such that seagrass in Cleveland Bay would meet desired state. There were a number of challenges in determining ERTs, including the spatial and temporal variability of seagrass in Cleveland Bay, the challenge of quantifying seagrass condition based on benthic light, and connecting benthic light to catchment sediment loads. eReefs was considered the ideal tool to undertake this task because it represents the hydrobiogeochemical processes which connect catchment inputs to ecological indicators and ecological response. However, the resolution of eReefs model was too coarse (at 1-4 km) to capture the processes relevant to seagrass. Therefore, we also used the Relocatable Coastal Model (RECOM) is designed for non-expert modellers to generate high-resolution models for local predictions from a nested model within the eReefs GBR-wide models, and applied these models to the following:

1. Analysis of benthic light predicted in Cleveland Bay by the eReefs GBR4 configuration (4 km resolution) using biogeochemical model versions B2p0, B3p0 and B3p1, under three Burdekin River catchment scenarios which each yielded different sediment loads. These predictions would form the basis of any estimates of ERTs, by relating different sediment loads to ecological outcomes in Cleveland Bay.
2. Comparison of RECOM's finer scale benthic light predictions with *in-situ* light data to verify use of the model for derivations of spatially-explicit K_d maps for setting ERTs.
3. Comparison of seagrass distribution predictions predicted by RECOM with seagrass monitoring data.
4. Based on the outcome of the three points above, quantify the catchment sediment loads required for seagrass in Cleveland Bay to meet desired state.

To address these objectives, we deployed light loggers in Cleveland Bay seagrass meadows to measure benthic light, and acquired additional sources of light data, and then compared this to eReefs light predictions. We also compared predicted seagrass distribution to monitoring data (described in previous sections). Our initial findings identified some challenges in modelling sediment dynamics with the eReefs modelling system. The eReefs team responded to this information by updating the sediment and biogeochemical models, which improved eReefs performance in predicting Secchi depth for the GBR as a whole.

We found in practice that there were substantial difficulties in using eReefs-RECOM model outputs to derive ecologically relevant targets because we were not able to validate the fine-scale predictions of benthic light and seagrass in Cleveland Bay. This reflects the challenges in using a model developed for large-scale predictions in a fine-scale application: the finest resolution feasible was 500 m, which is still quite coarse to capture local sediment and seagrass dynamics. Even if higher RECOM resolution is available, the local sediment-water quality interactions are likely to be strongly affected by sediment characteristics, but sediment data to initialize the model is only available at coarse spatial and temporal scales. Since the same sediment data is used to initialize the different catchment scenarios, it's also difficult to capture the legacy effects of long-term elevated sediment loads.

Therefore, we were unable to use eReefs to set ERTs based on predicted seagrass biomass and extent and their targets for the study site, and or to develop a method which would be broadly-applicable (i.e. for all 35 basins of the GBR). The insights gained from the data exploration could inform further model refinements in eReefs for application in nearshore areas, and so we present details of our results here. Our results highlight the very real challenge of quantifying connections between specific stressors and ecological responses, where ecological systems respond to a range of stressors, integrated over time and space: ERT are important for management, but challenging to quantify.

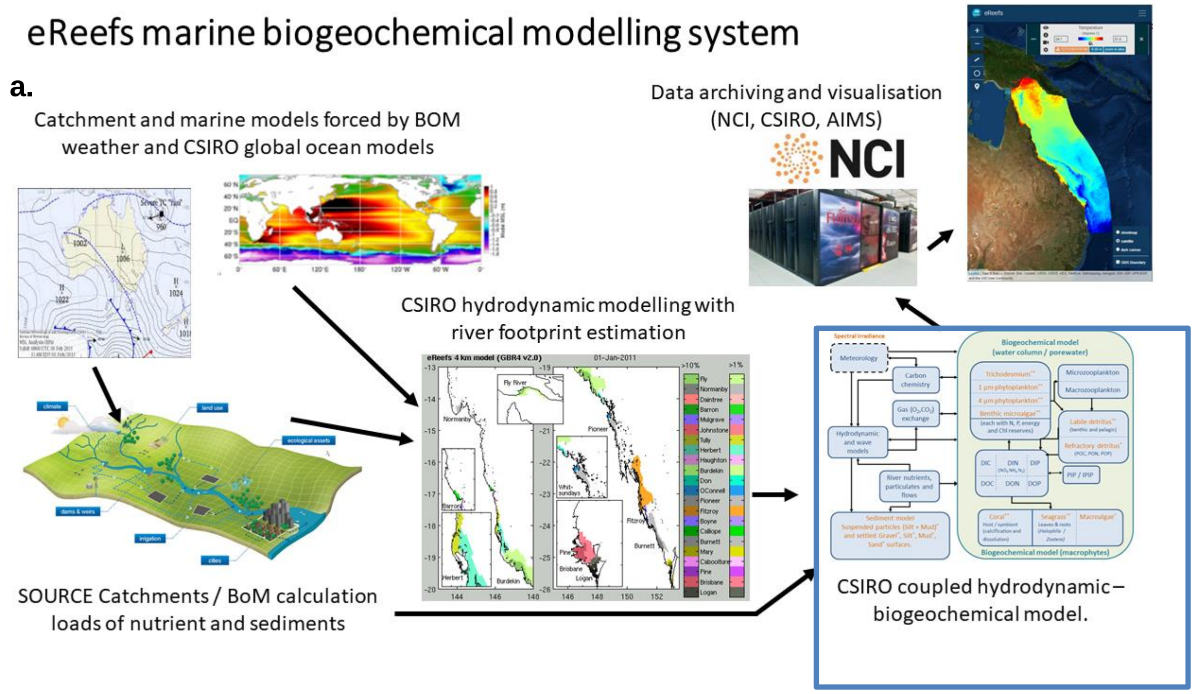
5.2 Background

The CSIRO Environmental Modelling Suite (EMS) (https://research.csiro.au/ereefs/) bring three dimensional hydrodynamic, sediment and biogeochemical models together as a powerful tool to support science, policy and management of the Great Barrier Reef (Figure 30). Both near real-time and hindcasting capabilities are provided, allowing land management change scenarios to be evaluated in terms of their impacts on water quality and key ecological indicators for the health of the Great Barrier Reef.

The three models (hydrodynamic, sediment and biogeochemical) that together form EMS have full documentation available online at https://research.csiro.au/cem/software/ems/ems-documentation/. Briefly, SHOC (Sparse Hydrodynamic Ocean Code) is the hydrodynamic model used in EMS: it is a three-dimensional finite-difference model (Herzfeld 2006, Gillibrand and Herzfeld 2016) that is applicable on spatial scales ranging from estuaries to regional ocean domains. The sediment transport model solves mass balance equations for sediment concentrations in coupled benthic and pelagic layers and the exchanges between them (Margvelashvili et al. 2018). The biogeochemical model (Baird et al. 2019) predicts the spectrally-resolved underwater light environment, and the ecological processes and nutrient conversions/exchanges in the pelagic, epibenthic and sediment zones. The ecology accounted for within the biogeochemical model includes phytoplankton, zooplankton, corals, seagrass, benthic microalgae and macroalgae.

Of key relevance to this project, the coupled hydrodynamic-biogeochemical model (see Figure 25) provides predictions of benthic light as photosynthetically active radiation (PAR) and seagrass distribution. Seagrass predictions from eReefs include estimates of biomass (g DW m^{-2}) for two growth types of seagrass – *Halophila*-like and *Zostera*-like – which loosely aim to distinguish between seagrass species that are small, fast-growing and have low minimum light requirements (*Halophila*-like) and species that are slightly larger, slower growing, and have higher minimum light requirements (*Zostera*-like) – see Baird et al. (2016) for more information.

As eReefs predictions of seagrass distribution are mechanistically dependent on benthic light availability, it is expected that the model will predict: (1) no seagrass in submerged areas of consistently low light, e.g. below 2.8 mol photons m^{-2} d^{-1} (2) predominantly *Halophila*-like seagrass in areas with light environment consistently between 2.8 and 6 mol photons m^{-2} d^{-1}, and (3) predominantly *Zostera*-like seagrass in underwater areas with higher light availability. These expectations will of course be modified by temporal variability in the underwater light environment, and other environmental factors accounted for in the eReefs seagrass submodel including nutrient availability, water temperature, and physical damage due to high bed shear stress.



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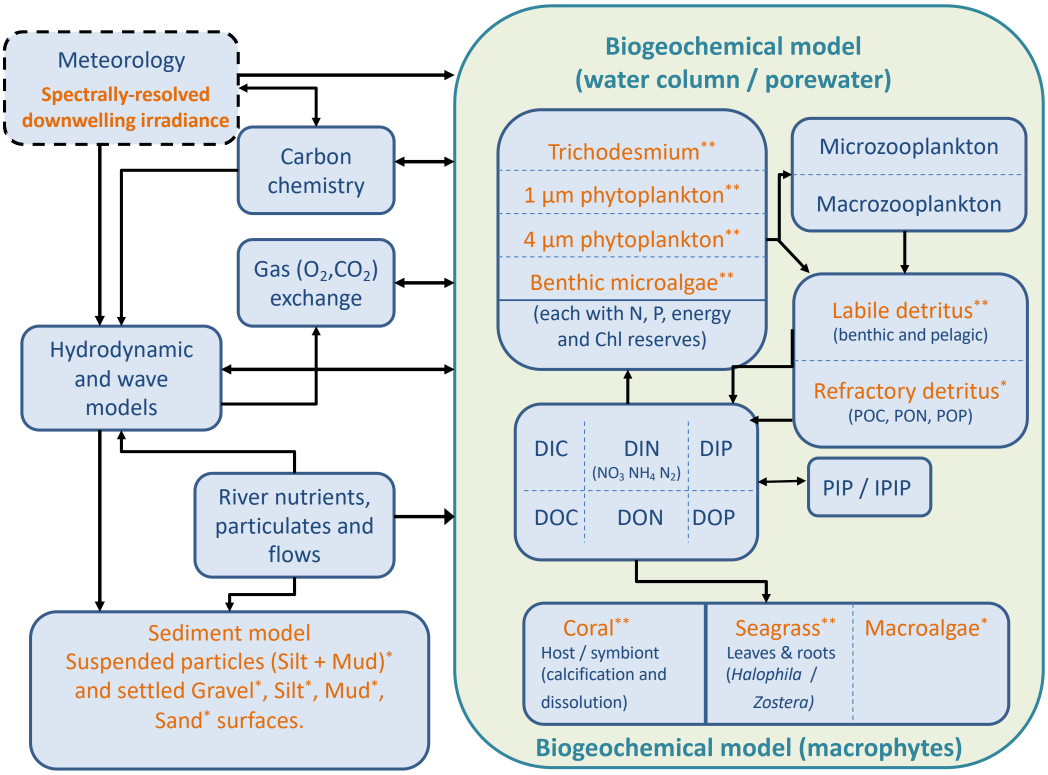

Figure 30. Schematic of eReefs model (Source: Baird et al. in preparation)

This section of the report (Section 5) summarises the analysis performed to investigate eReefs modelling capability for benthic light and seagrass at a fine resolution in Cleveland Bay. A complementary project, aimed at understanding the eReefs benthic light predictions in more depth, is also discussed in Section 5.9.

One of the key methods proposed for the NESP TWQ Hub Project 3.2.1 was to apply deterministic models (i.e. eReefs) for setting and testing ERTs according to seagrass biomass and extent targets, by comparing light outputs and seagrass distribution in Cleveland Bay under Burdekin sediment load scenarios based on different catchment land management practices. Such required fine-scale predictions, with higher resolution than the default 1 km or 4km grid of the eReefs model. Therefore, this project used the Relocatable Coastal Model (RECOM), which is a component of the eReefs model that solves the equations of the coupled hydrodynamic-biogeochemical model at higher resolution, for a local domain of interest within the GBR. RECOM has previously been used to simulate conditions around particular reefs (Baird et al. 2018) to assess the potential of suggested interventions such as sun-blocking surface films (Baird et al. 2019) and pumping of cooler water during heatwaves (Baird et al. 2019).

The aim of using eReefs GBR-wide configurations and RECOM-generated high-resolution models was to establish ERTs had the following objectives:

- Analysis of benthic light predicted in Cleveland Bay by the eReefs GBR4 model (4 km resolution) using biogeochemical (BGC) and sediment model versions B2p0, B3p0 and B3p1, under different Burdekin River catchment scenarios which yielded different

sediment loads. These predictions would form the basis of any estimates of ERTs, by relating different sediment loads to ecological outcomes in Cleveland Bay.
- Comparison of RECOM's finer scale benthic light predictions with *in-situ* light data to verify use of the model for derivations of spatially-explicit K_d maps for setting ERTs,
- Comparison of seagrass distribution predictions predicted by RECOM with seagrass monitoring data
- Quantify the Ecologically Relevant Target as the catchment sediment load reduction required for seagrass in Cleveland Bay to meet desired state

5.3 eReefs biogeochemical model versions

Since the initial delivery of eReefs in January 2016, there have been two major updates to the biogeochemical (BGC) and sediment models. The work in this report used both eReefs B2p0 and B3p1 as these were both available for fine-scale modelling in RECOM. Key changes in the eReefs model between these different versions are summarized in Table 15.

Table 15. eReefs model versions: B2p0 and B3p1 used in this study, B3p0 was not available in RECOM

eReefs version	*Sediment layers*	*Sediment classes*	*Source Catchment model input*	*BGC and sediment model changes*	*Date model results became available*
B2p0	4	5	Cq2 (2014)	Dust size fraction introduced and trialled	2018
B3p0	12	9	Cq2 (2014)	Load of dust size fraction increased to 20 g m^{-3} for catchment inputs	February 2019 (not in RECOM)
B3p1	12	9	Cq3 (2019)	Load of dust size fraction changed to 10% of sediment load Sediment optical properties refined	October 2019

5.4 eReefs catchment load scenarios

Prior to applying RECOM in Cleveland Bay, the output of the lower resolution eReefs model were explored. Various catchment load scenarios are available within eReefs GBR4 H2p0. The scenarios involved using identical ocean and meteorological conditions forced with three different catchment load simulations, to quantify the impact of reduction of anthropogenic loads on marine water quality. The three catchment load scenarios were a best estimate of loads with present land management (q3b Baseline), the loads with pre-industrial (synonymous with pre-development in this report) vegetation cover (q3p Pre-Industrial), and the target loads recommended in the Reef 2050 WQIP (q3R Reef Targets). All scenarios are initialised with the same conditions at 1 December 2010 and include dams (Table 16).

Table 16. Source Catchment input load for three scenarios modelled by eReefs B3p1

Scenario	***Description***	***Details***
Baseline	Current (2019) land use and cover	q3b, P2R SOURCE Catchments with 2019 catchment condition from Dec 1, 2010 30/6/2018 (used for GBR Report Card 8 published in 2019), Empirical SOURCE with 2019 catchment condition, Jul 1, 2018 to April 30, 2019.
Pre-Industrial	Pre-Industrial land use and cover	q3p, SOURCE Catchments (2019 version) with pre-industrial vegetation cover.
Reef Targets	Anthropogenic load (Baseline minus Pre-Industrial) reduced by 30%	q3R, SOURCE Catchments with 2019 catchment condition (q3b) with anthropogenic loads (q3b – q3p) reduced according to the percentage reductions of DIN, PN, PP and TSS specified in the Reef 2050 Water Quality Improvement Plan (WQIP) 2017-2022 as calculated in Brodie et al. (2017). Further, the reductions are adjusted to account for the cumulative reductions already achieved between 2014 and 2019 that will be reflected in the 2019 catchment condition used in q3b.

Benthic light predicted in Cleveland Bay by eReefs GBR4 H2p0_B3p1 was compared for the three catchment scenarios in Table 16, using the three different version of the eReefs model shown in Table 15. The difference in benthic light between the Baseline scenario (representing current land uses and cover) and the Pre-Industrial scenario (more vegetative cover) should represent the maximum impact that sediment load reduction measures could have in Cleveland Bay. However, a comparison of the eReefs B2p0 outputs revealed very similar predictions between the baseline and pre-industrial scenarios (Figure 31). This was surprising, given that there is substantial evidence that Burdekin River sediment loads affect turbidity and hence benthic light in Cleveland Bay as described in previous chapters (e.g. see section 1.1) (Fabricius et al. 2013, Fabricius et al. 2014, Fabricius et al. 2016, Lewis et al. 2018).

There are a number of reasons why eReefs might not capture the effects of changes in Burdekin River sediment loads on benthic light predicted in Cleveland Bay. All eReefs scenarios were initialised with identical conditions (including sediment composition) in December 2010. In practice sediment composition in Cleveland Bay may differ substantially between pre-industrial and baseline scenarios, but there is no data available to parameterize that difference. Sediment characteristics will affect both resuspension rates and the time taken for sediments to settle once they have been resuspended, and thus catchment inputs may well have a legacy effect which cannot be captured here with the data available to parameterize the model.

Benthic light predictions from RECOM model using B2p0 were too high compared to the benthic light loggers, and various modifications in RECOM were trialled to resolve the issue, without success. Subsequently, eReefs was upgraded in B3p0 to include a more complex sediment model with additional sediment layers and representation of sediment types (Table 15). Preliminary Baseline results from B3p0 predicted light were promising, as benthic light predictions were slightly lower than B2p0 during a flood event, and markedly lower after the flood (Figure 31). However, like the B3p0 model, predictions of benthic light were similar between the different catchment scenarios, which did not capture the observation that benthic light in Cleveland Bay is affected by sediment load. Results were found to be similar to B2p0, with negligible difference between scenarios (Figure 31).

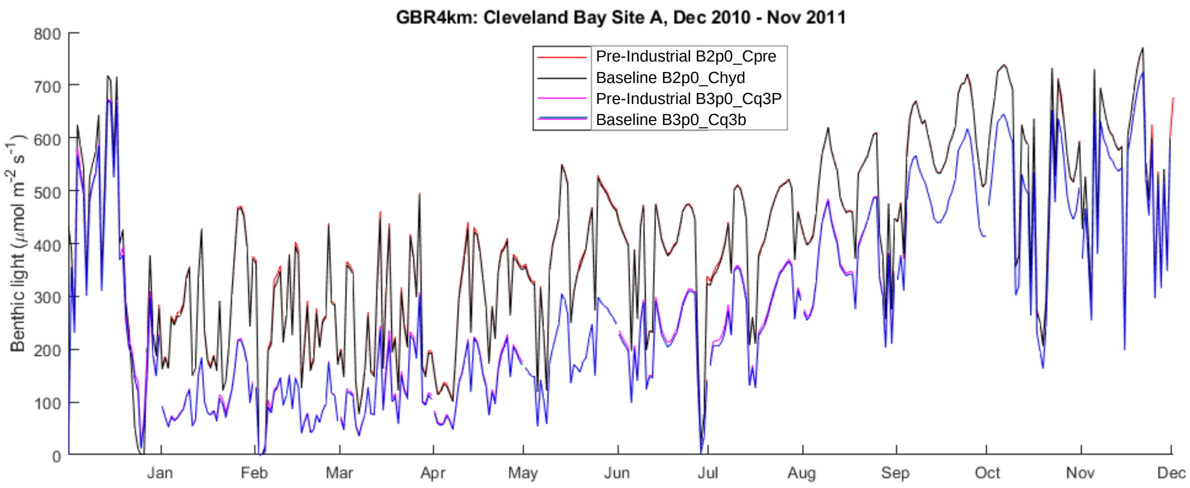

Figure 31. Midday instantaneous benthic light predictions (μmol m^{-2} s^{-1}) from eReefs B2p0 and B3p0 versions (4km resolution) at JCU Site A showing negligible difference between scenarios.

Further updates to the sediment model were incorporated in the eReefs model version B3p1 in Table 15), including use of the most recent Source Catchments model (Baird et al. 2019). Using eReefs GRB4 with version B3p1, benthic light levels within Cleveland Bay were predicted to diverge between Pre-Industrial (red) and Baseline (black) scenario at Site A following Burdekin River discharge events, as shown in Figure 32. Results from the intermediate Reef Target sediment load reduction scenario (blue) fall between the two scenarios as expected, but are closer to the Baseline than Pre-Industrial light levels. Results from all scenarios are similar during dry periods (i.e. 2015 and 2016). There is a common annual profile – mean monthly light exposure peaks over summer (December to February) before falling to a minimum usually during winter (June – August). eReefs predictions indicate that benthic light in Cleveland Bay can take a year or more to recover following a large Burdekin River discharge event.

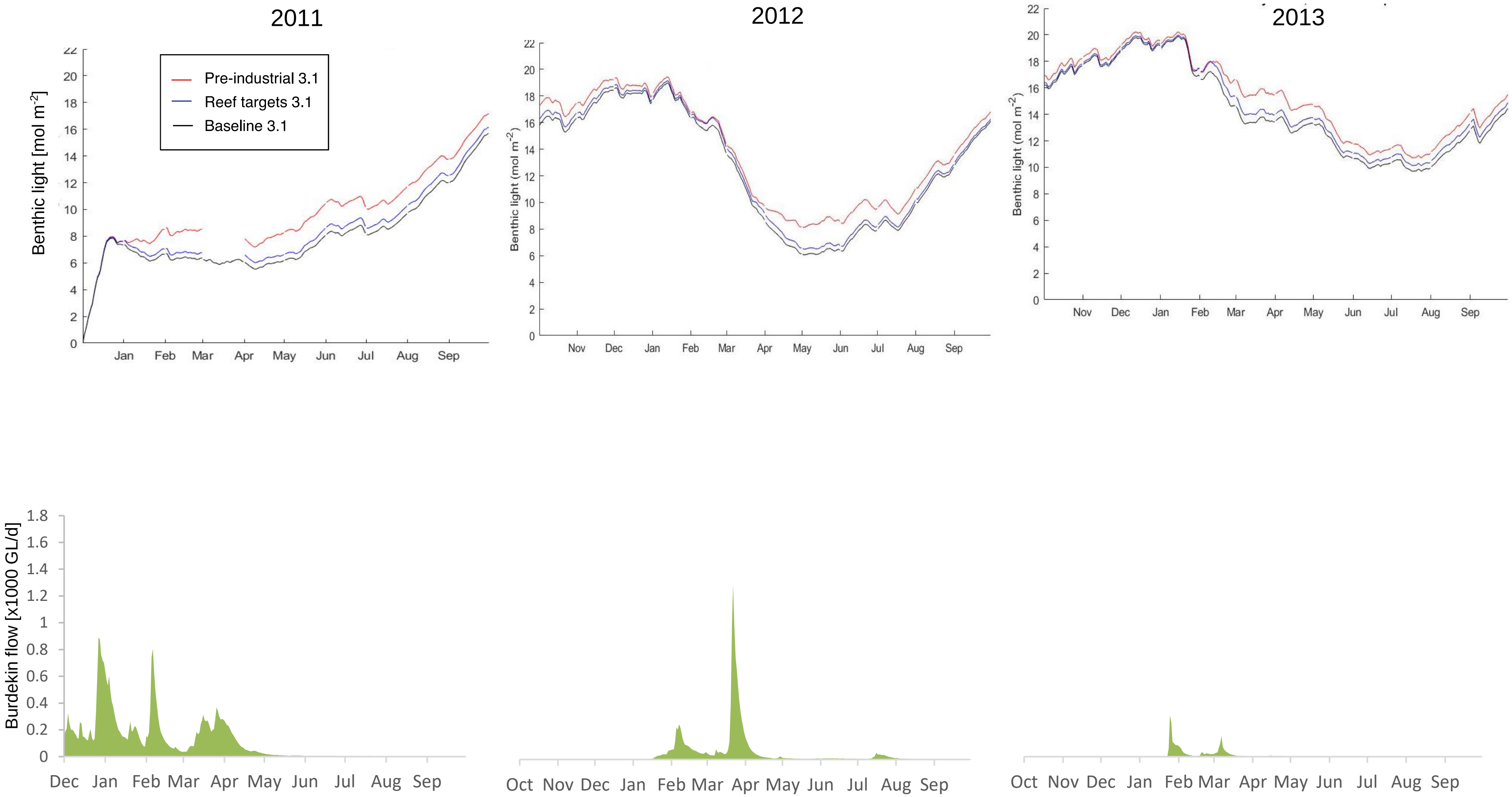

Figure 32 (part 1 of 3)

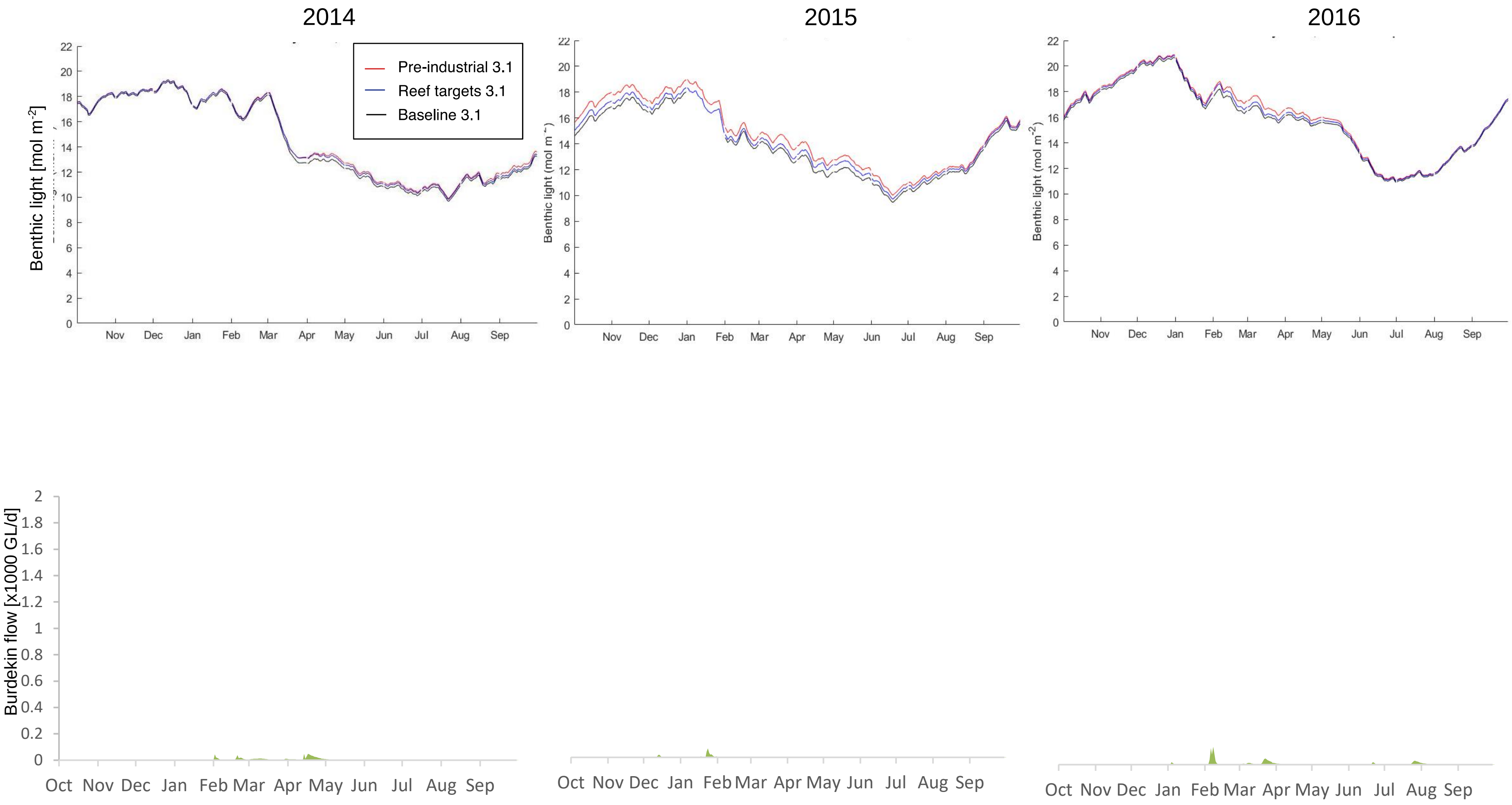

Figure 32 (part 2 of 3)

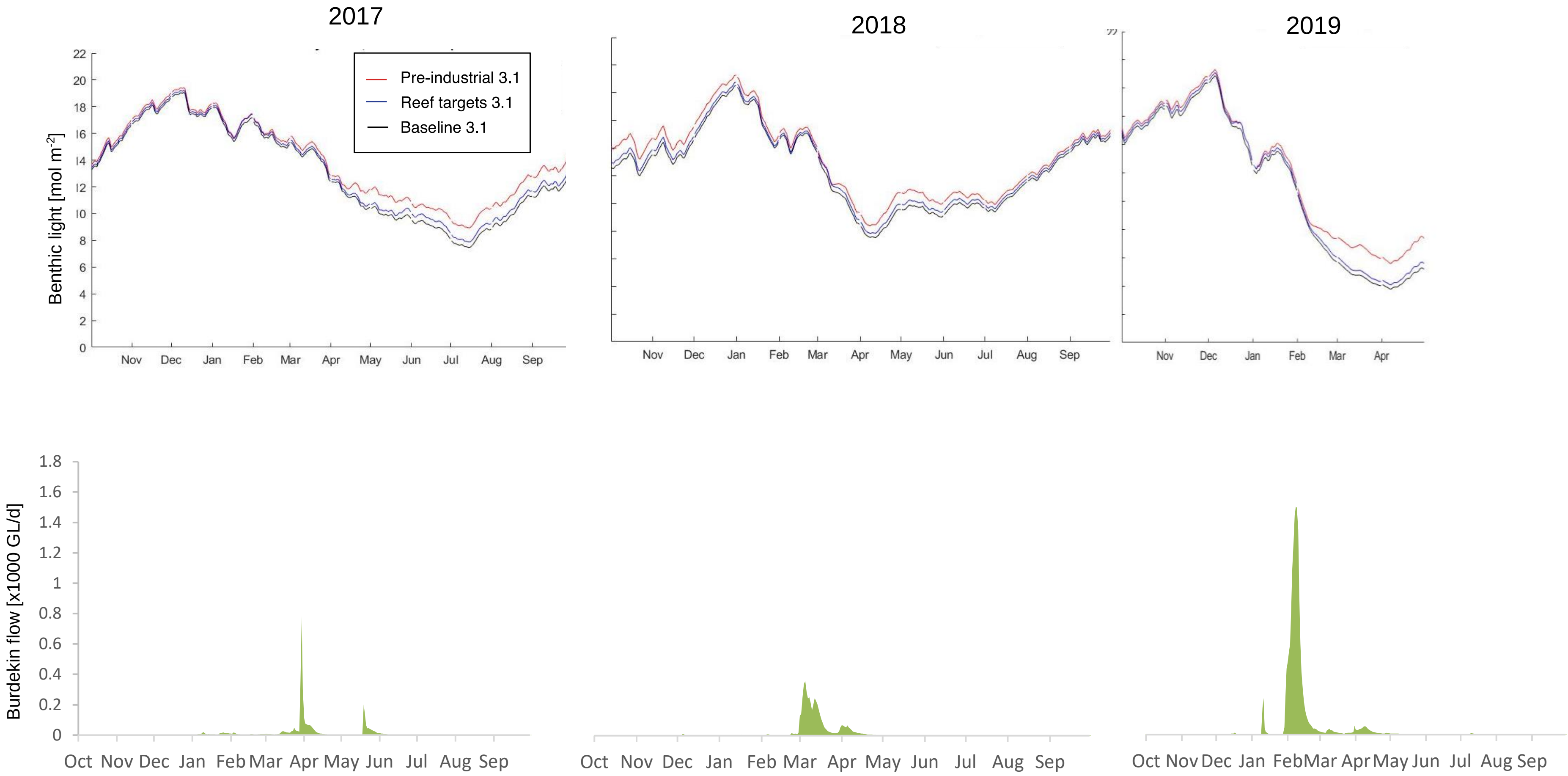

Figure 32 (part 3 of 3). In each of the three pairs of panels, the upper figures show monthly benthic light predictions (running average) from eReefs GBR 4km B3p1 at JCU Site A for 3 catchment scenarios: Pre-industrial catchment scenario (red line), Baseline catchment scenario (black line), Reef Targets catchment scenario (blue line). The lower panel in each pair shows daily Burdekin River (Clare gauge) discharge [x 1000 GL/day]. Comparing discharge with the benthic light predictions under the three catchment scenarios reveals little different under low or no flow. Following river discharge events, benthic light is predicted to be highest for the Pre-industrial scenario and lowest for the Baseline, with Reef Targets predicted to have slightly higher light than the Baseline.

5.5 RECOM setup

The CSIRO Relocatable Coastal Model (RECOM) nests within the coarser resolution eReefs model that provides initial and boundary conditions, while the RECOM model resolves a finer spatial resolution. The steps for running a RECOM simulation are (Herzfeld and Rizwi 2016):

1. Log on to RECOM using a web browser.
2. Select RECOM from the model list,
3. Define the curvilinear grid using the grid generation set of panels,
4. Select the time period to use and the forcing dataset to nest the RECOM model in,
5. Define the model configuration via tracer attribute, parameter and process sets,
6. Schedule the run

The GBR4km eReefs model outputs are available from December 2010 for a coarse grid resolution of 4km. There is a finer resolution eReefs model (GBR1km) however these outputs are only available from late December 2014, which therefore did not include the wet year of 2011. As seagrass is sensitive to sediment loads during wet years, and the test wet years are outside GBR1 availability, RECOM was nested with the GBR4 model. To ensure numerical stability and reasonable convergence times, a 40x60 grid was set up in RECOM (resolution 624.47m x 498.92m, bathymetry GBR 100 v5) to model Cleveland Bay (Figure 33). This grid size is still fairly large compared to the potential areas that seagrass can occupy, although we point out here the minimum spatial resolution possible with GBR 100 v5 bathymetry (the best available bathymetry dataset currently available) is 100 metres. This is a limitation worth noting when interpreting eReefs model predictions on a fine spatial scale. If finer scale predictions were desired, additional targeted measurements of local bathymetry are needed, which is a common issue in environmental modelling (Oreskes et al. 1994).

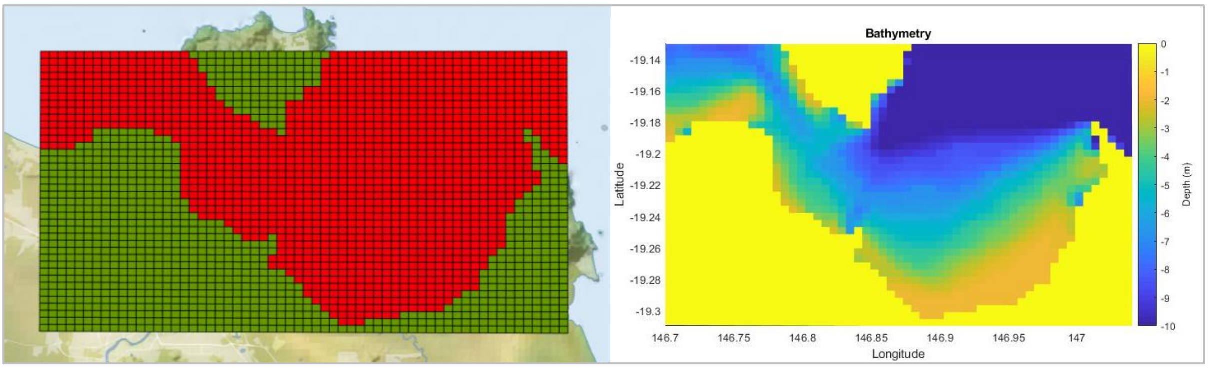

Figure 33. a) Cleveland Bay B3p1 RECOM grid 1438. b) Bathymetry for Cleveland Bay B3p1 RECOM model

The following sediment properties were used to set up RECOM runs:

- Sediment types:
  Dust FineSed Gravel-carbonate Sand-carbonate Mud-carbonate Gravel-mineral Sand-mineral Mud-mineral
- Initial sediment layer cell-centre depth:
  0.005 0.005 0.01 0.01 0.01 0.02 0.03 0.04 0.07 0.10 0.20 0.50

Table 17. eReefs is available at 1km and 4km resolution, across a range of time periods of interest, three catchment scenarios and a number of model versions. For each RECOM run, initialisation data and boundary conditions (for both the hydrodynamic model and the biogeochemical BGC model) are selected, as well as global atmosphere and global ocean datasets. In order to use the most recent version of the BGC and sediment model (BGC B3p1) and include the major discharge event of 2011, our final RECOM analysis was restricted to GBR 4km.

Input Dataset	*Resolution, scenario, application*	*Output availability range[1]*
RECOM Initialisation Data		
gbr1-recom-init (anest)	GBR1km	29/12/2014 15/11/2019
gbr4-recom-bgc-2p0-init (anest)	GBR4km – Catchment Real Time (Baseline)	30/11/2010 30/10/2016
gbr4-recom-bgc-2p0-nrt-init (anest)	GBR4km – Near real time	31/10/2016 20/11/2019
gbr4-recom-bgc-2p0-pre-init (anest)	GBR4km – Pre-Industrial	30/11/2010 30/10/2016
gbr4-recom-init (anest)	GBR4km	30/11/2014 23/09/2017
gbr4_H2p0_B3p1_Cq3b_Dhnd-init (anest)	GBR4km – Baseline	31/01/2011 29/04/2019
gbr4_H2p0_B3p1_Cq3p_Dhnd-bdry (anest)	GBR4km – Pre-Industrial	30/11/2010 29/04/2019
gbr4_H2p0_B3p1_Cq3R_Dhnd-bdry (anest)	GBR4km – Reef Targets	30/11/2010 29/04/2019
BGC Boundary[2]		
gbr1-recom-bgc-2p0-pre-bdry (anest)	GBR1km – Pre-Industrial	30/11/2015 29/04/2017
gbr1-recom-bgc-bdry (anest)	GBR1km	29/12/2014 11/09/2018
gbr4-recom-bgc-2p0-bdry (anest)	GBR4km – Catchment Real Time (Baseline)	30/11/2010 30/10/2016
gbr4-recom-bgc-2p0-nrt-bdry (anest)	GBR4km – Near real time	31/10/2016 20/11/2019
gbr4-recom-bgc-2p0-pre-bdry (anest)	GBR4km – Pre-Industrial	30/11/2010 30/10/2016
gbr4-recom-bdry (anest)	GBR4km	31/11/2014 26/07/2018
gbr4_H2p0_B3p1_Cq3b_Dhnd-init (anest)	GBR4km – Baseline	31/01/2011 29/04/2019
gbr4_H2p0_B3p1_Cq3p_Dhnd-bdry (anest)	GBR4km – Pre-Industrial	30/11/2010 30/03/2019
gbr4_H2p0_B3p1_Cq3R_Dhnd-bdry (anest)	GBR4km – Reef Targets	30/11/2010 29/04/2019
Hydro boundary[3]		
gbr1-recom-hydro-bdry (anest)	GBR1km	28/12/2014 22/11/2019
gbr4-recom-hydro-bdry (anest)	GBR4km	25/03/2008 24/11/2019
Global atmosphere		
Access-r-surface (client)	ALL	26/10/2011 01/12/2019
Global ocean		
Wavewatch3-r (client)	ALL	27/03/2013 01/12/2019

[1]As of 29 November 2019 https://recom.csiro.au/

[2]Biogeochemical (BGC) model boundary conditions at RECOM grid boundaries (scenario and 1km or 4km resolution)

[3]Hydrodynamic model boundary conditions (1km or 4km resolution)

Validation of RECOM assessment was undertaken as follows:

○ *Run the Baseline Catchment scenario (analogous to present day conditions):* Run RECOM 2010-2019 in Cleveland Bay nested in GBR4km grid at ~500m resolution, 1 year at a time, using previous year as initialisation file for the Baseline catchment scenario Baseline (this version was only available and working 12/11/19, which led to delay in project timelines)

○ *Validate RECOM predictions from Baseline catchment scenario with light and seagrass data.*

- Monthly averages of benthic light predictions compared against JCU, PoT and AIMS in situ logger data (specific sites: see Figure 34)
- Predicted seagrass presence, biomass and approximate species composition compared against monitoring data

- *Run the Pre-Industrial and Reef Targets scenarios (available 22/11/19)* and compare difference in results (light, seagrass) between scenarios

Results are also presented for earlier RECOM runs that were nested within the GBR1km B2p0 eReefs model using RECOM grid 1265 (70x200 cells, ~ 400m resolution, GBR 100 bathymetry), run from January 2017 to February 2018.

5.6 RECOM Benthic Light Predictions

5.6.1 Light logger data

In-situ light logger data was available from several sources, namely James Cook University (JCU) deployed loggers as part of this NESP project, Steve Lewis (SL) as part of the NESP 2.1.5 project, and the Port of Townsville (PoT) monitoring program, as shown in Figure 34. Coordinates and depths, from the GBR 100 v5 100m resolution Digital Elevation Model (DEM) (Beaman, 2010) and the RECOM grids, are listed in Table 18.

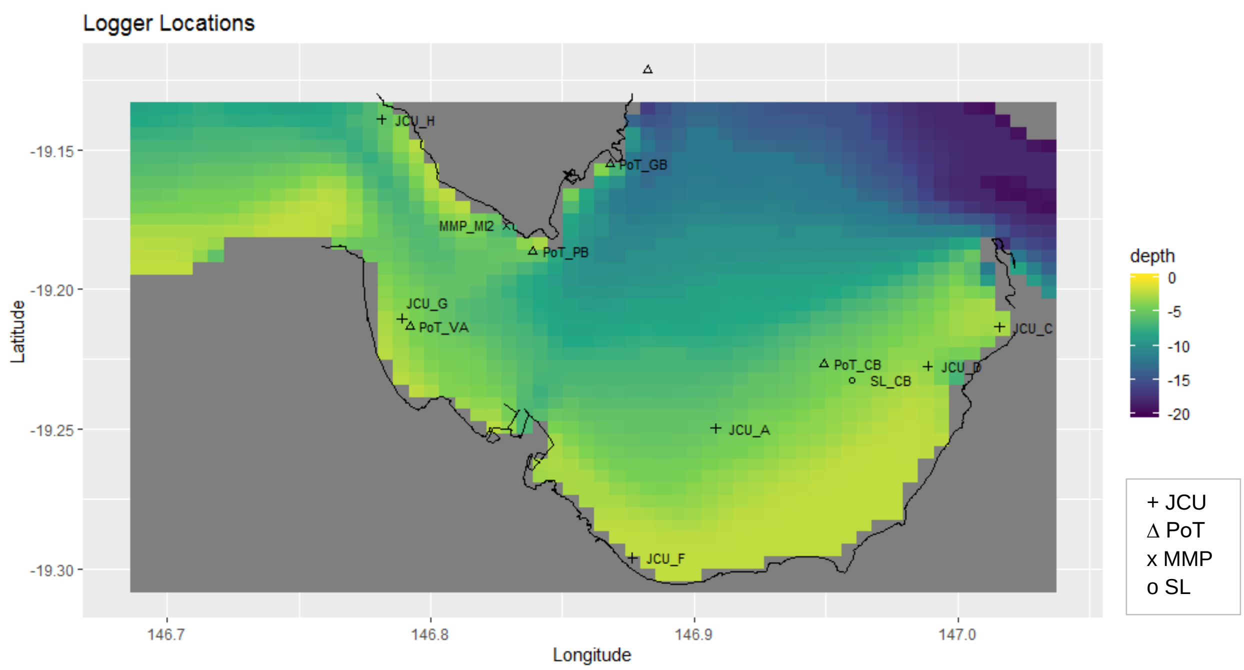

Figure 34. Cleveland Bay light logger locations as deployed by James Cook University (JCU), Port of Townsville (PoT) and Steve Lewis (SL).

Table 18. Light logger monitoring site depth and location. Depth reported at each site from the Digital Elevation Model (DEM) is compared with depth according to RECOM B3p1 and B2p0, which have slightly different grids, and lower resolution than the DEM. Shaded sites were located outside the RECOM model grid and not analysed further.

Site	*Depth from DEM [m]*	*Depth from RECOM B3p1 grid depth [m]*	*DEM depth – RECOM B3p1 Depth [m]*	*Depth from RECOM B2p0 grid depth [m]*	*DEM depth – RECOM B2p0 Depth [m]*	*Longitude*	*Latitude*
JCU_A	5.2	5.2	-	5.0	+0.2	146.9083	-19.2498
JCU_C	3.0	2.7	+0.3	3.1	-0.1	147.0159	-19.2134
JCU_D	3.4	3.4	-	3.0	+0.4	146.9886	-19.2275
JCU_F	2.2	99	-	2.1	+0.1	146.8766	-19.2962
JCU_G	3.5	3.5	-	3.7	-0.2	146.7892	-19.2105
JCU_H	7.1	5.5	+1.6	5.5	+1.6	146.7814	-19.1391
PoT_CB	4.9	4.9	-	4.6	+0.3	146.9494	-19.2266
PoT_FB	3.4	NA	-	99	-	146.8824	-19.1214
PoT_GB	3.1	6.8	-3.7	8.8	-5.7	146.8683	-19.1549
PoT_PB	5.0	5.5	-0.5	7.4	-2.4	146.8388	-19.1863
PoT_VA	4.1	4.1	-	3.7	+0.4	146.7924	-19.2133
SL_CB	4.0	4.0	-	3.8	+0.2	146.9601	-19.2325

5.6.2 Validation of RECOM light predictions

The Cleveland Bay RECOM grid was nested within eReefs GBR4km B3p1 model and run from February 2011 to April 2019. Light predictions were compared to *in-situ* observations and Figure 35 shows validation results were poor. RECOM predictions typically overestimated light availability (with the exception of sites JCU_D and PoT_GB). This was unexpected as Secchi depth results from eReefs B3p1 were generally well predicted across the GBR (Baird, M., pers comm.). Results from earlier B2p0 simulations (nested within eReefs GBR1km B2p0 from January 2017 to February 2018) are also plotted for comparison.

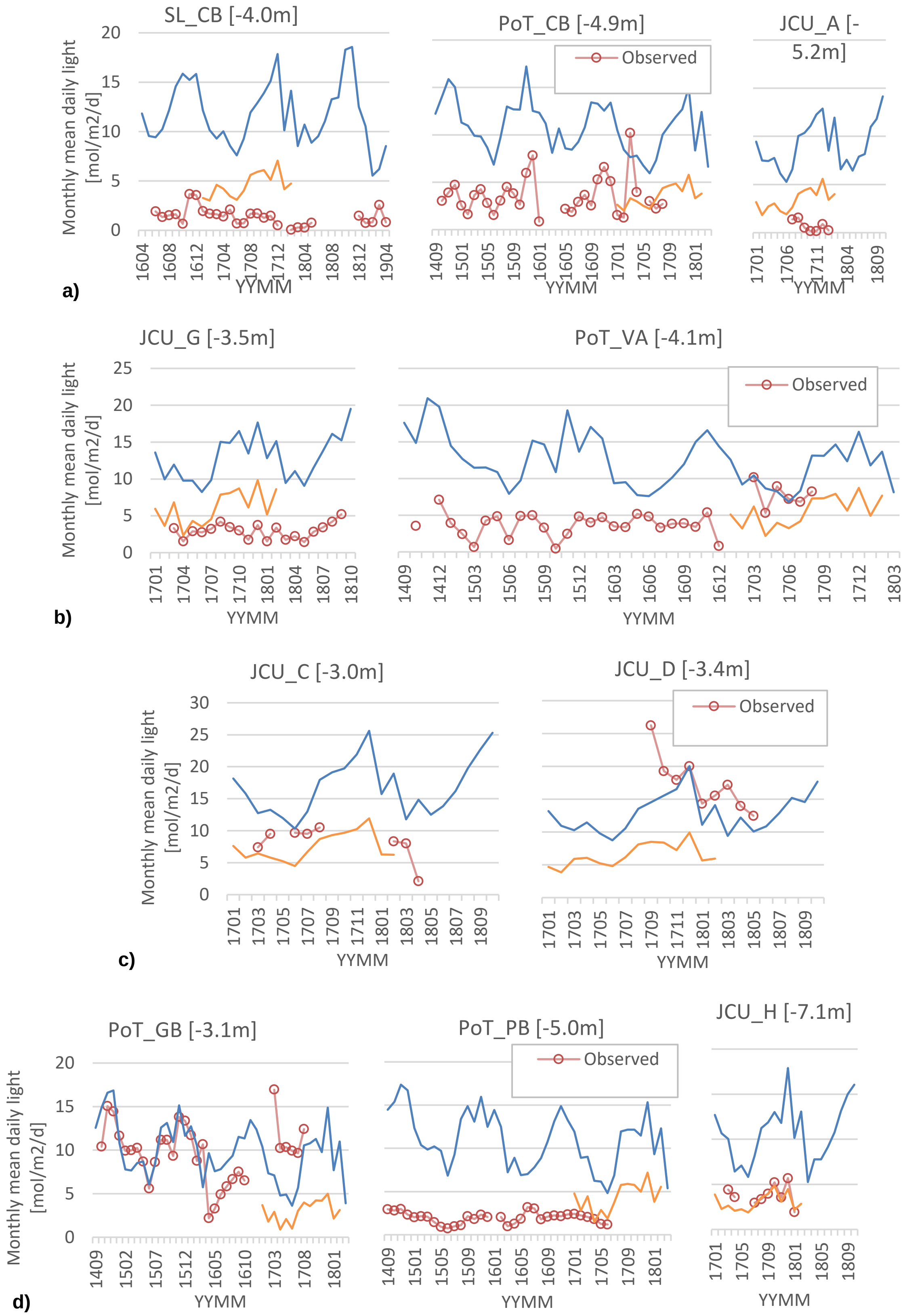

Figure 35. Monthly mean daily benthic light: RECOM predictions (~500 m resolution) using GBR4km model version B3p1, and GBR1km with BGC model version B2p0, and observations at three monitoring sites deployed by James Cook University (JCU), Steve Lewis (SL) and Port of Townsville (PoT).

Observations in deeper waters in the middle of Cleveland Bay (Figure 35a) were similar between JCU_A and SL_CB, while PoT CB recorded higher values. Depths were very similar for RECOM B3p1 and the DEM at the logger locations (Table 18), however benthic light predictions were much higher than values recorded by the loggers (Figure 6a). RECOM B2p0 modelled depths were 0.2m to 0.3m less than the DEM (Table 18), and B2p0 light predictions generally fell between observed values and B3p1 predictions (Figure 35a).

Light predictions from B3p1 in the vicinity of Virago Shoal in Rowes Bay (Sites JCU_G and PoT_VA) were overestimated despite no differences in depth (Figure 35b). B2p0 predictions were somewhat closer to observations.

Results varied at the shallow sites (Figure 35c). RECOM depth was 0.3m shallower and B3p1 predictions were overestimated at the shallower site JCU_C while B2p0 were similar. Results from B3p1 were reasonably accurate at JCU_D where modelled and measured depths were the same.

On Magnetic Island, Picnic Bay (PoT_PB) and JCU site H predictions are overestimated (Figure 35d). There are some differences in depth between measurements and model, which is unsurprising in this area as there could be abrupt change in depths around coral and rocky reefs. B2p0 predictions were a closer match for site JCU_H, although depth was different. Geoffrey Bay B3p1 predictions appear to align well with observations until April 2016, however there is a large discrepancy in depth between logger depth (-3.1m) and RECOM B3p1 model (-6.8m), and B2p0 is even deeper (-8.8m).

Across Cleveland Bay, light predictions from RECOM nested in eReefs B3p1 were higher than eReefs B2p0 (Figure 36Figure 36). This is also evident when comparing predictions from different versions of eReefs (4km resolution) over time (Figure 37). Benthic light predicted from eReefs B3p1 (blue line) greatly exceeds predictions from B3p0 (red) and B2p0 (pink). Vertical light attenuation is similar between B2p0 (pink) and B3p0 (blue) versions of eReefs, while B3p1 (black) has much lower light attenuation (Figure 38).

Resuspension thresholds, settling velocity, and optical scattering properties are some of the parameters within the sediment model of eReefs that could influence the performance of light attenuation predictions by RECOM in Cleveland Bay. There have been a number of changes between versions, many minor and some having more impact. Resuspension thresholds were modified between B2p0 and B3p0, visible in a comparison of suspended mud concentration (Figure 39) which shows higher mud concentration in eReefs B2p0 while lower, and similar, mud concentration between B3p0 and B3p1. Yet this does not explain the jump in benthic light predictions between B3p0 and B3p1.

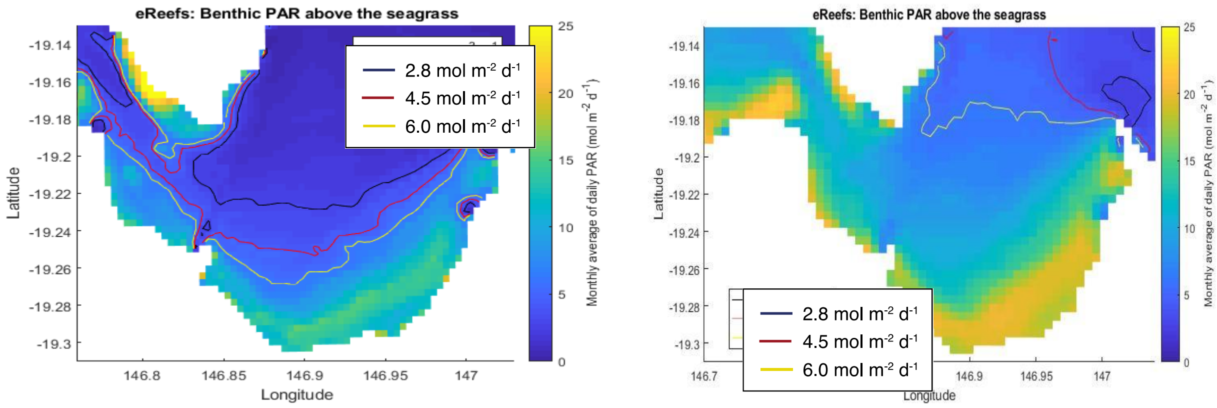

Figure 36. Monthly average of daily PAR, September 2017 a) B2p0; b) B3p1

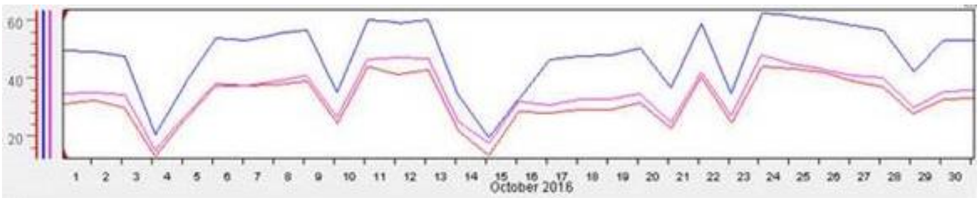

Figure 37. Light comparison over time shows that benthic light predicted in eReefs B3p1 (blue) greatly exceeds predictions from B3p0 (red) and B2p0 (pink).

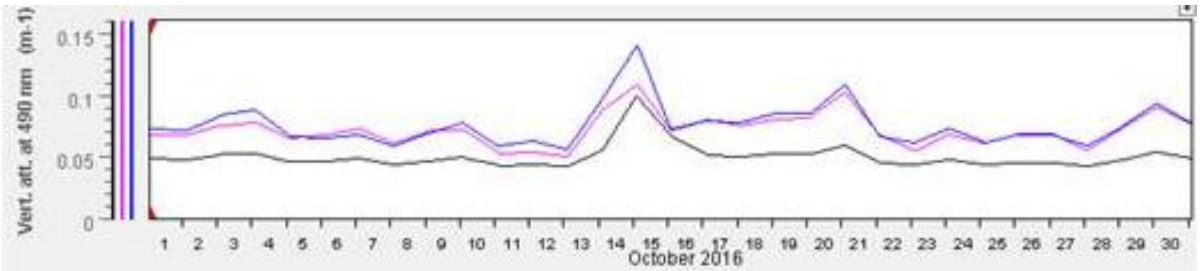

Figure 38. Vertical light attenuation is similar between B2p0 (pink) and B3p0 (blue) versions of eReefs, while B3p1 (black) has much lower light attenuation.

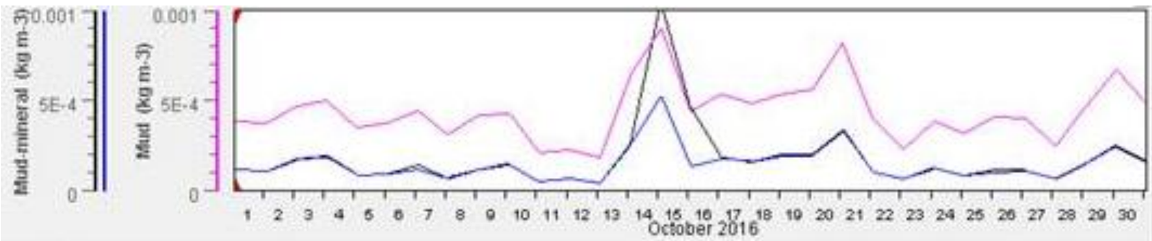

Figure 39. Suspended mud concentration shows higher mud levels in eReefs B2p0 (pink) while lower, and similar, mud levels between B3p0 (blue) and B3p1 (black)

Another change in eReefs was related to the optical properties (colour) of the suspended sediment. Previous versions of eReefs used optical properties of Gladstone harbour sediment, but B3p1 has been updated based on the latest scientific research (Soja-Wozniak et al., 2019) and uses Lucinda Jetty (north of Townsville) as a better match for sediment properties (particularly offshore or in deeper water). The new optical properties have improved light attenuation predictions across the GBR in general (Mark Baird, pers. comm), but unfortunately not in areas like Cleveland Bay (where sediment optical properties may be more similar to Gladstone Harbour than Lucinda Jetty).

The change in optical properties of sediment could elevate benthic light predictions in eReefs B3p1. To test this theory, RECOM was rerun with identical parameters except for reverting back to optical scattering properties of Gladstone Harbour sediment. Results indicate light predictions in Cleveland Bay improved but not sufficiently to approach the observed light logger data (Figure 40).

In summary, our analysis found that 500m resolution RECOM simulations nested within eReefs B3p1 4km model were unable to accurately predict benthic light in Cleveland Bay. Light availability is a major factor influencing seagrass growth, and eReefs seagrass predictions are explored in the next section.

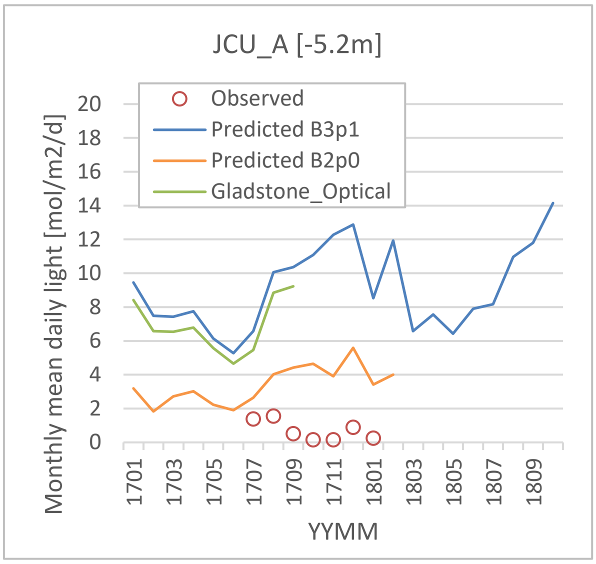

Figure 40. Light validation considering Gladstone optical properties

5.7 RECOM Predictions of Seagrass Biomass and Distribution in Cleveland Bay

5.7.1 Seagrass data

A survey in 1996 together with the annual seagrass surveys have been undertaken in Cleveland Bay since 2007, providing both presence/ absence data (Figure 41) as well as biomass for different seagrass species.

Previous work on this project has classified seagrass into community types (Chapter 2) and established desired state based on area and biomass. Variation in area and biomass between different community types and over time is illustrated in Figure 42.

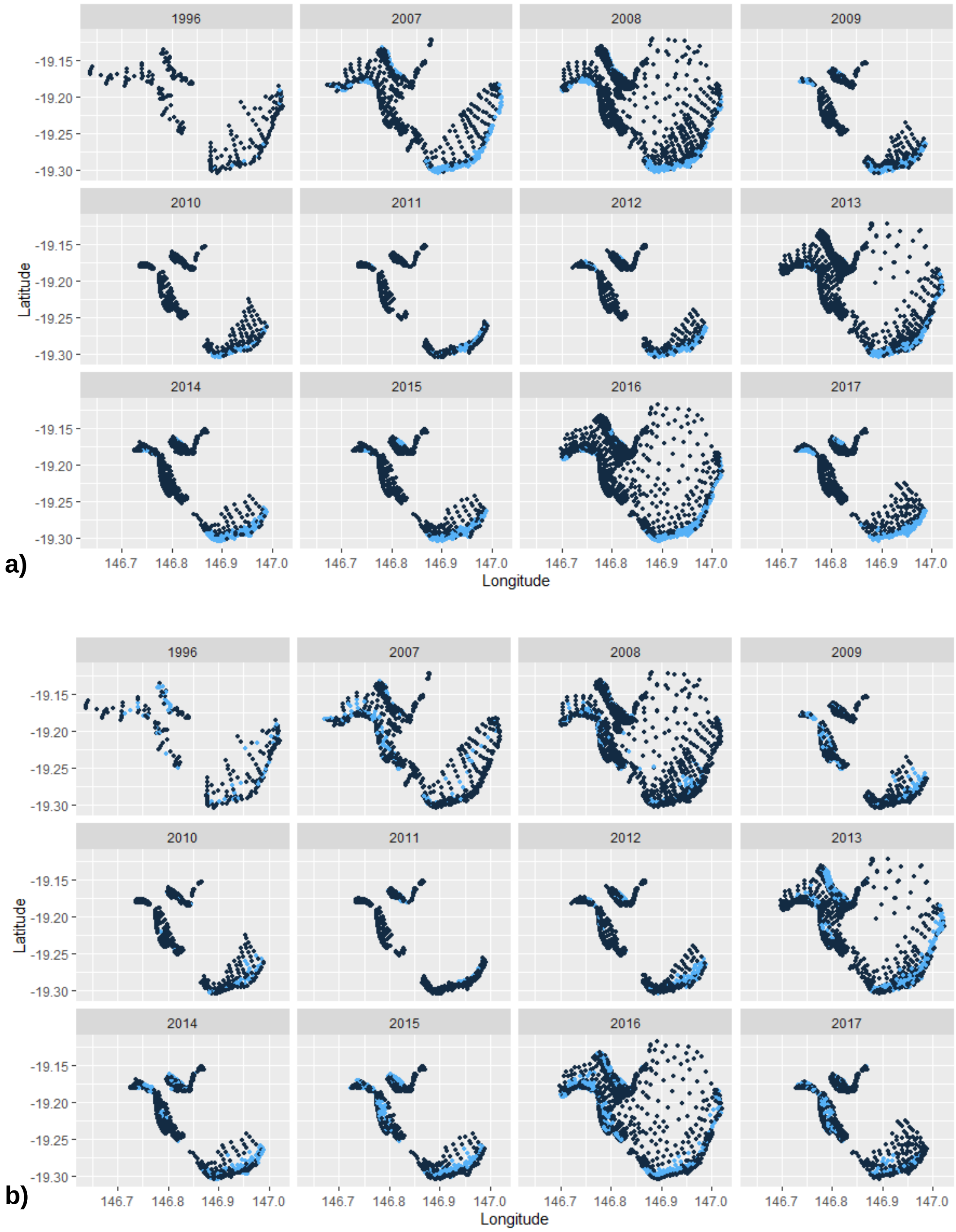

Figure 41. Seagrass presence and absence observations since 1996 for a) *Zostera muelleri* (ZC) and b) *Halophila ovalis* (HO). Light blue dots (1) represent monitored sites where species was detected (i.e. presence) while dark blue dots (0) represent monitoring sites where species was not detected (i.e. absence).

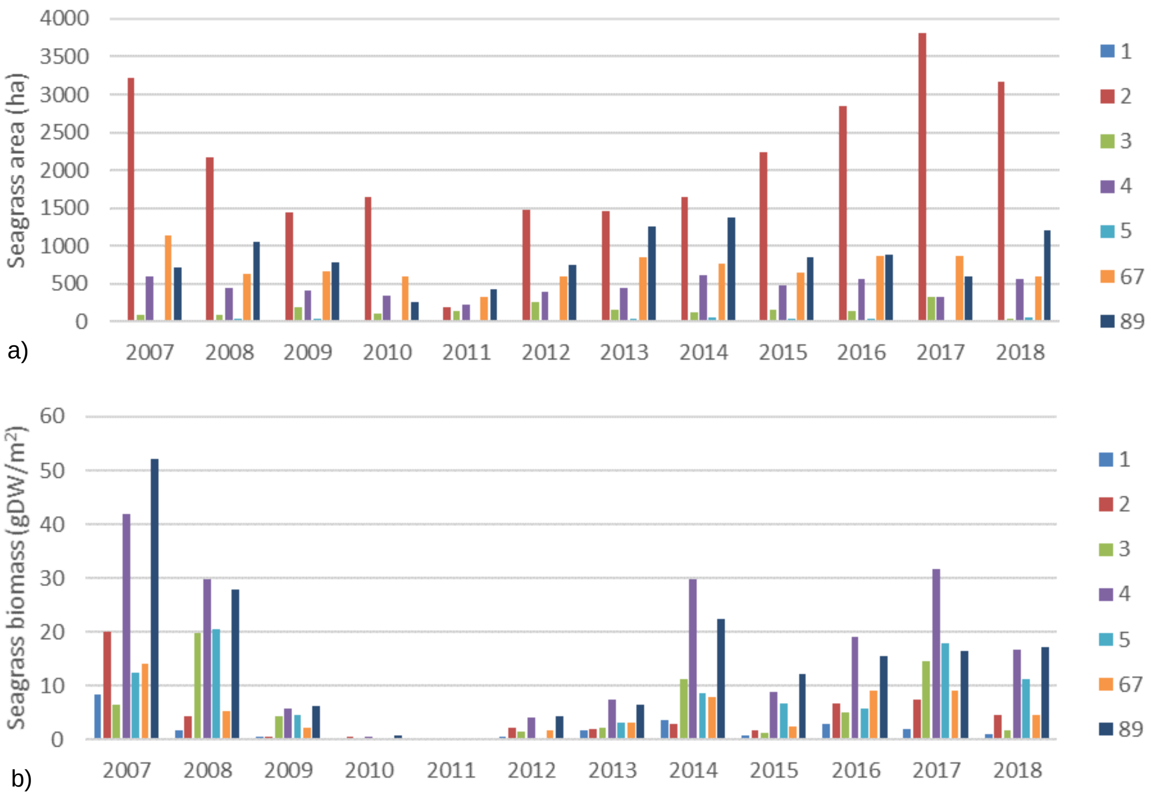

Figure 42. Annual variation in a) total area and b) mean biomass for different seagrass community types as defined in Collier et al. (in review). 1 and 2 are deep and shallow subtidal seagrass communities respectively; 3, 4, 5, 67, and 89 are intertidal seagrass communities.

5.7.2 Validation of RECOM seagrass biomass and area predictions

Seagrass growth is highly dependent on light availability, and this mechanisms is represented in the eReefs model (Baird et al. 2016). Since benthic light is over-estimated by RECOM it is unsurprising that seagrass presence is predicted deeper by RECOM that it is observed in monitoring data (Figure 43) and that the distribution does not match observations. The distribution of seagrass predicted in B2p0 more closely matches observations.

Where seagrass presence was observed, the biomass of *Zostera*-like seagrass that is predicted in eReefs B3p1 is typically underestimated compared to observations, while biomass of *Halophila*-like seagrass is over-predicted (Figure 44). The predicted range of biomass has narrowed from B2p0 to B3p1, and there is no clear relationship between eReefs predictions and observed data.

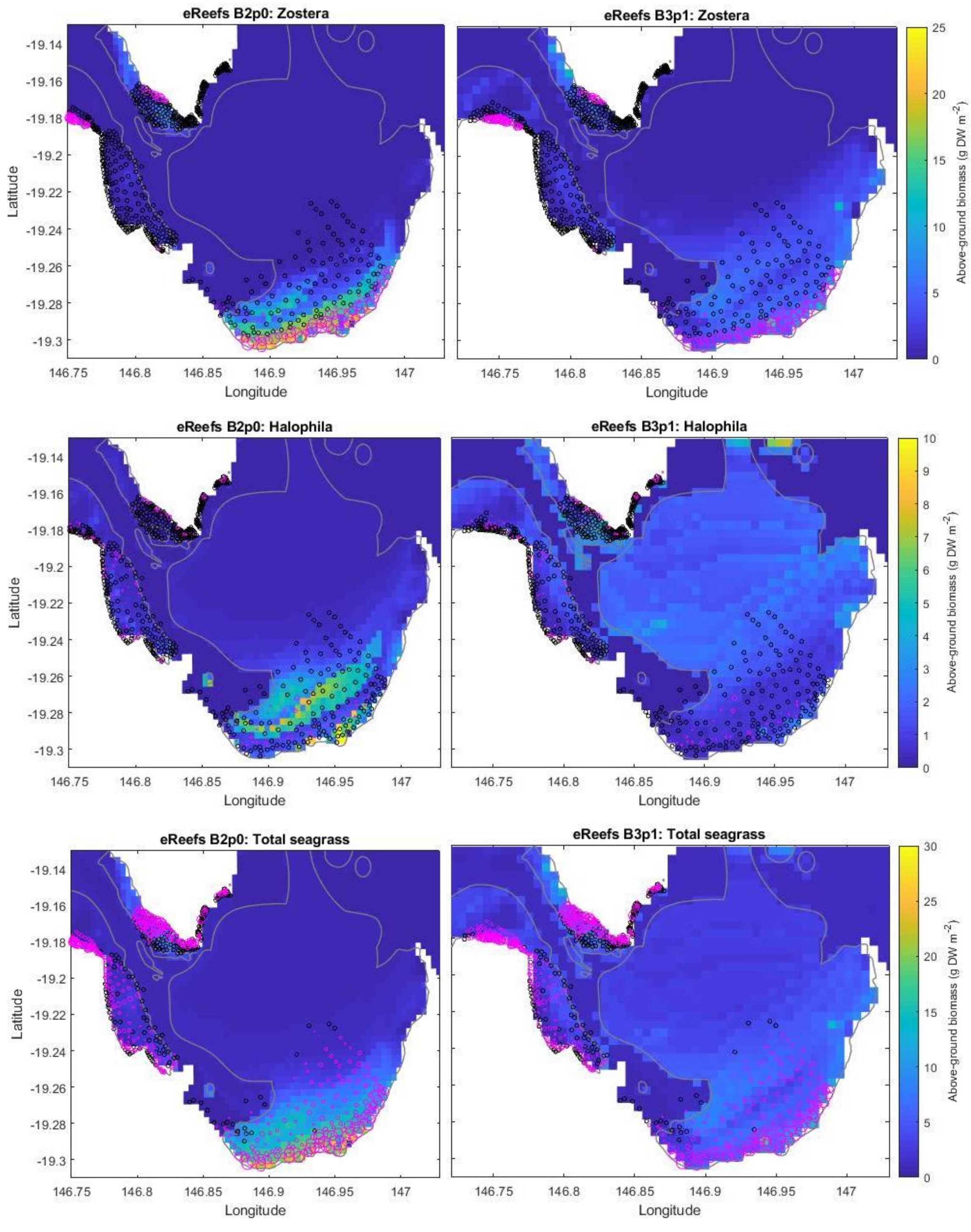

Figure 43. RECOM B2p0 (above) and B3p1 (below) predictions of seagrass biomass and distribution overlayed with observations of seagrass presence (pink circles, size denoting biomass magnitude) and absence (black circles) for *Zostera*-like, *Halophila*-like, and total seagrass as indicated by plot headings.

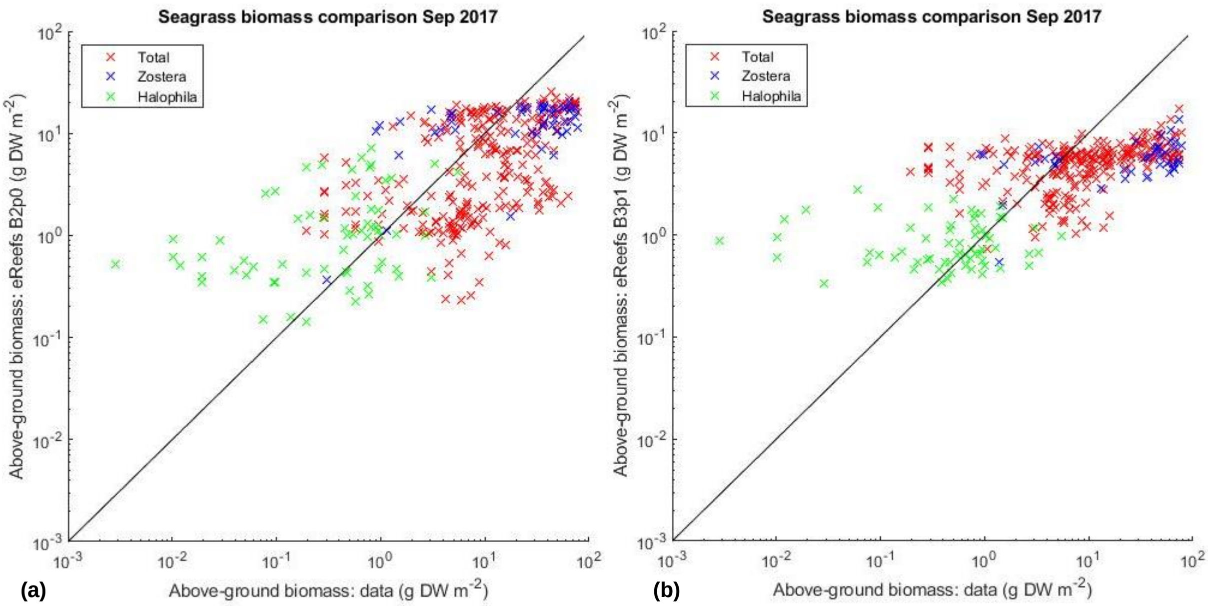

Figure 44. Observed vs predicted seagrass biomas for (a) RECOM/eReefs B2p0 predictions (y-axis); and b) RECOM/eReefs B3p1 predictions. Black line indicates x = y.

5.7.3 Seagrass predictions from different eReefs scenarios

In comparing RECOM predictions with data, it's important to consider spatial distribution, species composition and changes over time, and to consider how different related indicators change. eReefs GBR4km B3p1 predicted Pre-Industrial light levels to be slightly higher than those in the Baseline Source Catchment scenario (Figure 32), particularly after river discharge. Therefore, it would reasonably be expected that seagrass would be more widespread/prolific in the Pre-Industrial case than under current (Baseline) conditions. However, RECOM predictions of seagrass distribution show the opposite, with higher biomass for *Halophila*–like under the Baseline catchment scenario than Pre-Industrial or Reef Target scenarios, as shown for Site A (Figure 45a) and Site E (Figure 45b).

Halophila was predicted by eReefs to decline over the period 2011 to 2013 (Figure 45), whereas it was observed to expand in Cleveland Bay over this period (Figure 15). This could be due to increased *Zostera* growth in the eReefs model, which shades *Halophila* (Baird et al., 2016). The Baseline scenario predicted the biomass of *Zostera* at JCU Site A had greater variation (higher peaks, and lower troughs) than Pre-industrial predictions, which are more moderated Figure 45c and d). However, based on the poor light validation results above, there is low confidence in the accuracy of these predictions. Hence, we have not applied the eReefs B3p1 model to derive sediment load reduction targets.

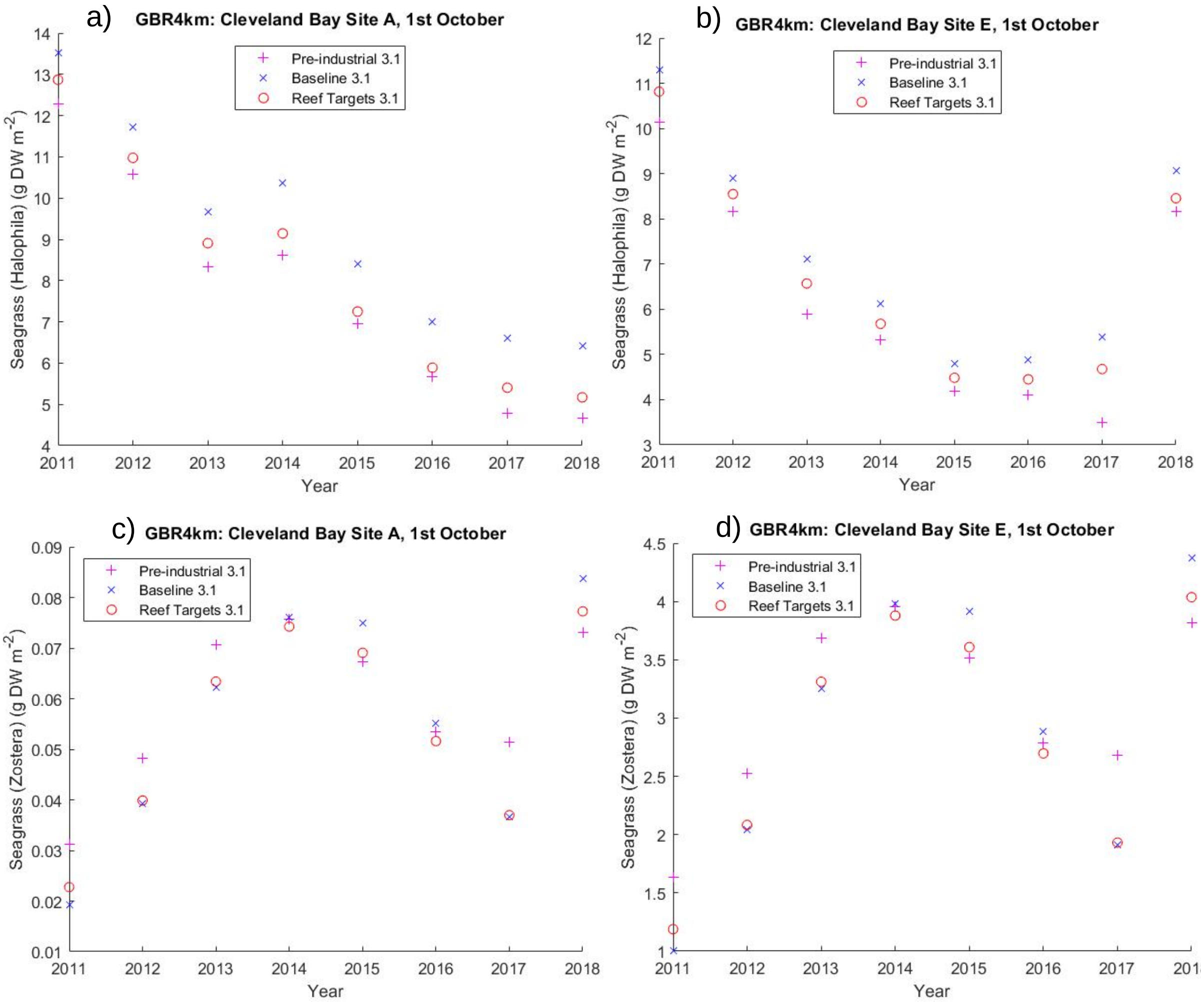

Figure 45. Predicted seagrass biomass at 1 October (top: *Halophila*; bottom: *Zostera*) for two locations (left: Site A, depth 4.62 m; and right: Site E, depth 2.52 m) within Cleveland Bay for different eReefs B3p1 scenarios (4km grid resolution).

5.8 RECOM Discussion

This analysis has shown that local application of eReefs to inshore environments is challenging, and presents fine-scale-specific issues that do not typically present a problem for eReefs predictions at its default, larger, spatial scales of 1 km and 4 km. The fine-scale-specific issues we experienced may be due to uncertainties around benthic sediment composition and distribution, complex bathymetry, and large spatial and rapid temporal variations in water quality in near shore areas, which represent ongoing challenges to environmental modelling (Oreskes et al. 1994). Hence we were unable to compare ecologically relevant targets from eReefs B3p1 to sediment load targets at this time.

Fit-for-purpose modelling is a powerful tool to evaluate management options including water quality management targets for benthic habitats (Baird et al. 2016, Fernandes et al. 2018, Fernandes et al. 2019). No one model can do everything however. A targeted localized model supported by relevant data can be used to define site-specific thresholds, as shown by Fernandes et al. 2019. However there are insufficient resources to apply this approach more widely. The eReefs model, at the other end of the spectrum, is able to capture key processes across a large spatial area, and therefore has the potential to be applied in many more locations, but fine-scale localized application is more challenging, because the model must be initialized with relevant data on similarly fine scales (e.g. sediment characteristics). This project faced the additional challenge in that fine-scale local processes within Cleveland Bay are affected by inputs from the Burdekin River, which is located some distance away and subject to episodic flows. Those flows affect Cleveland Bay directly, but will also have a cumulative effect (e.g. through deposition of fine sediment, liable for resuspension). In order to capture important hydrobiogeochemical processes occuring over short time frames, the eReefs model model is not able to run over the multi-decadal timescales which may be important for capturing long-term effects of sediment input. In addition to the challenges posed by the wide range of spatial and temporal scales involved in sediment dynamics, seagrass ecosystems are also highly dynamic, and affected by a range of stressors in addition to light.

Benthic light predictions from RECOM using eReefs B2p0 varied from light logger data between sties, but overall was over-predicted (Figure 35), although seagrass distribution matched observations well (Figure 43a). Expecting improvements from version B3p1 with extra sediment layers (increased from 4 to 12) and higher concentrations of dust particles (with slow settling velocity) in river discharges, it was surprising when the predicted light was actually much higher than earlier versions (Figure 36), and seagrass distribution worse (growing in deeper areas). This reflects the serious challenge of capturing the complex dynamics of sediment-water quality interaction, particularly in a model designed to run at large scales. While research on this topic is ongoing (Lewis et al. 2018) and insights incorporated into eReefs model updates, but further gaps in knowledge persist.

Some of the limitations of applying RECOM within coastal areas such as bays and estuaries include ((Herzfeld and Rizwi 2016)):

- Benthic sediment composition and distribution uncertainties
- High spatial and temporal variation in water quality due to resuspension
- Complex bathymetry

Future development could involve refining benthic sediment representation and bathymetry to achieve more accurate predictions in specific coastal locations, and nesting within the GBR1km eReefs model when available.

Customisation of a fine-scale RECOM model using more detailed data and knowledge of Cleveland Bay and other nearby bays at a finer resolution could achieve more accurate predictions of light and seagrass in these important habitats, and inform future water quality targets.

This project has enabled a better understanding of eReefs performance in coastal areas (Table 19) and has provided feedback for eReefs use and future development by connecting with monitoring data and remote sensing. In particular, efforts to improve the understanding of transport and changes in the properties of catchment-derived sediment that possesses a broad range of sizes and organic properties from rivers to non-adjacent coastal zones (e.g. Bahadori et al. 2019), and its link to the assumptions underpinning representations of pre-industrial vs present-day scenarios, will be worthwhile for consideration in future eReefs mechanistic representations of source catchment and sediment transport processes.

Table 19. Comparison of RECOM/eReefs performance in Cleveland Bay across different model versions.

eReefs Version	***Benthic light predictions***	***Seagrass distribution and biomass predictions***	***Model predictions distinguished between catchment scenarios***
B2p0	X	✓	X
B3p0[1]	-	-	X
B3p1	X X	X	✓

✓ Results good
X Results poor
XX Results very poor
[1] Fine scale light and seagrass predictions were not simulated for B3p0 as this version of eReefs was not available within the RECOM platform.

5.9 Complementary project: Understanding eReefs benthic light predictions in Cleveland Bay and adjacent bays

This project was unable to use eReefs predictions to quantify Ecologically Relevant Targets, but identified that finer-scale information and improved understanding of sediment-water column interactions is needed to use eReefs RECOM for predicting benthic light and associated variables (e.g. seagrass) in localized areas.

However further analysis of eReefs-RECOM output was undertaken in a preliminary investigation of the following:

- the relative proportions and accumulation rates of new sediment vs legacy sediment in Cleveland Bay, and the implications for benthic light and seagrass habitat;
- the impact of different sediment types on light availability in Cleveland Bay; and
- the influence of different river sources (e.g. Burdekin, Haughton, Ross rivers) on benthic light in Cleveland and/or other local bays (e.g. Upstart, Bowling Green Bay).

The Burdekin River can affect benthic light in Cleveland Bay via a number of mechanisms, including reduced clarity caused by flood plume and sediment resuspension (Fabricius et al. 2014) and delivery of nutrients which promote algal growth and floc formation (Bainbridge et al. 2012). Sediment resuspension is a major factor in water clarity and benthic light availability in Cleveland Bay (Fabricius et al. 2014, Fabricius et al. 2016), it's likely that both of these processes play a role in the spatial distribution of sediments in Cleveland Bay. Here we used eReefs to explore the spatial and temporal dynamics of how Burdekin sediment loads accumulate within Cleveland Bay.

eReefs-RECOM predicts that sediment erosion and deposition in Cleveland Bay vary over space and time over the simulation period between October 2011 and April 2019 (Figure 46Figure 46: cumulative net erosion, ie. erosion minus deposition, kg m^{-2}) An erosion hotspot is visible in a constricted area subject to strong currents, indicated on Figure 46a as red star. At this location, sediment erosion rates are initially very high, reducing over time (Figure 46b). Closer to shore in sheltered areas, net deposition occurs. At these locations (e.g. blue star on Figure 46a), the rate of deposition slows following a discharge event, as show in Figure 46, e. At nearby sites (e.g. green star Figure 46a), net erosion occurs, but through variable activity.

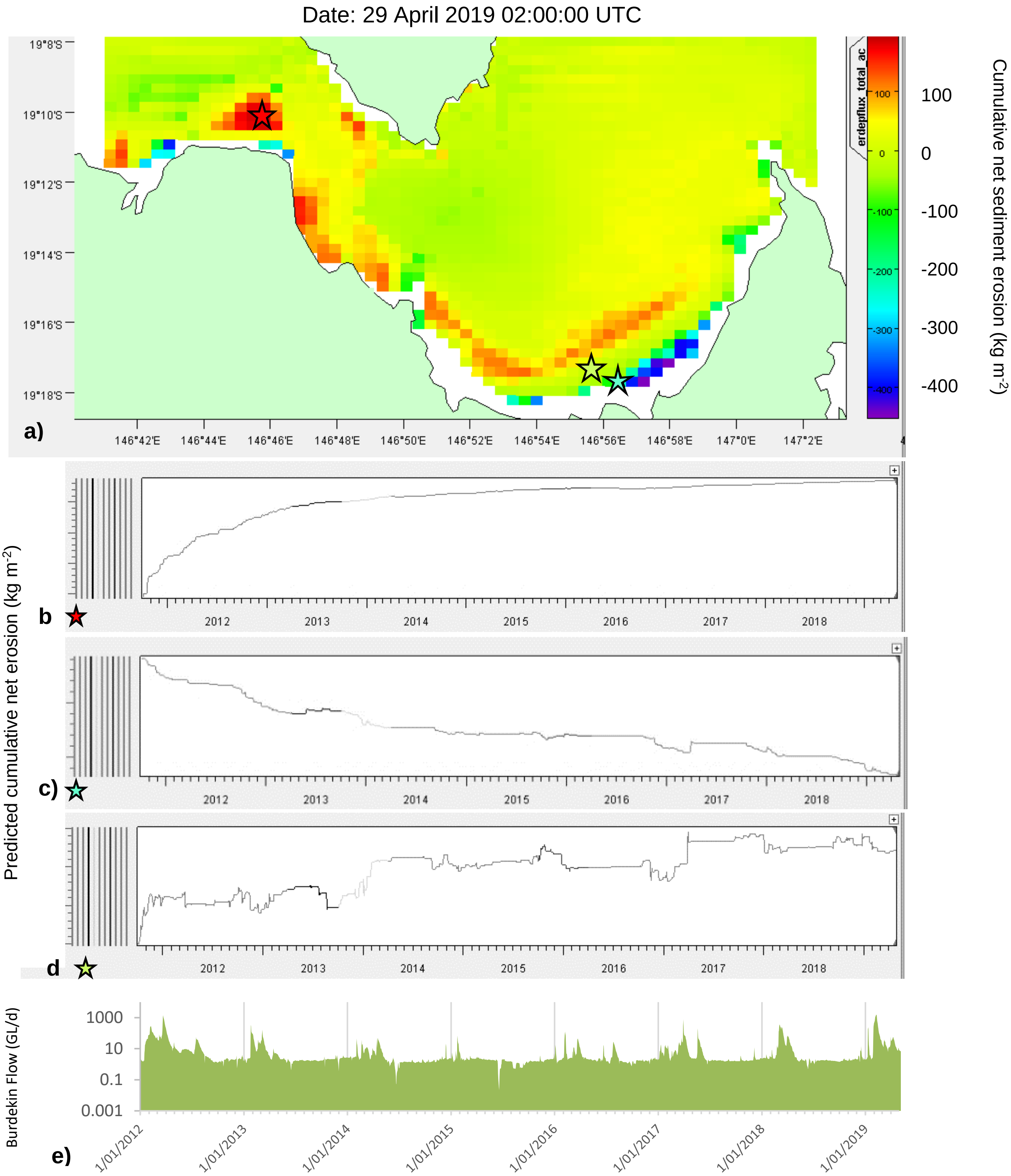

Figure 46: a) Cumulative net sediment erosion (kg/m^2) predicted within Cleveland Bay (2011 – 2019) by eReefs-RECOM GBR 4km model version B3p1: erosion represented as positive (warm tones), deposition as negative (cool tones). The three stars on the map correspond to the location of the three erosion/deposition flows blow; b) Net deposition over time predicted at site red star; c) deposition levels out when a subsequent discharge event delivers new sediment into Cleveland Bay; d) shows both erosion and deposition over time; e) shows major Burdekin discharge events over same time period.

5.9.1 Sediment legacy

eReefs tracks both legacy sediment (“Mud-mineral” and “Mud-carbonate”), which is sediment that is already present at the start of the simulation period and is subject to resuspension; and new sediment delivered from river discharge during the simulation, which can settle and also resuspend. New sediment contains both “FineSed” and “Dust” with different settling velocities (17 m/d and 1 m/d respectively). Spikes of “Mud-mineral” (the mud-carbonate fraction is small in Cleveland Bay) in the water column indicate sediment resuspension (e.g. wind-driven). Elevated levels of dust or fine sediment could reflect either resuspension or arrival of new sediment particles from river discharge.

Comparing mud concentration (black) and dust concentration (red) predicted by eReefs-RECOM over a period of one year (Figure 47), regular spikes of mud, and associated red peaks of dust, indicate cyclical patterns in resuspension, which may be related to tidal cycles. Similarly, (Anthony et al. 2004) found a strong 8 week and weak 2-4 week periodicity in benthic light, driven by turbidity on a coastal coral reef. The effect of a discharge event from the Burdekin River in late March (Figure 47b), where fine sediment (pink) also registers. After this time, dust takes some time to settle, which is consistent with fast timescales of sediment resuspension compared to sediment associated with river input as observed by (Fabricius et al. 2014).

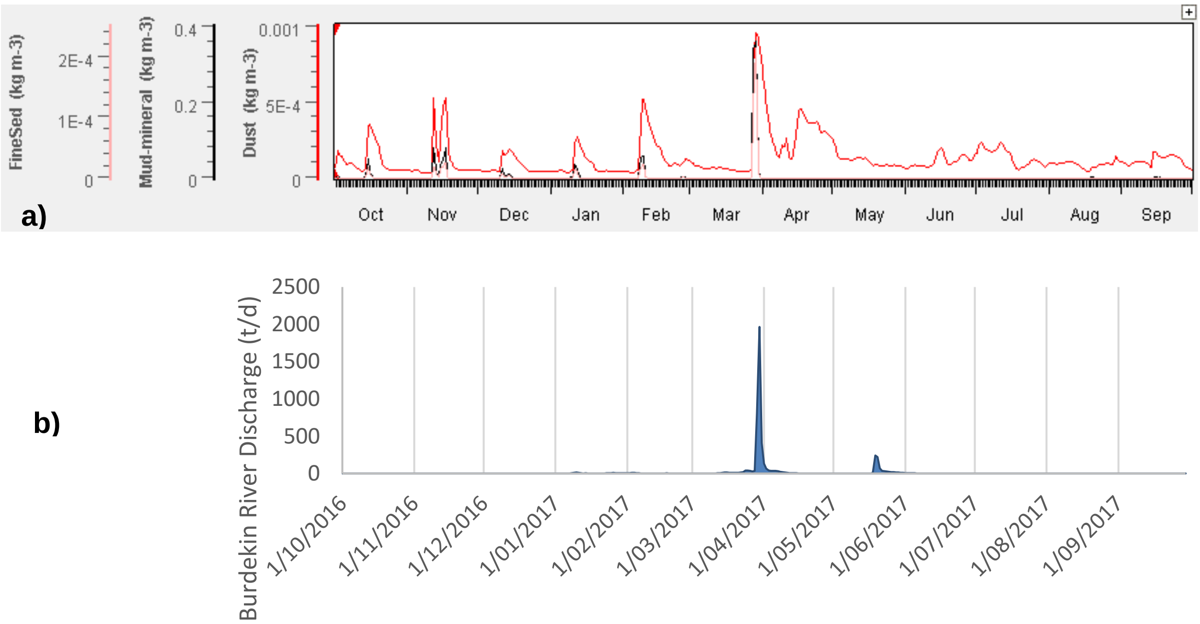

Figure 47. a) Concentration of sediment suspended in the water column predicted byeReefs-RECOM (GBR 4km model version B3p1): mud (black) is legacy sediment, and fine sediment (pink) and dust (red) are new sediment delivered during river discharges since the start of the model run; b) Burdekin River discharge

5.9.2 Nearby Bays

eReefs-RECOM predictions of benthic light in Cleveland Bay contained significant uncertainty, as outlined above. However the eReefs model has shown to be reasonably effective in predicting 'Secchi depth' — an internal and validated indicator of water clarity within eReefs — at larger scales on the GBR (Baird et al. 2019), therefore in undertaking a preliminary exploration of the benthic light predictions in nearby bays under different catchment scenarios, eReefs GBR 4km model version B3p1 was used.

Seagrass meadows within Bowling Green Bay and Upstart Bay – embayments closer to the Burdekin River mouth than Cleveland Bay – are important habitat for turtles and dugongs (Tol et al. 2017). However, these are not routinely monitored, and therefore, the analysis conducted throughout this report (including comparison to in situ light and seagrass data) could not be applied to these other bays. Here we conducted a first-pass exploration of how eReefs predictions of benthic light under the different Burdekin catchment load scenarios (Table 16) compared in wet periods in these different bays.

The Burdekin River discharges directly into Upstart Bay, and Bowling Green Bay is located between Upstart Bay and Cleveland Bay (Figure 48). The benthic light at one site in each bay is plotted under the three different eReefs B3p1 catchment scenarios for two wet periods: December 2010-September 2011, and May 2018 to April 2019, which both came after prolonged dry periods, the former with high discharge over a longer period, the latter with a higher peak flow (Figure 49, Figure 50). The absolute values of light can't be compared between these different sites, since each is at a different depth. What the figures both show is that under low/no flow, benthic light is similar under the three sediment catchment load scenarios. During and following Burdekin River discharge events, benthic light is predicted to be higher for pre-industrial sediment loads than under the baseline sediment load scenario, with the Reef Targets catchment scenario between the two, with slightly higher light predicted compared to the Baseline scenario. These results as consistent between the three sites, over the two different study periods. Over time the differences between scenarios diminished, although some divergence was still visible after six months.

Figure 48. Burdekin River plume on 11 February 2019. Note this was taken on a day when the plume was dispersed over the reef, but on 13 February 2019, it moved northwards, as is the typical direction of the plume. Source: NASA Ocean colour webmaster https://oceancolor.gsfc.nasa.gov/gallery/620/

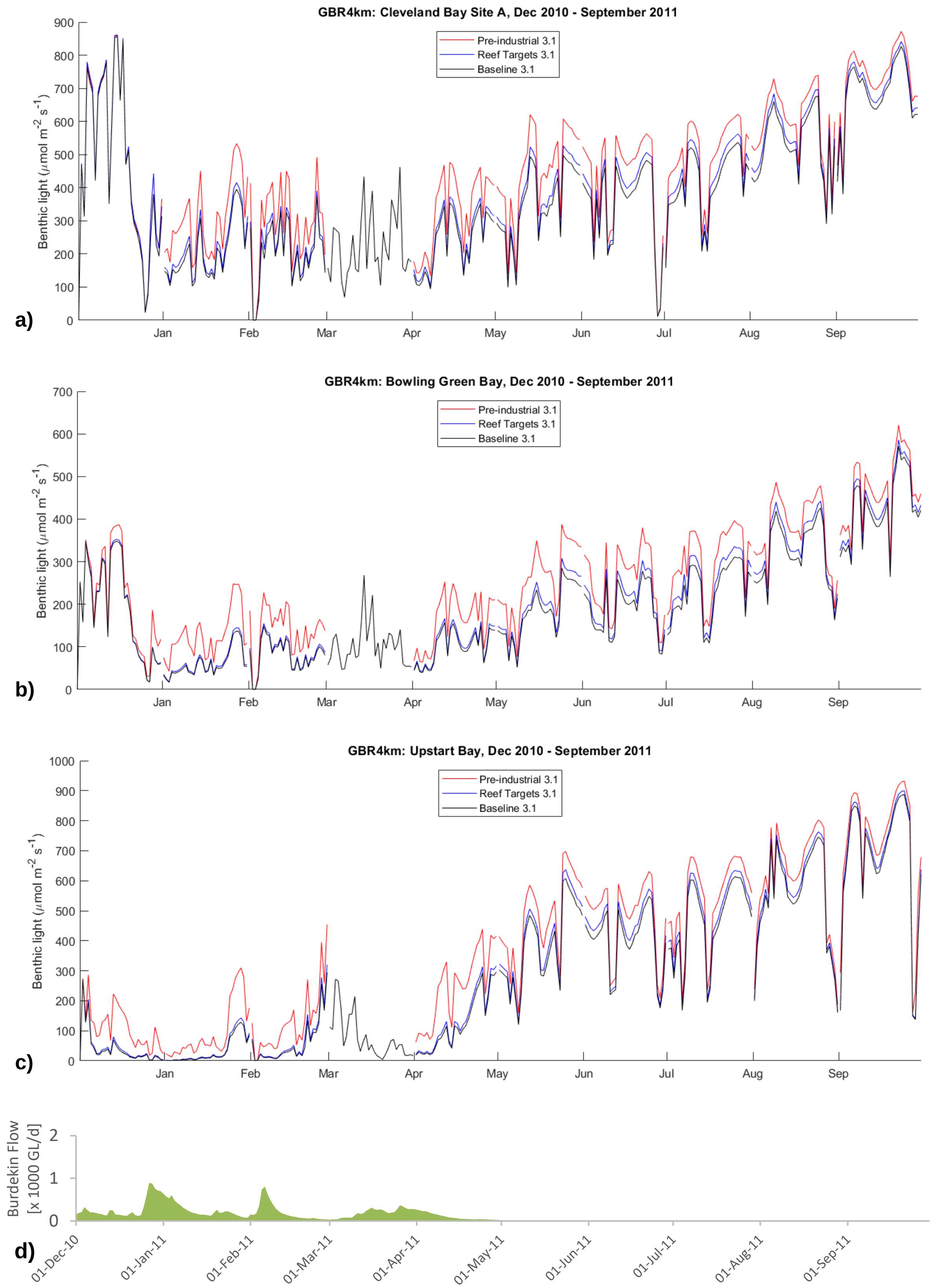

Figure 49. eReefs GBR4 km B3p1 predictions of midday instantaneous benthic light between 1 December 2010 and 30 September 2011 for different sediment load scenarios: Baseline (black), Pre-Industrial (red) and Reef Targets (blue) for a) Cleveland Bay; b) Bowling Green Bay; and c) Upstart Bay. d) Burdekin River daily discharge.

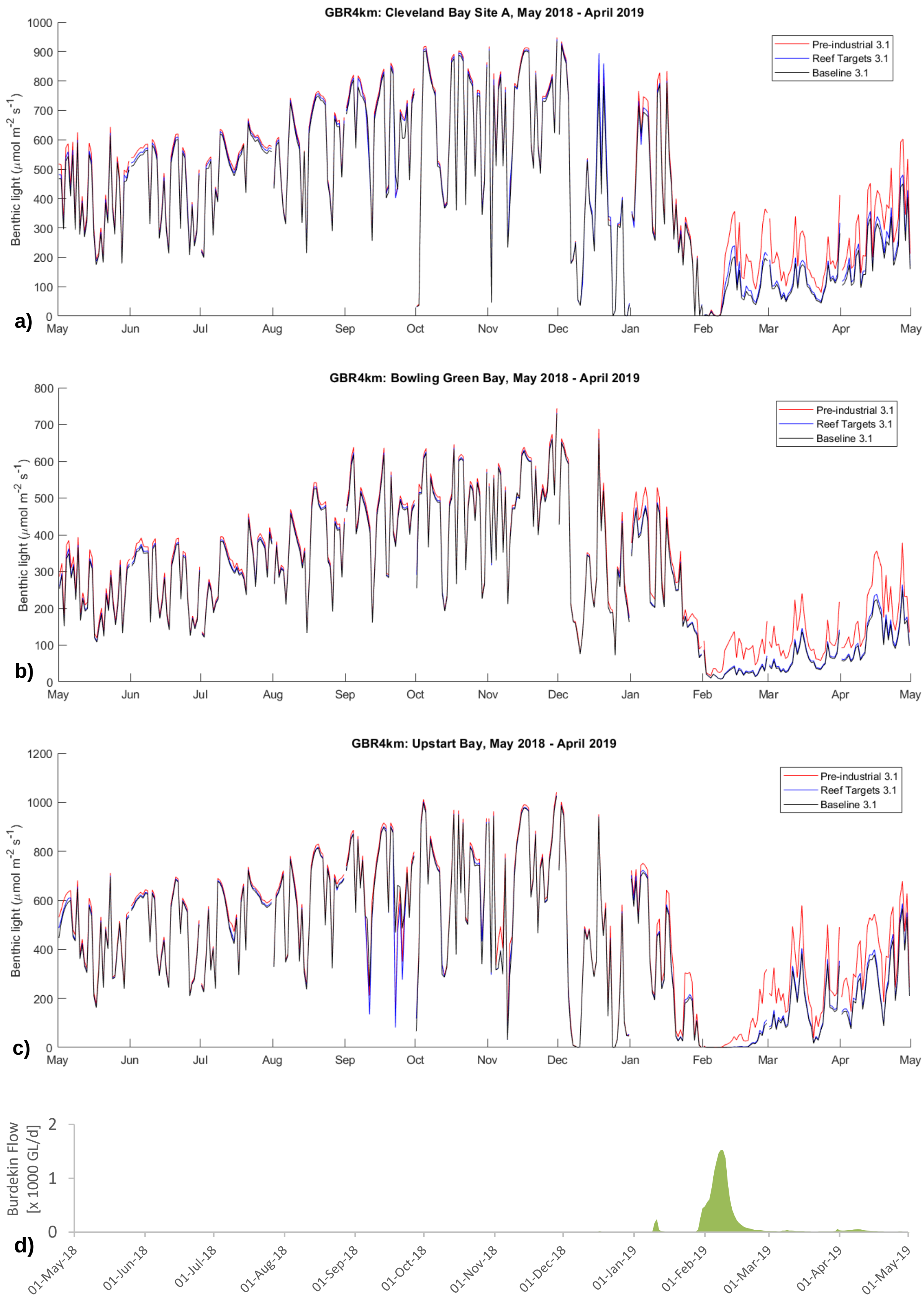

Figure 50. eReefs GBR4 km B3p1 predictions midday instantaneous benthic light between 1 May 2018 and 30 April 2019 different sediment load scenarios: Baseline (black), Pre-Industrial (red) and Reef Targets (blue) for a) Cleveland Bay; b) Bowling Green Bay; and c) Upstart Bay. d) Burdekin River daily discharge.

5.9.3 River tracers

With eReefs, river plumes can be tracked using river tracers to effectively “dye” the river with a unit concentration (e.g. 1 kg/m^3) based on river flow (and using circulation calculated in eReefs H2p0). River tracers can be analysed to determine the river footprint and observe the influence of different rivers on a location over time (https://research.csiro.au/ereefs/models/model-outputs/gbr4/salinity-and-temperature/).

Figure 51 shows the temporal and spatial variation in river tracers during periods of large discharge events (2011, 2012, 2017 and 2019) for the Burdekin and Haughton Rivers. The Burdekin River tracer was observed to reach over 10% in Cleveland Bay, while the Haughton River tracer was 4% or less. This means that at times (e.g. 16 February 2011, 28 March 2012), over 10% of the water at a particular location within Cleveland Bay came from the Burdekin River, and at other times (e.g. 5 February 2019) up to 4% came from the Haughton River. The bulk of the water is oceanic.

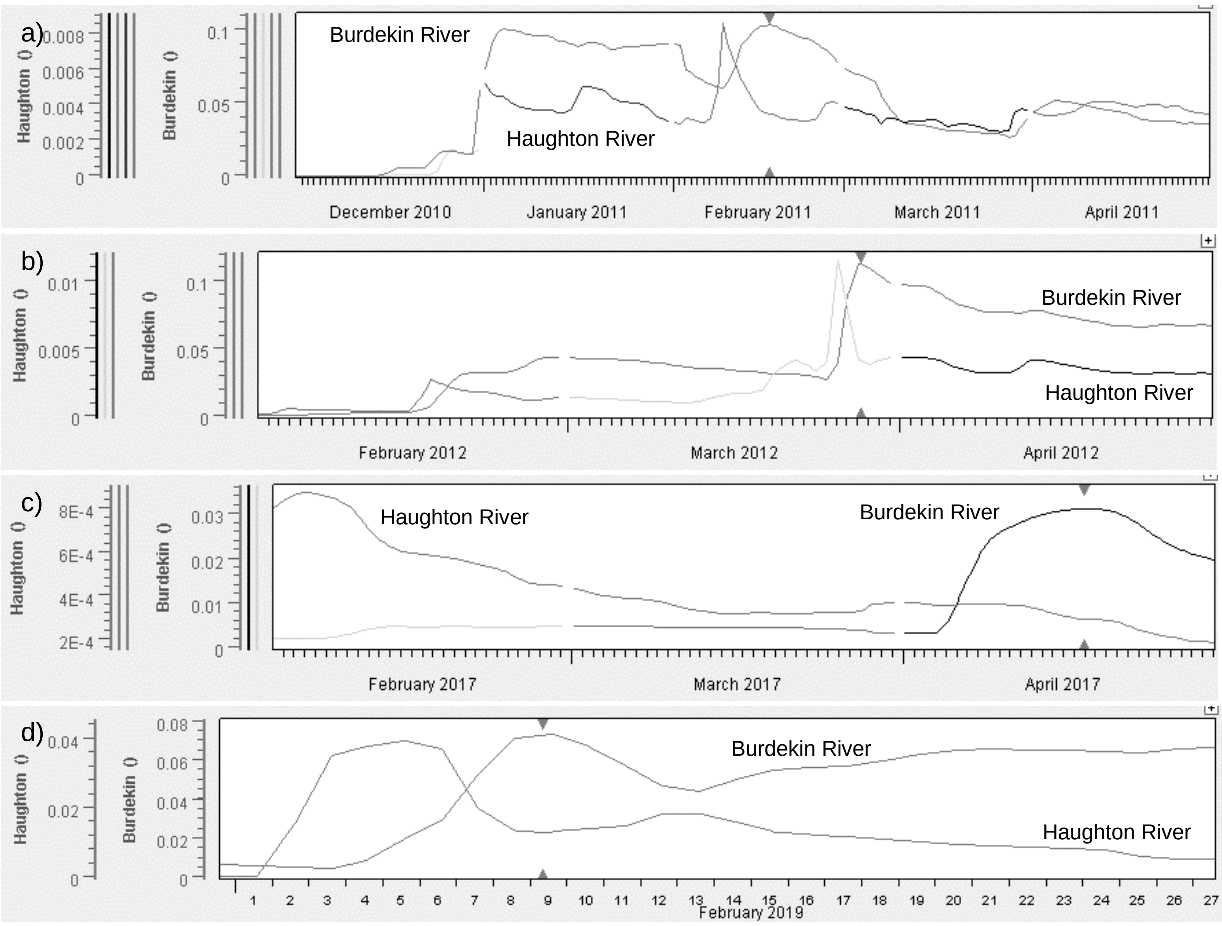

Figure 51. Variation in Burdekin and Haughton river tracers (fraction of water at a particular location coming from a specific source) during discharge events in a) 2011, b) 2012, c) 2017, and d) 2019. At times (e.g. 16 February 2011, 28 March 2012), over 10% of the water at a particular location within Cleveland Bay came from the Burdekin River. At other times (e.g. 5 February 2019) up to 4% came from the Haughton River. The bulk of the water is oceanic.

5.9.4 Summary

While the basic exploratory analysis above is not sufficient to validate these models or draw any conclusions, we present these findings to demonstrate how eReefs can be used to explore different aspects of river input on receiving waters and relevant ecological indicators (e.g. benthic light) over different locations. This information could be used in conjunction with sediment load measurements to better understand how much sediment load gets delivered to Cleveland Bay, as discussed in Chapter 3.

Future work could continue to explore the different impacts of resuspension and newly delivered sediment from various sources in order to better understand the relative contribution of each to benthic light attenuation in Cleveland Bay (see also the concluding text of Section 1.20). Future work could also compare modelled to measured suspended sediments.

6.0 CONCLUSIONS AND RECOMMENDATIONS

Our results highlight the importance, and difficulty, in procuring Ecologically Relevant Targets (ERTs) for aquatic ecosystems based on terrestrial inputs. Some of the key challenges are: access to data that adequately captures the pressures and ecological responses at the necessary spatial and temporal scales; identifying an ecological target (i.e. desired state) that satisfies over-arching management objectives; the challenges of establishing causality; and, the impact of cumulative pressures. Given this complexity and uncertainty, it is important that ERTs are estimated using a range of methods, in order to provide some indication of uncertainty, as we have done here. This multiple evidence-based approach is warranted given the huge investment into management activities to restore ecosystems based on meeting a defined target, including those in the Reef 2050 Water Quality Improvement Plan (The State of Queensland 2018). We were unable to use the eReefs RECOM model at a local scale for assessing ERTs (section 4), but have undertaken in-depth exploration and validation of eReefs RECOM within Cleveland Bay, yielding insights which will be used in future model updates.

Ecologically Relevant Targets are criteria that, if met, correspond to desired ecological outcomes for the Great Barrier Reef (e.g. desired state) and achieving the over-arching objective of Reef Plan. Setting these targets is important, but challenging. The project has made six main contributions to this issue:

1. The data needs for relating catchment loads to ecological outcomes are non-trivial, requiring compilation and re-analysis of a large number of different data sets. We compiled and analysed data from wide-ranging sources, not all of which are easily accessible (Figure 3), and have now made this data available for use by others.
2. The desired state case study is a demonstration of how to overcome multiple challenges in setting quantitative targets to satisfy over-arching management objectives, but is not a definitive method. In this study, desired state was defined as a separate independent step towards developing ERTs. Desired state can have other applications including for reporting on the condition and trend in the 5-yearly Outlook reports, which report against the over-arching objective that “the reef maintains its diversity of species and ecological habitats in at least a good condition with a stable to improving trend” (Great Barrier Reef Marine Park Authority and Queensland Government 2015). Desired state can also be adapted to other ERTs, in which case it may be applied at different time-scales (i.e. multi-annual loads were related to desired state). Targets can also be set based on gradients in pressures and ecological responses (De'ath and Fabricius 2010). Gradients in environmental conditions, including pressures will be explored in the GBR-wide up-scaling of desired state in project 5.4. As desired state formed a separate independent step, then uncertainty in the ecological targets can propagate through to the ERTs. To overcome this, the lowest margin of desired state (the lower confidence interval), was used for ERTs, and this was coupled with an additional ecological outcome – net change in biomass or extent to build a range of different options. The approach applied here will be refined as it is applied to other locations with different ecological characteristics.
3. Through considering multiple indicators of ecological response (desired spatial extent for all seagrass and avoiding decline in area or biomass for subtidal seagrass) and stressors over multiple timescales (1- and 4-year sediment loads), we produced a range of estimates for sediment load reduction targets. The seagrass ERTs derived in

this study found a range of 38% to 49% reduction in anthropogenic sediment load from the Burdekin River had the greatest likelihood of enabling seagrass to achieve minimum desired state or achieve net zero loss. Given the model uncertainty, these findings are comparable to the existing 2018 WQIP target of 30% reduction for the Burdekin River that was determined from an entirely different method. This highlights the importance of using multiple independent modelling approaches and data sources to increase confidence in recommendations for a system where uncertainty is high. It is worthy of note, that after considerable investment from the Reef 2050 WQIP, sediment loads are estimated to have been reduced by 0.7% in the two years leading up to June 2018 (Queensland Government and Australian Government, 2019).

4. Defining long-term seagrass light requirements is non-trivial, because seagrass response to light availability depends on species, light history and other environmental factors. However, our analysis of seagrass spatial extent and bPAR estimated from the satellite light product suggested that defining seagrass potential habitat by areas where bPAR exceeded 4-7 mol/m^2/day, correlates well to seagrass spatial extent metrics. Our analysis therefore demonstrates that bPAR explains variations in spatial extent and biomass of seagrass and could be an important data set for future modelling of seagrass species and community distribution. However, bPAR tends towards overprediction of benthic light in Cleveland Bay, and so it could not be used as an alternative to *in-situ* measured light in this location at this time.
5. Our models found stronger correlations between seagrass variables and river flow than sediment load, which has important implications: it indicates that the riverine discharge has other physico-chemical properties that could affect seagrass area and biomass, or it may also indicate that flow is a better proxy for the range of environmental conditions that affect seagrass. The Burdekin River carries nutrients and floc aggregates containing organic matter with the fine sediments (Bainbridge et al., 2012), which may affect light attenuation and influence the differences in response of seagrass indicators to flow compared to sediment loads, which only account for the mineral fraction. Flocs cannot be accounted for in our models as there is no long-term information on these fractions. Riverine discharge is also associated with meteorological conditions such as periods of cloud and high wind and wave power causing resuspension.
6. We were unable to differentiate between the relative contributions of recent catchment sediment loads, and the legacy effects of catchment inputs (including fine sediment, organics and nutrients) via sediment resuspension. This study has shown that local application of eReefs to inshore environments is challenging, and presents fine-scale-specific issues that are not a problem for eReefs application at its default, larger, spatial scales of 1 km and 4 km. The fine-scale-specific issues we experienced may be due to uncertainties around benthic sediment composition and distribution, complex bathymetry, and large spatial and rapid temporal variations in water quality in near shore areas. Hence we were unable to use eReefs at this time to explore ERTs. Further refinement of eReefs/RECOM to capture these fine-scale inshore processes is needed to explore the relative contributions of these two processes to seagrass light availability, and refine ERT accordingly.

This project took the step from defining sediment load targets based on seagrass light requirements, to connecting sediment loads with seagrass state. A logical next step is to incorporate wider ecosystem effects. The multiannual ecological responses are likely to arise from a number of factors. For example, hysteresis and delay in recovery is common in ecological systems (Duarte et al. 2014), and fine sediments can create a legacy effect, enhancing sediment resuspension for months or years after they are deposited. The combined effects of multiple stressors, including nutrients, organic matter and sediments, are complicated and rarely studied (but see Govers et al., 2014, Pérez et al., 2007), and feedbacks could make seagrasses liable to sudden and unpredictable transitions that do not link to an individual stressor, such as sediment loads (e.g. Duarte, 1995, Munkes, 2005, van der Heide et al., 2007, van der Heide et al., 2010). Further work is needed to explore whether feedbacks in the system are likely to create possible tipping points beyond which recovery would become difficult or impossible. Seagrass response is also likely to occur on shorter timescales than wider ecosystem effects, for example if seagrass decline caused large decline in dugong or turtle numbers, recovery of seagrass would not necessarily correspond to recovery of the dugong or turtle populations.

Recommendations

As a result of findings from this project, we recommend:

1. Light levels in shallow coastal waters where seagrass meadows dominate, such as the intertidal areas of Cleveland Bay, be thoroughly and accurately characterised. The satellite benthic light product (bPAR) over-predicted compared to measured light levels in the shallow areas of Cleveland Bay. Therefore, bPAR can be used for assessing light levels relative to bPAR light thresholds only, but not when using other sources of light data (i.e. bPAR is not comparable to *in situ* PAR). These light thresholds did not contribute towards an assessment of ERTs. Access to an accurate remote measurement of benthic light product would be of great value in developing seagrass habitat models for the Great Barrier Reef.
2. Ongoing multiple evidence-based approaches are used for future updates to the targets, since estimates generated from independent approaches strengthens confidence in these targets. The statistical method of investigating the effects of loads on seagrasses applied into this study is constrained to areas where adequate data is available, such as Cleveland Bay, and is not able to verify the underlying processes causing these correlations. Data 'hot-spots' such as Cleveland Bay can provide independent approaches in support of broad-scale applications such as eReefs (e.g. Brodie et al. 2017).
3. The processes governing how river discharge affects turbidity and ecological health continues to be investigated. At this stage we are unable to account for interacting effects of multiple different environmental conditions on turbidity, including organic matter and nutrients, or interacting effects of other environmental conditions on seagrass such as temperature and salinity.
4. Long-term data sets on seagrass species, abundance and area continue to be collected so that management targets can be assessed using ecological data in the future. The data sets used here relied on survey data funded by the Port of Townsville. NESP TWQ Hub Project 5.4 is exploring methods to set desired state for the entire GBR data set, but at present, the data sets available for use in that project mostly focus on areas of high risk around ports. This calls into question how well the data is able to capture the historical and desirable level of seagrass communities in general (Collier et al., 2020). A comprehensive understanding of desired state should also be based on habitats in areas of lower risk, and based on a comprehensive understanding of the ecological

services that seagrasses can provide. Recommendations from the Reef Integrated Monitoring and Reporting Program (RIMReP) included the need for a co-ordinated program that includes comprehensive spatial data sets across a range of spatial and temporal scales and across gradients of pressure (Udy et al., 2018). The present project has highlighted the need for these spatial data sets in tracking ecological health and for setting and assessing progress in meeting management targets. Meanwhile, it is imperative that existing data sets continue to be built upon, with greater resolution, and even further capacity so that monitoring data can continue to answer increasingly specific management questions.

REFERENCES

Abal, E. G. and W. C. Dennison (1996). "Seagrass depth range and water quality in southern Moreton Bay, Queensland, Australia." Marine and Freshwater Research **47**(6): 763-771.

Adams, M. P., R. K. Hovey, M. R. Hipsey, L. C. Bruce, M. Ghisalberti, R. J. Lowe, R. K. Gruber, L. Ruiz-Montoya, P. S. Maxwell, D. P. Callaghan, G. A. Kendrick and K. R. O'Brien (2016). "Feedback between sediment and light for seagrass: Where is it important?" Limnology and Oceanography **61**(6): 1937-1955.

Adams, M. P., M. I. Saunders, P. S. Maxwell, D. Tuazon, C. M. Roelfsema, D. P. Callaghan, J. Leon, A. R. Grinham and K. R. O'Brien (2015). "Prioritizing localized management actions for seagrass conservation and restoration using a species distribution model." Aquatic Conservation: Marine and Freshwater Ecosystems.

Alcoverro, T., M. Manzanera and J. Romero (2001). "Annual metabolic carbon balance of the seagrass *Posidonia oceanica*: the importance of carbon reserves." Marine Ecology Progress Series **211**: 105-116.

Álvarez-Romero, J. G., M. Devlin, E. Teixeira da Silva, C. Petus, N. C. Ban, R. L. Pressey, J. Kool, J. J. Roberts, S. Cerdeira-Estrada, A. S. Wenger and J. Brodie (2013) "A novel approach to model exposure of coastal-marine ecosystems to riverine flood plumes based on remote sensing techniques." Journal of Environmental Management **119**, 194-207 DOI: http://dx.doi.org/10.1016/j.jenvman.2013.01.036.

Anthony, K. R. N., P. V. Ridd, A. R. Orpin, P. Larcombe and J. Lough (2004). "Temporal variation of light availability in coastal benthic habitats: effects of clouds, turbidity, and tides." Limnology and Oceanography **49**(6): 2201-2211.

Aragones, L. and H. Marsh (2000) "Impact of dugong grazing and turtle cropping on tropical seagrass communities." Pacific Conservation Biology **5**, 277-288 DOI: https://doi.org/10.1071/PC000277.

Bahadori, M., C. Chen, S. Lewis and M. Rezaei Rashti (2019). "A novel approach of combining isotopic and geochemical signatures to differentiate the sources of sediments and particulate nutrients from different land uses." The Science of the total environment **655**: 129-140.

Bainbridge, Z., S. Lewis, S. Smithers, S. Wilkinson, G. Douglas, S. Hillier and J. Brodie (2016). "Clay mineral source tracing and characterisation of Burdekin River (NE Australia) and flood plume fine sediment." Journal of Soils and Sediments **16**(2): 687-706.

Bainbridge, Z. T., S. Lewis, R. Bartley, K. Fabricius, C. Collier, J. Waterhouse, A. Garzon-Garcia, B. Robson, J. Burton, A. Wenger and J. Brodie (2018) "Fine sediment and particulate organic matter: a review and case study on ridge-to-reef transport, transformations, fates and impacts on marine ecosystems." Marine Pollution Bulletin **135** DOI: https://doi.org/10.1016/j.marpolbul.2018.08.002.

Bainbridge, Z. T., S. E. Lewis, S. G. Smithers, P. M. Kuhnert, B. L. Henderson and J. E. Brodie (2014). "Fine-suspended sediment and water budgets for a large, seasonally dry tropical catchment: Burdekin River catchment, Queensland, Australia." Water Resources Research **50**(11): 9067-9087.

Bainbridge, Z. T., E. Wolanski, J. G. Álvarez-Romero, S. E. Lewis and J. E. Brodie (2012) "Fine sediment and nutrient dynamics related to particle size and floc formation in a Burdekin

River flood plume, Australia." Marine Pollution Bulletin **65**, 236-248 DOI: http://dx.doi.org/10.1016/j.marpolbul.2012.01.043.

Baird, M., R. Green and R. Lowe (2019). Reef Restoration and Adaption Program: Cool water injection. A report provided to the Australian Government by the Reef Restoration and Adaptation Program**:** 15.

Baird, M., M. Mongin and E. Bouget (2019). "Reef Restoration and Adaption Program: Ultra-thin surface films. A report provided to the Australian Government by the Reef Restoration and Adaptation Program." 23.

Baird, M. E., M. P. Adams, R. C. Babcock, K. Oubelkheir, M. Mongin, K. A. Wild-Allen, J. Skerratt, B. J. Robson, K. Petrou, P. J. Ralph, K. R. O'Brien, A. B. Carter, J. C. Jarvis and M. A. Rasheed (2016). "A biophysical representation of seagrass growth for application in a complex shallow-water biogeochemical model." Ecological Modelling **325**: 13-27.

Baird, M. E., M. Mongin, F. Rizwi, L. K. Bay, N. E. Cantin, M. Soja-Woźniak and J. Skerratt (2018). "A mechanistic model of coral bleaching due to temperature-mediated light-driven reactive oxygen build-up in zooxanthellae." Ecological Modelling **386**: 20-37.

Baird, M. E., K. A. Wild-Allen, J. Parslow, M. Mongin, B. Robson, J. Skerratt, F. Rizwi, M. Soja-Woznaik, E. Jones, M. Herzfeld, N. Margvelashvili, J. Andrewartha, C. Langlais, M. P. Adams, N. Cherukuru, M. Gustafsson, S. Hadley, P. J. Ralph, U. Rosebrock, T. Schroeder, L. Laiolo, D. Harrison and A. D. L. Steven (2019). "CSIRO Environmental Modelling Suite (EMS): Scientific description of the optical and biogeochemical models (vB3p0)." Geosci. Model Dev. Discuss. **2019**: 1-107.

Barbier, E. B. (2014) "Valuing ecosystem services as productive inputs." Economic Policy **22**, 178-229 DOI: 10.1111/j.1468-0327.2007.00174.x.

Barbier, E. B., S. D. Hacker, C. Kennedy, E. W. Koch, A. C. Stier and B. R. Silliman (2011). "The value of estuarine and coastal ecosystem services." Ecological Monographs **81**(2): 169-193.

Bartley, R., Z. T. Bainbridge, S. E. Lewis, F. J. Kroon, S. N. Wilkinson, J. E. Brodie and D. M. Silburn (2014) "Relating sediment impacts on coral reefs to watershed sources, processes and management: A review." Science of the Total Environment **468–469**, 1138-1153 DOI: http://dx.doi.org/10.1016/j.scitotenv.2013.09.030.

Bartley, R., J. Croke, Z. T. Bainbridge, J. M. Austin and P. M. Kuhnert (2015). "Combining contemporary and long-term erosion rates to target erosion hot-spots in the Great Barrier Reef, Australia." Anthropocene **10**: 1-12.

Bartley, R., D. Waters, R. E. Turner, F. Kroon, S. N. Wilkinson, A. Garzon-Garcia, P. Kuhnert, S. Lewis, R. Smith, Z. T. Bainbridge, J. Olley, A. Brooks, J. Burton, J. Brodie and J. waterhouse (2017). Chapter 2: Sources of sediment, nutrients, pesticides and other pollutants to the Great Barrier Reef. Scientific Concensus Statement 2017: A synthesis of the science of land-based water quality impacts on the Great Barrier Reef, State of Queensland, 2017.

Beaman, R. J. (2010). Project 3DGBR: A high-resolution depth model for the Great Barrier Reef and Coral Sea. Cairns, Australia, Marine and Tropical Sciences Research Facility (MTSRF)**:** 13.

Beer, S., M. Bjork, R. Gademann and P. J. Ralph (2001). Measurements of photosynthetic rates in seagrasses. Global seagrass research methods. F. T. T. Short and R. Coles, Elsevier Publishing, The Netherlands.

Beer, S., M. Bjork, F. Hellblom and A. Lennart (2002). "Inorganic carbon utilization in marine angiosperms (seagrasses)." Functional Plant Biology **29**: 349-354.

Borja, Á., D. M. Dauer and A. Grémare (2012) "The importance of setting targets and reference conditions in assessing marine ecosystem quality." Ecological Indicators **12**, 1-7 DOI: http://dx.doi.org/10.1016/j.ecolind.2011.06.018.

Borja, A., M. Elliott, J. H. Andersen, A. C. Cardoso, J. Carstensen, J. G. Ferreira, A.-S. Heiskanen, J. C. Marques, J. M. Neto, H. Teixeira, L. Uusitalo, M. C. Uyarra and N. Zampoukas (2013) "Good Environmental Status of marine ecosystems: What is it and how do we know when we have attained it?" Marine Pollution Bulletin **76**, 16-27 DOI: https://doi.org/10.1016/j.marpolbul.2013.08.042.

Breiman, L., J. H. Friedman, R. A. Olshen and C. J. Stone (1984). Classification and Regression Trees, Chapman and Hall/CRC.

Brodie, J., M. E. Baird, J. Waterhouse, M. Mongin, J. Skerratt, C. Robillot, R. D. Smith, R. Mann and M. Warne (2017). Development of basin-specific ecologically relevant pollutant load reduction targets. EHP16055 - Updated Scientific Consensus Statement.

Brodie, J. E., S. Lewis, S. Wooldridge, Z. T. Bainbridge, J. Waterhouse, C. Honchin, G. Holmes, K. Fabricius, C. J. Collier and M. Rasheed (2017). "Setting ecologically relevant targets for river pollutant loads so as to meet marine water quality requirements for the Great Barrier Reef, Australia: A preliminary methodology and analysis." Ocean and Coastal Management **143**: 136-147.

Brodie, J. E., S. E. Lewis, C. J. Collier, S. Wooldridge, Z. T. Bainbridge, J. Waterhouse, M. A. Rasheed, C. Honchin, G. Holmes and K. Fabricius (2017). "Setting ecologically relevant targets for river pollutant loads to meet marine water quality requirements for the Great Barrier Reef, Australia: A preliminary methodology and analysis." Ocean & Coastal Management.

Bryant, C. V. and M. A. Rasheed (2018). Port of Townsville Annual Seagrass Monitoring Survey: September 2017. Cairns, James Cook University Publication, Centre for Tropical Water & Aquatic Ecosystem Research (TropWATER)**:** 47

Butler, J. R. A., G. Y. Wong, D. J. Metcalfe, M. Honzák, P. L. Pert, N. Rao, M. E. van Grieken, T. Lawson, C. Bruce, F. J. Kroon and J. E. Brodie (2013) "An analysis of trade-offs between multiple ecosystem services and stakeholders linked to land use and water quality management in the Great Barrier Reef, Australia." Agriculture, Ecosystems & Environment **180**, 176-191 DOI: http://dx.doi.org/10.1016/j.agee.2011.08.017.

Canty, A. and B. Ripley (2017). Boot: Bootstrap R (S-Plus) Functions, R package version 1.3-20.

Carter, A. B., C. J. Collier, M. A. Rasheed, L. McKenzie and J. W. Udy (2018). A framework for defining seagrass habitat for the Great Barrier Reef, Australia. Report to the National Environmental Science Programme. Cairns, Reef and Rainforest Research Centre.

Chartrand, K. M., C. V. Bryant, A. B. Carter, P. J. Ralph and M. A. Rasheed (2016) "Light Thresholds to Prevent Dredging Impacts on the Great Barrier Reef Seagrass, *Zostera muelleri* ssp. capricorni." Frontiers in Marine Science **3** DOI: 10.3389/fmars.2016.00106.

Chartrand, K. M., P. J. Ralph, K. Petrou and M. A. Rasheed (2012). Development of a light-based seagrass management approach for the Gladstone Western basin dredging program. Cairns, Fisheries Queensland, Department of Agriculture Fisheries and Forestry**:** 126.

Chartrand, K. M., M. Szabó, S. Sinutok, M. A. Rasheed and P. J. Ralph (2018). "Living at the margins – The response of deep-water seagrasses to light and temperature renders them susceptible to acute impacts." Marine Environmental Research **136**: 126-138.

Choice, Z. D., T. K. Frazer and C. A. Jacoby (2014) "Light requirements of seagrasses determined from historical records of light attenuation along the Gulf coast of peninsular Florida." Marine Pollution Bulletin **81**, 94-102 DOI: http://dx.doi.org/10.1016/j.marpolbul.2014.02.015.

Clark, L. A. and D. Pregibon (1992). Tree-based models in S. Statistical models. J. M. Chambers and T. J. Hastie, Pacific Grove, CA: Wadsworth and Brooks**:** 377-417.

Coles, R., L. McKenzie, G. De'ath, A. Roelofs and W. Lee Long (2009) "Spatial distribution of deepwater seagrass in the inter-reef lagoon of the Great Barrier Reef World Heritage Area." Marine Ecology Progress Series **392**, 57-68 DOI: https://doi.org/10.3354/meps08197.

Coles, R. G., M. A. Rasheed, L. McKenzie, A. Grech, P. H. York, M. Sheaves, S. McKenna and C. Bryant (2015) "The Great Barrier Reef World Heritage Area seagrasses: managing this iconic Australian ecosystem resource for the future." Estuarine, Coastal and Shelf Science **153**, A1-A12 DOI: https://doi.org/10.1016/j.ecss.2014.07.020.

Collier, C. and M. Waycott (2009). Drivers of change to seagrass distributions and communities on the Great Barrier Reef: Literature review and gaps analysis. Report to the Marine and Tropical Sciences Research Facility. Cairns, Reef and Rainforest Research Centre Limited.

Collier, C. J., M. Adams, L. Langlois, M. Waycott, K. O'Brien, P. Maxwell and L. McKenzie (2016) "Thresholds for morphological response to light reduction for four tropical seagrass species." Ecological Indicators **67**, 358-366 DOI: 10.1016/j.ecolind.2016.02.050.

Collier, C. J., A. B. Carter, M. Rasheed, L. McKenzie, J. Udy, R. Coles, J. Brodie, M. Waycott, K. O'Brien, M. Saunders, M. Adams, K. Martin, C. Honchin, C. Petus and E. Lawrence (2020). "An evidence-based approach for setting desired state in a complex Great Barrier Reef seagrass ecosystem: a case study from Cleveland Bay." Environmental and Sustainability Indicators **7**: 100042.

Collier, C. J., K. Chatrand, C. Honchin, A. Fletcher and M. Rasheed (2016). Light thresholds for seagrasses of the GBR: a synthesis and guiding document. Cairns, Reef and Rainforest Research Centre.

Collier, C. J., M. Devlin, L. Langlois, L. J. McKenzie, C. Petus, E. Teixera da Silva, K. McMahon, M. Adams, K. O'Brien, J. Statton and M. Waycott (2014). Final report on thresholds and indicators of declining water quality as tools for tropical seagrass management. A summary of findings from Project 5.3 Vulnerability of seagrass habitats in the GBR to flood plume impacts: light, nutrients, salinity. Report to the National Environmental Research Program, Reef and Rainforest Research Centre Limited, Cairns**:** 46.

Collier, C. J., L. Langlois, Y. X. Ow, C. Johansson, M. Giammusso, M. A. Adams, K. O'Brien and S. Uthicke (2018). "Losing a winner: thermal stress and local pressures outweigh the positive effects of ocean acidification for tropical seagrasses " New Phytologist **219**(3): 1005-1017.

Collier, C. J., P. S. Lavery, R. J. Masini and P. J. Ralph (2009). "Shade-induced response and recovery of the seagrass *Posidonia sinuosa*." Journal of Experimental Marine Biology and Ecology **370**: 89-103.

Collier, C. J., Y. X. Ow, L. Langlois, S. Uthicke, C. Johansson, K. O'Brien, V. Hrebien and M. P. Adams (2017) "Optimum temperatures for net primary productivity of three tropical seagrass species." Frontiers in Plant Science **8**, 1446 DOI: 10.3389/fpls.2017.01446.

Collier, C. J., S. Uthicke and M. Waycott (2011). "Thermal tolerance of two seagrass species at contrasting light levels: implications for future distribution in the Great Barrier Reef." Limnology and Oceanography **56**: 2200-2210.

Collier, C. J., C. Villacorta-Rath, K.-j. van Dijk, M. Takahashi and M. Waycott (2014). "Seagrass proliferation precedes mortality during hypo-salinity events: a stress-induced morphometric response." PLoS ONE **9**(4): e94014.

Collier, C. J., M. Waycott and A. Giraldo-Ospina (2012). "Responses of four Indo-West Pacific seagrass species to shading." Marine Pollution Bulletin **65**(4-9): 342-354.

Collier, C. J., M. Waycott and A. Giraldo-Ospina (2012) "Responses of four Indo-West Pacific seagrass species to shading." Marine Pollution Bulletin **65**, 342-354 DOI: 10.1016/j.marpolbul.2011.06.017.

Collier, C. J., M. Waycott and L. J. McKenzie (2012). "Light thresholds derived from seagrass loss in the coastal zone of the northern Great Barrier Reef, Australia." Ecological Indicators **23**(0): 211-219.

Collier, C. J., M. Waycott and L. J. McKenzie (2012) "Light thresholds derived from seagrass loss in the coastal zone of the northern Great Barrier Reef, Australia." Ecological Indicators **23**, 211-219 DOI: 10.1016/j.ecolind.2012.04.005.

Connolly, R. M., E. L. Jackson, P. I. Macreadie, P. S. Maxwell and K. R. O'Brien (2018). Seagrass dynamics and resilience. Chapter 7. Seagrasses of Australia. A. W. D. Larkum, G. A. Kendrick and P. J. Ralph, Springer.

Cook, B. I., J. G. Palmer, E. R. Cook, C. S. M. Turney, K. Allen, P. Fenwick, A. O'Donnell, J. M. Lough, P. F. Grierson, M. Ho and P. J. Baker (2016) "The paleoclimate context and future trajectory of extreme summer hydroclimate in eastern Australia." Journal of geophysical research. Atmospheres : JGR **121**, 12820-12838 DOI: 10.1002/2016JD024892.

Cullen-Unsworth, L. and R. Unsworth (2013) "Seagrass Meadows, Ecosystem Services, and Sustainability." Environment: Science and Policy for Sustainable Development **55**, 14-28 DOI: 10.1080/00139157.2013.785864.

Cullen-Unsworth, L. C., L. M. Nordlund, J. Paddock, S. Baker, L. J. McKenzie and R. K. F. Unsworth (2014) "Seagrass meadows globally as a coupled social–ecological system: Implications for human wellbeing." Marine Pollution Bulletin **83**, 387-397 DOI: http://dx.doi.org/10.1016/j.marpolbul.2013.06.001.

Cunha, A. H., R. P. Santos, A. P. Gaspar and M. F. Bairros (2005) "Seagrass landscape-scale changes in response to disturbance created by the dynamics of barrier-islands: A case study from Ria Formosa (Southern Portugal)." Estuarine, Coastal and Shelf Science **64**, 636-644 DOI: 10.1016/j.ecss.2005.03.018.

Daan, N. (2005). "An afterthought: ecosystem metrics and pressure indicators." ICES Journal of Marine Science **62**: 612-613.

Davison, A. C. and D. V. Hinkley (1997). Bootstrap methods and their applications. Cambridge, Cambridge University Press.

De'ath, G. (2002) "Multivariate Regression Trees: A new technique for modeling species-environment relationships." Ecology **83**, 1105-1117.

De'ath, G. and K. Fabricius (2010). "Water quality as a regional driver of coral biodiversity and macroalgae on the Great Barrier Reef." Ecological Applications **20**(3): 840-850.

De'ath, G. (2004). "Multivariate partitioning. The mvpart Package version 1.1-1. Available in archive form on CRAN, https://cran.r-project.org)."

Delandmeter, P., S. E. Lewis, J. Lambrechts, E. Deleersnijder, V. Legat and E. Wolanski (2015). "The transport and fate of riverine fine sediment exported to a semi-open system." Estuarine, Coastal and Shelf Science **167**: 336-346.

Dennison, W. C. and R. S. Alberte (1985). "Role of daily light period in the depth distribution of *Zostera marina* (eelgrass)." Marine Ecology Progress Series **25**: 51-61.

Dennison, W. C., R. J. Orth, K. A. Moore, C. Stevenson, V. Carter, S. Kollar, P. W. Bergstrom and R. A. Batiuk (1993) "Assessing water quality with submersed aquatic vegetation: habitat requirements as barometers of Chesapeake Bay health." BioScience **43**, 86-94 DOI: 10.2307/1311969.

DiPerna, S., M. Hoogenboom, S. Noonan and K. Fabricius (2018). "Effects of variability in daily light integrals on the photophysiology of the corals *Pachyseris speciosa* and *Acropora millepora*." Plos One **13**(9).

Duarte, C. M. (1995). "Submerged aquatic vegetation in relation to different nutrient regimes." Ophelia **41**(1): 87-112.

Duarte, C. M., D. J. Conley, J. Carstensen and M. Sánchez-Camacho (2009) "Return to Neverland: Shifting baselines affect eutrophication restoration targets." Estuaries and Coasts **32**, 29-36 DOI: https://doi.org/10.1007/s12237-008-9111-2.

Duarte, C. M., W. C. Dennison, R. J. W. Orth and T. J. B. Carruthers (2008). "The charisma of coastal ecosystems: Addressing the imbalance." Estuaries and Coasts **31**(2): 233-238.

Erftemeijer, P. L. A. and R. R. Robin Lewis III (2006) "Environmental impacts of dredging on seagrasses: A review." Marine Pollution Bulletin **52**, 1553-1572 DOI: https://doi.org/10.1016/j.marpolbul.2006.09.006.

Fabricius, K. E. (2005). "Effects of terrestrial runoff on the ecology of corals and coral reefs: Review and synthesis." Marine Pollution Bulletin **50**(2): 125-146.

Fabricius, K. E., G. De'ath, C. Humphrey, I. Zagorskis and B. Schaffelke (2013). "Intra-annual variation in turbidity in response to terrestrial runoff on near-shore coral reefs of the Great Barrier Reef." Estuarine, Coastal and Shelf Science **116**: 57-65.

Fabricius, K. E., M. Logan, S. Weeks and J. Brodie (2014) "The effects of river run-off on water clarity across the central Great Barrier Reef." Marine Pollution Bulletin **84**, 191-200 DOI: http://dx.doi.org/10.1016/j.marpolbul.2014.05.012.

Fabricius, K. E., M. Logan, S. J. Weeks, S. E. Lewis and J. Brodie (2016). "Changes in water clarity in response to river discharges on the Great Barrier Reef continental shelf: 2002–2013." Estuarine, Coastal and Shelf Science **173**: A1-A15.

Faithful, J. and L. L. Griffiths (2000). "Turbid flow through a tropical reservoir (Lake Dalrymple, Quieensland, Australia): Responses to a summer storm event." Lakes and Reservoirs Research and Management **5**(4): 231-247.

Fernandes, M. B., R. Daly, J. van Gils, T. Kildea, S. Caires and P. L. A. Erftemeijer (2018). "Parameterization of an optical model to refine seagrass habitat requirements in an urbanized coastline." Estuarine, Coastal and Shelf Science **207**: 471-482.

Fernandes, M. B., J. van Gils, P. L. A. Erftemeijer, R. Daly, D. Gonzalez and K. Rouse (2019). "A novel approach to determining dynamic nitrogen thresholds for seagrass conservation." Journal of Applied Ecology **56**(1): 253-261.

Flores, F., C. J. Collier, P. Mercurio and A. P. Negri (2013). "Phytotoxicity of Four Photosystem II Herbicides to Tropical Seagrasses." PLoS ONE **8**(9): e75798.

Gallen, C., P. Thai, C. Paxman, P. Prasad, G. Elisei, T. Reeks, G. Eaglesham, R. Yeh, D. Tracey, S. Grant and J. Mueller (2019). Marine Monitoring Program: Annual report for inshore pesticide monitoring 2017-18. Report for the Great Barrier Reef Marine Park Authority. Townsville, Great Barrier Reef Marine Park Authority.

Geoscience Australia (2017). Intertidal Extents Model 25m. R. f. https://ecat.ga.gov.au/geonetwork/srv/eng/catalog.search?node=srv#/metadata/7d6f3432-5f93-45ee-8d6c-14b26740048a.

Gillibrand, P. A. and M. Herzfeld (2016). "A mass-conserving advection scheme for offline simulation of scalar transport in coastal ocean models." Ocean Modelling **101**: 1-16.

Govers, L. L., J. H. F. de Brouwer, W. Suykerbuyk, T. J. Bouma, L. P. M. Lamers, A. J. P. Smolders and M. M. van Katwijk (2014). "Toxic effects of increased sediment nutrient and organic matter loading on the seagrass *Zostera noltii*." Aquatic Toxicology **155**: 253-260.

Great Barrier Reef Marine Park Authority (2018). Seagrass Value Assssment. Townsville, Australia.

Great Barrier Reef Marine Park Authority and Queensland Government (2015). Reef 2050 Long-term Sustainability Plan. Townsville, Great Barrier Reef Marine Park Authority.

Great Barrier Reef Marine Park Authority, G. (2019). Great Barrier Reef Outlook report 2019. Townsville, Queensland, Australia, Great Barrier Reef Marine Park Authority.

Grech, A., R. Coles and H. Marsh (2011). "A broad-scale assessment of the risk to coastal seagrasses from cumulative threats." Marine Policy **35**(5): 560-567.

Grech, A., E. Hanert, L. McKenzie, M. Rasheed, C. Thomas, S. Tol, M. Wang, M. Waycott, J. Wolter and R. Coles (2018) "Predicting the cumulative effect of multiple disturbances on seagrass connectivity." Global Change Biology **0** DOI: 10.1111/gcb.14127.

Grech, A., C.-M. K.M., P. L. A. Erftemeijer, M. S. Fonseca, L. McKenzie, M. Rasheed, H. Taylor and R. Coles (2012). "A comparison of threats, vulnerabilities and management approaches in global seagrass bioregions." Environmental Research Letters **7**: 1-8.

Grech, A., J. Wolter, R. Coles, L. McKenzie, M. Rasheed, C. Thomas, M. Waycott, E. Hanert and D. Schoeman (2016) "Spatial patterns of seagrass dispersal and settlement." Diversity and Distributions **22**, 1150-1162 DOI: 10.1111/ddi.12479.

Griffiths, L. L., R. M. Connolly and C. J. Brown (2019). "Critical gaps in seagrass protection reveal the need to address multiple pressures and cumulative impacts." Ocean and Coastal Management.

Hallett, C. S., F. Valesini and M. Elliott (2016) "A review of Australian approaches for monitoring, assessing and reporting estuarine condition: III. Evaluation against international best practice and recommendations for the future." Environmental Science & Policy **66**, 282-291 DOI: http://dx.doi.org/10.1016/j.envsci.2016.07.015.

Head, B. W. (2014) "Evidence, uncertainty, and wicked problems in climate change decision making in Australia." Environment and Planning C: Government and Policy **32**, 663-679 DOI: 10.1068/c1240.

Herzfeld, M. (2006). "An alternative coordinate system for solving finite difference ocean models." Ocean modelling (Oxford) **14**(3): 174-196.

Herzfeld, M. and F. Rizwi (2016). RECOM User Manual V1.1, Commonwealth Scientific and Industrial Research Organisation.

Hoegh-Guldberg, O., R. Cai, E. S. Poloczanska, P. G. Brewer, S. Sundby, K. Hilmi, V. J. Fabry and S. Jung (2014). The Ocean. Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part B: Regional Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel of Climate Change. V. R. Barros, C. B. Field, D. J. Dokken et al. Cambridge, United Kingdom and New York, NY, USA, Cambridge University Press**:** 1655-1731.

Hughes, T. P., K. D. Anderson, S. R. Connolly, S. F. Heron, J. T. Kerry, J. M. Lough, A. H. Baird, J. K. Baum, M. L. Berumen, T. C. Bridge, D. C. Claar, C. M. Eakin, J. P. Gilmour, N. A. J. Graham, H. Harrison, J.-P. A. Hobbs, A. S. Hoey, M. Hoogenboom, R. J. Lowe, M. T. McCulloch, J. M. Pandolfi, M. Pratchett, V. Schoepf, G. Torda and S. K. Wilson (2018) "Spatial and temporal patterns of mass bleaching of corals in the Anthropocene." Science **359**, 80 DOI: 10.1126/science.aan8048.

Hughes, T. P., J. T. Kerry, M. Álvarez-Noriega, J. G. Álvarez-Romero, K. D. Anderson, A. H. Baird, R. C. Babcock, M. Beger, D. R. Bellwood, R. Berkelmans, T. C. Bridge, I. R. Butler, M. Byrne, N. E. Cantin, S. Comeau, S. R. Connolly, G. S. Cumming, S. J. Dalton, G. Diaz-Pulido, C. M. Eakin, W. F. Figueira, J. P. Gilmour, H. B. Harrison, S. F. Heron, A. S. Hoey, J.-P. A. Hobbs, M. O. Hoogenboom, E. V. Kennedy, C.-y. Kuo, J. M. Lough, R. J. Lowe, G. Liu, M. T. McCulloch, H. A. Malcolm, M. J. McWilliam, J. M. Pandolfi, R. J. Pears, M. S. Pratchett, V. Schoepf, T. Simpson, W. J. Skirving, B. Sommer, G. Torda, D. R. Wachenfeld, B. L. Willis and S. K. Wilson (2017) "Global warming and recurrent mass bleaching of corals." Nature **543**, 373-377 DOI: 10.1038/nature21707.

Kendrick, G. A., J. Eckersley and D. I. Walker (1999) "Landscape-scale changes in seagrass distribution over time: a case study from Success Bank." Aquatic Botany **65**, 293-309 DOI: 10.1016/S0304-3770(99)00047-9.

Kenworthy, J. W. (1999). "The role of sexual reproduction in maintaining populations of Halophila decipiens: implications for the biodiversity and conservation of tropical seagrass ecosystems." Pacific Conservation Biology **5**(4): 260-268.

Kerr, E. A. and S. Strother (1985). "Effects of irradiance, temperature and salinity on photosynthesis of *Zostera muelleri*." Aquatic Botany **23**: 177-183.

Kilminster, K., K. McMahon, M. Waycott, G. A. Kendrick, P. Scanes, L. McKenzie, K. R. O'Brien, M. Lyons, A. Ferguson, P. Maxwell, T. Glasby and J. Udy (2015). "Unravelling complexity in seagrass systems for management: Australia as a microcosm." Science of the Total Environment **534**: 97-109.

Kirk, J. T. O. (2011). Light and photosynthesis in aquatic ecosystems. New York, Cambridge University Press.

Kremen, C. (2005) "Managing ecosystem services: what do we need to know about their ecology?" Ecology Letters **8**, 468-479 DOI: 10.1111/j.1461-0248.2005.00751.x.

Kroon, F. J., P. M. Kuhnert, B. L. Henderson, S. N. Wilkinson, A. Kinsey-Henderson, B. Abbott, J. E. Brodie and R. D. R. Turner (2012). "River loads of suspended solids, nitrogen, phosphorus and herbicides delivered to the Great Barrier Reef lagoon." Marine Pollution Bulletin **65**(4): 167-181.

Kroon, F. J., P. M. Kuhnert, B. L. Henderson, S. N. Wilkinson, A. Kinsey-Henderson, B. Abbott, J. E. Brodie and R. D. R. Turner (2012) "River loads of suspended solids, nitrogen, phosphorus and herbicides delivered to the Great Barrier Reef lagoon." Marine Pollution Bulletin **65**, 167-181 DOI: 10.1016/j.marpolbul.2011.10.018.

Lamb, J. B., J. A. J. M. van de Water, D. G. Bourne, C. Altier, M. Y. Hein, E. A. Fiorenza, N. Abu, J. Jompa and C. D. Harvell (2017) "Seagrass ecosystems reduce exposure to bacterial pathogens of humans, fishes, and invertebrates." Science **355**, 731 DOI: 10.1126/science.aal1956.

Lambert, V. M., M. P. Adams, C. Collier, A. Carter, M. Saunders, J. Brodie, Z. T. Bainbridge, M. Rasheed, R. E. Turner and K. R. O'Brien (2019). Towards ecologically relevant targets: impact of flow and sediment discharge on seagrass communities in the Great Barrier Reef. 23rd Internation Congress on Modelling and Simulation. Canberra, ACT, Australia.

Lambrechts, J., C. Humphrey, L. McKinna, O. Gourge, K. E. Fabricius, A. J. Mehta, S. Lewis and E. Wolanski (2010). "Importance of wave-induced bed liquefaction in the fine sediment budget of Cleveland Bay, Great Barrier Reef." Estuarine, Coastal and Shelf Science **89**(2): 154-162.

Larcombe, P. and P. Ridd (2018). "The need for a formalised system of Quality Control for environmental policy-science." Marine Pollution Bulletin **126**: 449-461.

Larcombe, P. and P. Ridd (2019). "Viewpoint: The need for a formalised system of Quality Assurance for Environmental Policy-Science and for improved policy advice to Government on the Great Barrier Reef. Reply to – "Support for improved quality control but misplaced criticism of GBR science" by Britta Schaffelke, Katharina Fabricius, Frederieke Kroon, Jon Brodie, Glenn De'ath, Roger Shaw, Diane Tarte, Michael Warne, Peter Thorburn (Marine Pollution Bulletin 129: 357–363, 2018)." Marine Pollution Bulletin **143**: 50-57.

Lee, K.-S., S. R. Park and Y. K. Kim (2007) "Effects of irradiance, temperature, and nutrients on growth dynamics of seagrasses: A review." Journal of Experimental Marine Biology and Ecology **350**, 144-175 DOI: https://doi.org/10.1016/j.jembe.2007.06.016.

Lewis, S., Z. Bainbridge, T. Stevens, A. Garzon-Garcia, C. Chen, J. Burton, M. Bahadori, M. R. Rashti, J. Gorman, S. Smithers, J. Olley, M. P. and R. Dehayr (2018). Sediment tracing from the catchment to reef 2016 to 2018: Flood plume, marine sediment trap and logger data time series. Report to the National Environmental Science Program. Cairns, Reef and Rainforest Research Centre Limited**:** 94.

Lewis, S., Z. Bainbridge, T. Stevens, A. Garzon-Garcia, C. Chen, J. Burton, M. Bahadori, M. Rezaei Rashti, J. Gorman, S. Smithers, J. Olley, P. Moody and R. Dehayr (2018). Sediment tracing from the catchment to reef 2016 to 2018: Flood plume, marine sediment trap and logger data time series. Report to the National Environmental Science Program. Reef and Rainforest Research Centre Limited. Cairns**:** 94.

Lewis, S. E., Z. T. Bainbridge, P. M. Kuhnert, B. S. Sherman, B. Henderson, C. Dougall, M. Cooper and J. E. Brodie (2013). "Calculating sediment trapping efficiencies for reservoirs in tropical settings: A case study from the Burdekin Falls Dam, NE Australia." Water Resources Research **49**(2): 1017-1029.

Lewis, S. E., J. Olley, T. Furuichi, A. Sharma and J. Burton (2014). "Complex sediment deposition history on a wide continental shelf: Implications for the calculation of accumulation rates on the Great Barrier Reef." Earth and Planetary Science Letters **393**: 146-158.

Lewis, S. E., G. A. Shields, B. S. Kamber and J. M. Lough (2007). "A multi-trace element coral record of land-use changes in the Burdekin River catchment, NE Australia." Palaeogeography, Palaeoclimatology, Palaeoecology **246**(2): 471-487.

Longstaff, B. J., N. R. Loneragan, M. J. O'Donohue and W. C. Dennison (1999). "Effects of light deprivation on the survival and recovery of the seagrass *Halophila ovalis* (R.Br.) Hook." Journal of Experimental Marine Biology and Ecology **234**: 1-27.

Lough, J. M., K. D. Anderson and T. P. Hughes (2018) "Increasing thermal stress for tropical coral reefs: 1871–2017." Scientific Reports **8**, 6079 DOI: 10.1038/s41598-018-24530-9.

Lough, J. M. and A. J. Hobday (2011) "Observed climate change in Australian marine and freshwater environments." Marine and Freshwater Research **62**, 984-999 DOI: https://doi.org/10.1071/MF10272.

Madden, C. J., D. T. Rudnick, A. A. McDonald, K. M. Cunniff and J. W. Fourqurean (2009) "Ecological indicators for assessing and communicating seagrass status and trends in Florida Bay." Ecological Indicators **9**, S68-S82 DOI: http://dx.doi.org/10.1016/j.ecolind.2009.02.004.

Magno-Canto, M., B. J. Robson, L. McKinna and K. Fabricius (2019). "Model for deriving benthic irradiance in the Great Barrier Reef from MODIS satellite imagery." Optics Express **27**(20).

Marbá, N. and C. M. Duarte (2010) "Mediterranean warming triggers seagrass (*Posidonia oceanica*) shoot mortality." Global Change Biology **16**, 2366-2375 DOI: 10.1111/j.1365-2486.2009.02130.x.

Marbà, N., D. Krause-Jensen, T. Alcoverro, S. Birk, A. Pedersen, J. M. Neto, S. Orfanidis, J. M. Garmendia, I. Muxika, A. Borja, K. Dencheva and C. M. Duarte (2013) "Diversity of

European seagrass indicators: patterns within and across regions." Hydrobiologia **704**, 265-278 DOI: 10.1007/s10750-012-1403-7.

Margvelashvili, N., J. Andrewartha, M. Baird, M. Herzfeld, E. Jones, M. Mongin, F. Rizwi, B. J. Robson, J. Skerratt, K. Wild-Allen and A. Steven (2018). "Simulated fate of catchment-derived sediment on the Great Barrier Reef shelf." Marine Pollution Bulletin **135**: 954-962.

Marsh, H., T. J. O'Shea and J. E. Reynolds III (2011). Ecology and conservation of the Sirenia. Cambridge, Cambridge University Press.

Martinez-Crego, B., A. Verges, T. Alcoverro and J. Romero (2008) "Selection of multiple seagrass indicators for environmental biomonitoring." Marine Ecology Progress Series **361**, 93-109 DOI: 10.3354/meps07358.

Massa, S., S. Arnaud-Haond, G. Pearson and E. Serrão (2009) "Temperature tolerance and survival of intertidal populations of the seagrass *Zostera noltii* (Hornemann) in Southern Europe (Ria Formosa, Portugal)." Hydrobiologia **619**, 195-201 DOI: 10.1007/s10750-008-9609-4.

Maxwell, P. S., J. S. Eklöf, M. M. van Katwijk, K. R. O'Brien, M. de la Torre-Castro, C. Boström, T. J. Bouma, D. Krause-Jensen, R. K. F. Unsworth, B. I. van Tussenbroek and T. van der Heide (2017). "The fundamental role of ecological feedback mechanisms for the adaptive management of seagrass ecosystems – a review." Biological Reviews **92**(3): 1521-1538.

McCloskey, G. L., D. Waters, R. Baheerathan, S. Darr, C. Dougall, R. Ellis, B. Fentie and L. R. Hateley (2017). Modelling reductions of pollutant loads due to improved management practices in the Great Barrier Reef catchments: updated methodology and results. Technical Report for Reef Report Card 2015. Brisbane, Queensland, Queensland Department of Natural Resources and Mines.

McCook, L. J., B. Shaffelke, S. C. Apte, R. Brinkman, J. Brodie, P. L. A. Erftemeijer, B. Eyre, F. Hoogerwerf, I. Irvine, R. J. Jones, B. King, H. Marsh, R. J. Masini, R. Morton, R. Pitcher, M. Rasheed, M. Sheaves, A. Symonds and M. S. Warne (2015). Synthesis of current knowledge of the biophysical impacts of dredging and dispoal on the Great Barrier Reef: Report of an independant panel of experts, Great Barrier Reef Marine Park Authority.

McCulloch, M., S. Fallon, T. Wyndham, E. Hendy, J. Lough and D. Barnes (2003). "Coral record of increased sediment flux to the inner Great Barrier Reef since European settlement." Nature **421**(6924): 727-730.

McKenna, S., J. C. Jarvis, T. Sankey, C. Reason, R. Coles and M. Rasheed (2015) "Declines of seagrasses in a tropical harbour, North Queensland, Australia, are not the results of a single event." Journal of Biosciences (Bangalore) **40**, 389-398 DOI: 10.1007/s12038-015-9516-6.

McKenzie, L., C. J. Collier, L. Langlois, R. L. Yoshida, N. Smith and M. Waycott (2016). Marine Monitoring Program: Annual report for inshore seagrass monitoring: 2014 to 2015. Report for the Great Barrier Reef Marine Park Authority. Cairns, TropWATER, James Cook University**:** 236 pages.

McKenzie, L. J., C. J. Collier, L. A. Langlois, R. L. Yoshida, J. Uusitalo, N. Smith and M. Waycott (2019). Marine Monitoring Program: Annual Report for inshore seagrass monitoring 2017-2018. Report for the Great Barrier Reef Marine Park Authority, Great Barrier Reef Marine Park Authority.

McMahon, K. M., C. J. Collier and P. S. Lavery (2013) "Identifying robust bioindicators of light stress in seagrasses: A review." Ecological Indicators **30**, 7-15 DOI: https://doi.org/10.1016/j.ecolind.2013.01.030.

MEA, M. E. A. (2005). Ecosystems and human well-being: Current state and trends, Volume 1: findings of the Condition and Trends working Group. The Millenium Ecosystem Assessment Series. R. Hassan, R. Scholes and N. Ash. Washington, Island Press.

Mullahy, J. (1986) "Specification and testing of some modified count data models." Journal of Econometrics **33**, 341-365 DOI: https://doi.org/10.1016/0304-4076(86)90002-3.

Munkes, B. (2005). "Eutrophication, phase shift, the delay and the potential return in the greifswalder bodden, baltic sea." Aquatic Sciences **67**(3): 371-381.

Negri, A. P., F. Flores, P. Mercurio, J. F. Mueller and C. J. Collier (2015). "Lethal and sub-lethal chronic effects of the herbicide diuron on seagrass." Aquatic Toxicology **165**(0): 73-83.

Nordlund, L. M., E. W. Koch, E. B. Barbier and J. C. Creed (2016) "Seagrass Ecosystem Services and Their Variability across Genera and Geographical Regions." PLOS ONE **11**, e0163091 DOI: 10.1371/journal.pone.0163091.

Nordlund, L. M., R. K. F. Unsworth, M. Gullström and L. C. Cullen-Unsworth (2017). "Global significance of seagrass fishery activity." Fish and Fisheries **19**(3): 399-412.

O'Brien, K. R., M. P. Adams, A. J. P. Ferguson, J. Villarreal-Samper, P. S. Maxwell, M. E. Baird and C. J. Collier (2018). Seagrass resistance to light deprivation: implications for resilience. Seagrasses of Australia. A. W. D. Larkum, R. P.J. and G. Kendrick, Springer International Publishing AG, part of Springer Nature 2018.

O'Brien, K. R., M. Waycott, P. Maxwell, G. A. Kendrick, J. W. Udy, A. J. P. Ferguson, K. Kilminster, P. Scanes, L. J. McKenzie, K. McMahon, M. P. Adams, J. Samper-Villarreal, C. Collier, M. Lyons, P. J. Mumby, L. Radke, M. J. A. Christianen and W. C. Dennison (2017) "Seagrass ecosystem trajectory depends on the relative timescales of resistance, recovery and disturbance." Marine Pollution Bulletin DOI: https://doi.org/10.1016/j.marpolbul.2017.09.006.

O'Hara, T. D., M. D. Norman and D. A. Staples (2002). "Baseline monitoring of Posidonia seagrass beds in Corner Inlet, Victoria." Museum Victoria Science Reports **1**: 1-44.

Oreskes, N., K. Shrader-Frechette and K. Belitz (1994). "Verification, validation, and confirmation of numerical models in the earth sciences." Science **263**(5147): 641-646.

Orth, R. J., T. J. B. Carruthers, W. C. Dennison, C. M. Duarte, J. W. Fourqurean, K. L. Heck, A. R. Hughes, G. A. Kendrick, W. J. Kenworthy, S. Olyarnik, F. T. Short, M. Waycott and S. L. Williams (2006). "A global crisis for seagrass ecosystems." Bioscience **56**(12): 987-996.

Perrings, C., S. Naeem, F. S. Ahrestani, D. E. Bunker, P. Burkill, G. Canziani, T. Elmqvist, J. A. Fuhrman, F. M. Jaksic, Z. i. Kawabata, A. Kinzig, G. M. Mace, H. Mooney, A.-H. Prieur-Richard, J. Tschirhart and W. Weisser (2011) "Ecosystem services, targets, and indicators for the conservation and sustainable use of biodiversity." Frontiers in Ecology and the Environment **9**, 512-520 DOI: 10.1890/100212.

Personnic, S., C. F. Boudouresque, P. Astruch, E. Ballesteros, S. Blouet, D. Bellan-Santini, P. Bonhomme, D. Thibault-Botha, E. Feunteun, M. Harmelin-Vivien, G. Pergent, C. Pergent-Martini, J. Pastor, J.-C. Poggiale, F. Renaud, T. Thibaut and S. Ruitton (2014) "An ecosystem-based approach to assess the status of a Mediterranean ecosystem, the *Posidonia oceanica* seagrass meadow." PLOS ONE **9**, e98994 DOI: 10.1371/journal.pone.0098994.

Petrou, K., I. Jimenez-Denness, K. Chartrand, C. McCormack, M. Rasheed and P. J. Ralph (2013). "Seasonal heterogeneity in the photophysiological response to air exposure in two tropical intertidal seagrass species." Marine Ecology Progress Series **482**: 93-106.

Petus, C., C. J. Collier, M. Devlin, M. Rasheed and S. McKenna (2014) "Using MODIS data for understanding changes in seagrass meadow health: a case study in the Great Barrier Reef (Australia)." Marine Environmental Research **137**, 163-177 DOI: http://dx.doi.org/10.1016/j.jenvman.2013.11.050.

Petus, C., M. Devlin, A. Thompson, L. McKenzie, E. Teixeira da Silva, C. Collier, D. Tracey and K. Martin (2016) "Estimating the Exposure of Coral Reefs and Seagrass Meadows to Land-Sourced Contaminants in River Flood Plumes of the Great Barrier Reef: Validating a Simple Satellite Risk Framework with Environmental Data." Remote Sensing **8** DOI: 10.3390/rs8030210.

Petus, C., J. Waterhouse, S. Lewis, M. Vacher, D. Tracey and M. Devlin (2019) "A flood of information: Using Sentinel-3 water colour products to assure continuity in the monitoring of water quality trends in the Great Barrier Reef (Australia)." Journal of Environmental Management **248**, 109255 DOI: https://doi.org/10.1016/j.jenvman.2019.07.026.

Preen, A. R., W. J. L. Long and R. G. Coles (1995). "Flood and cyclone related loss, and partial recovery, of more than 1000 km^2 of seagrass in Hervey Bay, Queensland, Australia." Aquatic Botany **52**(1-2): 3-17.

QGIS Development Team (2018). QGIS Geographic Information System. Open Source Geospatial Foundation Project. .

Ralph, P. (1998). "Photosynthetic responses of *Halophila ovalis* (R. Br.) Hook. *f*. to osmotic stress." Journal of Experimental Marine Biology and Ecology **227**: 203-220.

Ralph, P. J. (1999). "Photosynthetic response of *Halophila ovalis* (R. Br.) Hook. *f*. to combined environmental stress." Aquatic Botany **65**: 83-96.

Ralph, P. J. and R. Gademann (2005). "Rapid light curves: a powerful tool to assess photosynthetic activity." Aquatic Botany **82**: 222-237.

Rasheed, M. A. (1999) "Recovery of experimentally created gaps within a tropical *Zostera capricorni* (Aschers.) seagrass meadow, Queensland, Australia." Journal of Experimental Marine Biology and Ecology **235**, 183-200 DOI: https://doi.org/10.1016/S0022-0981(98)00158-0.

Rasheed, M. A. (2004). "Recovery and succession in a multi-species tropical seagrass meadow following experimental disturbance: the role of sexual and asexual reproduction." Journal of Experimental Marine Biology and Ecology **310**: 13-45.

Rasheed, M. A., S. A. McKenna, A. B. Carter and R. G. Coles (2014). "Contrasting recovery of shallow and deep water seagrass communities following climate associated losses in tropical north Queensland, Australia." Marine Pollution Bulletin **83**(2): 491-499.

Rasheed, M. A., S. A. McKenna, A. B. Carter and R. G. Coles (2014) "Contrasting recovery of shallow and deep water seagrass communities following climate associated losses in tropical north Queensland, Australia." Marine Pollution Bulletin **83**, 491-499 DOI: http://dx.doi.org/10.1016/j.marpolbul.2014.02.013.

Rasheed, M. A. and R. K. F. Unsworth (2011) "Long-term climate-associated dynamics of a tropical seagrass meadow: implications for the future." Marine Ecology Progress Series **422**, 93-103 DOI: 10.3354/meps08925.

Rheuban, J. E., P. Berg and K. J. McGlathery (2014). "Multiple timescale processes drive ecosystem metabolism in eelgrass (*Zostera marina*) meadows." Marine Ecology Progress Series **507**: 1-13.

Rice, J. C. and M.-J. Rochet (2005). "A framework for selecting a suite of indicators for fisheries management." ICES Journal of Marine Science **62**(3): 516-527.

Robson, B., M. Canto, C. Collier, S. di Perna, M. Logan, P. Menendez, L. McKinna, S. Noonan and K. Fabricius (2019). Benthic light as an ecologically-validated GBR-wide indicator for water quality. Report to the National Environmental Science Program. Cairns, Reef and Rainforest Research Centre Limited**:** 40.

Roca, G., T. Alcoverro, D. Krause-Jensen, T. J. S. Balsby, M. M. van Katwijk, N. Marbà, R. Santos, R. Arthur, O. Mascaró, Y. Fernández-Torquemada, M. Pérez, C. M. Duarte and J. Romero (2016) "Response of seagrass indicators to shifts in environmental stressors: A global review and management synthesis." Ecological Indicators **63**, 310-323 DOI: https://doi.org/10.1016/j.ecolind.2015.12.007.

Samhouri, J. F., S. E. Lester, E. R. Selig, B. S. Halpern, M. J. Fogarty, C. Longo and K. L. McLeod (2012) "Sea sick? Setting targets to assess ocean health and ecosystem services." Ecosphere **3**, 1-18 DOI: 10.1890/ES11-00366.1.

Samhouri, J. F. and P. S. Levin (2012) "Linking land- and sea-based activities to risk in coastal ecosystems." Biological Conservation **145**, 118-129 DOI: http://dx.doi.org/10.1016/j.biocon.2011.10.021.

Samhouri, J. F., P. S. Levin, C. Andrew James, J. Kershner and G. Williams (2011). "Using existing scientific capacity to set targets for ecosystem-based management: A Puget Sound case study." Marine Policy **35**(4): 508-518.

Saunders, M. I., S. Atkinson, C. J. Klein, T. Weber and H. P. Possingham (2017) "Increased sediment loads cause non-linear decreases in seagrass suitable habitat extent." PLOS ONE **12**, e0187284 DOI: 10.1371/journal.pone.0187284.

Saunders, M. I., J. X. Leon, D. P. Callaghan, C. M. Roelfsema, S. Hamylton, C. J. Brown, T. Baldock, A. Golshani, S. R. Phinn, C. E. Lovelock, O. Hoegh-Guldberg, C. Woodroe and P. J. Mumby (2014). "Interdependency of tropical marine ecosystems in response to climate change." Nature Climate Change **4(8)**: 724-729.

Schaffelke, B., C. Collier, F. Kroon, J. Lough, L. McKenzie, M. Ronan, S. Uthicke and J. Brodie (2017). Chapter 1: The condition of coastal and marine ecosystems of the Great Barrier Reef and their responses to water quality and disturbances. Scientific Consensus Statement 2017: A synthesis of the science of land-based water quality impacts on the Great Barrier Reef, State of Queensland, 2017.

Schliep, M., M. Pernice, S. Sinutok, C. V. Bryant, P. H. York, M. A. Rasheed and P. J. Ralph (2015) "Evaluation of reference genes for RT-qPCR studies in the seagrass *Zostera muelleri* exposed to light limitation." Scientific Reports **5**, 17051 DOI: 10.1038/srep17051

http://www.nature.com/articles/srep17051#supplementary-information.

Scott, A. L., P. H. York, C. Duncan, P. I. Macreadie, R. M. Connolly, M. T. Ellis, J. C. Jarvis, K. I. Jinks, H. Marsh and M. A. Rasheed (2018) "The Role of Herbivory in Structuring Tropical Seagrass Ecosystem Service Delivery." Frontiers in Plant Science **9**, 127.

Shafer, D. J., T. D. Sherman and S. Wyllie-Echeverria (2007) "Do desiccation tolerances control the vertical distribution of intertidal seagrasses?" Aquatic Botany **87**, 161-166 DOI: https://doi.org/10.1016/j.aquabot.2007.04.003.

State of Queensland (2018). Reef 2050 Water Quality Improvement Plan 2017-2020. Brisbane, Australia, Queensland Government.

Steffen, W., W. Broadgate, L. Deutsch, O. Gaffney and C. Ludwig (2015) "The trajectory of the Anthropocene: The Great Acceleration." The Anthropocene Review **2**, 81-98 DOI: 10.1177/2053019614564785.

Steward, J. S. and W. C. Green (2007) "Setting load limits for nutrients and suspended solids based upon seagrass depth-limit targets." Estuaries and Coasts **30**, 657-670 DOI: 10.1007/BF02841963.

Steward, J. S., R. W. Virnstein, L. J. Morris and E. F. Lowe (2005) "Setting seagrass depth, coverage, and light targets for the Indian River Lagoon system, Florida." Estuaries **28**, 923-935 DOI: 10.1007/BF02696020.

Strahl, J., M. M. Rocker and K. E. Fabricius (2019). "Contrasting responses of the coral Acropora tenuis to moderate and strong light limitation in coastal waters." Marine Environmental Research **147**: 80-89.

Strange, C. J. (2007) "Facing the brink without crossing It." BioScience **57**, 920-926 DOI: 10.1641/B571103.

Tett, P., R. J. Gowen, S. J. Painting, M. Elliott, R. Forster, D. K. Mills, E. Bresnan, E. Capuzzo, T. F. Fernandes, J. Foden, R. J. Geider, L. C. Gilpin, M. Huxham, A. L. McQuatters-Gollop, S. J. Malcolm, S. Saux-Picart, T. Platt, M. F. Racault, S. Sathyendranath, J. van der Molen and M. Wilkinson (2013) "Framework for understanding marine ecosystem health." Marine Ecology Progress Series **494**, 1-27 DOI: 10.3354/meps10539.

The State of Queensland (2018). Reef 2050 Water Quality Improvement Plan 2017-2022. Brisbane, Reef Water Quality Protection Plan Secretariat.

Thomson, J. A., D. A. Burkholder, M. R. Heithaus, J. W. Fourqurean, M. W. Fraser, J. Statton and G. A. Kendrick (2015) "Extreme temperatures, foundation species, and abrupt ecosystem change: an example from an iconic seagrass ecosystem." Global Change Biology **21**, 1463-1474 DOI: 10.1111/gcb.12694.

Tol, S. J., R. G. Coles and B. C. Congdon (2016) "*Dugong dugon* feeding in tropical Australian seagrass meadows: implications for conservation planning." PeerJ **4**, e2194 DOI: 10.7717/peerj.2194.

Tol, S. J., J. C. Jarvis, P. H. York, A. Grech, B. C. Congdon and R. G. Coles (2017). "Long distance biotic dispersal of tropical seagrass seeds by marine mega-herbivores." Scientific Reports **7**(1): 4458.

Tweedie, M. C. K. (1984). An index that distinguishes between some important exponential families. Statistics: Applications and new directions. Proceedings of the Indian Statistical Institute Golden Jubilee International Conference, Calcutta: Indian Statistical Institute.

Unsworth, R., K. F. , S. Hinder, L. , O. Bodger, G. and L. Cullen-Unsworth, C. (2014). "Food supply depends on seagrass meadows in the coral triangle." Environmental Research Letters **9**(9): 094005.

Unsworth, R. K. F., C. J. Collier, M. Waycott, L. J. McKenzie and L. C. Cullen-Unsworth (2015) "A framework for the resilience of seagrass ecosystems." Marine Pollution Bulletin **100**, 34-46 DOI: 10.1016/j.marpolbul.2015.08.016.

Unsworth, R. K. F., L. J. McKenzie, C. J. Collier, L. C. Cullen-Unsworth, C. M. Duarte, J. S. Eklöf, J. C. Jarvis, B. L. Jones and L. M. Nordlund (2019) "Global challenges for seagrass conservation." Ambio DOI: 10.1007/s13280-018-1115-y.

Unsworth, R. K. F., L. M. Nordlund and L. C. Cullen-Unsworth (2018) "Seagrass meadows support global fisheries production." Conservation Letters **e12566** DOI: https://doi.org/10.1111/conl.12566.

Unsworth, R. K. F., M. A. Rasheed, K. M. Chartrand and A. J. Roelofs (2012). "Solar radiation and tidal exposure as environmental drivers of *Enhalus acoroides* dominated seagrass meadows." PLOS ONE **7**(3): e34133.

Van der Heide, T., A. Smolders, B. Riikens, E. H. van Nes, M. M. van Katwick and J. Roelofs (2008). "Toxicity of reduced nitrogen in eelgrass (*Zostera marina*) is highly dependent on shoot density and pH." Oecologia **158**: 411-419.

van der Heide, T., E. H. van Nes, M. M. van Katwijk, M. Scheffer, A. Jan Hendriks and A. J. P. Smolders (2010). "Alternative stable states driven by density-dependent toxicity." Ecosystems **13**(6): 841-850.

Walker, B. and D. Salt (2012). Resilience thinking: Sustaining ecosystems and people in a changing world, Island Press.

Waterhouse, J., J. Brodie, D. Tracey, R. D. Smith, M. Vandergragt, C. Collier, C. Petus, M. E. Baird, F. Kroon, R. Mann, T. Sutcliffe and F. Adame (2017). Chapter 3, The risk from anthropogenic pollutants to Great Barrier Reef coastal and marine ecosystems. Scientific Consensus Statement 2017: A synthesis of the science of land-based water quality impacts ont he Great Barrier Reef, State of Queensland, 2017.

Waterhouse, J., C. Lønborg, M. Logan, C. Petus, D. Tracey, C. Howley, E. Harper, H. Tonin, M. Skuza, J. Doyle, P. Costello, J. Davidson, K. Gunn, M. Wright, I. Zagorskis and F. Kroon (2018). Marine Monitoring Program: Annual Report for inshore water quality monitoring 2016-2017. Report for the Great Barrier Reef Marine Park Authority. Townsville, Great Barrier Reef Marine Park Authority.

Waterhouse, J., B. Schaffelke, R. Bartley, R. Eberhard, J. Brodie, M. Star, P. Thorburn, J. Rolfe, M. Ronan, B. Taylor and F. Kroon (2017). 2017 Scientific Consensus Statement: Land-use impacts on Great Barrier Reef water quality and ecosystem condition. Brisbane, The State of Queensland.

Waycott, M., C. M. Duarte, T. J. B. Carruthers, R. J. Orth, W. C. Dennison, S. Olyarnik, A. Calladine, J. W. Fourqurean, K. L. Heck, A. R. Hughes, G. A. Kendrick, W. J. Kenworthy, F. T. Short and S. L. Williams (2009) "Accelerating loss of seagrasses across the globe threatens coastal ecosystems." Proceedings of the National Academy of Sciences **106**, 12377-12381 DOI: 10.1073/pnas.0905620106.

Waycott, M., B. J. Longstaff and J. Mellors (2005) "Seagrass population dynamics and water quality in the Great Barrier Reef region: A review and future research directions." Marine Pollution Bulletin **51**, 343-350 DOI: https://doi.org/10.1016/j.marpolbul.2005.01.017.

Waycott, M., K. McMahon, J. Mellors, A. Calladine and D. Kleine (2004). A guide to tropical seagrasses of the Indo-West Pacific. Townsville, James Cook University.

Wickham, H. (2016). ggplot2: Elegant graphics for data analysis. New York, Springer-Verlag

Wicks, E. C., B. J. Longstaff, B. Fertig and W. C. Dennison (2010). Chapter 5 Ecological indicators: Assessing ecosystem health using metrics. Integrating and applying science: A handbook for effective coastal ecosystem assessment, IAN Press, Cambridge, maryland.

Wilkinson, A. D., C. J. Collier, F. Flores, L. Langlois, P. J. Ralph and A. P. Negri (2017). "Combined effects of temperature and the herbicide diuron on Photosystem II activity of the tropical seagrass *Halophila ovalis*." Scientific Reports **7**: 45404.

Wilkinson, A. D., C. J. Collier, F. Flores, P. Mercurio, J. O'Brien, P. J. Ralph and A. P. Negri (2015). "A Miniature bioassay for testing the acute phytotoxicity of photosystem II herbicides on seagrass." PLoS ONE **10**(2): e0117541.

Wilkinson, A. D., C. J. Collier, F. Flores and A. P. Negri (2015). "Acute and additive toxicity of ten photosystem-II herbicides to seagrass." Scientific Reports **5**: 17443.

York, P. H., A. B. Carter, K. Chartrand, T. Sankey, L. Wells and M. A. Rasheed (2015) "Dynamics of a deep-water seagrass population on the Great Barrier Reef: annual occurrence and response to a major dredging program." Scientific Reports **5**, 13167 DOI: 10.1038/srep13167

http://www.nature.com/articles/srep13167#supplementary-information.

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