Assessing the Effectiveness of Local Management of Coral Reefs Using Expert Opinion and Spatial Bayesian Modeling

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Abstract

Multiple stressors are an increasing concern in the management and conservation of ecosystems, and have been identified as a key gap in research. Coral reefs are one example of an ecosystem where management of local stressors may be a way of mitigating or delaying the effects of climate change. Predicting how multiple stressors interact, particularly in a spatially explicit fashion, is a difficult challenge. Here we use a combination of an expert-elicited Bayesian network (BN) and spatial environmental data to examine how hypothetical scenarios of climate change and local management would result in different outcomes for coral reefs on the Great Barrier Reef (GBR), Australia. Parameterizing our BN using the mean responses from our experts resulted in predictions of limited efficacy of local management in combating the effects of climate change. However, there was considerable variability in expert responses and uncertainty was high. Many reefs within the central GBR appear to be at risk of further decline based on the pessimistic opinions of our expert pool. Further parameterization of the model as more data and knowledge become available could improve predictive power. Our approach serves as a starting point for subsequent work that can fine-tune parameters and explore uncertainties in predictions of responses to management.

Introduction

In an ecological context, a stressor has been defined as a perturbation that is either foreign to the system being studied, or natural to that system but influencing it at an excessive level [1]. Multiple stressors are an increasing concern in the management and conservation of ecosystems because interactions between stressors can potentially exacerbate biodiversity declines [2–6]. Interactions between stressors can result in "ecological surprises" [7], as have been observed in freshwater [3], marine [8], and terrestrial [9] ecosystems. Multiple stressors do not affect ecosystems uniformly, however. Instead, they can exhibit spatial heterogeneity (e.g., salt marshes [10], and kelp beds [11]) that can affect the probability of regime shifts at particular sites [12].

Models of the effects of multiple stressors that provide spatially explicit outputs would be useful for informing management, yet few such models exist to date, at least in a marine context. Spatially explicit models would be particularly helpful in marine ecosystems, where ocean zoning has been proposed as one way of addressing cumulative impacts [13]. Interactions between stressors may occur at multiple spatial scales, ranging from local to global, with some stressors manageable, others not. Ecosystem managers (i.e., those responsible for recommending public policies directly or indirectly affecting an ecosystem) may be able to influence anthropogenic stressors by building resistance or resilience to non-manageable stressors such as storms and disease [14, 15]. With the increasing threat of climate change, assessing management options at the local and regional scales at which managers operate will be increasingly important [16, 17] as one way to delay or mitigate climate-change effects [8, 18, 19]. However, few practical approaches assess, model, or guide management of multiple stressors, particularly in marine ecosystems, largely due to data limitations. Data are limited partly by the number of interactions increasing exponentially with the number of stressors (i.e., the number of possible n-way interactions between n variables increases according to 2^n), and by the general lack of ecological data from monitoring and assessment surveys that are sufficiently comprehensive to statistically examine the interactions between stressors. Additionally, estimating the strength of interactions between stressors is difficult for several reasons. One is the non-linear behaviour of ecosystem responses; another is the potential for mis-matches in timescale between discretely-measured empirical data and the assumption of instantaneous changes used by many mathematical models [20].

There are several modeling approaches for working in situations where data are either insufficient to fully parameterize a model, or provide insufficient statistical power for the number of variables being examined. Holmes and Johnstone [21], for example, used a dynamic systems model that was not spatially explicit but was parameterized at least partly with expert judgment and input. However, the predictive ability of models using classical inference is limited by scale-dependent effects, constraints on model dimension and parameterization, and uncertainty about which model components are stochastic or deterministic [22]. Some techniques that have been applied to multiple-stressor management have included qualitative ranking of ecosystem stressors by experts [23] and relative risk models [24]. Bayesian networks (BNs) have also found increasing application as a decision-support tool in ecology and adaptive management (e.g., [25], [26–28]) where predictive utility is paramount but data are limited and uncertainty is high [29]. Furthermore, the expert elicitation process commonly used in the development of Bayesian networks allows experts to contribute to the development of model structure as well as informing model parameters, thereby conceptualizing interactions between stressors as well as understanding their effects [25]. Expert elicitation has seen increasing use in decision-making in the context of problems in conservation biology where data are missing or incomplete [30].

Despite the increasing acceptance of BNs in ecology and management, spatial implementations of these models through management decisions remain rare; searching Web of Science using the keywords "Bayesian belief", "spatial", and "marine", for example, finds only six papers [31–36]. In a marine-planning context, a recent paper [36] did use a BN in conjunction with a GIS to evaluate cumulative human impacts on the coastal waters of England and Wales; however, the cumulative impact score in Stelzenmüller et al.'s [36] study was simply the sum of the qualitative scores for each of three human activities given equal weighting, rather than a combination of stressors that recognized their different relative weights and effects.

In terms of evaluating ecosystem effects of climate change, many climate-change models and scenarios focus on slow-changing variables such as average temperature and acidification. Such models may not take into account interactions with variables that change on much

shorter (annual or seasonal) timescales, and thus may underestimate the ecosystem effects of climate change. Thus few models are readily applicable to the short- and medium-term time-frames most useful for ecosystem managers (but see [37, 38]), and fewer still attempt to incorporate interaction effects between multiple stressors.

Multiple stressors have been identified as a key problem facing managers in coral reef ecosystems [16, 39] because reefs face threats on both global and local scales [40]. However, these threats vary over both time and space, and effective conservation planning for dynamic threats requires a spatially explicit prediction of those threats [41]. Furthermore, spatial heterogeneity becomes increasingly important for reserve system design as the scale of management diverges from the scale of underlying ecosystem processes [42]. Thus, in this paper, we spatially implement an expert-elicited Bayesian network (BN) in a coral reef ecosystem: the Great Barrier Reef (GBR) in Queensland, Australia. We chose the GBR as a case study because the key stressors (i.e., those having the greatest influence on reef condition) have been identified [43–49], and because good spatial data exist for many of these stressors. Stressors that may be locally manageable include nutrient loading, sedimentation, pollution, and fishing pressure, whereas stressors that are infeasible to manage directly include coral disease, coral bleaching, and cyclones. Outbreaks of crown-of-thorns (CoTS) starfish are possible to control, but the required management is highly labour-intensive and impractical at large scales [50]. Also, management of certain stressors, including CoTS, is made difficult by their unpredictability in time and space. Another advantage of the GBR as a case study is the existence of an extensive protected-area network, meaning that many reefs suffer little or no extractive pressures, allowing us to examine the potential effectiveness of these managed areas in reducing multiple-stressor effects, where coral cover is used as a proxy for reef condition.

Scenario planning is a way of considering possible futures for systems that contain high levels of uncertainty where direct experimental manipulations of the system are impractical [51]. Scenarios are one way to frame complex and uncertain factors that define the boundaries of a problem, but are neither forecasts nor predictions [52, 53]. In this study, we use scenarios in the form of possible combinations of stressor levels to model the effects of potential stressor interactions. We then use these model outputs to identify which management actions might most affect the future trajectory of coral cover. We present this study, not as a policy prescription, but as a first step towards better characterizing the complexity and realities of multiple stressors as they pertain to coral reefs. Our broad aim is to provide a foundation that can be built upon and fine-tuned to guide future management.

Methods

Ethics statement

Our survey design was approved by James Cook University's Human Research Ethics Committee (Application ID #H4542). We obtained written consent from all survey participants.

Model development

We created a Bayesian network model using two types of data: empirical data and expert opinion (Fig 1). All of the spatial environmental data put into the model were empirical; the consequences of various combinations of these environmental conditions were generated from the BN model using expert opinions. Within our model, we devised a set of four scenarios, each one describing a different qualitative combination of possible conditions approximately 10 years into the future (Table 1). In these scenarios, changes in stressors or stressor indicators like bleaching and disease were described in terms of a one standard deviation change from the long-term mean in terms of either frequency for discrete events (cyclones, floods, crown-of-
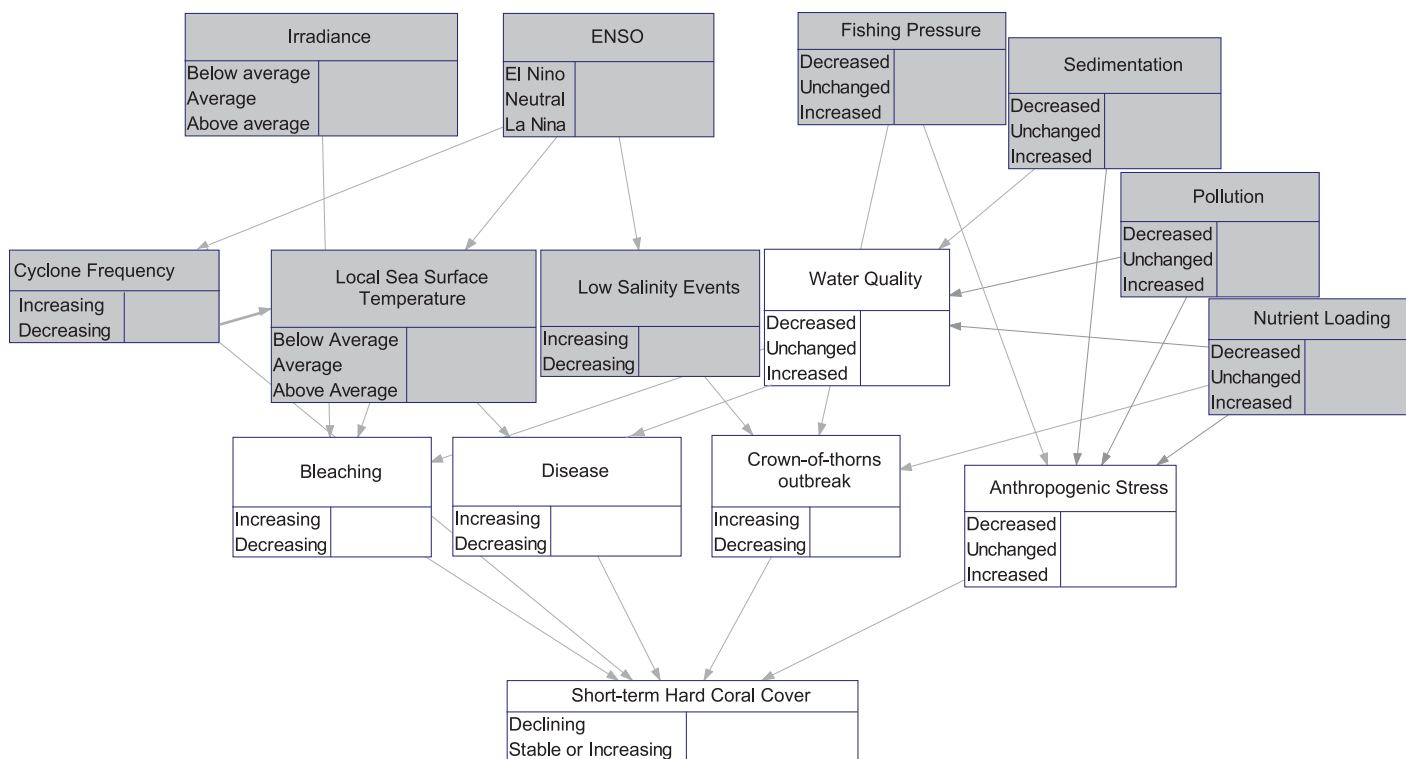
Fig 1. Schematic of the Bayesian network structure. Nodes in grey are informed by empirical data; nodes in white are elicited from experts. The nodes for water quality and anthropogenic stress are composite nodes that assign a weight to each of their parent nodes to create an overall index. Note that some of the nodes (e.g., bleaching, disease) reflect symptoms of stress, rather than being stressors *per se*.

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thorns outbreaks, mass bleaching, disease outbreaks) or intensity for fishing pressure, sedimentation, pollution, and nutrient loading. The choice of one standard deviation was arbitrary, but was chosen to be readily interpretable by the experts and consistent across variables, and to represent a significant enough change to lie outside the bounds of normal variations without being extreme enough to be unlikely. In the case of temperature, an increase of 1°C above the climatological mean was used as a conservative threshold value for coral bleaching [54]. It should be clarified that, in the survey, experts were asked how a temperature anomaly above this threshold would affect the chances of a mass bleaching event occurring, not the probability that these anomalies would occur. The scenarios were as follows:

Table 1. Climate change and management scenarios with associated changes to input layers. n.c. = no change from baseline (current conditions); plus sign = 1 standard deviation increase above baseline; minus sign = 1 standard deviation decrease below baseline condition, except for temperature (0.2 degree above/below climatological mean). CoTS = Crown-of-thorns-starfish. Scenarios refer to the change in conditions after approximately a 10-year timeframe.

Scenario number (see text for description)	Temperature	Cyclones	Disease	Bleaching	Irradiance	CoTS	Nutrients	Sediment	Pollution	Fishing
1	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.
2	+	+	+	+	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.
3	+	+	+	+	n.c.	n.c	-	-	-	-
4	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	-	-	-	-

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1. Baseline: all variables unchanged from present conditions (i.e., at the time the surveys were conducted in 2012)

2. Climate change without local management: assume that temperature anomalies increase 0.2 degrees (based on 1°C of mean ocean warming by 2050) above those observed to date, with a concomitant increase in cyclone frequency, disease outbreaks, and mass bleaching events, without any reductions in fishing pressure or terrestrial inputs (nutrients, sediments, pollution)

3. Climate change with local management: as in the previous scenario, but with management actions to reduce fishing pressure and terrestrial inputs (i.e. terrigenous nutrient, sediment, pollutants) by approximately one standard deviation (~30%) relative to current levels.

4. Local management without further climate change: implementation of management actions as in the previous scenario, but without any change in climate-related variables beyond present conditions.

The empirical data for the model came from several sources (Table A in S1 File, grey nodes in Fig 1). Historical cyclone tracks were obtained from IBTRACS [55]. Only Category II and higher cyclones were included, and the tracks were buffered asymmetrically as per Fabricius et al. [56]. The average and maximum extent of flood plumes from 2007–2011 were obtained from Alvarez-Romero et al. [57], as were data on loadings of nutrients (dissolved inorganic nitrogen) and sediment. Sea surface temperature anomalies were identified from satellite climatology data (1985–2007) as per the methods described in Ban et al. [58]. Mean solar irradiance was obtained from NASA SeaWiFS satellite data (1997–2010). Data on fishing catch and effort for line fisheries were obtained from the Queensland Department of Agriculture, Fisheries and Forestry. Some data on commercial catch and effort were available only at a resolution of 30 nautical miles (nm) due to confidentiality rules, whereas others had a resolution of 6 nm. We downscaled the lower-resolution data by assuming that the relative effort distribution of the data at 30 nm resolution was similar to that of the 6 nm-resolution data, and reapportioned the 30 nm data accordingly. This approach is commonly used in stock assessments of Queensland fisheries [59]. Reefs within no-take areas were assumed to have no fishing effort or catch. Except for temperature, all input data layers were re-coded into three categories to be consistent with the survey questions, which specified 3 possible states or conditions for each variable: 1 standard deviation or more above average; within 1 standard deviation of average; and 1 standard deviation or more below average. For temperature, anomalies were coded as being greater than/less than/within 1°C from the climatological mean. All of the input layers, consisting of spatially-explicit values for individual reefs, were then placed in different combinations for each of our scenarios (Table 1).

The second type of data used in the model was based on expert opinions about the degree of influence each empirical variable had on the probability of a certain event (white nodes, Fig 1). The expert pool consisted of 21 coral reef ecologists with extensive experience with the GBR specifically. These experts were asked to consider the probability of various events occurring within a ten-year timeframe for a hypothetical mid-shelf, mid-latitude reef with approximately 30% hard coral cover. Experts were interviewed on an individual basis, using the 4-point elicitation method [60], whereby respondents are asked for the lowest possible value, highest possible value, best estimate, and confidence in their estimate. Prior to answering the questionnaire, to reduce variability, each expert was read a statement that provided definitions for key terms and set the context of the questions. Experts were also provided with a schematic diagram of the model, and asked to annotate the diagram to add or delete any stressors or stressor relationships as necessary. The initial selection of the expert pool—based on scientists with the largest

number of publications pertaining to coral reef ecology on the GBR—was expanded using the snowball method [61], wherein each expert was also asked to provide the names of two other people whom they recognized as experts in the field. In our model, the events considered by the experts were: probability of a mass bleaching event, probability of a coral disease outbreak, and probability of a crown-of-thorns starfish (CoTS) outbreak. For nodes where the number of possible permutations of event states was impractical to elicit directly from our experts, we instead asked for probability estimates of the extreme endpoints (all stressors high vs. all stressors low), and interpolated between those estimates. The complete methodology of this expert elicitation process is described in Ban et al [62]. The ultimate endpoint of the model was the probability of hard coral cover declining below present levels over a ten-year timeframe (2012–2022), which was also estimated by our experts. This probability was contingent upon the various events (bleaching, disease, CoTS) increasing or decreasing in frequency. We used three sets of probabilities of events from the expert elicitation process as inputs (parameterizations) to the model: the group mean, the 25th percentile (pessimistic), and the 75th percentile (optimistic). The pessimistic parameterization corresponded to higher probabilities of adverse events; the optimistic parameterization corresponded to lower probabilities of adverse events.

Both the empirical data and the expert-elicited probabilities were entered in the form of conditional probability tables into Netica [63], where each unique combination of event states (e.g, high/average/low temperature, presence/absence of a flood plume) is associated with a discrete probability of an outcome (e.g., mass bleaching). All data layers were plotted onto a common 500 metre geographic grid, which was the finest resolution of the input layers. Model predictions for the probability of coral cover declining below current levels were then calculated for each mid-shelf reef by supplying the model with input values from that location. These overall probabilities of decline were also the result of expert opinions regarding various combinations of events (e.g., a mass bleaching event and a disease outbreak event occurring in close succession on the same reef). Additionally, due to the decade-scale time frame, these probabilities of decline were intended to capture the net result of both mortality events and subsequent recovery (i.e., whether a reef would be able to recover its pre-disturbance coral cover following a certain combination of events).

We limited the extent of the study area for two reasons: first, to match the availability of our input spatial data layers, and second to avoid over-generalizing the applicability of our scenarios given the very different characteristics of inshore, mid-shelf, and offshore reefs. Our study area was thus confined to the central GBR (inset, Fig 2). We constrained the model inputs and outputs only to those areas designated as "mid-shelf" under GBRMPA's bioregional classification system [64, 65]; this encompassed 775 individual reefs in a latitudinal range extending between 15.77°S and 22.31°S, corresponding with the minimum extent of the data input layers.

The four scenarios compared model predictions using four different combinations of conditions: with and without management action, and with and without additional climate change effects (Table 1; Table B in S1 File). These four scenarios were: Baseline, Climate Change without Local Management, Climate Change with Local Management, and a best-case scenario of Management without (further) Climate Change. The Baseline scenario represented the mean of the available environmental data for each grid cell. Under the climate-change scenarios, we increased the risk category uniformly for cyclones so that the chance of any given reef being hit by a cyclone increased by 30%, added 0.2°C to historical temperature anomalies (based on the IPCC A1B scenario of ~2.2°C average SST rise by 2100; [66]), and increased the extent/severity of flood plumes, sedimentation, and nutrient loading by one standard deviation (~30%). Incident irradiance and frequency of CoTS outbreaks remained unchanged across all scenarios. In the improved management scenarios, fishing pressure, sedimentation, and nutrient loading were reduced by one standard deviation.
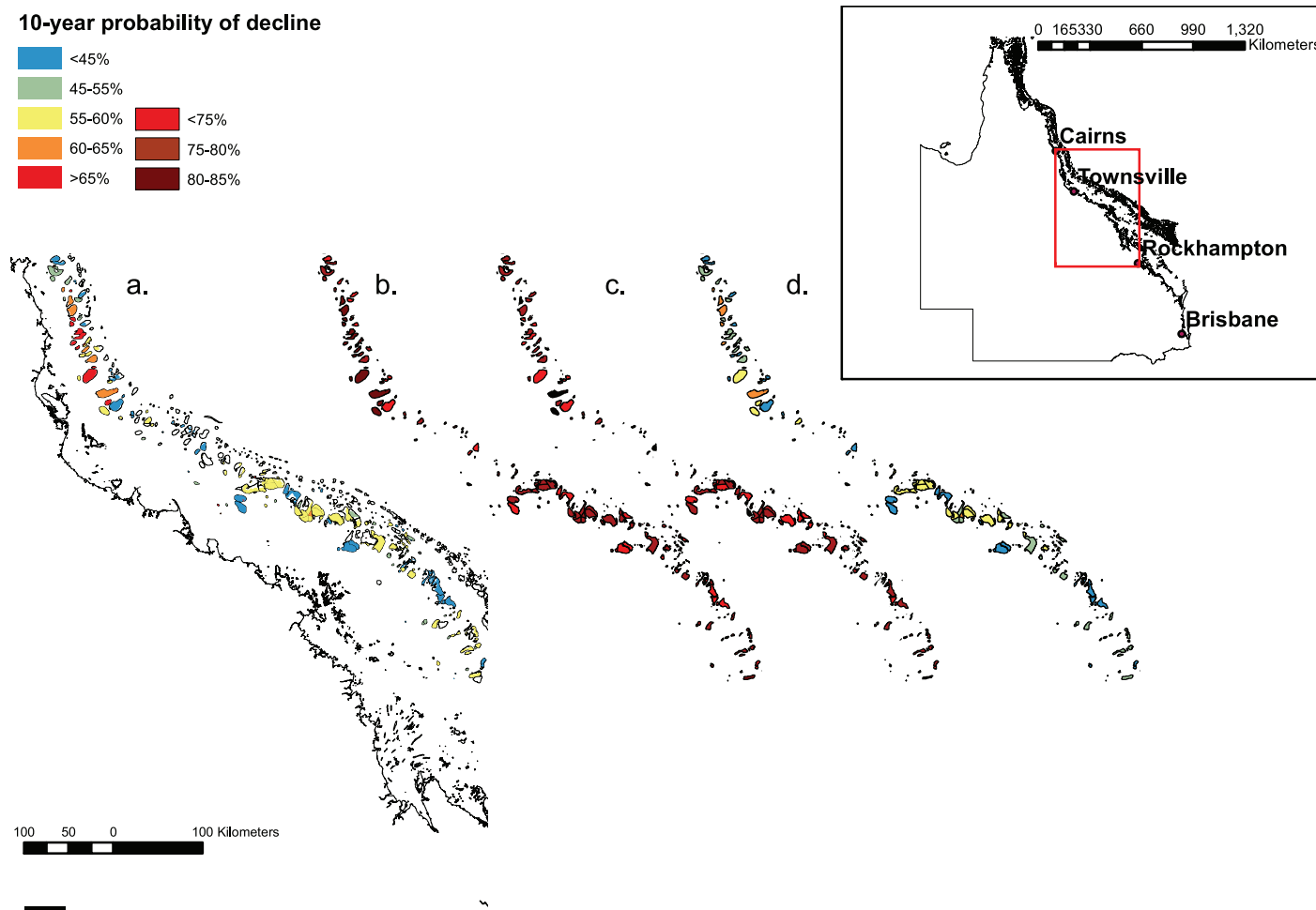
Fig 2. Model outputs for 10-year probability of decline of hard coral cover for each scenario: a) baseline; b) climate change without local management c) climate change with local management; d) local management without further climate change. The baseline scenario map (a) depicts all reefs, including inner- and outer-shelf reefs for context; model results were applied only to mid-shelf reefs. Inset: study area, focused on central portion of the GBR, excluding far-northern and far-southern reefs.

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We used the centroid (geographic centre) of each reef within the study area to determine the values of the input layers, and mapped the corresponding model-predicted probability of coral decline for each scenario at that location. The output values of the model thus corresponded to the input values for the centroid of each reef. We then compared the average probability of predicted decline of hard coral cover for reefs both within highly protected (no-take) zones (green, orange, and pink zones: [67]) and outside these zones. Finally, we produced a series of change maps by taking the difference in predicted probability of decline between two scenarios and calculating the relative change by dividing this difference by the first scenario's predicted value.

1. Climate change with local management vs. baseline

2. Climate change with local management vs. climate change without local management

3. Local management without further climate change (best-case scenario) vs. baseline

Results

Under the baseline scenario, our model predicted probabilities of decline for mid-shelf reefs ranging from about 35% to 75% (Fig 2a), with a mean of 59% with respect to the number of reefs. Under the climate change without local management scenario, few reefs had a probability of decline of less than 70%, with some having probabilities of more than 85% and most falling into the 70–80% range (Fig 2b). The mean probability of decline in this scenario was 77%. Under the climate change with local management scenario, in which fishing pressure, sedimentation, and nutrient loading were reduced by at least 30% (Fig 2c), the mean decline was also 77%, and most reefs showed a very similar probability of decline to those in the scenario of climate change without local management. Finally, under the best-case scenario (reduced fishing, sediment and nutrient loading without further climate change), the mean predicted probability of decline was 58% (Fig 2d). In short, the baseline scenario resulted in a mean probability of decline of 59%, climate change with or without management action had a probability of decline of 77%, and the best-case scenario had a mean probability of decline of 58%.

The climate change without local management scenario increased the mean probability of decline by approximately 30% over the baseline value, from a mean decline probability of 59% to 77% (Fig 3). For the other scenario pairs, although the means differed very little, the distributions of decline probabilities did differ (Fig 4). Local management without further climate change (best-case) reduced the probability of decline by a mean of 0.7% relative to baseline (Fig 4a). Climate change with local management resulted in a mean 0.3% reduction of probability of decline relative to climate change without local management (Fig 4b).

Reefs outside no-take zones had marginally higher mean probabilities of decline than reefs inside no-take zones in each of our scenarios (Fig 5). The mean difference in probability of decline between no-take and other zones ranged from just under 1% in the climate change with local management scenario (Fig 5d) to just over 5% in the baseline scenario (Fig 5a).

Using the 25th (pessimistic) and 75th (optimistic) percentile model parameterizations with the same input data scenarios shifted the distribution of probabilities of decline accordingly (Figs A,B in S1 File). There was less variability between reefs in both the 25th and 75th percentile parameterizations compared to the mean parameterization, particularly in the case of the 25th percentile under both climate change scenarios (Fig B in S1 File), for which the mean predicted probability of decline was more than 90%.

Discussion

We used an expert-elicited BN to explore possible differences in vulnerability to multiple stressors on mid-shelf reefs within the GBR, and found a moderate probability of continued decline in coral cover, even in the best-case scenario of no further climate change combined with reductions in local stressors. Our intent was to construct a model that could be used to generate spatially explicit outputs using only basic and readily-available input data and to compare hypothetical outcomes of different management and stressor scenarios over a relatively short (10-year) time frame. However, given the relatively coarse parameterization and applicability of the models, and the range of likely values in the expert responses (see Ban et al [62] for more detail on the spread of parameter values), we believe this should be only the first step in constructing more sophisticated models that are tailored specifically to different types of reefs.

Our results highlight experts' opinions of the dire situation of coral reefs in the GBR, as well as the uncertainty or lack of consensus between experts about many stressor effects. Even under our baseline scenario, in which we assumed that all stressors remained unchanged, our model predicted a moderate probability that coral cover on mid-shelf reefs would decline. This result is consistent with recent findings that coral cover on the Great Barrier Reef as a whole
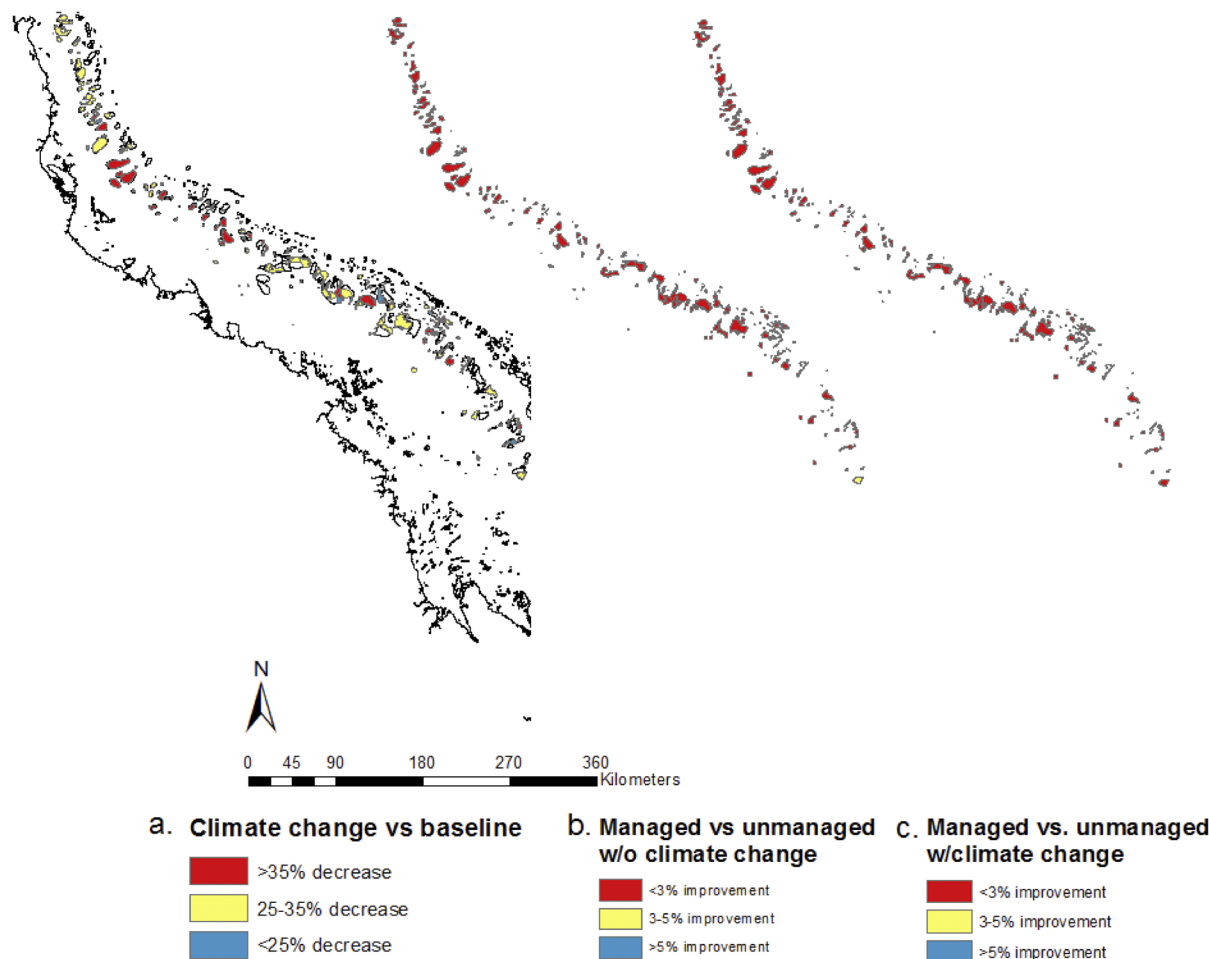
Fig 3. Relative change in probability of decline in hard coral cover between two scenarios: climate change without local management and the baseline scenario. Differences between other scenarios not shown because they were minimal.

has been declining at an average rate of 0.5% per year since surveys began in 1985, with a steepening rate of decline since 2006 [44]. Perhaps more surprising is how little the best-case scenario (reduction of all locally-manageable stressors without further climate change) differed from the baseline scenario. There are several possible explanations for this lack of change. One is that many mid-shelf reefs rarely experience the effects of terrigenous flood plumes and their associated chemicals, sediment, and nutrients [68], so reductions in any or all of these factors would be unlikely to have a significant effect on the trajectory of coral cover on these reefs. Secondly, the effects of stressors that are not under direct management control (such as outbreaks of CoTS, mass bleaching, and cyclones) are likely to have a much stronger immediate influence on coral mortality and subsequent declines in cover than many of the manageable stressors. This also comports with the findings of De'ath et al [44], who concluded that CoTS outbreaks and cyclones, along with bleaching, were key drivers of coral decline in the GBR.

Based on expert opinion, our model predicted a slight but consistent difference in the predicted probability of decline between reefs within and outside the existing protected area network on the GBR. Since fishing pressure is one of the stressors in the model, and we assumed that fishing pressure inside protected areas was zero, this result is not surprising. Research on the GBR has shown higher coral cover on reefs inside versus outside no-take areas—partly due
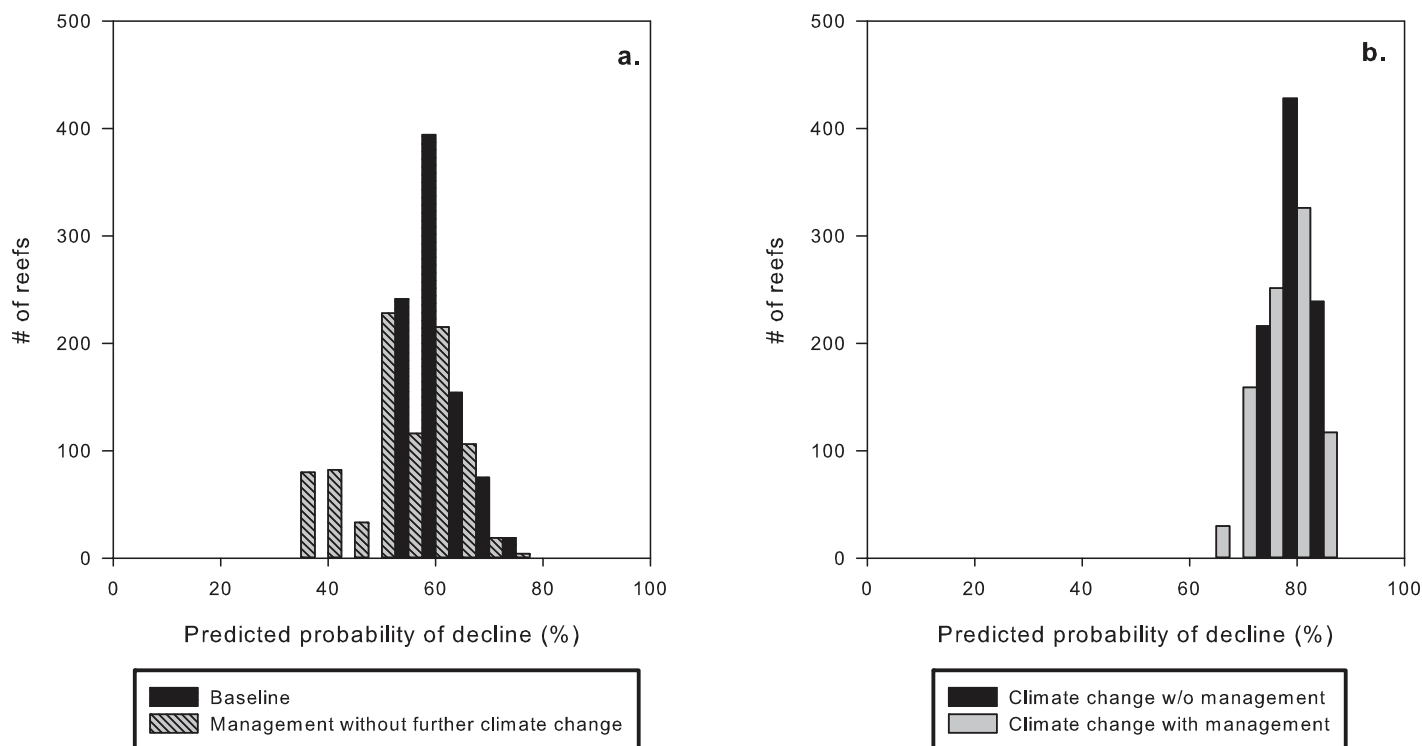
Fig 4. Difference in decline probability between paired management scenarios. a) Baseline vs management without further climate change. b) Climate change with management action vs climate change without management action.

to protection from direct damage from fishing gear and anchors and partly from indirect effects possibly associated with trophic interactions [69]. More generally, fishing pressure has been linked to changes in coral cover through a trophic cascade process [70, 71]. Although weak, the association between fishing pressure and probability of declining coral cover in our model remaining even in all of the improved management scenarios where the 30% reduction in fishing pressure was simulated to occur outside reserves. While commercial fishing pressure within the GBR is thought to be sustainable [72], insufficient data exist for many species, and increased shark landings are a particular concern [73]; thus, a 30% across-the-board reduction in fishing may be less effective than larger catch reductions in selected keystone or apex species [74, 75]. Since our model did not incorporate patterns of larval dispersal or connectivity between reefs, it did not capture the benefits of a protected area network as a recruitment source, and overlooked some of the other benefits of marine reserves beyond direct fishing impacts, such as trophic cascade effects that may reduce outbreaks of crown-of-thorns starfish and sea urchins and so result in increases in coral cover [14, 69, 76].

Our findings should not be interpreted to mean that local management actions to mitigate or reverse declines in coral cover are futile or unimportant. Recent studies have demonstrated possible effects of local management on enhancing resistance and resilience of coral reefs to stresses [14, 17, 18, 77]. One example is where rebuilding fish biomass and diversity may increase the resistance of reefs to disturbances such as bleaching and disease [77]. The effectiveness of local management actions may also depend on the nature of the interaction between stressors, because reducing a stressor that is interacting in an antagonistic or mitigative fashion with another may actually make the net result worse [18, 78]. However, marine reserves are not a panacea for dealing with stress and disturbance to coral reefs [79–83], particularly if
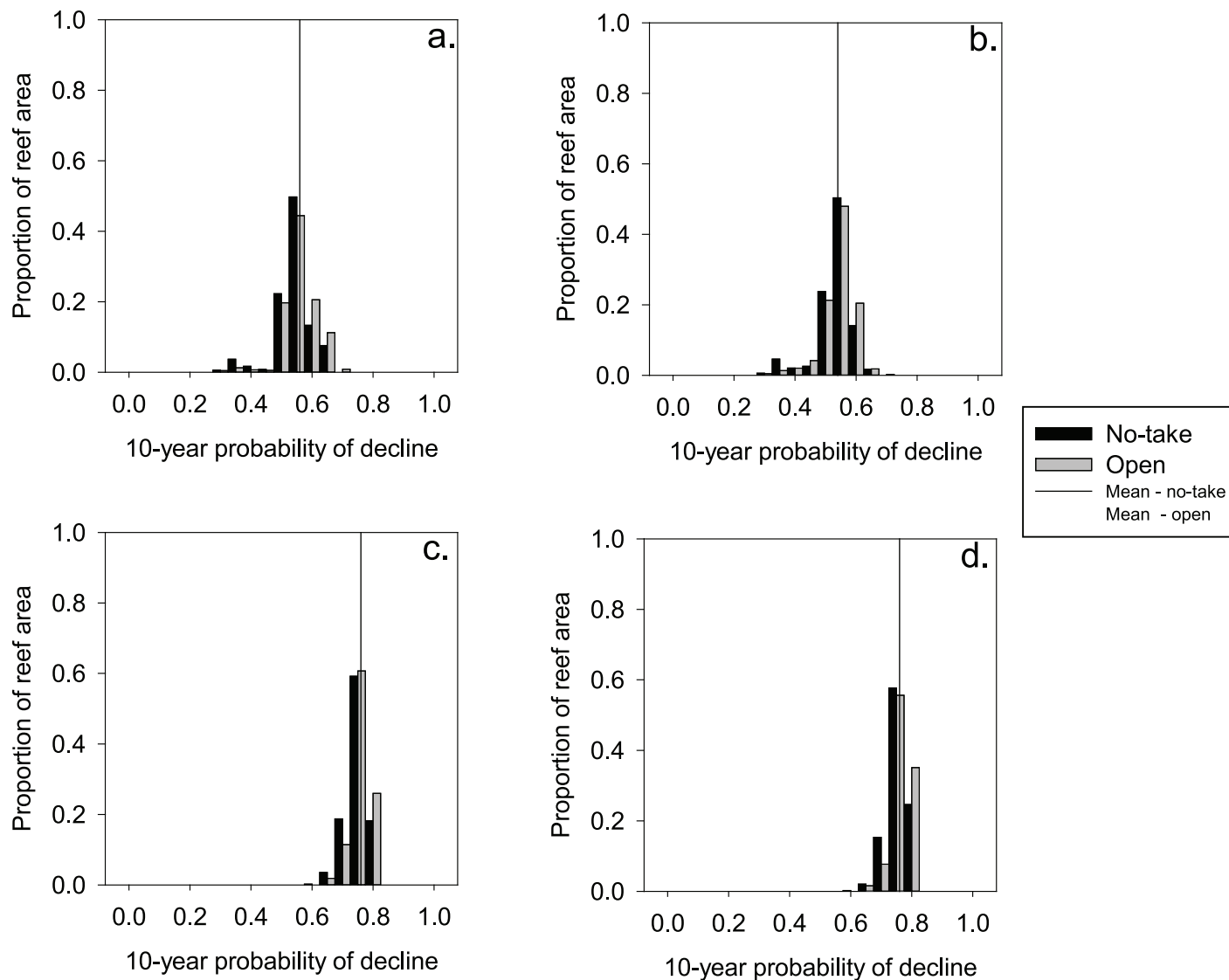
Fig 5. Comparison of predicted 10-year decline probabilities between all four scenarios: a) baseline vs management with no further climate change; b) climate change with management action vs climate change without management action.

activities other than fishing are not restricted. Other local management actions include reductions in sediment and pollutant loading. One possible implication of our model is that the current level of anthropogenic stress is such that even a 30% reduction in all local impacts may be insufficient to stop or reverse the trend of declining coral cover, and thus that more drastic management interventions are required. For example, Wooldridge et al [84] reported that a 50–80% in dissolved inorganic nitrogen inputs would be necessary to return the GBR to pre-European conditions.

There are some limitations to the model we have developed. First, it was parameterized for only one type of reef (mid-shelf and mid-latitude) within the GBR, and it assumes uniform susceptibilities to threats like disease and bleaching, regardless of community composition. Since our model was high-level and not mechanistic, it can only paint a general picture of these reefs' possible responses to stressor scenarios. We also deliberately confined the model to have a

limited number of input states. This was mainly a limitation of the expert-elicitation approach and the need to have a tractable number of stressor permutations within scenarios, but it also required us to interpolate responses of intermediate stressor conditions linearly between end-points (See [62] for more details). It is also important to recognize the limitations of expert judgment, especially in tasks requiring weighting and combining factors [85]. Our model was also intended as a form of hypothesis generation and testing rather than as a prescriptive guide. Furthermore, conclusions about the effectiveness of management actions depend upon the structure of the model; different model structures would likely result in quite different qualitative (and quantitative) predictions.

Our study is one of the few examples of expert-elicited Bayesian networks that have been applied spatially in a marine environment [31–36]. Expert elicitation has seen increasing application in ecological contexts where empirical data are absent, incomplete, or uncertain and is especially useful in combination with Bayesian methods [86]. While the model we developed and applied here was somewhat simplified, it is also one of the few that has attempted to capture the effects of simultaneous multiple stressors in an explicit fashion where the nature of stressor interactions (e.g., additive, synergistic, mitigative) is not assumed a priori. Despite their relatively crude nature, coarse or approximate models can still be useful as a decision-support tools [87], and conservation biology in particular benefits from the use of such models to "simulate uncertain but plausible scenarios, explore the consequences of decisions, and test alternative decision strategies" [87]. Further development of this model—such as by developing more sophisticated sub-models and incorporating specific elements affecting recovery and resilience factors, and, if possible, ground-truthing the results—will likely be necessary before it can be used in a real-world management context. However, spatially-explicit models informed by expert-opinion are ultimately likely to be useful to assess and prioritize areas of conservation concern in many data-limited and/or time-sensitive systems beyond coral reefs. Such models should, of course, also be subjected to peer-review before being applied in a management context.

Supporting Information

S1 File. Input data layers (Table A). Modified environmental data layers for scenarios. (Table B) Comparison between optimistic, pessimistic, and mean model outputs for probability of decline of hard coral cover for a) baseline scenario, reefs open to fishing; b) baseline scenario, reefs closed to fishing; c) Local management without further climate change, open reefs; and d) Local management without further climate change, closed reefs. (Fig A) Comparison between optimistic, pessimistic, and mean model outputs for probability of decline of hard coral cover for a) climate change without local management scenario, reefs open to fishing; b) climate change without local management, reefs closed to fishing; c) climate change with local management, open reefs; and d) climate change with local management, closed reefs. (Fig B). (DOCX)

Author Contributions

Conceived and designed the experiments: SB. Performed the experiments: SB. Analyzed the data: SB. Contributed reagents/materials/analysis tools: SB. Wrote the paper: SB RLP NG.

References

1. Barrett GW, Van Dyne GM, Odum EP. Stress ecology. BioScience. 1976; 26(3):192–4.
2. Folt CL, Chen CY, Moore MV, Burnaford J. Synergism and antagonism among multiple stressors. Limnology and Oceanography. 1999; 44(3 II):864–77.

3. Hecky RE, Muginne R, Ramlal PS, Talbot MR, Kling GW. Multiple stressors cause rapid ecosystem change in Lake Victoria. Freshwater Biology. 2010; 55(Suppl. 1):241–57.

4. Przeslawski R, Davis AR, Benkendorff K. Synergistic effects associated with climate change and the development of rocky shore molluscs. Global Change Biology. 2005; 11(3):515–22. doi: 10.1111/j.1365-2486.2005.00918.x

5. Salbu B, Rosseland BA, Oughton DH. Multiple stressors—a challenge for the future. Journal of Environmental Monitoring. 2005; 7(6):539-. doi: 10.1039/b506220a. ISI:000230928100009. PMID: 15933768

6. Vinebrooke RD, Cottingham KL, Norberg J, Scheffer M, Dodson SI, Maberly SC, et al. Impacts of multiple stressors on biodiversity and ecosystem functioning: The role of species co-tolerance. Oikos. 2004; 104(3):451–7.

7. Lindenmayer DB, Likens GE, Krebs CJ, Hobbs RJ. Improved probability of detection of ecological "surprises". Proc Natl Acad Sci U S A. 2010; 107(51):21957–62. doi: 10.1073/pnas.1015696107. WOS:000285521800008. PMID: 21098660

8. Russell BD, Thompson JI, Falkenberg LJ, Connell SD. Synergistic effects of climate change and local stressors: CO_2 and nutrient-driven change in subtidal rocky habitats. Global Change Biology. 2009; 15 (9):2153–62. doi: 10.1111/j.1365-2486.2009.01886.x

9. Bansal S, Hallsby G, Lofvenius MO, Nilsson MC. Synergistic, additive and antagonistic impacts of drought and herbivory on *Pinus sylvestris*: leaf, tissue and whole-plant responses and recovery. Tree Physiology. 2013; 33(5):451–63. doi: 10.1093/treephys/tpt019. WOS:000319430900002. PMID: 23525156

10. Kujala H, Burgman MA, Moilanen A. Treatment of uncertainty in conservation under climate change. Conservation Letters. 2013; 6(2):73–85. doi: 10.1111/j.1755-263X.2012.00299.x

11. Marcot BG. Characterizing species at risk I: Modeling rare species under the northwest forest plan. Ecology and Society. 2006; 11(2).

12. van Nes EH, Scheffer M. Implications of spatial heterogeneity for catastrophic regime shifts in ecosystems. Ecology. 2005; 86(7):1797–807. doi: 10.1890/04-0550

13. Halpern BS, McLeod KL, Rosenberg AA, Crowder LB. Managing for cumulative impacts in ecosystem-based management through ocean zoning. Ocean & Coastal Management. 2008; 51:203–11.

14. Page CA, Baker DM, Harvell CD, Golbuu Y, Raymundo L, Neale SJ, et al. Influence of marine reserves on coral disease prevalence. Dis Aquat Org. 2009; 87(1–2):135–50. doi: 10.3354/dao02112. ISI:000272675600013. PMID: 20095248

15. Wooldridge S. Quantifying the synergistic interaction between thermal stress and water quality in determining the bleaching sensitivity of inshore reefs in the Great Barrier Reef Marine Park. Marine and Tropical Sciences Research Facility; 2007. p. 21.

16. NOAA (National Oceanic and Atmospheric Administration). NOAA's Integrated Assessment Program Washington, D.C.2012 [cited 2012 22 October, 2012]. Available from: http://www.noaa.gov/iea/.

17. Carilli JE, Norris RD, Black BA, Walsh SM, McField M. Local stressors reduce coral resilience to bleaching. PLoS ONE. 2009; 4(7):e6324. doi: 10.1371/journal.pone.0006324 PMID: 19623250

18. Brown CJ, Saunders MI, Possingham HP, Richardson AJ. Managing for interactions between local and global stressors of ecosystems. PLoS ONE. 2013; 8(6):e65765. doi: 10.1371/journal.pone.0065765 PMID: 23776542

19. MacNeil MA, Graham NAJ. Enabling regional management in a changing climate through Bayesian meta-analysis of a large-scale disturbance. Global Ecology and Biogeography. 2010; 19(3):412–21. doi: 10.1111/j.1466-8238.2009.00515.x

20. Wootton JT, Emmerson M. Measurement of interaction strength in nature. Annual Review of Ecology, Evolution, and Systematics 2005. p. 419–44.

21. Holmes G, Johnstone RW. Modelling coral reef ecosystems with limited observational data. Ecological Modelling. 2010; 221(8):1173–83. doi: 10.1016/j.ecolmodel.2010.01.010

22. Clark JS. Why environmental scientists are becoming Bayesians. Ecology Letters. 2005; 8:2–14.

23. Halpern BS, Walbridge S, Selkoe KA, Kappel CV, Micheli F, D'Agrosa C, et al. A global map of human impact on marine ecosystems. Science. 2008; 319(5865):948–52. doi: 10.1126/science.1149345 PMID: 18276889

24. Landis WG, Durda JL, Brooks ML, Chapman PM, Menzie CA, Stahl RG, et al. Ecological risk assessment in the context of global climate change. Environmental Toxicology and Chemistry. 2013; 32 (1):79–92. doi: 10.1002/etc.2047. WOS:000312545700010. PMID: 23161373

25. Marcot BG, Steventon JD, Sutherland GD, McCann RK. Guidelines for developing and updating Bayesian belief networks applied to ecological modeling and conservation. Canadian Journal of Forest Research. 2006; 36(12):3063–74.

26. Thomas CR. Bayesian belief network development for ecological decision support in data-sparse domains with a case study on tropical seagrass in the Great Barrier Reef, Australia: Monash University; 2008.

27. Smith CS, Howes AL, Price B, McAlpine CA. Using a Bayesian belief network to predict suitable habitat of an endangered mammal—The Julia Creek dunnart (Sminthopsis douglasi). Biological Conservation. 2007; 139(3–4):333–47. WOS:000250330700010.

28. Mantyka-Pringle CS. Understanding and predicting the combined effects of climate change and land-use change on freshwater macroinvertebrates and fish. The Journal of applied ecology. 2014; 51 (3):572–81. doi: 10.1111/1365-2664.12236

29. Cain J. Planning improvements in natural resources management: Guidelines for Bayesian networks to support the planning and management of development programmes in the water sector and beyond. Wallingford, UK.: Centre for Ecology and Hydrology, 2001.

30. Martin TG, Burgman MA, Fidler F, Kuhnert PM, LOW-CHOY S, McBride M, et al. Eliciting expert knowledge in conservation science. Conservation Biology. 2012; 26(1):29–38. doi: 10.1111/j.1523-1739. 2011.01806.x PMID: 22280323

31. Grech A, Coles RG. An ecosystem-scale predictive model of coastal seagrass distribution. Aquat Conserv-Mar Freshw Ecosyst. 2010; 20(4):437–44. doi: 10.1002/aqc.1107. WOS:000279822100009.

32. Kininmonth S, van Oppen MJH, Possingham HP. Determining the community structure of the coral Seriatopora hystrix from hydrodynamic and genetic networks. 101016/jecolmodel200710033. 2010; 221 (24):2870–80. doi: 10.1016/j.ecolmodel.2010.08.042. WOS:000284444300002.

33. Palmer M, Balle S, March D, Alos J, Linde M. Size estimation of circular home range from fish mark-release-(single)-recapture data: case study of a small labrid targeted by recreational fishing. Marine Ecology Progress Series. 2011; 430:87–U146. WOS:000291826600007.

34. Payo DA, Leliaert F, Verbruggen H, D'Hondt S, Calumpong HP, De Clerck O. Extensive cryptic species diversity and fine-scale endemism in the marine red alga Portieria in the Philippines. Proc R Soc B-Biol Sci. 2013; 280(1753). doi: 10.1098/rspb.2012.2660. WOS:000313510600018.

35. Stelzenmüller V, Schulze T, Fock HO, Berkenhagen J. Integrated modelling tools to support risk-based decision-making in marine spatial management. Marine Ecology Progress Series. 2011; 441:197–212. doi: 10.3354/meps09354. WOS:000298061000017.

36. Stelzenmüller V, Lee J, Garnacho E, Rogers S. Assessment of a Bayesian Belief Network–GIS framework as a practical tool to support marine planning. Marine Pollution Bulletin. 2010; 60(10):1743–54. doi: 10.1016/j.marpolbul.2010.06.024 PMID: 20619861

37. Meesters EH, Bak RPM, Westmacott S, Ridgley M, Dollars S. A fuzzy logic model to predict coral reef development under nutrient and sediment stress. Conservation Biology. 1998; 12(5):957–65.

38. Melbourne-Thomas J, Johnson CR, Alino PM, Geronimo RC, Villanoy CL, Gurney GG. A multi-scale biophysical model to inform regional management of coral reefs in the western Philippines and South China Sea. Environmental Modelling & Software. 2011; 26(1):66–82. doi: 10.1016/j.envsoft.2010.03. 033. WOS:000283891600009.

39. Great Barrier Reef Marine Park Authority Research Priorities [Internet]. 2009 [cited 29 June, 2009]. Available from: http://www.gbrmpa.gov.au/corp_site/info_services/science_management/research_ priorities/database/.

40. Riegl B, Bruckner A, Coles SL, Renaud P, Dodge RE. Coral reefs threats and conservation in an era of global change. Year in Ecology and Conservation Biology 2009. Annals of the New York Academy of Sciences. 1162. Oxford: Blackwell Publishing; 2009. p. 136–86.

41. Pressey R, Cabeza M, Watts ME, Cowling RM, Wilson KA. Conservation planning in a changing world. Trends Ecol Evol. 2007.

42. Possingham HP, Franklin J, Wilson K, Regan TJ. The roles of spatial heterogeneity and ecological processes in conservation planning. Ecosystem function in heterogeneous landscapes: Springer; 2005. p. 389–406.

43. Schroeder T, Devlin MJ, Brando VE, Dekker AG, Brodie JE, Clementson LA, et al. Inter-annual variability of wet season freshwater plume extent into the Great Barrier Reef lagoon based on satellite coastal ocean colour observations. Marine pollution bulletin. 2012; 65(4–9):210–23. MEDLINE:22459495. doi: 10.1016/j.marpolbul.2012.02.022 PMID: 22459495

44. De'ath G, Fabricius KE, Sweatman H, Puotinen M. The 27–year decline of coral cover on the Great Barrier Reef and its causes. Proceedings of the National Academy of Sciences. 2012. doi: 10.1073/pnas. 1208909109

45. Brodie J, Waterhouse J. A critical review of environmental management of the 'not so Great' Barrier Reef. Estuarine, Coastal and Shelf Science. 2012; 104–105(0):1–22.

46. Haynes D, Brodie J, Waterhouse J, Bainbridge Z, Bass D, Hart B. Assessment of the Water Quality and Ecosystem Health of the Great Barrier Reef (Australia): Conceptual Models. Environmental Management. 2007; 40(6):993–1003. PMID: 17786511

47. Lewis SE, Brodie JE, Bainbridge ZT, Rohde KW, Davis AM, Masters BL, et al. Herbicides: A new threat to the Great Barrier Reef. Environmental Pollution. 2009; 157(8–9):2470–84. doi: 10.1016/j.envpol. 2009.03.006 PMID: 19349104

48. Maynard J, Marshall P, Johnson J, Harman S. Building resilience into practical conservation: identifying local management responses to global climate change in the southern Great Barrier Reef. Coral Reefs. 2010; 29(2):381–91.

49. Osborne K, Dolman AM, Burgess SC, Johns KA. Disturbance and the Dynamics of Coral Cover on the Great Barrier Reef (1995–2009). PLoS ONE. 2011; 6(3):e17516. doi: 10.1371/journal.pone.0017516 PMID: 21423742

50. Bos AR, Gumanao GS, Mueller B, Saceda-Cardoza MM. Management of crown-of-thorns sea star (Acanthaster planci L.) outbreaks: removal success depends on reef topography and timing within the reproduction cycle. Ocean & Coastal Management. 2013; 71:116–22.

51. Peterson GD, Cumming GS, Carpenter SR. Scenario Planning: a Tool for Conservation in an Uncertain World Planificación de un Escenario: una Herramienta para la Conservación en un Mundo Incierto. Conservation Biology. 2003; 17(2):358–66.

52. Swart RJ, Raskin P, Robinson J. The problem of the future: sustainability science and scenario analysis. Global Environmental Change. 2004; 14(2):137–46. doi: 10.1016/j.gloenvcha.2003.10.002

53. Huss WR. A move toward scenario analysis. International Journal of Forecasting. 1988; 4(3):377–88. doi: 10.1016/0169-2070(88)90105-7

54. Goreau TJ, Hayes RL. Coral bleaching and ocean hot-spots. Ambio. 1994; 23(3):176–80. ISI: A1994NR47000003.

55. Knapp KR, Kruk MC, Levinson DH, Diamond HJ, Neumann CJ. The international best track archive for climate stewardship (IBTrACS): Unifying tropical cyclone best track data. Bulletin of the American Meteorological Society. 2010; 91:363–76.

56. Fabricius KE, De'ath G, Puotinen ML, Done T, Cooper TF, Burgess SC. Disturbance gradients on inshore and offshore coral reefs caused by a severe tropical cyclone. Limnology and Oceanography. 2008; 53:690–704.

57. Alvarez-Romero JG, Devlin M, Petus C, Teixeira da Silva E, Ban NC, Kool J, et al. A novel approach to model exposure of coastal-marine ecosystems to riverine flood plumes based on remote sensing techniques. Journal of Environmental Management. 2013; 119:194–207. doi: 10.1016/j.jenvman.2013.01. 036 PMID: 23500022

58. Ban NC, Pressey RL, Weeks S. Conservation objectives and sea-surface temperature anomalies in the Great Barrier Reef. Conservation Biology. 2012; 26(5):799–809. doi: 10.1111/j.1523-1739.2012. 01894.x. WOS:000308484500006. PMID: 22808910

59. Leigh GM, Campbell AB, Lunow CP, O'Neill MF. Stock assessment of the Queensland east coast common coral trout (Plectropomus leopardus) fishery In: Queensland Department of Agriculture F, and Forestry, editor. Brisbane, Queensland: State of Queensland; 2014.

60. Speirs-Bridge A, Fidler F, McBride M, Flander L, Cumming G, Burgman M. Reducing overconfidence in the interval judgments of experts. Risk Analysis. 2010; 30(3):512–23. doi: 10.1111/j.1539-6924.2009. 01337.x PMID: 20030766

61. Faugier J, Sargeant M. Sampling hard to reach populations. Journal of advanced nursing. 1997; 26 (4):790–7. PMID: 9354993

62. Ban SS, Pressey RL, Graham NAJ. Assessing interactions of multiple stressors when data are limited: A Bayesian belief network applied to coral reefs. Global Environmental Change. 2013; 27:64–72.

63. Norsys Software Corporation. Netica. 4.16 ed. Vancouver, B.C.1992-2010.

64. Day J, Fernandes L, Lewis A, De'Ath G, Slegers S, Barnett B, et al., editors. The representative areas program for protecting biodiversity in the Great Barrier Reef World Heritage Area. Proceedings of the Ninth International Coral Reef Symposium, Bali, 23–27 October 2000; 2002.

65. Fernandes L, Day JON, Lewis A, Slegers S, Kerrigan B, Breen DAN, et al. Establishing representative no-take areas in the Great Barrier Reef: Large-scale implementation of theory on marine protected areas. Conservation Biology. 2005; 19(6):1733–44. doi: 10.1111/j.1523-1739.2005.00302.x

66. IPCC. Climate Change 2007: Synthesis Report. Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Geneva, Switzerland: IPCC, 2007.

67. Great Barrier Reef Marine Park Authority. Zoning, Permits, and Plans 2013 [October 8, 2013]. Available from: http://www.gbrmpa.gov.au/zoning-permits-and-plans/.

68. Brodie JE, Kroon FJ, Schaffelke B, Wolanski EC, Lewis SE, Devlin MJ, et al. Terrestrial pollutant runoff to the Great Barrier Reef: An update of issues, priorities and management responses. Marine Pollution Bulletin. 2012; 65(4–9):81–100. doi: 10.1016/j.marpolbul.2011.12.012 PMID: 22257553

69. McCook LJ, Ayling T, Cappo M, Choat JH, Evans RD, De Freitas DM, et al. Adaptive management of the Great Barrier Reef: A globally significant demonstration of the benefits of networks of marine reserves. Proceedings of the National Academy of Sciences. 2010:-. doi: 10.1073/pnas.0909335107

70. Mumby PJ, Dahlgren CP, Harborne AR, Kappel CV, Micheli F, Brumbaugh DR, et al. Fishing, trophic cascades, and the process of grazing on coral reefs. Science. 2006; 311(5757):98–101. doi: 10.1126/science.1121129 PMID: 16400152

71. Hughes TP, Rodrigues MJ, Bellwood DR, Ceccarelli D, Hoegh-Guldberg O, McCook L, et al. Phase shifts, herbivory, and the resilience of coral reefs to climate change. Curr Biol. 2007; 17(4):360–5. ISI:000244463100028. PMID: 17291763

72. DPI&F. Annual Status Report 2011—Coral Reef Fin Fish Fishery. In: Department of Primary Industries and Fisheries, editor. Brisbane, Australia: State of Queensland; 2012.

73. Chin A, Tobin A, Simpfendorfer C, Heupel M. Reef sharks and inshore habitats: patterns of occurrence and implications for vulnerability. Marine Ecology Progress Series. 2012; 460:115–25. doi: 10.3354/meps09722

74. Roberts CM. Effects of fishing on the ecosystem structure of coral reefs. Conservation Biology. 1995; 9 (5):988–95. doi: 10.1046/j.1523-1739.1995.9051332.x-i1

75. Goeden GB. Intensive fishing and a 'keystone' predator species: Ingredients for community instability. Biological Conservation. 1982; 22(4):273–81.

76. Mumby PJ, Steneck RS. Coral reef management and conservation in light of rapidly evolving ecological paradigms. Trends in Ecology & Evolution. 2008; 23(10):555–63. doi: 10.1016/j.tree.2008.06.011

77. Graham NAJ, Bellwood DR, Cinner J, Hughes TP, Norström A, Nyström M. Managing resilience to reverse phase shifts in coral reefs. Frontiers in Ecology and the Environment. 2013; 11:541–8.

78. Darling ES, McClanahan TR, Côté IM. Combined effects of two stressors on Kenyan coral reefs are additive or antagonistic, not synergistic. Conservation Letters. 2010; 3(2):122–30. doi: 10.1111/j.1755-263X.2009.00089.x

79. Côté IM, Darling ES. Rethinking ecosystem resilience in the face of climate change. PLoS Biol. 2010; 8 (7):e1000438. doi: 10.1371/journal.pbio.1000438 PMID: 20668536

80. Bellwood D, Hughes T, Folke C, Nyström M. Confronting the coral reef crisis. Nature. 2004; 429 (6994):827–33. PMID: 15215854

81. Allison GW, Lubchenco J, Carr MH. Marine reserves are necessary but not sufficient for marine conservation. Ecological applications. 1998; 8(sp1):S79–S92.

82. McClanahan TR, Marnane MJ, Cinner JE, Kiene WE. A comparison of marine protected areas and alternative approaches to coral-reef management. Curr Biol. 2006; 16(14):1408–13. PMID: 16860739

83. Graham NAJ, McClanahan TR, MacNeil MA, Wilson SK, Polunin NVC, Jennings S, et al. Climate warming, marine protected areas and the ocean-scale integrity of coral reef ecosystems. PLoS ONE. 2008; 3(8):e3039. doi: 10.1371/journal.pone.0003039 PMID: 18728776

84. Wooldridge S, Brodie J, Furnas M. Exposure of inner-shelf reefs to nutrient enriched runoff entering the Great Barrier Reef Lagoon: Post-European changes and the design of water quality targets. Marine Pollution Bulletin. 2006; 52(11):1467–79. doi: 10.1016/j.marpolbul.2006.05.009 PMID: 16814810

85. Camerer CF, Johnson EJ. The process-performance paradox in expert judgment: How can experts know so much and predict so badly? In: Goldstein W, Hogarth R, editors. Research on judgment and decision making: Currents, connections and controversies. Cambridge: Cambridge University Press; 1997. p. 342–64.

86. Drescher M, Perera AH, Johnson CJ, Buse LJ, Drew CA, Burgman MA. Toward rigorous use of expert knowledge in ecological research. Ecosphere. 2013; 4(7):art83.

87. Burgman MA, Yemshanov D. Risks, decisions and biological conservation. Diversity and Distributions. 2013; 19(5–6):485–9. doi: 10.1111/ddi.12060