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Special Series

Evaluating the effects of climate change and chemical, physical, and biological stressors on nearshore coral reefs: A case study in the Great Barrier Reef, Australia

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EDITOR'S NOTE:

This article is part of the special series "Integrating Global Climate Change into Ecological Risk Assessment: Strategies, Methods and Examples." The papers were generated from a SETAC Pellston Workshop held at Oscarsborg Fortress near Oslo, Norway, in June 2022. The international workshop included climate change modelers, risk assessors, toxicologists, and other specialists with a diversity of backgrounds and experience. The findings of the series demonstrate that climate change can successfully be incorporated as an integral part of risk assessment for a wide range of environments to address the issues of long-term, adaptive environmental management.

Abstract

An understanding of the combined effects of climate change (CC) and other anthropogenic stressors, such as chemical exposures, is essential for improving ecological risk assessments of vulnerable ecosystems. In the Great Barrier Reef, coral reefs are under increasingly severe duress from increasing ocean temperatures, acidification, and cyclone intensities associated with CC. In addition to these stressors, inshore reef systems, such as the Mackay–Whitsunday coastal zone, are being impacted by other anthropogenic stressors, including chemical, nutrient, and sediment exposures related to more intense rainfall events that increase the catchment runoff of contaminated waters. To illustrate an approach for incorporating CC into ecological risk assessment frameworks, we developed an adverse outcome pathway network to conceptually delineate the effects of climate variables and photosystem II herbicide (diuron) exposures on scleractinian corals. This informed the development of a Bayesian network (BN) to quantitatively compare the effects of historical (1975–2005) and future projected climate on inshore hard coral bleaching, mortality, and cover. This BN demonstrated how risk may be predicted for multiple physical and biological stressors, including temperature, ocean acidification, cyclones, sediments, macroalgae competition, and crown of thorns starfish predation, as well as chemical stressors such as nitrogen and herbicides. Climate scenarios included an ensemble of 16 downscaled models encompassing current and future conditions based on multiple emission scenarios for two 30-year periods. It was found that both climate-related and catchment-related stressors pose a risk to these inshore reef systems, with projected increases in coral bleaching and coral mortality under all future climate scenarios. This modeling exercise can support the identification of

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risk drivers for the prioritization of management interventions to build future resilient reefs. *Integr Environ Assess Manag* 2024;20:401–418.

KEYWORDS: Adverse outcome pathways; Bayesian network; Conceptual model; Risk assessment

INTRODUCTION

The Great Barrier Reef (GBR), Queensland, Australia, is under increasing threat from multiple stressors (Ban et al., 2014). It is the world's largest reef system and was designated a UNESCO World Heritage site, indicating its high global value. An understanding of the combined effects of chemical, physical, and biological stressors in combination with climate change (CC) is essential for improving ecological risk assessments of such highly valued but vulnerable ecosystems. However, there continues to be limited knowledge and study of the collective effects of multistressor exposures (Carrier-Belleau et al., 2022), particularly in complex land- and seascapes.

The strongest driver of ecological change for the GBR is CC (Hughes et al., 2018). In 2020, prolonged sea surface temperature anomalies exceeding 2 °C across broad regions caused a marine heat wave leading to extensive coral bleaching (Hughes & Pratchett, 2020). It was the GBR's third mass coral bleaching event in five years, which led to changes in coral reef assemblages on a regional scale (Hughes et al., 2018). In addition, catchment run-off that transports loads of sediments, nutrients, and pesticides to inshore reefs can potentially increase the susceptibility of corals to disturbances and compromise their recovery. Although extensive climatological data and long-term monitoring of water quality and reef habitats have been reported in the Reef Scientific Consensus Statement (Scientific Consensus Statement, 2017), there is still limited understanding of the risks of multiple stressors on the coral reef system, particularly under future climate scenarios. Condie et al. (2021) used a system modeling approach to investigate a combination of stressors, including ocean acidification, cyclones, flood plumes, predation by the crown of thorns starfish (COTS), and heat waves on corals under several future climate scenarios from 1950 to 2070. Their future projections suggested a continued decline in coral cover even under a moderate emission scenario. Their focus, however, was on testing a combination of interventions under various greenhouse emission scenarios.

Adverse outcome pathway (AOP) networks are one approach that facilitates describing and arraying evidence of potential chemical and nonchemical interactions that may lead to population-level effects (Ankley et al., 2010; Hooper et al., 2013). They can be useful in providing both retrospective descriptions as well as prospective changes in future exposure scenarios. The AOP networks can be useful conceptualizations allowing for more quantitative approaches outlined below.

In ecological risk assessment, relationships between sources and their associated stressors and receptors can also be represented as pathways that aim to develop cause-and-effect linkages among stressors and ecological responses while considering the uncertainty involved. Causal networks can use underlying conceptual models that contain causal pathway interactions linking activities and valued assets so that their use retains the conceptual model's communication value (Peeters et al., 2022; Stauber et al., 2022). As for this case study, they are especially useful when comprehensive quantitative parameters or ecosystem relationships are unknown or not available (Stauber et al., 2022). Bayesian networks (BNs) are one type of causal network that builds on conceptual models and allows the effects of uncertainty on management decisions to be explored (Sperotto et al., 2017).

The overall goal of this article was to integrate information on CC into risk assessment for coral reefs through a case study example for inshore reefs in the central Mackay-Whitsunday region. To meet this goal, our approach was to build upon previous studies that provide relevant information for one or more components of the study system. We constructed an AOP network to better understand how multiple biological, physical, and chemical stressors could impact corals at different levels of biological organization. A conceptual model of the major causal pathways from stressors to the receptor coral was developed and applied in a quantitative BN to demonstrate how future CC projections could be used to assess the risk to several coral endpoints. It is important to note that this case study did not aim to quantitatively determine risks for all identified causal pathways. Rather, we have used this case study to illustrate how CC variables could be incorporated into more traditional risk assessments of contaminants. This article is one of three case studies resulting from the SETAC Pellston workshop on incorporating CC into environmental risk assessment (Moe et al., 2023; Stahl et al., 2023).

STUDY AREA

The Mackay–Whitsunday region (Figure 1) is a natural resource management region in the GBR that includes coral reefs important for the local tourism industry. In the central Mackay–Whitsunday region, the major river is the Pioneer River, which, together with a number of smaller streams, contributes catchment run-off to coastal waters. River flow is seasonally variable and characterized by infrequent, high-intensity flood events during the wet season from December to April. This regularly exposes the GBR estuarine and

FIGURE 1 Mackay–Whitsunday–Isaac (MWI) reporting region showing locations of inshore reefs. Modified from the MWI report card technical methods document: Mackay–Whitsunday–Isaac Healthy Rivers to Reef Partnership Report Card, 2021 (2022)

inshore waters to herbicide runoff from agricultural lands (Lewis et al., 2012).

Extensive monitoring and modeling of water quality parameters and habitat conditions have been reported annually in the Mackay–Whitsunday–Isaac report cards since 2014. The inshore marine area is divided into four zones. The central zone, which is the focus of this risk assessment (Figure 1), includes monitoring sites at three shallow reefs: Round Top Island (5 m depth), Slade Island (2 m depth), and Victor Island (2 m depth). These reefs have continued to score poorly for water quality and total coral cover over several years, with macroalgal density particularly high at Victor Island reefs. Studies have shown that loads of herbicides used in sugar cane farming are greatest in these catchments and at the Sandy Creek estuary mouth where, using the multisubstance-affected fraction method (Traas et al., 2002), 30% of aquatic species are at risk from a mixture of the 22 pesticides monitored (Mackay–Whitsunday–Isaac Healthy Rivers to Reef Partnership Report Card, 2021 [2022]).

CONCEPTUAL MODEL DEVELOPMENT

Sources, stressors, and endpoints for coral reef communities

While the central zone includes other important habitats, such as seagrasses and mangroves, for the purposes of our case study, hard corals were selected as the receptor of interest due to their importance in providing structural habitat for multiple reef invertebrate and fish species. Coral bleaching, coral mortality, and coral cover extent were selected as the assessment endpoints. We recognize that other reef endpoints and receptors (e.g., soft corals and coralline algae) may also be impacted by CC stressors in combination with contaminants.

These coral communities are susceptible to a range of stressors, both acute and chronic. Acute stressors include anomalously high summer temperatures that may result in coral bleaching, physical damage from tropical cyclones, and exposure to low salinity waters during flood events. Chronic stressors include acidification, turbidity from resuspension events, as well as elevated contaminants, sediment, and nutrients from catchment runoff. Key climate and catchment stressors and their possible effects on the GBR coral reefs are described in detail in the Supporting Information S1.

Model tools and frameworks used: AOPs and BNs

To inform the selection of inputs for the BN analysis, an AOP network was developed based on a literature review of the combined effects of climate stressors and photosystem II (PSII) herbicide exposures on scleractinian corals. It specifically focused on the effects of ocean warming and ocean

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acidification, together with the PSII herbicide diuron to inshore coral reef systems, as well as associated climate-related increases in runoff and sedimentation. While not intended to capture all potential pathways of combined responses and feedbacks (e.g., COTS predation and nutrients are not captured), it illustrates how multiple lines of evidence ranging from mechanistic testing to whole organism bioassays and population-level evaluations can be mapped to molecular initiating events (MIEs, e.g., production of reactive oxygen species) and key events (KEs, e.g., reduced photosynthetic efficiency, zooxanthellae expulsion) along a biological gradient to adverse outcomes (e.g., coral bleaching, species population declines). The KE relationships (KERs) that connect MIEs to KE nodes and adverse outcomes may be considered empirical, established, plausible, or predicted, depending on the strength of the evidence. An important feature of AOPs is that they provide one means of integrating mechanistic evidence that informs biological plausibility and potentially shared sensitivities across species that, in turn, can be useful in extrapolating effects from one species to another (Hooper et al., 2013; Knapen et al., 2018). The identification of shared response pathways may further aid in identifying inputs for quantitative modeling, such as the BN approaches that were undertaken herein. In BNs, qualitative expert elicitation can be combined with empirical data in probability distribution functions to quantitatively determine risks and uncertainty associated with various exposure pathways (Norton, 2010; Sperotto et al., 2017).

Quantification of relationships for the BN input

The main conceptual steps involved in characterizing the distribution of stressors for the BN are illustrated in Figure 2. First, knowledge (including data, relationships, and processes) of the Mackay–Whitsunday ecosystem was compiled from literature and expert sources (Figure 2, Step 1). These data sources were then used to build the AOP network with a focus on the effect of diuron and other climate-related stressors on corals (Figure 2, Step 2). This AOP network then informed the BN conceptualization, which also incorporated some additional anthropogenic and CC stressors from the "knowledge acquisition" step. The BN was then constructed based on available relationships between the different nodes (Figure 2, Step 3). Although time series for several parameters in the BN were used, there was no direct link between the historical scenario and the future scenarios; hence, the BN was not a dynamic model (i.e., it does not have a temporal dimension) but rather, it represented the average situation during a temporal period of a year.

During the BN parameterization step (Figure 2, Step 4), climate models were used to derive projections of rainfall and temperature under the selected climate scenarios. Three climate scenarios were selected representing baseline (historical) and two plausible future conditions corresponding to moderate and high warming assumptions. The climate variables of rainfall and temperature were required by the hydrological model to derive the corresponding streamflow time series, where the time series of nutrient and sediment loads to the GBR were derived from a water quality model based on streamflow inputs. The time series of nutrients and sediments corresponding to the selected climate scenarios were then analyzed to derive the distributions of stressors required by the BN. Then, an ensemble of air temperature time series was obtained from the climate models to inform the likelihood of coral bleaching events.

The modeling chain used in the environmental variable prediction component shown in Figure 2 represents a generic sequence of steps that is common to most climate impact studies. The effort required to undertake each modeling step depends on the data and resources available, where the objective is to ensure that the degree of complexity involved in each component is commensurate with other steps in the analysis and with the objectives of the study. The approach took advantage of existing datasets available from detailed modeling studies. The available processed datasets of most value consisted of (Figure 2, Step 4): (1) climate model projections of precipitation, maximum and minimum air temperature, solar radiation and 2-m surface wind speed, rainfall, and sea surface temperature; (2) hydrological model simulations of streamflow using the climate model projections for two catchments that drain into the GBR; and (3) hydrodynamic, nutrient, sediment, diuron, and biogeochemical model simulations of environmental conditions of the GBR.

Knowledge about stressor and endpoint relationships was obtained through a more case-specific literature review on the relationships between the different nodes (variables) in the BN (Figure 2, Step 4). In the last conceptual step, a sensitivity analysis was carried out. Thereafter, the BN was used to predict the effect of CC on the intermediate and endpoint nodes in the network (Figure 2, Step 5).

Environmental variable prediction

Climate models and projections. Three climate scenarios were selected, each of which covered a 30-year period: a baseline historical period centered on the year 1990 and two CC scenarios centered on the years 2040 and 2085. The adopted CC scenarios were based on two Intergovernment Panel on Climate Change (IPCC) representative concentration pathways (RCP), 4.5 (RCP4.5) and 8.5 (RCP8.5) (IPCC, 2021). RCP4.5 represents a moderate level of greenhouse gas emissions, and RCP8.5 represents a very high level of emissions. The mid-point of each 30-year period was selected to ensure that the adopted scenarios evenly spanned the 125 years of climate projections available from the global climate models from 1975 to 2100.

Climate projections were derived using a 16-member model ensemble based on four global climate models, each of which was downscaled using three statistical methods and one dynamic model (Table 1). More details are given in the Supporting Information S1. The (epistemic) uncertainty associated with the different global climate models and downscaling estimates is illustrated for estimates of mean annual temperature and rainfall in Figure 3. Figure 3A shows that the ensemble estimates of temperature over the

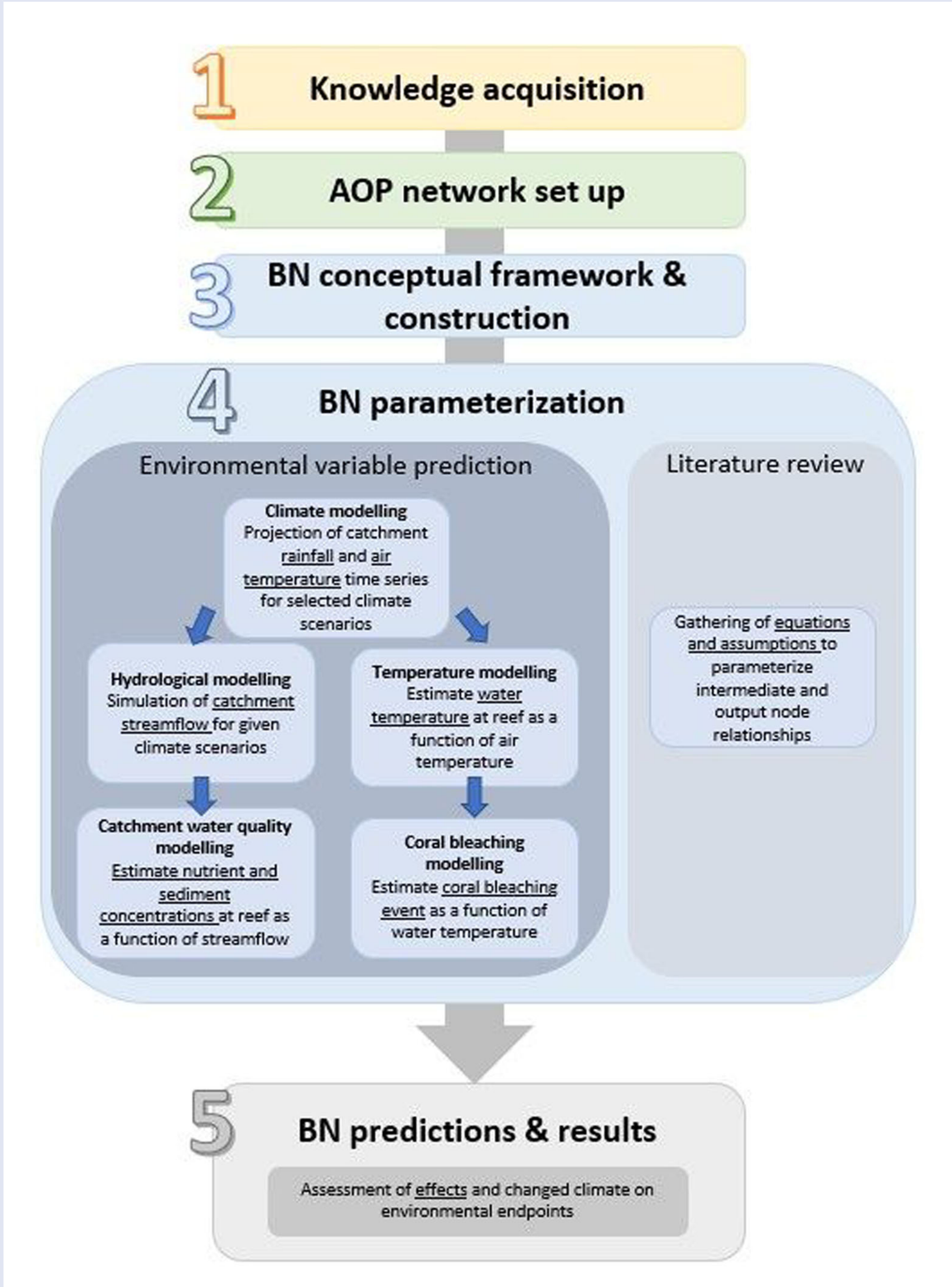

FIGURE 2 Conceptual steps used in this study from knowledge acquisitions, including a detailed overview of the approach used to develop the modeling chain to derive projections of climate stressors and effects on a near shore reef system. AOP, adverse outcome pathway; BN, Bayesian network

historic period are clustered closely around the ensemble mean but that the uncertainty due to model differences increases for future climate scenarios. The differences in model projections of rainfall are larger than for temperature (Figure 3B), but again, the range of estimates is larger for future climate scenarios than for historic conditions.

Streamflow projections. Projections of streamflow corresponding to the above climate scenarios were obtained from outputs derived using the Australian Water Resource Assessment Landscape modeling system. More details on this model are given in the Supporting Information S1. The nonlinear relationship between runoff and rainfall results in a proportional spread in runoff results that was more than twice the spread of rainfall (Figure 3C).

Nutrient and sediment projections. Information on historical environmental conditions in the GBR was obtained from the eReefs information system (www.ereefs.info) (CSIRO, 2015). This information system can simulate the GBR's

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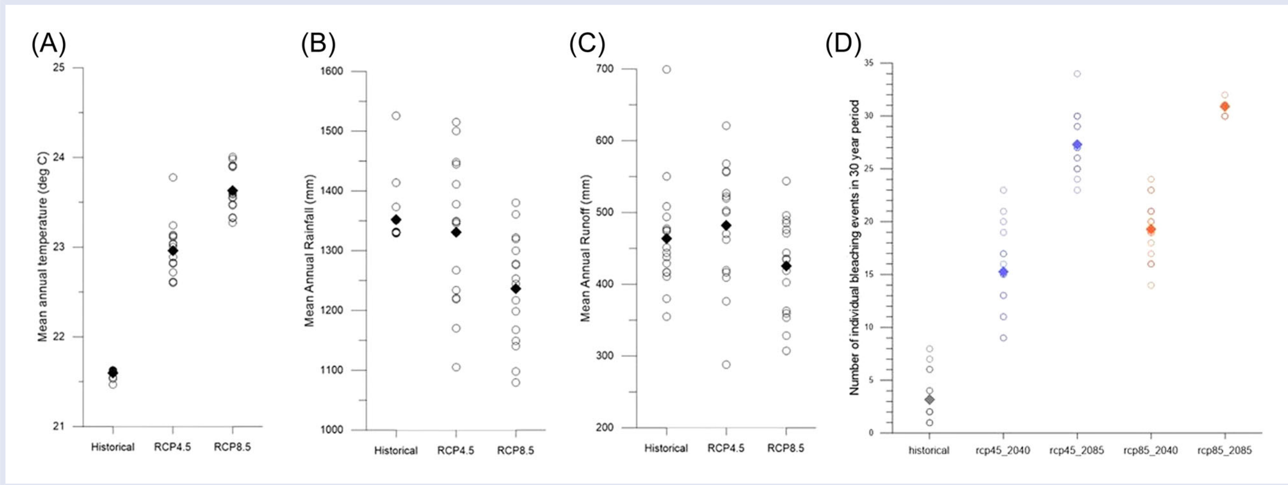

FIGURE 3 Projections of average annual (A) air temperature, (B) rainfall, and (C) runoff in Blacks Creek catchment derived from a 16-member ensemble based on four climate models and four downscaling methods. Historical projections are provided for the period 1976–2005, and those for future scenarios extend from 2006 to 2100. Hollow symbols represent the estimates from each individual ensemble member and the filled diamond symbols are the ensemble average. (D) Projected distributions of the frequency of bleaching events in a 30-year period, obtained from individual climate models (open circle symbols) and the mean of the ensemble (solid diamond symbol)

environmental conditions at multiple scales by coupling biogeochemical, hydrodynamic, and sediment models (Baird et al., 2021; Steven et al., 2019). For this case study, monthly simulations of ecology fine inorganics (to represent suspended sediments) and total nitrogen (TN) at a water depth of 1.5 m were obtained for a location adjacent to Slade Island for a period extending from December 2010 to April 2019 (simulation reference GBR4 BGC q3b). While dissolved inorganic nitrogen is potentially the most available form for corals and algae, we have focused our assessment on TN due to the availability of high-quality data. The required projections of nutrients and sediments were obtained from a stochastic version of the regression model, where the input streamflows were obtained from the climate and Australian Water Resource Assessment Landscape modeling system models as described in the Supporting Information S1. The impact assessment undertaken for the different climate scenarios is summarized in the Supporting Information S1.

Diuron data. Daily modeled diuron concentrations from the Pioneer River catchment from 1 January 2016 to 23 June 2018 were obtained from the 1 km eReefs model (Jennifer Skerratt, CSIRO, personal communication, November 15, 2022) and compared to catchment flow. There was no correlation between diuron concentrations and monthly flow (mL/d). However, the diuron data were used to populate the diuron node in the BN.

Chlorophyll a and pH data. Historical monthly modeled chlorophyll *a* and pH for Round Top and Slade Island at −1.5 m depth from 1 December 2010 to 30 April 2019 were extracted from the eReefs model GBR 4BGC q3b.

Projections of bleaching events. Given the high degree of similarity between the climate model projections and the historical observations (Figure S3), the analysis herein evaluated the relationship between sea surface temperature (at Hardy's Reef) and air temperatures (Blacks Creek catchment) using the ensemble of climate model projections directly. This was then used to predict the likelihood of bleaching events using degree heat months, where the temperature threshold was selected to match the observed frequency of bleaching events over the historic period (Figure S3). Inferences about the impacts of CC on the likelihood of bleaching can thus be made by the relative change in the adopted degree heat months metric. Full details are given in the Supporting Information S1.

The projected shift in the distribution of bleaching events is shown in Figure 3D. The figure highlights the difference in results obtained from the individual climate models, where less than 16 results are visible in each scenario, as multiple models may project the same (integer) number of bleaching events. The mean of the ensemble provides the most robust indication of the shift in frequency for each given climate scenario considered. The most striking feature of these results is the projected shift in the frequency of bleaching events with warming global temperatures, where even under the most benign scenario, the number of bleaching events occurs every 2–3 years on average. There was little overlap in the spread of time-projected results exhibited by the individual climate models.

RESULTS

AOP network of interactive effects of climate and PSII herbicide stressors

The qualitative AOP network illustrating biological response pathways leading to potential adversity of CC and diuron exposures is depicted in Figure 4. Rather than being an exhaustive representation of all stressors and effect

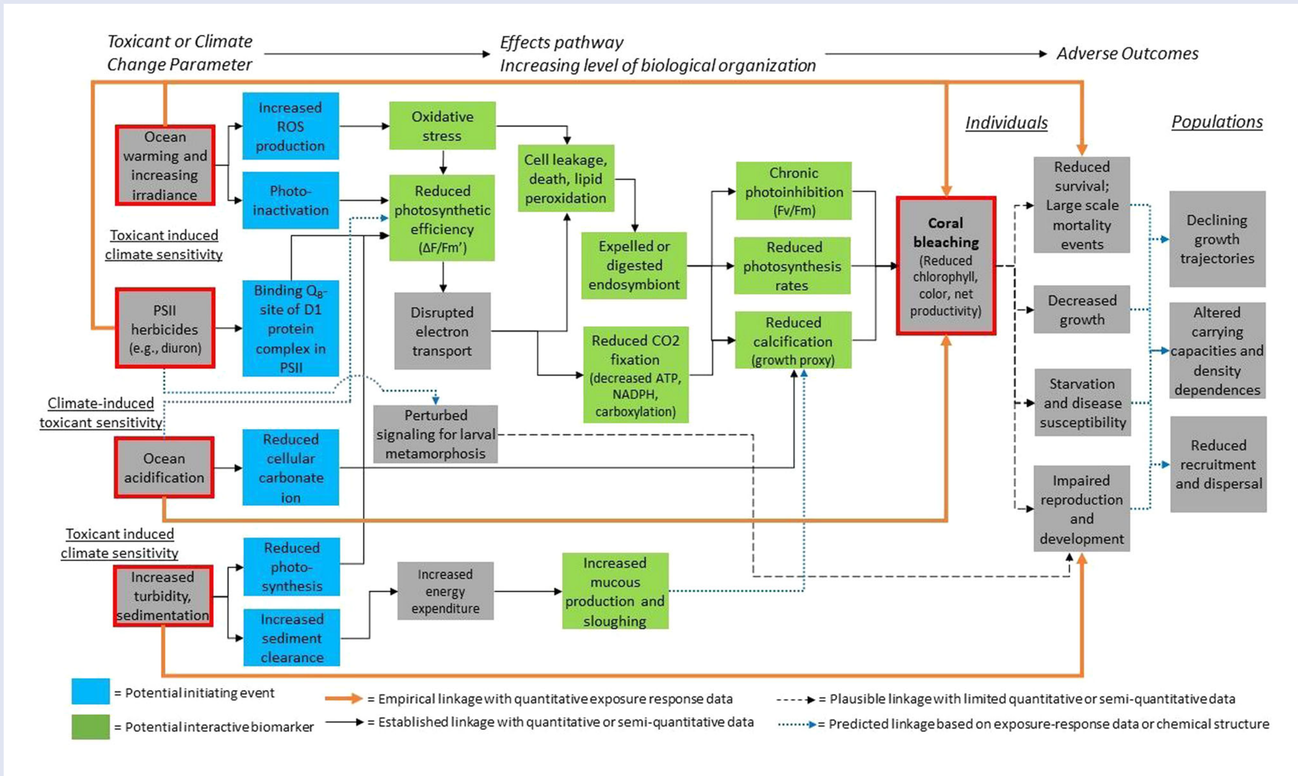

FIGURE 4 Illustrative AOP network of potential effects of PSII herbicide and sedimentation interactions with climate change parameters, ocean warming, and ocean acidification on GBR coral reef systems. Toxicant-induced climate sensitivities are presented involving PSII herbicides exacerbating thermal stress, showing differing but related molecular initiation events that proceed through shared key events and adverse outcomes. Climate-induced toxicant sensitivities are depicted by PSII herbicide, potentially worsening the effects of ocean acidification on downstream calcification and growth by pathways of photosynthetic inhibition that perturb electron flow, leading to reductions in ATP and NADPH and impeded carboxylation and calcification. Additional interactions are shown by climate-related increases in sedimentary runoff that increase the effects of PSII herbicides. Red highlighted variables were implemented as nodes in the Bayesian network. $\Delta F/F_{m'}$, effective quantum yield in light-adapted samples (measure of open reaction centers and proportional to energy conversion in PSII); AOP, adverse outcome pathway; F_v/F_m, maximum quantum yield in dark-adapted samples (indicator of potential energy conversion at PSII; reductions indicate photodamage; Jones, 2005); GBR, Great Barrier Reef; PSII, photosystem II; ROS, reactive oxygen species

pathways, the AOP network herein serves as an example of how evidence of climate and chemical stressors can be mapped to highlight major biological response pathways and to serve as a tool to inform research priorities, quantitative analyses, and decision-making. Key events relationships with varying degrees of quantitative evidence of empirical and established linkages are shown with solid orange and black lines, respectively. Putative KE relationships with less data are shown in blue (predicted KERs) and black (plausible KERs) dashed lines.

One response of scleractinian corals to ocean warming is shown in the AOP network in Figure 4. Chronic stress from CC, in combination with low levels of chemical exposures, can lead to more severe bleaching, reducing coral health, survival, and reproductive output with consequent population declines (Cantin et al., 2007; Negri et al., 2011). The agricultural runoff of PSII herbicides into these coastal reef ecosystems can be an effect node in the pathway that contributes to temperature-induced coral bleaching events as a toxicant-induced climate sensitivity. Exposure to PSII herbicides, such as diuron, may elicit a toxicological response in coral symbionts that is analogous to that of oceanic warming by related but somewhat differing initiating mechanisms. While the MIEs of ocean warming and diuron exposure differ, they proceed through shared pathways of physiological stress, including decreases in photosynthetic efficiencies and oxidative stress that can overwhelm acclimation capacities and result in coral bleaching. Thus, low-level chronic exposure to PSII herbicides (as is observed in inshore reefs of the GBR) can prompt toxicant-induced climate sensitivities that can make coral symbionts more vulnerable to climate-related temperature stress (Cantin et al., 2007; van Dam et al., 2015; Flores et al., 2021; Negri et al., 2011).

Ocean acidification is another important climate pathway of coral reef ecosystem declines that is depicted in the AOP and intersects with ocean warming and PSII chemical exposure pathways, although the relative roles of ocean acidification and rising temperatures cannot yet be discerned (De'ath et al., 2009). Elevated pCO_2 acts as a bleaching agent with irradiance working synergistically with rising temperatures to lower bleaching thresholds (Anthony et al., 2008). This is a climate-induced toxicant sensitivity in which ocean acidification leads to reductions in skeletal calcification that may exacerbate diuron-induced decreases in calcification by photodamage pathways of oxidative stress.

Increasing runoff of sediments into the inshore GBR is another source of vulnerability with impacts of sedimentation to corals depending on sediment composition, grain size, and exposure duration. Sedimentation and turbidity reduce the rate of photosynthesis by blocking light, and it is possible that this could counteract some impacts of increasing irradiance with temperature increases. However, this is considered a short-term response, and as shown in the AOP network, both pathways operate over longer terms by downregulating photosynthesis, although by differing mechanisms. Increased sedimentation also increases coral respiration and mucous production to facilitate the sloughing of accumulating sediments. This behavioral response comes at an energetic cost that may reduce carboxylation, which leads to bleaching and mortality (Erftemeijer et al., 2012; Tuttle & Donahue, 2022). A study on *Porolithon onkodes* observed that combined exposures to diuron (≥0.79 μg/L) and fine-grained, calcareous sediments (<0.63 μm) caused steep declines in photosynthetic efficiency ($\Delta F/F_{m'}$) after a 24-h exposure, with persistent reductions in photosynthesis after exposures had ceased and mortality in some fragments (Harrington et al., 2005). Taken together, the current database suggests potentially heightened vulnerabilities to corals with increases in climate-induced sedimentation with other climate and chemical effect pathways.

Conceptual BN model

The conceptual model was based on the knowledge gained when setting up the AOP network (Figure 4). The variables' connections in the BN were informed by identified pathways and relationships, for example, "coral bleaching" resulting from ocean acidification, increased ocean temperature, PSII herbicides, or "increased sedimentation" resulting in smothering. Other stressors that are known to affect coral or their predators, which were not included in the AOP, were also added to the conceptual model, for example, cyclones and nutrients (Figure 5A).

The BN includes three modules: climate scenarios (light blue) and projections (blue), stressors and effects (yellow), and coral endpoints (red) (Figure 5A). Climate scenarios influence environmental processes and conditions, for example, ocean acidification or sedimentation. This, in turn, influences the effect on coral reef variables, for example, coral bleaching or phytoplankton density (yellow). The output node of the conceptual BN is a coral cover, which is influenced by coral recruitment and mortality (Figure 5A). The BN cannot account for cumulative effects, as interactions (i.e., synergistic, or antagonistic effects) have not been modeled explicitly. This is technically possible with BN models, but we did not have information on the interactive effects of the given stressors from the literature for each of the variables in the network.

Overview of nodes of the BN and assumptions made for parameterization. The parameterized BN was restructured from the conceptual model according to data and knowledge availability and contained 24 nodes. Some intermediate nodes were added to enable the incorporation of assumptions; also, some links between nodes were changed according to the availability of relationships between nodes (Figure 5B). An overview of the BN nodes, relationships, and assumptions is given in Table 2 A more detailed overview of all assumptions used for parameterization can also be found in the Supporting Information S2: 1–3. To limit the complexity of the BN, the discretization was limited to 4–6 states per node. The coral endpoint nodes and most of the intermediate nodes were discretized into equidistant intervals. For each of the nodes in the model "Climate scenarios and projects," the discretisation was based on the five quintiles of the respective variable in the historical scenario (see Supporting Information). A finer discretization could be chosen for several of the intermediate nodes that are based on equations, for example, coral cover (macroalgal overgrowth) or coral bleaching, as this would increase precision.

The BN was parameterized according to the assumptions about the relationships between the different nodes. For example, some literature stated a direct relationship from "macroalgal overgrowth" to "coral cover," although the relationship to "smothering" could not be identified. Therefore, the network was modified, and the direct link between "macroalgal overgrowth" and "coral cover" was included instead (Figure 5B).

After parameterization, a sensitivity analysis was carried out for the endpoint nodes and selected intermediate nodes. This was carried out with "sensitivity to findings," a built-in function in Netica software. With this, the node's effect on the selected endpoints (output nodes) could be evaluated. The sensitivity was measured as the expected reduction in variance of the expected real value of the response node when evidence was set at the predictor node (Moe et al., 2020). The sensitivity analysis showed that coral calcification had no sensitivity to the parent nodes in the model with the current discretization and was therefore excluded from further analysis. Coral reproduction showed low sensitivity to diuron (herbicide), whereas coral mortality had high sensitivity to the cyclone category node and, through that, low sensitivity to the climate scenarios. The coral cover node had high sensitivity to the total suspended solids. An overview of the sensitivity analysis findings can be found in the Supporting Information S2: 4–5.

BN results. The BN clearly showed that there was close to 100% probability of bleaching under all future climate scenarios, decreased probability of total suspended solids, and increased probability of cyclone intensity with increasing climate extremes. Under all climate scenarios, several bleaching events were projected to occur on average every 2–3 years, compared to historical data, with bleaching occurring once every 5–10 years (Figure 3D). The BN predictions support these conclusions, with the probabilities of

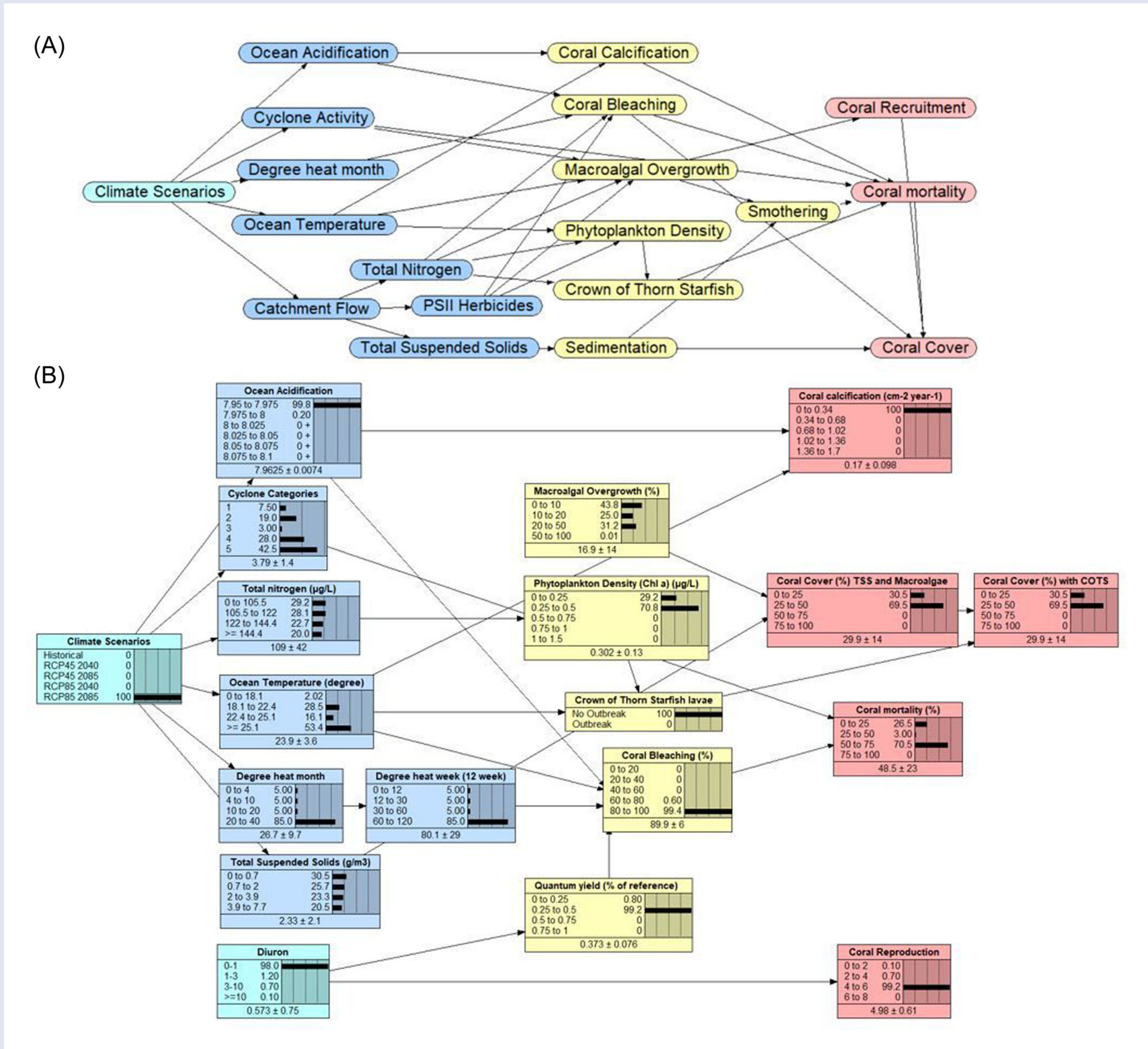

FIGURE 5 (A) Conceptual model used for construction of the BN and (B) an example parameterized BN for an RCP8.5 scenario in 2080. BN, Bayesian network

severe bleaching to 90% of corals increasing to 99% under all future RCPs (Figure 6A).

Except for RCP4.5 to 2040 (where the climate model ensemble average projected a slight increase in runoff), in all other climate scenarios, rainfall and, hence, runoff were predicted to decrease slightly compared to historical conditions. Consequently, inputs of TN and sediments into inshore coastal waters were projected to decrease in future scenarios. This is clearly seen in Figure 6B, with the probability of total suspended solids concentrations decreasing slightly with increasing severity of CC. However, it is possible that predicted drier conditions could also lead to increased land erosion and increased inputs during extreme events, such as cyclones. Cyclones were predicted to intensify under all four future climate scenarios tested, with an increase in the probability of Category 4 and 5 cyclones compared to historical conditions (Figure 6C).

The data needed to develop a quantitative relationship between coral mortality and coral cover were unavailable, so these were treated as separate endpoints and/or output nodes in the BN. Coral cover decreased for the more severe climate scenarios (RCP8.5) for the different time periods (Figure 6D). Increased macroalgal overgrowth in combination with total suspended solids influenced coral cover under all climate scenarios. Coral mortality was predicted to increase with more severe climate scenarios for the different time periods due to increased coral bleaching and cyclone intensity (Figure 6E). It is likely that increased coral mortality could ultimately decrease coral cover if there is insufficient time between events for coral regrowth and recovery.

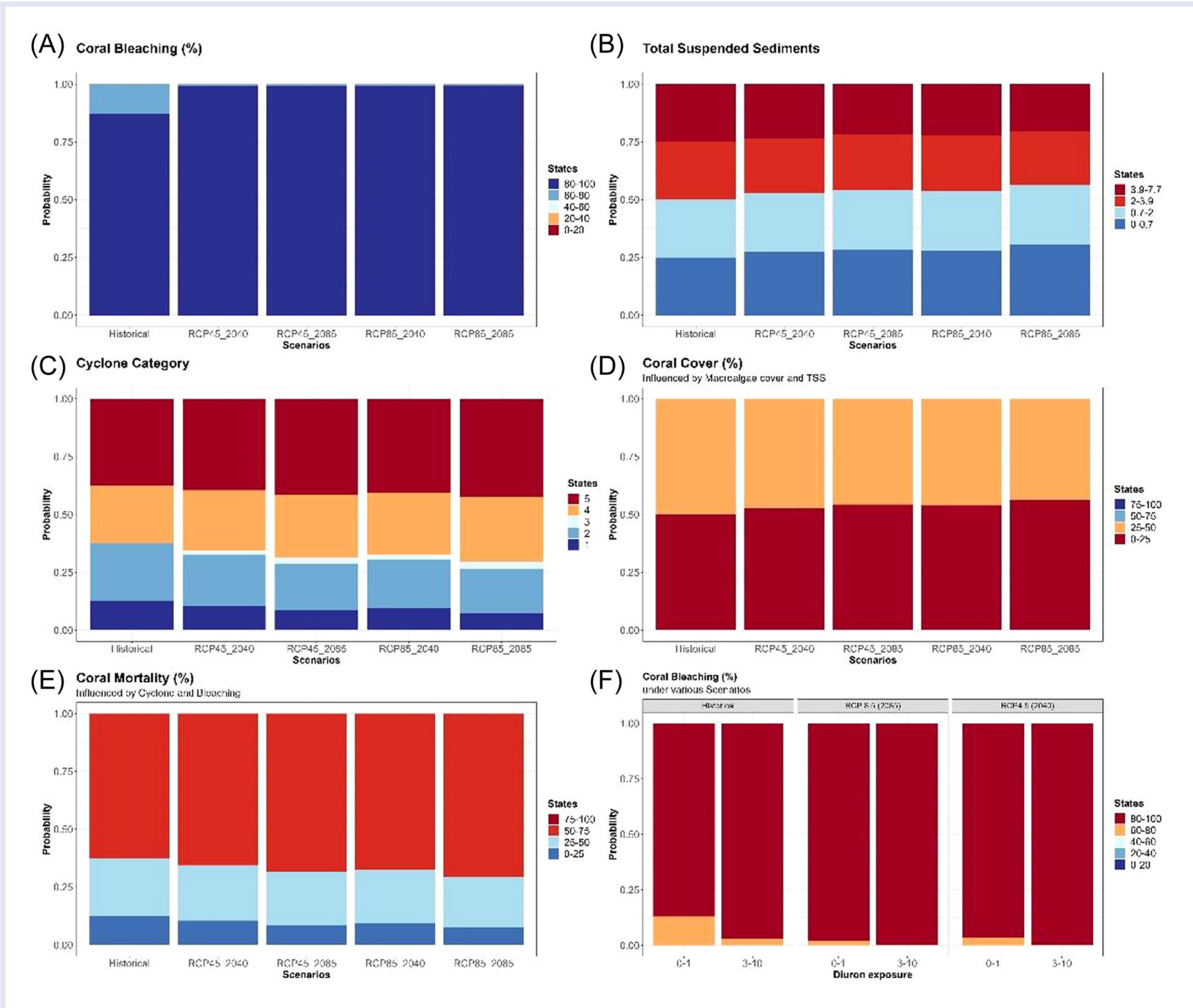

FIGURE 6 Probability distribution for some of the selected endpoints (output nodes) depending on the climate scenarios for (A) coral bleaching, (B) total suspended sediments (TSS), (C) cyclone category, (D) coral cover influenced by macroalgal cover and TSS, (E) Coral mortality influenced by cyclone and bleaching, and (F) coral bleaching uder various scenarios.

An increase in diuron concentrations above 3 μg/L was predicted to increase coral bleaching, even under historical conditions (Figure 6F). Under all climate scenarios, coral bleaching with increasing sea surface temperature was predicted to be further exacerbated by any increases in diuron concentrations from coastal catchment runoff. These two stressors combined increase the risk of coral bleaching (with probability to be in the highest state "80%–100%" of about 3%–4% (RCP4.5 and RCP8.5) and 3%–10% (historical), which in turn may impact coral mortality and reduce coral resilience and recovery.

DISCUSSION

This exercise demonstrated that both the AOP and BN were useful constructs to explore the impacts of CC stressors together with catchment-related stressors on coral reefs in the Mackay region of the GBR. Because quantitative relationships were not available for all exposure pathways for all stressors, we selected several key stressors and pathways only to illustrate how these frameworks could be used to predict the risks of multiple stressors under four future climate scenarios.

AOP network of interactive effects

To our knowledge, this is the first study to use AOPs to map climate and chemical stressor impacts on coral reef systems. The AOP network depicts examples of some of the combined effects of ocean warming and ocean acidification with PSII herbicide exposures, as well as associated climate-related increases in runoff off and sedimentation to inshore coral reef systems. It illustrates both chemical-induced climate sensitivities and climate-induced chemical sensitivities, which informed the conceptualization and development of the BN. While useful in the identification of toxicity pathways and biomarkers that may be shared among species, another important challenge is that the integration of ecological factors is typically beyond the scope of AOP frameworks (Rohr et al., 2016). Coral populations may reside at the edges of their physiological tolerance ranges, and there are ecological forcings that may confer potential advantages or disadvantages, such as the selection of habitat and more resilient *Symbiodinium* clades that may facilitate adaptation.

While studies have examined the effects of ocean warming, ocean acidification, and PSII herbicides on corals individually, there are just a handful of studies that have examined the interactive effects of these stressors in just a few species. Flores et al. (2021) evaluated the combined effects of CC and diuron on *Acropora millepora* using ambient 2018 and IPCC-predicted elevated ocean warming and ocean acidification for 2050 and 2100 diuron exposures of 0.29–29 μg/L for 14 days caused dose-dependent reductions in coral survival, coral color, photosynthetic efficiency, net photosynthesis, and calcification. EC50 values for net photosynthesis (measured as changes in dissolved oxygen) and coral color (measured using standard image processing) decreased with increasing temperature and pCO_2, suggesting that diuron, in combination with increasing temperature and acidification, may lead to bleaching in *A. millepora*. These results are consistent with other studies by Negri et al. (2011), who found that diuron at 1 μg/L, in combination with elevated temperatures of 31 °C and 32 °C, caused chronic photoinhibition that was greater than additive (synergistic). The lack of effects of CC on photosynthetic efficiency ($\Delta F/F_{m'}$) but evidence of downstream impacts on photoinhibition, rates of photosynthesis, and color indices point to the importance of targeting multiple endpoints or biomarkers when evaluating stressor interactions such as these. Moreover, the use of photosynthetic efficiency as an endpoint is debated since the response is a reversible adaptive stress response and may not be predictive of downstream effects on the organism or population. Thus, AOP networks such as that in Figure 4 provide a useful starting point for characterizing and mapping multiple endpoints that may serve as biomarkers to facilitate the interpretation of effects data. However, the database in this case is small, and AOPs have not been successfully scaled to communities or ecosystems (Rohr et al., 2016).

BN model for multiple stressors effects on coral cover

The developed BN was intended to present an illustrative tool for exploring multiple stressors and incorporating CC in the assessment. The bleaching projections (Figure 3D) and the BN (Figure 6A) suggest that there is a higher risk of coral bleaching under a warming climate, and this may be exacerbated by additional catchment-related stressors. The sensitivity analysis also showed that climate-related environmental variables have a stronger influence on the assessment endpoints than the chemical stressor (diuron). However, the PSII herbicide node was limited due to the sparsity of data that was amenable to modeling input, and thus, chemical effects have not been fully evaluated, and the results should not be interpreted to conclude that chemical exposures are not having deleterious impacts.

Two other studies, to our knowledge, have published BNs to predict climate risks to coral reefs in general. Carriger et al. (2020) used BN and a machine learning approach to evaluate the spatial co-occurrence of a range of threats with coral reef systems regionally and globally. An augmented naïve BN was used in a very comprehensive but complex approach, with some counterintuitive findings. Their analysis identified overfishing and destructive fishing as a relatively high risk to living corals in Australia, along with a relatively strong association between acidification and coral bleaching, although nearly half the acidification data were extrapolated from offshore, not inshore modeling projections.

Another study, by Ban et al. (2014), developed a causal BN based on monitoring and/or observational data for the exposure module and expert elicitation for the effect module using the GBR as a case study. Their aim was to better understand the interactions of multiple stressors and associated uncertainty. Their focus was on mid-shelf reefs largely removed from terrestrial sources of contaminants and excluded the inshore reefs, which were the focus of our BN, and which are most prone to impacts from catchment contaminants.

Climate projections and predictions from the BN can be compared to actual historical monitoring data from the Mackay–Whitsunday–Isaac Healthy Rivers to Reef Partnership Report Card, 2021 (2022). There were 4–6 degree heat weeks observed in the central zone in 21/22, and in the summer of 2022, there was another mass bleaching event, the fourth on the GBR since 2016. Despite widespread bleaching, coral recovery occurred across most of the Mackay–Whitsunday–Isaac region, although lingering impacts from Tropical Cyclone Debbie in 2017 were still observed. In 2022, annual rainfall in the Pioneer Basin was 73% below average, with fewer inputs of sediments and nutrients due to lower runoff and no cyclones, which resulted in low actual coral mortality. Median monitored chlorophyll *a* concentration in 21/22 was 0.47 μg/L at Round Top Island and 0.66 μg/L at Slade Island, slightly higher than predicted in the BN. Water clarity has also improved around Round Top and Slade Islands for the last two years. During such periods of low rainfall, turbidity near the reefs is more related to the resuspension of sediments due to wind and/or waves, currents, and tidal patterns, which were not considered in the BN. These monitoring data suggest a declining trend in nutrient inputs, supporting the conclusions from the BN, which predicts fewer inputs of sediments and nutrients under all four future climate scenarios tested.

Due to intensive land use in the region, diuron remains the key herbicide contributing to risk. Although there appeared to be no relationship between runoff and diuron concentrations, there may be accumulation of diuron due to its long half-life in the marine environment (Taucare et al., 2022). For the purposes of the BN, diuron concentrations were kept constant under the four future climate scenarios. However, expert advice (Jennifer Skerratt, CSIRO, personal communication, February 2023) is that pesticides in the GBR will likely decrease in the future due to improving farm practices and government and stakeholder stewardship to reduce pesticide usage and to control application times. There is still some uncertainty around this prediction as there is a possibility that diuron and other pesticides could attach to particles or get resuspended from already contaminated sediments in the vicinity of the reef.

The Mackay–Whitsunday–Isaac Healthy Rivers to Reef Partnership Report Card, 2021 (2022) gave corals in the central region a moderate score overall, with moderate macroalgal cover. Scores for coral endpoints were very reef- and site-specific, with juvenile recruitment declining at Slade Island to poor, while coral cover improved at Round Top Island to moderate over the past monitoring year. In the BN, projections for macroalgal cover were based on historical data (Chartrand et al., 2021), and future trends were difficult to predict. On the one hand, projections for nutrient and sediment runoff are projected to be similar to historical conditions, so macroalgal cover will likely not change due to these stressors. However, with increasing temperatures, macroalgal cover could increase but could also decrease with increasing cyclone intensity. Based on maximum wind speeds, predictions under CC are that cyclone intensity will likely increase between 2% and 11% by 2100 (Knutson et al., 2010), but there is large uncertainty around cyclone frequency. Condie et al. (2021) suggested that while the frequency of Category 1–3 cyclones may remain unchanged, increases by up to 21% for Category 4 cyclones and 42% for Category 5 cyclones could occur, depending on the climate scenarios selected. Hence, the future cyclone activity and impact remain uncertain, and with these competing effects, it was assumed that there was no net change in macroalgal cover in the BN climate scenarios.

Crown of thorns starfish is not currently monitored at inshore reefs in Mackay coastal waters and remains a bigger threat to reefs further offshore (Chartrand et al., 2021). However, bioeroding sponges are observed in inshore reefs, but there was no quantitative data available to use in the BN. Instead, COTS was used as an example of a coral predator as there were data available on the links between phytoplankton density, COTS larvae, and coral mortality. Including COTS in the BN also makes the developed model applicable to other study areas where COTS might be more prevalent.

Limitations and sources of uncertainty

The climate and catchment model simulations were undertaken at varying time steps and the outputs aggregated to time periods ranging from daily to annual. The choice of what time step to adopt for evaluation was influenced by the objectives of our study and consideration of the different sources of uncertainty. One of the largest sources of uncertainty involved in climate impact studies is associated with the wide range of possible emissions scenarios (and hence the wide range of possible future climate outcomes) and the uncertainty inherent in the different assumptions and knowledge of feedback processes on which the climate model projections are based. Adopting fine spatial and temporal scales in the subsequent catchment modeling chain may provide highly precise results, but this may not improve the accuracy or defensibility of the projections. Another consideration in the decision about time steps is the need to adopt a commensurate degree of complexity in the different modeling steps (John et al., 2020). The relationships between streamflows and catchment loads used to characterize the input probability distributions to the BN model were most accurately developed using monthly data, and given all the other uncertainties involved, a monthly time step was deemed suitable for all analyses.

The current BN was used for screening purposes and to demonstrate the incorporation of climate variables and the impacts on ecological risk predictions for assessment endpoints. Some shortcomings of the BN are related to unknown relationships between nodes (variables in the network, e.g., coral mortality and coral cover; reproduction and coral cover; coral calcification and coral cover; climate scenarios and macroalgal overgrowth; climate scenarios and herbicide exposure). Other shortcomings were related to the input node parameterization, and where more defined relationships were unavailable for some nodes, best estimates were used. In addition, we have weighted the parent node inputs equally to calculate the joint probability, for example, coral bleaching, mortality, and coral cover. Once information about more realistic weighting of stressors becomes available, the model can easily be updated.

Future analyses could better elucidate the structural components of the BN and evaluate how uncertainty quantification impacts risk predictions. Uncertainty around the regression lines could be better included in the equations by expanding the regression equations to a distribution with uncertainty. Time and space are also often difficult to incorporate into BNs. In a causal model like the one developed here, the connections, or lack thereof, may need additional exploration and evidence sources as knowledge of stressors and their interactions increases.

One of the limitations of BNs is the discretization (Nojavan et al., 2017). Discretizing continuous variables or developing discrete intervals was required for the analysis but can bias the inferences made from the network (Table S2: state discretization). As previously mentioned, discretization was based on rough estimates and could be improved to increase accuracy, for example, the ocean temperature maximum is 25.1 °C for coral calcification and this changes when ocean temperature is above 26.7 °C. In this case, having a higher number of intervals in the "ocean temperature" node could enable a better reflection of the effect of the high temperatures on coral calcification in the future (Figure 5 and Table S2).

The lack of quantitative data, including data specific to the Mackay inshore reefs for many stressors, necessitated many assumptions in the BN development (Table S2: assumption prior probability). Several stressors and pathways in the original conceptual model could not be carried through into the developed BN. These included irradiance, salinity, and anthropogenic impacts from fishing, shipping, tourism, and coastal urban development, as well as the endpoint of coral disease. This supported our aim to illustrate how multiple stressors from CC and catchment loads could be combined in an example BN rather than do a complete risk assessment of these stressors on inshore coral reefs.

Multistressor effects extend beyond impacts to coral and may also cause adverse effects to other parts of the marine ecosystem, including seagrass, microalgae, foraminifera, and fish that are also impacted by climate factors such as temperature. The ability to begin to quantify these other important related ecological-level effects continues to be limited. Ideally, the use of AOPs, conceptual models, and BNs at differing scales can begin to identify the critical interactions (direct and indirect) that would be most beneficial to characterize and quantify effects. Understanding the spatial and temporal factors of these interactions is another important consideration at individual, population, and community assemblage scales, particularly in terms of characterizing uncertainty. Our ability to predict chemical–climate interactions generally decreases as we move to larger spatial scales and over longer time horizons (Figure 4). However, applying these data to quantify population outcomes (e.g., metamorphosis, survival) and ecosystem and/or community impacts lacks data (Rohr et al., 2016). There is also a lack of understanding of how one might apply some of these regional and/or local scale evidence streams (qualitative and quantitative) to other localities.

Risk mitigation and management

Large investments by the agricultural industry and government have been made over the past 20 years to reduce nutrient, sediment, and pesticide loads into the coastal waters of the GBR. Policy responses have been to set ambitious targets for the reduction of the end-of-catchment anthropogenic loads (80% for nutrients and 50% for sediments by 2025) while also protecting 99% of aquatic species from the risk of pesticides (Baird et al., 2021; Commonwealth of Australia, 2021). Emphasis has been on reducing gully and bank erosion, improving farm spraying practices and timing of spraying, reducing the application of fertilizers, and establishing stewardship programs and reporting for each of the agricultural sectors across the GBR. While rigorous risk management will continue to be needed with careful study of progress, the focus on actions to improve water quality through reduction in catchment-related stressors could contribute to coral reef resilience to CC stressors, which may be more difficult to control (Scientific Consensus Statement, 2017).

Currently, measures are also being taken to control COTS outbreaks to mitigate their impacts on hard coral cover on reefs, including manual control, mainly using lethal injections by scuba diving, but also automated methods using robots (Westcott et al., 2020). Condie et al. (2021) used a metacommunity modeling approach to evaluate combinations of interventions that may reduce coral cover declines in the GBR over the next 50 years. Interventions included reducing flood plumes, controlling COTS populations, stabilizing coral rubble, managing solar radiation, and introducing heat-tolerant coral strains. They found that the most effective strategies to prevent coral decline were when

TABLE 1 Overview of models used for current and future exposure projections and data sources

Projection	Model	Method	Data source	Projected variables
Climate projections	GCM: ACCESS1-0, CNRM-CM5, GFDL-ESM2M and MIROC5 Downscaling: ISIMIP2b, MRNBC, QME, CCAM	16-Member ensemble used to estimate mean and spread of outcomes	National Hydrological Projections dataset (Srikanthan et al., 2022; Wilson et al., 2022).	Climate output precipitation and temperature for historic, RCP4.5 and RCP8.5 scenarios
Streamflow projections	Australian Water Resource Assessment Landscape modeling system (AWRA-L)	Semi-distributed hydrological model representing water stores at the surface, shallow, and deep soil layers (Frost et al., 2018).	National Hydrological Projections dataset (Srikanthan et al., 2022; Wilson et al., 2022).	Infiltration, evaporation and evapotranspiration, overland flow, subsurface storage and flow
Nutrient, sediment and diuron projection	eReefs model	GBR4 BGC q3b	https://research.csiro.au/ereefs/models/	Simulated concentrations of total nitrogen, diuron and ecology fine inorganics

Abbreviations: GBR, Great Barrier Reef; RCP, representative concentration pathway.

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TABLE 2 Overview of Bayesian network nodes, their relationships, and assumptions

Module	Node name	Unit	State discretization	Assumption prior probability	References
Climate scenarios and projections	Climate scenario	–	Historical, RCP4.5 -2040, RCP4.5 -2085, RCP8.5 -2040, RCP8.5 -2085	Projection	Wilson et al. (2022)
					National Hydrological Projections Database
	Ocean acidification	pH	[7.95–8.10]/8	Distribution based on historical data	CSIRO eReefs (2015)
	Cyclone category	–	1, 2, 3, 4, 5	Distribution based on historical data	Chartrand et al. (2021)
	Total nitrogen	mg N/m^3	<105.5, 105.5–122, 122–144.4, >144.4	Projection	CSIRO eReefs (2015)
	Ocean temperature	°C	0–18.1, 18.1–22.4, 22.4–25.1, >25.2	Projection	Tables 1 and SI-I
	Degree heat month (DHM)	Months	0–16, 16–40, 40–80, 80–100	Projection	Tables 1 and SI-I
	Degree heat weeks (DHW)	Weeks	0–16, 16–40, 40–80, 80–100	Distribution based on DHM	TableS 1 and SI-I
	Total suspended solids (TSS)	g/m^3	<0.7, 0.7–2, 2–3.9, >3.9	Projection	Tables 1 and SI-I
	PSII herbicide (diuron)	µg/L	0–1, 1–3, 3–10, >10	Distribution based on historical data	CSIRO eReefs (2015)
Stressors and effects	Macroalgal overgrowth	%	0–10, 10–20, 20–50, 50–100	Distribution based on historical data	Chartrand et al. (2021)
	Phytoplankton density	µg/L	0–0.25, 0.25–0.5, 0.5–0.75, 0.75–1, >1	$y = 0.00534x - 0.3499$	CSIRO eReefs (2015)
	Effective quantum yield	% Inhibition	0–0.25, 0.25–0.5, 0.5–0.75, 0.75–1	$y = 0.5274e^{(-0.115x)}$	Calculated from data in Cantin et al. (2007)
	Crown of thorns starfish larvae	–	No outbreak, outbreak		Wooldridge and Brodie (2015)
	Coral bleaching (ocean acidification)	%	0–20, 20–40, 40–60, 60–80, 80–100	25.5 °C: $y = -0.3812x + 3.2212$	Anthony et al. (2008)
				28.5 °C: $y = -0.5155x + 4.3421$	
	Coral bleaching (DHW)	%	0–20, 20–40, 40–60, 60–80, 80–100	$y = 48.62\ln(x) - 21.2$	Hughes et al. (2017), Eakin et al. (2010)
	Coral bleaching (diuron)	%	0–20, 20–40, 40–60, 60–80, 80–100	$y = 0.5274e^{[-0.115x]}$	Calculated from data in Cantin et al. (2007)
	Coral bleaching	%	0–20, 20–40, 40–60, 60–80, 80–100	Joint probability of coral bleaching by ocean acidification, diuron and DHW	Uthicke et al. (2015)

(*Continued*)

TABLE 2 (*Continued*)

Module	Node name	Unit	State discretization	Assumption prior probability	References
Coral endpoints	Coral reproduction	No. eggs per polyp	0–2, 2–4, 4–6, 6–8	$y = -0.4863x + 5.883$	Calculated from data in Cantin et al. (2007)
	Coral calcification	cm^{-2} $year^{-1}$	[0–1.87]/6	Topt: $y = 0.2351x - 4.4295$ Topt: $y = -0.1366x + 5.4743$	Cooper et al. (2008)
	Coral mortality (cyclones)	%	0–20, 20–40, 40–60, 60–80, 80–100	$y = 22.979x - 24.473$	Condie et al. (2018)
	Coral mortality (coral bleaching)	%	0–20, 20–40, 40–60, 60–80, 80–100	$y = 0.353x - 11.753$	Marshall and Baird (2000)
	Coral mortality (MO)	%	0–20, 20–40, 40–60, 60–80, 80–100	Weighting of the probabilities of coral mortality by cyclones and coral bleaching	Uthicke et al. (2015)
	Coral mortality (cyclones)	%	0–20, 20–40, 40–60, 60–80, 80–100	$y = 22.979x - 24.473$	Condie et al. (2018)
	Coral mortality (coral bleaching)	%	0–20, 20–40, 40–60, 60–80, 80–100	$y = 0.353x - 11.753$	Marshall and Baird (2000)
	Coral cover (macroalgal overgrowth)	%	0–20, 20–40, 40–60, 60–80, 80–100	$y = -0.4343x + 52.253$	Liu et al. (2012)
	Coral cover (TSS)	%	0–20, 20–40, 40–60, 60–80, 80–100	$y = 69.262x - 0.3509$	Liu et al. (2012)
	Coral cover MO and TSS	%	0–20, 20–40, 40–60, 60–80, 80–100	Joint probability of coral cover by MO and TSS	Uthicke et al. (2015)
	Coral cover (COTS)	%	Increase, decrease		WWF (2015)
	Coral cover MO and TSS and COTS	%	0–20, 20–40, 40–60, 60–80, 80–100	Increase with no outbreak, decrease with outbreak	Uthicke et al. (2015)

Abbreviations: COTS, crown of thorns starfish; PSII, photosystem II; RCP, representative concentration pathways.

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large-scale combinations of interventions were used that reduced both thermal stress and predation.

CONCLUSION

This article has shown that AOPs and BNs are both promising approaches for conceptualizing and integrating climate information into environmental risk assessment frameworks. While data adequacy and computational challenges remain, these tools are useful for conceptualizing and mapping complex multistressor pathways to generate defensible hypotheses on potential hazards and risks to inform research and decision-making. The BN enables quantitative links between climate model projections, multiple stressors, and effects on assessment endpoints. Both approaches support the combination of data, evidence, and expert elicitation to identify risks and prioritize future management interventions. For inshore reefs in the Mackay region, the risk of coral bleaching under a warming climate is severe, although managing water quality may help increase reef resilience and recovery from climate stressors in the future.

AUTHOR CONTRIBUTION

Sophie Mentzel: Conceptualization; data curation; formal analysis; investigation; methodology; project administration; resources; software; validation; visualization; writing—original draft; writing—review and editing. **Rory Nathan**: Conceptualization; data curation; formal analysis; investigation; methodology; resources; software; validation; visualization; writing—original draft; writing—review and editing. **Pamela Noyes**: Conceptualization; data curation; formal analysis; investigation; methodology; resources; software; validation; visualization; writing—original draft; writing—review and editing. **Kevin V. Brix**: Conceptualization; funding acquisition; investigation; methodology; project administration; resources; software; supervision; writing—original draft; writing—review and editing. **S. Jannicke Moe**: Funding acquisition; methodology; project administration; resources; software; supervision; visualization; writing—original draft; writing—review and editing. **Jason R. Rohr**: Data curation; investigation; writing—review and editing. **Julie Verheyen**: Data curation; investigation; resources; writing—review and editing. **Paul J. Van den Brink**: Writing—original draft; writing—review and editing. **Jennifer Stauber**: Conceptualization; data curation; formal analysis; funding acquisition; investigation; methodology; project administration; resources; software; supervision; validation; visualization; writing—original draft; writing—review and editing.

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DISCLAIMER

The views expressed in this article are those of the authors and do not necessarily reflect the views or policies of the USEPA. The peer review for this article was managed by the Editorial Board without the involvement of S. Jannicke Moe.

DATA AVAILABILITY STATEMENT

Bayesian network modeling was carried out using Netica 6.05 (www.norsys.com/). Files are included as Supporting Information.

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SUPPORTING INFORMATION

(1) Detailed overview of coral stressors, assumptions and technical details for the exposure projections, details on AOP, and BN node input and results, (2) BN prior probabilities, posterior probabilities and sensitivity analysis, (3) Results BN intermediate nodes, (4) Results BN output nodes, (5) Results selected scenarios coral bleaching, (6) BN Netica file.

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