Identifying low climate exposure coral reefs for climate-relevant coral reef management

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Abstract

Climate change is causing worldwide degradation of coral reef ecosystems. Climate-relevant conservation strategies often identify reef areas with low exposure to thermal stress using remote sensing data and climate model projections. However, the coarse spatial resolution (≥4 km) of climate data and lack of projections for climate stressors other than thermal stress limit the identification of low climate exposure coral reefs.

The overarching aim of this PhD project was to develop and test new tools for identifying low exposure coral reefs to better protect coral reef ecosystems from climate change. This aim was explored through the following three research questions: 1. Can climate models project local and regional scale changes in coral reef climate exposure? 2. How will extreme climate exposure on coral reefs change at local and regional scales in the future? 3. Are local-scale climate projections useful in conservation planning?

Addressing these research questions, this thesis consists of four papers. Firstly, I highlighted the importance of integrating thermal stressors with other environmental threats and ecological characteristics when evaluating reef vulnerability to climate (Paper 1). Second, to address the first and second research questions, I developed a novel 1 km spatial resolution thermal stress dataset for the global coral reef area by increasing the resolution of climate model projections using statistical downscaling (Paper 2). In addition, I tested the suitability of downscaled tropical cyclones for predicting coral reef damage at the scale of coral reef regions (e.g. the Great Barrier Reef) and projected future changes in tropical cyclone-related reef damage (Paper 3). Finally, I determined whether the dataset used alters spatial planning solutions by inputting climate datasets at two resolutions and from two sources to the spatial planning software Marxan (Paper 4).

My PhD's body of work updates projections of coral reef futures under climate change and advances the use of climate data in conservation planning. In answer to the first two research questions, I found that >90% of coral reefs globally are projected to experience

an intolerable frequency of severe thermal stress events with just 1.5°C of global warming relative to pre-industrial levels. Even at the high resolution of 1 km, very few refuges from thermal stress remained. In contrast, I found projections of tropical cyclone-induced coral reef damage in the future are uncertain, with some models projecting increases and others decreases. Additionally, the downscaled models were limited in their ability to represent observed tropical cyclone exposure at the coral reef region scale. In answer to the third research question, I found that both the data source and spatial resolution of climate data altered which coral reefs were prioritised for protection, highlighting both the uncertainty in which data sources conservation planners should use as well as the differences in and potential benefits of using higher resolution data.

Even though there remains uncertainty in observed climate data and model projections of thermal stress, I conclude that they can have value in climate-relevant conservation planning if uncertainty is factored into decision making. To aid conservation planning, I provide a new tool consisting of different thermal stress metrics catering to a variety of climate conservation approaches. My findings also demonstrate where projections are not yet suitable for use in conservation planning. Together, my findings should aid the development of climate-relevant conservation planning for coral reefs.

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List of Acronyms

AR – Assessment Report

AVHRR – Advanced Very High Resolution Radiometer

CCI – Climate Change Initiative

CMIP - Coupled Model Intercomparison Project

CRW – Coral Reef Watch

DHM – Degree Heating Month

DHW - Degree Heating Week

ENSO - El Niño Southern Oscillation

ESA – European Space Agency

GCM – General Circulation Model

GHG – Greenhouse-Gas

HighResMIP - High Resolution Model Intercomparison Project

IBTrACS - International Best Track Archive for Climate Stewardship

IPCC – Intergovernmental Panel on Climate Change

KDE – Kernel Density Estimates

MMM – Maximum Monthly Mean

MUR - Multi-scale Ultra-high Resolution

NOAA - National Oceanic and Atmospheric Administration

OSTIA – Operational Sea Surface Temperature and Sea Ice Analysis

RCM – Regional Climate Model

RCP – Representative Concentration Pathway

RMS – Root Mean Square

RMSE – Root Mean Square Error

SSES – Single Sensor Error Statistics

SSP – Shared Socioeconomic Pathway

SST - Sea Surface Temperature

A Note on Style

Chapter 2 has been written as a Concepts and Questions piece for publication in Frontiers in Ecology and the Environment. Chapter 3 has been written as a Research Article published in PLOS Climate and so follows the format: introduction, results and discussion and materials and methods. Chapter 4 has been written as a Research Article in Earth's Future and follows the classic manuscript format: introduction, methods, results and discussion. This Chapter includes a key points section and plain language summary in accordance with Earth's Future formatting requirements. Chapter 5 has been formatted for submission to Conservation Science and Practice and follows the manuscript format: introduction, methods, results and discussion. In Chapters 2-5, I have used 'we' and 'our' to refer to the work that I have undertaken as lead author alongside my co-authors. In Chapters 1 and 6, I have used 'I' and 'my' as the work is solely my own.

Chapter 1 - Introduction

1.1 Background

Climate change is causing worldwide degradation of coral reefs, many of which are already under substantial local-scale pressure resulting from overfishing and pollution (Hughes *et al.*, 2017a). Coral reefs are valued at $9.8 trillion annually through ecosystem services including tourism and fishing, building and biochemical resources and coastal protection (West and Salm, 2003; Hoegh-Guldberg *et al.*, 2007; Costanza *et al.*, 2014). Rapid climate change in coral reef ecosystems requires urgent implementation of effective climate-relevant coral reef management (Frieler *et al.*, 2013). Current efforts in climate-relevant coral reef management use a range of different approaches and there is no consensus on best practice for conservation of coral reefs against future climate change. Conservation should ideally be divided into global and local management strategies; global strategies to reduce emissions limiting future climate exposure and allowing more time for coral reef adaptation (Frieler *et al.*, 2013; Hughes *et al.*, 2017a) and local strategies to reduce local-scale threats and so promote resistance to and recovery from climate disturbance (Levy and Ban, 2013). However, global climate mitigation is out of the control of local coral reef managers, so conservation efforts focus on local to regional spatial plans (Mumby *et al.*, 2011; Levy and Ban, 2013; Makino *et al.*, 2014; Beger *et al.*, 2015; Magris *et al.*, 2015; Harris *et al.*, 2017; Asaad *et al.*, 2018; Beyer *et al.*, 2018; Chollett *et al.*, 2022), with a few exceptions that quantify the level of global warming or emissions at which coral reefs might still persist (Donner, 2009; Frieler *et al.*, 2013; Schleussner *et al.*, 2016; van Hooidonk *et al.*, 2016). Effective local-scale climate-relevant coral reef management is limited by uncertainty in which coral reefs should be protected; e.g. low exposure reefs (Beyer *et al.*, 2018) or a range of reefs with different climate exposure regimes to bet-hedge against uncertainty in climate projections and future coral reef adaptation (Mumby *et al.*, 2011; Magris *et al.*, 2015). If low exposure reefs are to be prioritised due to their higher likelihood of survival, there is uncertainty in which are the low exposure coral reefs and whether these reefs will continue to experience low exposure under future warming. This PhD project (Figure 1.1) will develop and test new tools for identifying low exposure coral reefs to aid both local and global coral reef conservation.

In the Intergovernmental Panel on Climate Change (IPCC) Third and Fourth Assessment Reports (AR4), climate exposure was one of three components of climate vulnerability, alongside ecological sensitivity and adaptive capacity (IPCC, 2007). Despite the disassociation of exposure from the vulnerability definition in the IPCC Fifth Assessment Report, much of the climate vulnerability literature continued to use the AR4 conceptualisation (Ishtiaque *et al.*, 2022). Climate exposure is the rate and magnitude of climatic variations experienced by a system (Dawson *et al.*, 2011) and is considered a key component of vulnerability assessments. The three aspects of climate vulnerability defined in AR4 interact and thus comparing climate vulnerability between locations, for example in conservation planning, often requires the consideration of all three (Ishtiaque *et al.*, 2022). As a result, they have been embedded in many climate vulnerability assessment frameworks (e.g. Hahn *et al.*, 2009; Margles Weis *et al.*, 2016; Pandey *et al.*, 2017; Edmonds *et al.*, 2020). Climate vulnerability is being incorporated in coral reef conservation, though some aspects of climate vulnerability are often oversimplified or omitted. For example, Beyer et al. (2018) aimed to identify 50 coral reef regions with low climate vulnerability to target for conservation investment. However, their approach was based predominantly on coarse resolution climate exposure metrics, largely omitting ecological sensitivity and adaptive capacity. This thesis focuses on improvements in climate exposure estimates for coral reefs, though gaps in the quantification of ecological sensitivity and adaptive capacity are also discussed in Chapter 2.

Ocean warming and acidification, tropical cyclones, salinity changes and sea level rise threaten coral reef ecosystems globally (Ban *et al.*, 2014). Of these, ocean warming is most often considered in conservation decision making. Corals are sustained by symbiotic microalgae that lives within their tissue providing an essential food source

(Hoegh-Guldberg, 1999). High sea surface temperature (SST), above the level corals are accustomed to, can cause the symbiotic relationship between microalgae and coral host to break down resulting in the expulsion of the algae from the coral tissue in a phenomenon known as coral bleaching (Hughes *et al.*, 2017b). Prolonged bleaching results in coral mortality which can occur over large spatial scales (e.g. across the northern Great Barrier Reef; Hughes *et al.*, 2017b).

High resolution remote sensing SST datasets are necessary to capture the local-scale thermal exposure affecting coral reefs because seasonal and inter-annual SST variability, which are key drivers of coral bleaching frequency and severity, (Langlais *et al.*, 2017), are affected by local-scale oceanographic processes (Kida and Richards, 2009). Remote sensing SST datasets are used to calculate thermal stress metrics that indicate the thermal exposure a coral reef has experienced or is projected to experience in the future. Thermal stress metrics are based on degree heating weeks (DHW); the accumulated SST anomalies, known as HotSpots (HS), more than 1°C higher than the historical baseline SST over a 12-week (84-day) period (Liu *et al.*, 2014):

$$DHW = \frac{1}{7}\sum_{i=1}^{84}(HS_i, if\ HS_i \geq 1°C)$$

For example, SST 1.5°C higher than the baseline for two weeks will have a DHW of 3°C-weeks. DHW is used to indicate bleaching severity and mortality based on two commonly used thresholds; 4°C-weeks indicates significant coral bleaching and 8°C-weeks indicates severe bleaching with widespread mortality (Eakin *et al.*, 2009).

Climate models are an essential tool for projecting future changes in SST but their coarse spatial resolution limits their ability to replicate observed seasonal and inter-annual cycles leading to inaccurate bleaching predictions (van Hooidonk and Huber, 2012). The spatial resolution of climate model output can be increased by downscaling (Fowler *et al.*, 2007). The term “downscaling” encompasses a range of techniques, of which statistical downscaling is most commonly used in coral reef conservation (Magris *et al.*, 2015; Harris *et al.*, 2017; Asaad *et al.*, 2018). Under the umbrella of “statistical downscaling”, different approaches are implemented which have varying levels of sophistication, but all involve the use of observed datasets. At the most basic level, the change factor technique involves adding the difference between the climate model projections and control to the observations (Fowler *et al.*, 2007). This technique has been used to generate high resolution data for the marine environment (Magris *et al.*, 2015; van Hooidonk *et al.*, 2016; Harris *et al.*, 2017; Asaad *et al.*, 2018). More sophisticated statistical downscaling methods are based on the relationship between fine-scale climate variables and large-scale atmospheric predictors (Fowler *et al.*, 2007) and are also applied in marine ecological studies (Donner *et al.*, 2005; Mcleod *et al.*, 2010). In both cases, the resolution that climate model output can be downscaled to is limited by the resolution of the observed data.

Remote sensing SST datasets have been used in marine spatial prioritisation at 4 km, 5 km and 25 km spatial resolution using the National Oceanic and Atmospheric Administration (NOAA) Pathfinder, CoralTemp and Optical Interpolation SST datasets (Mumby *et al.*, 2011; Makino *et al.*, 2014; Magris *et al.*, 2015; Beyer *et al.*, 2018). Climate model SST output is used to project the SSTs coral reefs will experience under future climate warming at coarse spatial resolution (>25 km; Levy and Ban, 2013; Makino *et al.*, 2014, 2015; Beyer *et al.*, 2018) or finer resolution (4 km) through downscaling (Magris *et al.*, 2015; Harris *et al.*, 2017; Asaad *et al.*, 2018). However, thermal conditions are known to vary on spatial scales smaller than the 4 km resolution currently used in conservation planning (Safaie *et al.*, 2018). While a 1 km spatial resolution remote sensing SST dataset is openly available (JPL MUR MEaSUREs Project, 2015), it is yet to be used in coral reef conservation planning.

Projections of other climate stressors impacting coral reefs are rarely included in conservation plans. Downscaled tropical cyclone projections have been available for many years (Emanuel, 2006, 2013; Emanuel *et al.*, 2008; Knutson *et al.*, 2013, 2015) but their suitability for use in coral reef climate exposure studies is yet to be tested.

Projected changes in tropical cyclone characteristics, such as intensity, are currently made at global and ocean-basin scales (e.g. Atlantic Ocean; Emanuel *et al.*, 2008; Knutson *et al.*, 2013). Whether these projections can represent coral reef scale changes in tropical cyclones under future climate change is unknown. Furthermore, future changes in some of the tropical cyclone characteristics that determine coral reef damage severity, such as circulation size and translation speed, are uncertain (Knutson *et al.*, 2020). If these projections are able to simulate the observed tropical cyclone characteristics, their use in conservation planning could avoid investment in areas at risk of frequent and severe tropical cyclone damage in the future (Beyer *et al.*, 2018).

Higher resolution thermal stress projections may better predict future bleaching risk, but whether conservation planning and outcomes will benefit from these new tools is unknown. A range of considerations contribute to conservation decision making including ecological factors such as biodiversity or presence of target species, and socioeconomic factors such as the cost of protection or impact of protection on local people (Beger *et al.*, 2015). Given the range of factors that determine protected area selection, using finer resolution climate data may not affect which areas are selected.

1.2 Research objectives

In this PhD thesis, I will explore opportunities to improve the identification of low climate exposure coral reefs for effective climate-relevant coral reef management (Figure 1.1). In order to better protect coral reef ecosystems in a changing climate, I investigated the following research questions:

1. Can climate models project local and regional scale changes in coral reef climate exposure?
2. How will extreme climate exposure on coral reefs change at local and regional scales in the future?
3. Are local-scale climate projections useful in conservation planning?

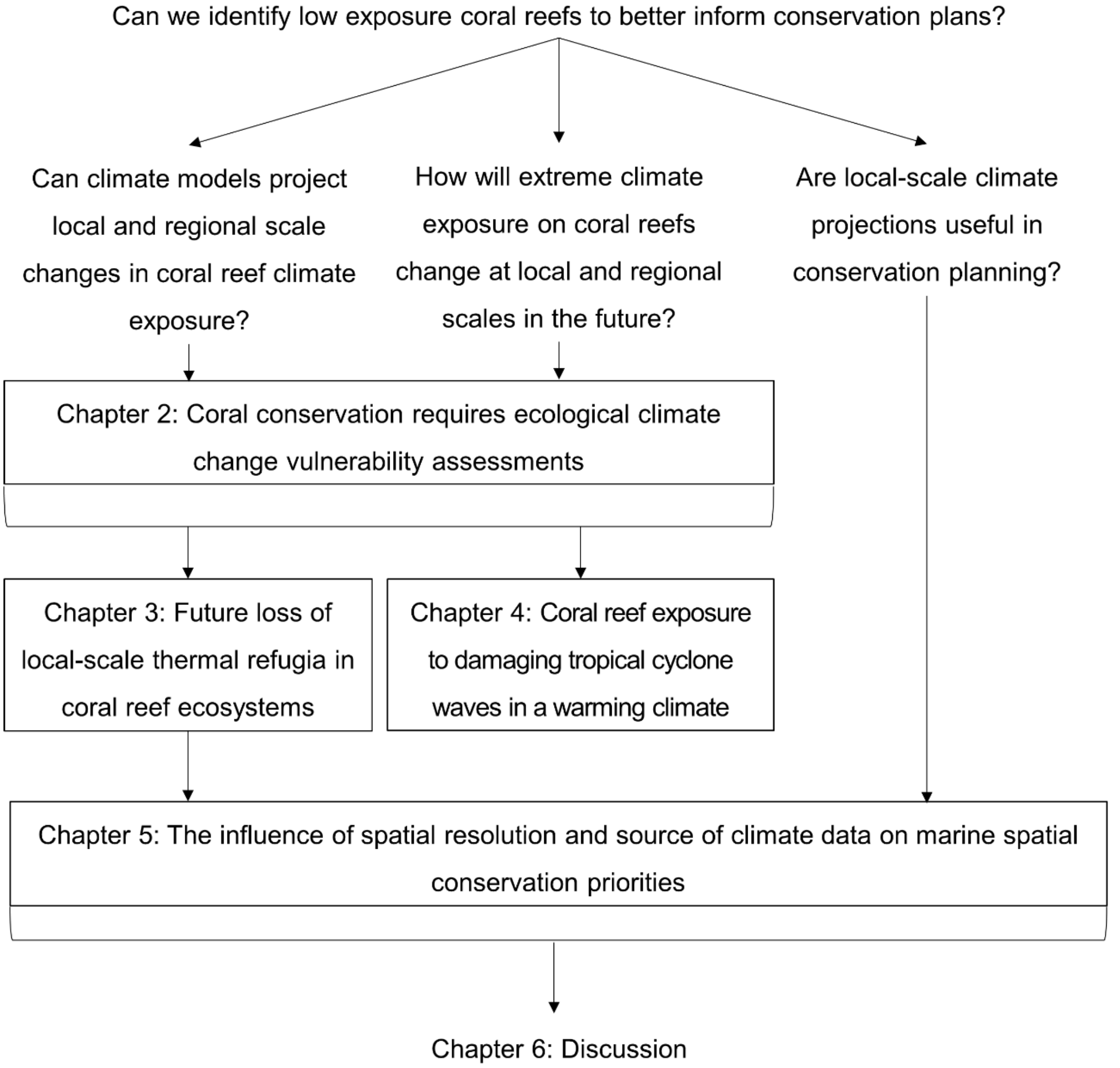

Figure 1.1: Flow diagram showing how each chapter of this thesis relates to the research questions introduced in Chapter 1.

Chapter 2 (Dixon *et al.*, 2021) focuses on improvements to current assessments of coral reef climate exposure that will provide a more comprehensive view of reef vulnerability to climate change including the appropriate use of climate model projections, and incorporation of stressor interactions and ecological response data. Chapter 3 (Dixon *et al.*, 2022b) presents a novel thermal stress dataset for the past and future at 1 km spatial resolution and includes global and regional projections of the proportion of low exposure coral reefs remaining under future warming scenarios. The suitability of downscaled tropical cyclones for representing observed tropical cyclone characteristics is examined in Chapter 4 (Dixon *et al.*, 2022a). Finally, Chapter 5 determines whether the novel 1 km thermal stress dataset adds value to conservation planning and whether altering the observed climate data source alters marine spatial planning solutions.

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Chapter 2 - Coral conservation requires ecological climate-change vulnerability assessments

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2.0 Abstract

Climate-driven changes to environmental conditions are driving severe declines of coral reef ecosystems. Current climate vulnerability estimates commonly focus on ocean warming and typically overlook ecological responses or use broad proxies to represent responses, leading to management decisions based on incomplete views of coral reef futures. We explore four underdeveloped aspects of climate vulnerability assessments and make the following recommendations: (1) use climate projections based on changes in global warming as future scenarios in place of the more common emissions scenarios; (2) include available high-resolution projections for climate variables in addition to thermal stress; (3) combine projected climate stressors accounting for uncertainty in future outcomes; and (4) quantitatively assess historical and project future ecological sensitivity and adaptive capacity of corals to multiple stressors. We demonstrate how this framework can be used to reduce uncertainty in projected climate vulnerability and facilitate targeted investment in managing reefs most likely to endure climatic disturbances.

In a nutshell:

- Coral reef management under climate change is hindered by the inability to evaluate differences in reef vulnerability
- Using changes in global mean temperature (e.g. 1.5°C or 2.0°C) instead of emissions pathways can reduce uncertainty in future warming scenarios
- Stressors other than thermal stress should be included in vulnerability assessments; high-resolution climate projections are available for other coral reef-relevant climate variables
- Interactions among stressors can be applied to projected climate stressors by utilising statistical techniques that account for uncertainty in future scenarios
- Past ecological responses to multiple climate disturbances must be used to project responses to future climate conditions to estimate ecological climate vulnerability

2.1 Introduction

Climate change impacts on tropical marine ecosystems are extensive and increasing in severity as global greenhouse-gas (GHG) emissions continue to rise (Hughes *et al.*, 2018). The decline of coral reef systems worldwide is of extreme concern due to the considerable economic and ecological value associated with the planet's most biodiverse marine ecosystem (Hughes *et al.*, 2017a). Coral reef climate vulnerability refers to the predisposition of coral species, populations, and/or communities to be negatively affected by climate change, and encompasses three aspects: climate exposure, ecological sensitivity, and adaptive capacity (Dawson *et al.*, 2011). Current management solutions generally focus on removing local threats from reefs that are least vulnerable to climate change (Beyer *et al.*, 2018), and therefore global policy and regional or local reef management depend on robust estimates of spatiotemporal climate change impacts on marine habitats. However, the diverse range of factors affecting ecological responses to multiple climatic changes complicates coral reef vulnerability assessment (Safaie *et al.*, 2018), leading to uncertain or incorrect estimates that potentially compromise climate change-resilient management strategies.

Climate-relevant conservation for coral reefs requires global climate change mitigation along with the establishment of marine protected areas that control local-scale threats and consequently reduce the combined impact of global-scale stressors (Tittensor *et al.*, 2019). The dismal outlook for the future of coral reefs has forced conservation efforts into two general approaches: protect the least exposed areas (Beyer *et al.*, 2018) or protect a range of areas subjected to varying exposure regimes (Webster *et al.*, 2017). Identifying a range of areas minimises uncertainty associated with ecological responses to historical warming and bleaching events (Mumby *et al.*, 2011) and incorporates multiple habitat types subjected to varying levels of exploitation (Webster *et al.*, 2017). However, climate conditions are projected to render large areas uninhabitable to corals, and – in light of limited conservation resources – protecting low climate exposure areas will be considered most efficient because they are more likely to survive (Beyer *et al.*, 2018; Mcleod *et al.*, 2019). This selective identification of the least-exposed sites can be successful only if exposure estimates prove to be correct (Webster *et al.*, 2017) and if exposure is a valid predictor of reef vulnerability.

2.2 Challenges in coral reef climate vulnerability assessments

Coral reefs are impacted by a range of global-scale environmental changes, of which past and future ocean warming are most commonly used to evaluate the risk of reefs experiencing large-scale coral bleaching and mortality, typically using cumulative thermal stress metrics like degree heating weeks (DHWs) or degree heating months (DHMs). DHWs and DHMs refer to the accumulated weekly or monthly sea-surface temperature (SST) anomalies, also known as HotSpots, that exceed the long-term maximum monthly mean by 1°C or more (Donner *et al.*, 2005; Liu *et al.*, 2006). Bleaching occurs when reef-building corals expel their symbiotic algae under thermal stress (Hughes *et al.*, 2017b), but the commonly used DHW and DHM parameterisations used to represent such ecological responses to thermal stress are now known to have limited predictive value (Ainsworth *et al.*, 2016; Kim *et al.*, 2019; McClanahan *et al.*, 2019). Subsequent prevailing warming or cooling of the water determines whether corals die or regain their symbionts. Measures of thermal stress alone are not an indicator of coral bleaching because other environmental factors (e.g. daily temperature patterns, light intensity, water mixing, nutrient input; Yee and Barron, 2010; Ainsworth *et al.*, 2016; Donovan *et al.*, 2020) influence bleaching severity and consequently predictions of bleaching events. Moreover, coral species exhibit differential responses to thermal stress, leading to varying degrees of bleaching among community types (Kim *et al.*, 2019). Predicting and managing reef responses to climate change-related thermal stress therefore hinges on our ability to accurately quantify the link between multiple exposure metrics and reef-specific responses to thermal stress, particularly with respect to bleaching-associated mortality.

Climate exposure projections are required in order for relevant conservation goals to be established, but there are model and scenario uncertainties associated with such projections (Levy and Ban, 2013). There is also a spatial mismatch between the scale of climate model projections (typically hundreds of kilometres) and that of local management (1–2 km for the smallest marine protected areas; Kwiatkowski *et al.*, 2014). Downscaling techniques increase the resolution of thermal stress projections indicating the spatial distribution of low exposure areas for targeted intervention. However, ocean warming represents just one of a range of climate variables that influence ecological responses to climate change; other factors, such as storms, irradiance and UV exposure, salinity, and sea-level rise, also impact coral reefs (Ban *et al.*, 2014). Storm exposure is recognised as a criterion in reef conservation for climate change prioritisations but is based solely on historical data (Beyer *et al.*, 2018). Projected storm exposure is required to prioritise areas for climate change management that conserve multiple communities as insurance against future damage (Webster *et al.*, 2017; Beyer *et al.*, 2018).

Interactions between and among various stressors further complicate assessments of projected climate exposure because the negative ecological effect may be the sum (additive), less than the sum (antagonistic), or greater than the sum (synergistic) of the combined impacts (Ban *et al.*, 2014), but how these relationships will play out in the future is largely unknown (Camp *et al.*, 2018). Metrics of interacting climate variables alone are likely insufficient for quantifying reef vulnerability, as varying tolerance to disturbance alters ecological responses to stress (Dawson *et al.*, 2011). Failure to consider differences in disturbance-related tolerance in estimates of ecological sensitivity risks focusing scarce conservation resources in areas with low exposure but high sensitivity failing to meet management objectives. Although we focus here on management of reefs with climate vulnerability in mind, effective conservation clearly also requires consideration of other management objectives, such as addressing local stressors (e.g. overexploitation, pollution), and of socioeconomic factors (Mcleod *et al.*, 2019).

Current reef climate vulnerability assessments typically use past climate exposure or projected thermal stress metrics alone (Figure 2.1; see also Supplementary Table 2.1). Maximising the success of conservation approaches requires identification of reef vulnerability with improved estimates of multiple sources of climate exposure at the relevant scale and set in an ecological context (Figure 2.1). For this approach, we propose the following four steps: (1) reduce uncertainty in climate model projections by assessing different levels of warming (e.g. 1.5°C or 2.0°C) instead of emissions scenarios; (2) make use of existing downscaled climate projections for a range of climate variables to predict future climate exposure; (3) estimate combined climate exposure accounting for different types of interactions between multiple stressors; and (4) calculate reef vulnerability using both projected, local-scale, and multi-stressor climate exposure, and ecological responses to these stressors.

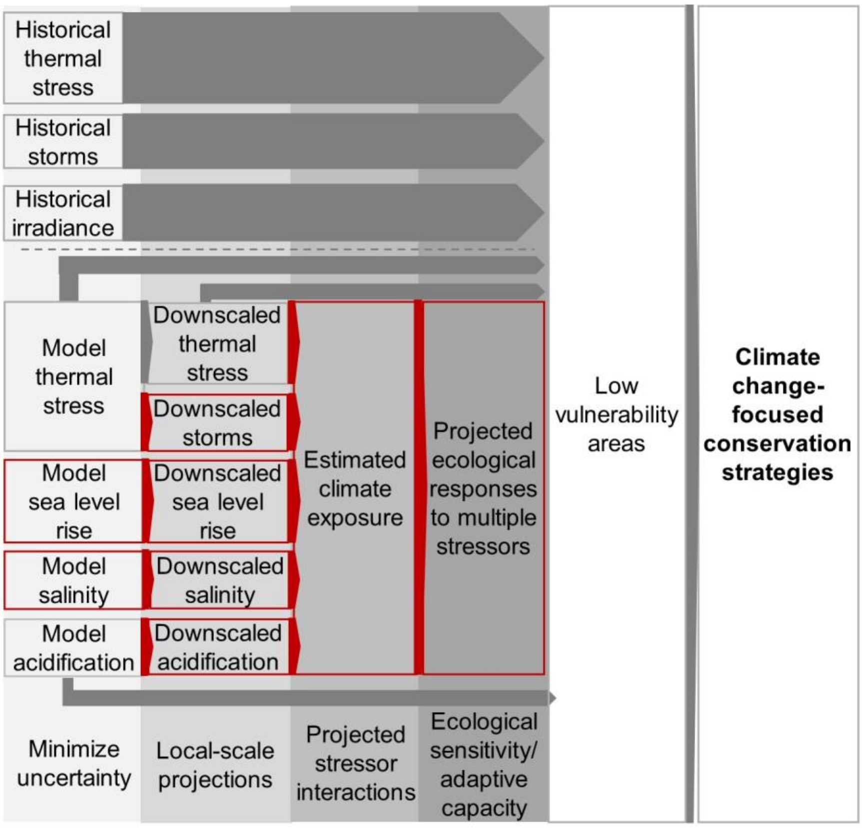

Figure 2.1: Schematic showing the current methods and our updated framework to assess climate vulnerability of coral reefs for conservation and climate policy. Many current approaches use historical metrics and/or climate model predictions (outlined in grey) to assess reef vulnerability, whereas fewer rely on downscaled thermal stress. Our framework is shown by the improvements outlined in red and is further detailed in the main text.

2.3 Minimising uncertainty in climate model projections

General circulation models (GCMs) that predict future atmospheric and ocean states inform exposure assessments (Frieler *et al.*, 2013), but there is uncertainty associated with climate model projections (Levy and Ban, 2013). Model uncertainty can be reduced using a multi-model ensemble mean. The approach assumes that biases among a range of models will be reduced or cancelled out, and has been validated by the improved performance of the ensemble compared to any single model when simulating present-day climate (Knutti *et al.*, 2010). However, the multi-model mean dampens extreme values that can have major ecological impacts on coral reefs (e.g. extreme thermal stress leading to coral bleaching) and on biological systems generally (Harris *et al.*, 2018). Uncertainty in future emissions trajectories is an additional source of error exacerbated in studies selecting single emissions scenarios that are already known to be an inaccurate representation of future trajectories.

International climate policy has driven studies examining biological responses to global warming of 1.5°C or 2.0°C (Hoegh-Guldberg *et al.*, 2018), although only a few examples of this exist for coral reefs (Frieler *et al.*, 2013; Schleussner *et al.*, 2016). We recommend that coral reef climate vulnerability studies transition from the widespread use of emissions scenarios and relatively small model ensembles to the warming-based approach for climate model projections. Assessing different global-warming scenarios removes a large proportion of the uncertainty in future emissions and varying climate model sensitivities. The warming-based approach uses a large ensemble from all models and emissions scenarios to compare regional extreme events associated with a specified change in global temperature (Mitchell *et al.*, 2017). Focusing on the level of global warming allows for assessment of the risk of climate change becoming dangerous to unique and threatened ecosystems like coral reefs (Hoegh-Guldberg *et al.*, 2018), with results that are compatible with international climate policy established by the Paris Agreement (Mitchell *et al.*, 2017).

Global warming is determined by the change from a natural baseline that can be defined by a century-scale (King *et al.*, 2017) or pre-industrial (Frieler *et al.*, 2013; Schleussner *et al.*, 2016; Mitchell *et al.*, 2017) average temperature. The global warming scenarios (e.g. 2.0°C) are determined using all model years from all GCMs and model experiments where 10- or 20-year average temperatures are 2.0°C above the natural baseline (Schleussner *et al.*, 2016; King *et al.*, 2017). Available model output for each model year, such as SST, can be used to calculate extreme climatic conditions impacting coral reefs (Frieler *et al.*, 2013; Schleussner *et al.*, 2016). The large ensemble of thermal stress values enables robust statistical comparisons of different magnitudes of global temperature change (Schleussner *et al.*, 2016), indicating the reduction in climate vulnerability that can be achieved through international climate policy. This approach reduces uncertainty in the projected climate exposure estimates that feed into climate vulnerability assessments.

2.4 Projecting climate variables to local management scales

Global-scale climate models are effective in simulating historical warming at larger spatial scales, but their coarse-scale resolution fails to match the local management scales at which local processes create fine-scale variability (Kwiatkowski *et al.*, 2014). Increasing the resolution of climate predictions by downscaling GCM outputs (Figure 2.2) improves the relevance of model projections for ecological processes and forms a better basis for identifying low exposure sites for local-scale conservation measures (van Hooidonk *et al.*, 2015). Downscaling has been applied to assess thermal stress exposure of coral reefs (e.g. Donner *et al.*, 2005; van Hooidonk *et al.*, 2015; Wolff *et al.*, 2018). Downscaled coral bleaching projections are publicly available at 4 km resolution from the US National Oceanic and Atmospheric Administration's Coral Reef Watch (van Hooidonk *et al.*, 2015), and long-term remote-sensing SST data at 1 km resolution enable the downscaling of temperature projections to even finer scales (Chin *et al.*, 2017). However, downscaling has yet to be applied to other coral reef climate stressors (Supplementary Table 2.1).

Although neglected in coral reef research, downscaling GCM projections of other environmental factors could improve conservation decision making (e.g. when applied to tropical cyclone projections). Tropical cyclones require consideration in climate exposure estimates given that the proportion of high-intensity storms is projected to increase with climate change (Knutson *et al.*, 2015) and thermal stress and local-scale impacts impede coral recovery following storm damage (Puotinen *et al.*, 2016). Tropical cyclones are not well simulated by global-scale climate models because they occur at relatively small spatial and temporal scales. Downscaling storms requires the accurate simulation of changes in storm-associated marine climate variables (e.g. SST) and the atmospheric processes that link these changes to storm activity (Knutson *et al.*, 2015). Storms create feedbacks (e.g. the cooling wake associated with tropical cyclones) that further complicate the downscaling of storm projections (Carrigan and Puotinen, 2014). Dynamical and statistical downscaling techniques simulate a range of tropical cyclone characteristics (Emanuel *et al.*, 2008; Villarini and Vecchi, 2013; Knutson *et al.*, 2015) that determine coral reef damage, including intensity, size, duration, translation speed, and temporal variability (Puotinen *et al.*, 2016; Wolff *et al.*, 2016), as well as tropical cyclone-associated cold wakes at <10 km resolution, indicating the storm exposure distributions projected for coral reefs worldwide.

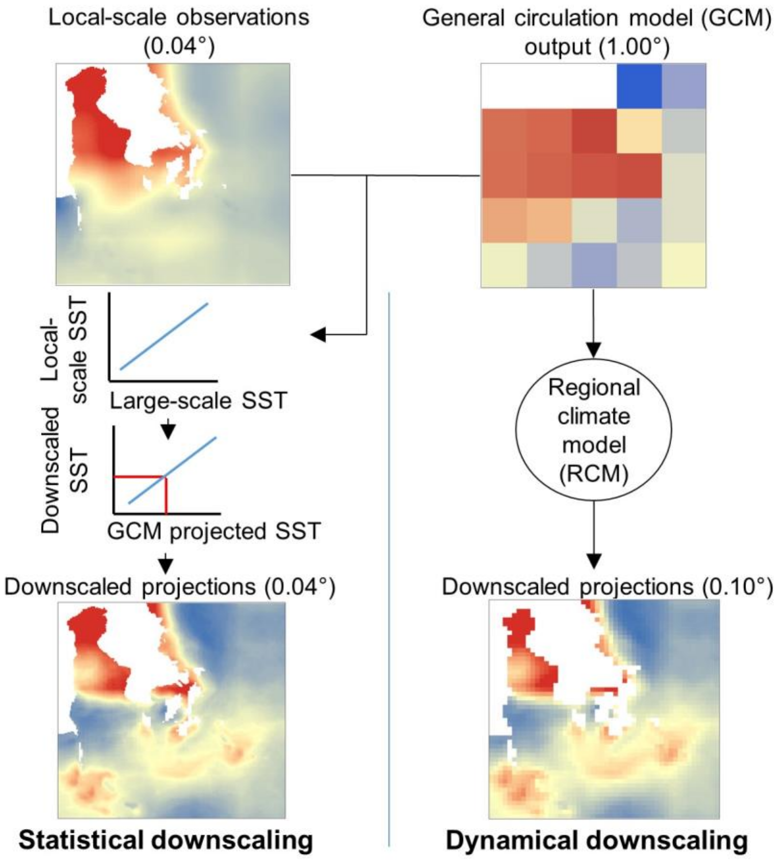

Figure 2.2: Summary of the main downscaling techniques. Statistical downscaling uses the relationship between the large-scale atmospheric circulation and local-scale observations (Fowler *et al.*, 2007). The dynamical technique uses regional climate models with large-scale boundary conditions, such as relative temperature and humidity (Knutson *et al.*, 2010). Technique selection is study-specific, as each of the techniques has its pros and cons. Examples of the processes were adapted from Donner *et al.* (2005), Fowler *et al.* (2007), and van Hooidonk *et al.* (2015). Resolutions previously used

in coral reef literature are given for observed, general circulation model (GCM), and downscaled data (van Hooidonk *et al.*, 2015).

Downscaling is necessary for other abiotic factors impacting coral reefs, such as ocean acidification and light availability. These factors are also affected by local features (e.g. presence of carbon dioxide vents and seagrass meadows (for ocean acidification); water turbidity and cloud cover (for light); Camp *et al.*, 2018). Dynamical downscaling is useful when the long-term records required for statistical techniques are lacking (Camp *et al.*, 2018), and has been applied to other climate variables, such as salinity (Townhill *et al.*, 2017), sea-level rise (Liu *et al.*, 2016), waves (Wandres *et al.*, 2017), and ocean acidification (Skogen *et al.*, 2014; Wallhead *et al.*, 2017). Although remote-sensing observational data are available for such variables as photosynthetically active radiation – a proxy for incoming solar radiation (Donner and Carilli, 2019) – the dataset currently does not extend far enough back in time for establishment of a statistical relationship between the fine and large scales, and light intensity is heavily influenced by feedback processes (e.g. clouds) that are not captured by statistical downscaling (van Hooidonk *et al.*, 2015). However, dynamical studies are limited by their geographic extent, as they focus on small geographic areas through computationally intensive regional climate models. The next generation of GCMs involved in the High Resolution Model Intercomparison Project (HighResMIP) for the Coupled Model Intercomparison Project Phase 6 (CMIP6) provide future opportunities to incorporate higher resolution model output (e.g. 25-km resolution; Haarsma *et al.*, 2016) for neglected climate variables in climate exposure estimates.

We recommend that currently available downscaled coral reef-relevant climate variables like tropical cyclone projections be incorporated into climate vulnerability assessments. Where regional climate models exist for coral reef regions, additional variables, such as ocean acidification and salinity, may inform regional-scale climate vulnerability assessments.

2.5 Combining projections of interacting climate stressors

Ideally, a comprehensive view of future climate exposure requires consideration of the combined impacts of interacting stressors (Hughes *et al.*, 2017a). Coral reef impacts resulting from multiple stressors have been assessed extensively for the past (e.g. Maina *et al.*, 2011; Zinke *et al.*, 2018; Donner and Carilli, 2019) and although projections of future interactions have been initiated (Maina *et al.*, 2016; Wolff *et al.*, 2018), past climate exposure for stressors for which there is greater uncertainty in projections, such as storms, is still being used (Supplementary Table 2.1). Ocean warming and storms have many ecological impacts, interacting with a variety of local and climatic disturbances in a complex web of stressors that affect ecological change (Ban *et al.*, 2014). Bleaching responses of corals are better predicted by the combined effects of both heat and light stress (Yee and Barron, 2010), which tropical cyclones mitigate somewhat via increased cloud cover and sediment loading reducing irradiance (Ban *et al.*, 2014). Storms also alleviate thermal stress by causing upwelling of cool subsurface waters, which influence coral bleaching dynamics (Carrigan and Puotinen, 2014). Incidences of tropical cyclones preventing bleaching and enhancing coral recovery during thermal stress events were recorded in the Caribbean in 2005 and 2010 (Carrigan and Puotinen, 2014), and eastern and western Australia in 2016 (Hughes *et al.*, 2017b).

Projecting the climate exposure resulting from the two stressors must account for the uncertainty in climate projections and the strength of interactions. We introduce a novel and flexible approach that can be easily adapted for use in conservation decision making. For each reef pixel, the size of which is determined by the resolution of the climate data, the total climate exposure is dependent on the combined impacts of storm damage and thermal stress mitigated by the tropical cyclone cold wake (Figure 2.3). Uncertainty can be incorporated into estimates of climate exposure by combining probabilities of different exposures from large ensembles of climate models (e.g. using Monte Carlo simulations). We present an example of a climate exposure model incorporating both additive and antagonistic interactions between projected stressors (Figure 2.3). If the units of each climate exposure estimate are the same, the exposure types can be combined to inform overall risk. This example considers only physical damage by storms and thermal stress respite resulting from the cold wake and advances the approach by Wolff *et al*. (2018) by allowing for cold wakes that are not necessarily sufficient to negate all the thermal stress for a given year (Carrigan and Puotinen, 2014). Although other storm-related impacts (e.g. sedimentation, freshwater influx, nutrient injection; Ban *et al.*, 2014) are excluded here, this serves as an example of how multiple future climate disturbances could be combined.

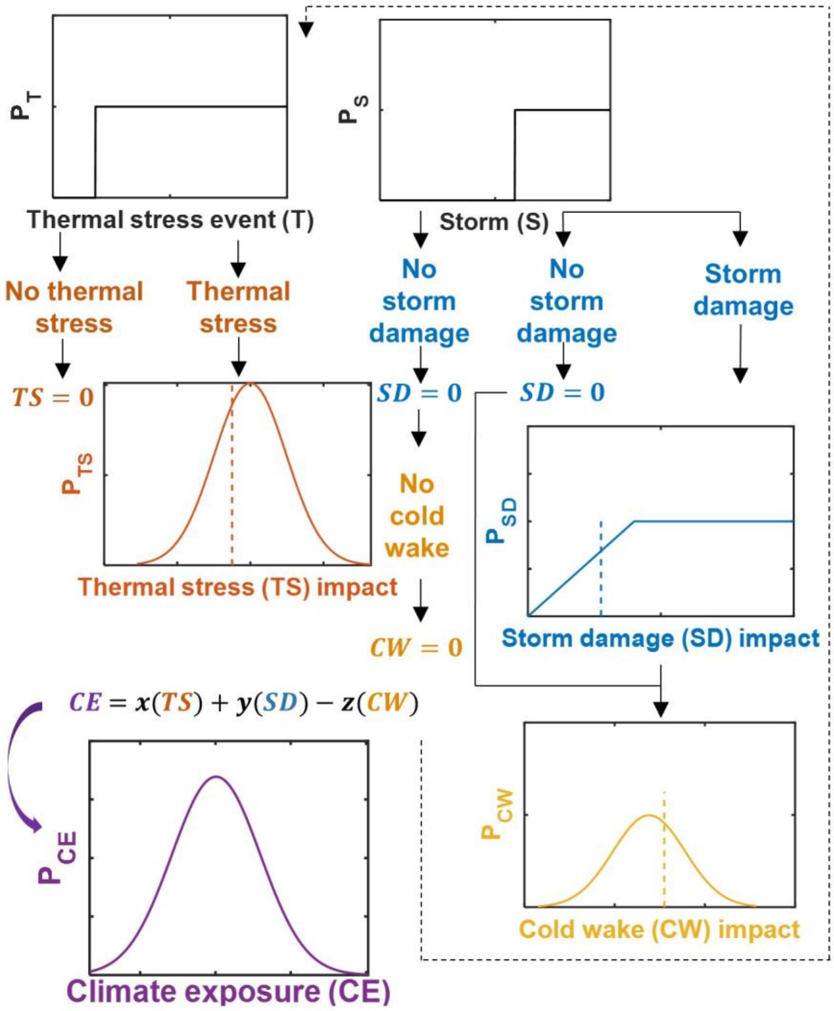

Figure 2.3: Probability model combining the additive and antagonistic interactions between thermal stress and storms; *x*, *y*, and *z* refer to the correlation between stressors, indicating the probability of one stressor occurring alongside another (e.g. a cold wake following every storm would have a correlation of 1).

Combining interacting stressors for future climate projections is necessary to determine future climate exposure on coral reefs, as trends in climate variables are projected to vary in the future; for example, whereas thermal stress is projected to increase (Hoegh-Guldberg *et al.*, 2018), the overall frequency of global tropical cyclones is projected to decrease (Knutson *et al.*, 2020), impacting future cold wake benefits. Changes to stressor interactions under climate change may result in further climate-related impacts on coral reefs through potential feedbacks. For instance, the beneficial effect of ocean acidification on hard coral competitors like macroalgae may increase coral reef susceptibility to other stressors, such as disease, facilitating further macroalgal dominance (Ateweberhan *et al.*, 2013). The type of analysis recommended here can be applied to different future scenarios to best address management objectives related to climate change vulnerability and should include iterative sensitivity analysis to account for uncertainty in the strengths and types of future interactions (Figure 2.3).

2.6 Linking climate change exposure to ecological responses and adaptive capacity

Estimates of climate exposure deriving from thermal stress projections provide an indication of the spatial variation in ocean warming, but without incorporating ecological sensitivity to environmental change, they are insufficient in determining coral reef vulnerability (Dawson *et al.*, 2011). Cumulative heat stress of 4°C and 8°C weeks are commonly used to predict moderate and severe bleaching (Donner *et al.*, 2005), yet these measures are now known to be inconsistent predictors of bleaching (Ainsworth *et al.*, 2016; McClanahan *et al.*, 2019) and do not account for variation in responses between coral species, genera, and community types (Figure 2.4; Kim *et al.*, 2019).

Specific reef recovery responses to past thermal exposure should ideally inform any prediction of future ecological responses to projected climate exposure (Donner and Carilli, 2019). However, to date, studies by Ortiz *et al*. (2014), Van Woesik *et al*. (2018), and Wolff *et al*. (2018) are unique examples of ecological responses to accumulated thermal stress (e.g. DHWs/DHMs) or monthly SST. These measures account for shorter term thermal extreme events causing coral bleaching and mortality but cannot represent the effects of protective pre-bleaching exposure (Ainsworth *et al.*, 2016), diurnal SST variability (Safaie *et al.*, 2018), peak SST, thermal history, and duration of cool periods (McClanahan *et al.*, 2019). Similarly, the wind-derived metrics of tropical cyclone intensity/category serve as typical surrogates to estimate coral reef damage, omitting size, duration, and translation speed measures to adequately quantify tropical cyclone-induced wave damage (Puotinen *et al.*, 2020). Approaches that project ecological responses to future change showcase the best pathways for including ecological sensitivity in vulnerability assessments. These approaches should integrate a greater range of climate variables that dictate ecological responses and will often require regional specificity to effectively predict future ecological change.

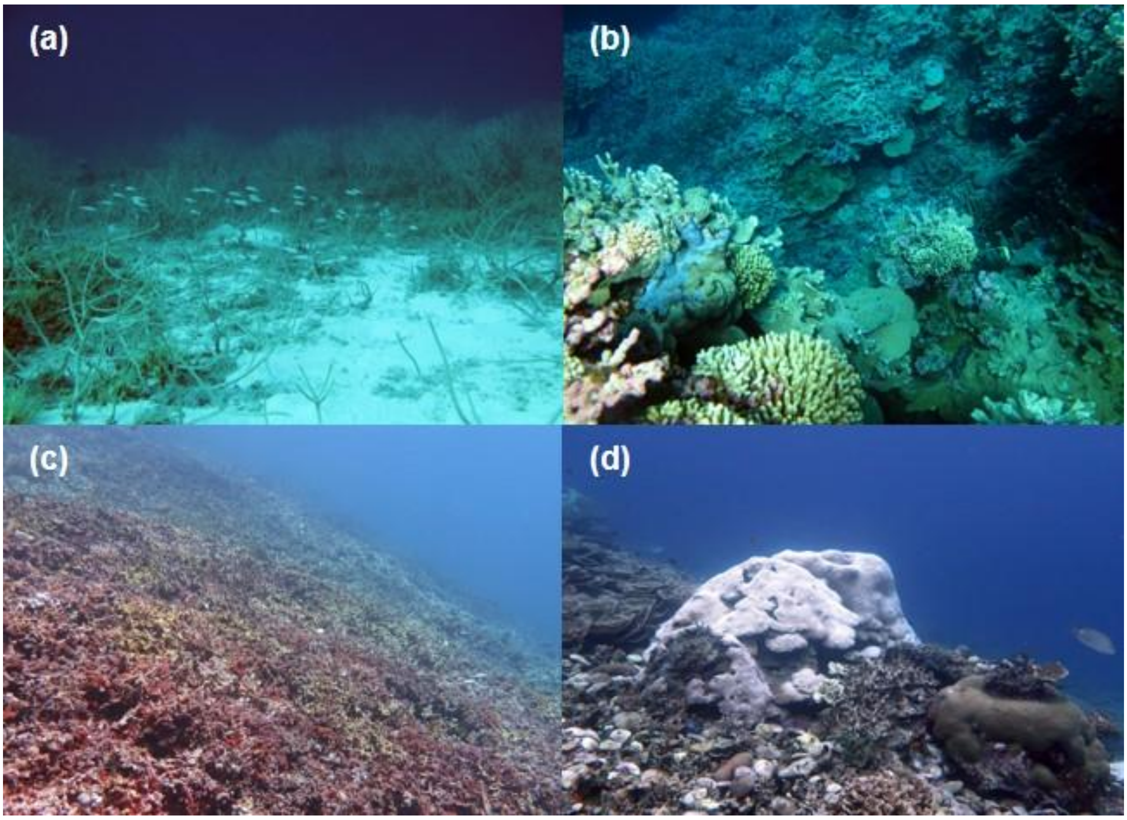

Figure 2.4: Responses of coral reef communities to climate stressors are specific to community type: for example, (a) a lagoon habitat in the Marshall Islands dominated by a fine-branching coral species versus (b) a diverse reef habitat on hard substrate (also in the Marshall Islands). The habitat in (a) is sensitive to thermal stress and may experience more extensive and long-term damage following disturbance such as that

depicted in (c), showing a damaged reef in Indonesia. The diverse reef in (b) may exhibit more varied responses to thermal stress, with some coral species experiencing bleaching and others relatively unaffected (as in the Indonesian reef in (d)). Photo credits (a-d): Maria Beger.

Historical ecological responses to climate change are often determined by coral bleaching or growth responses (Supplementary Table 2.1). Bleaching and growth provide indicators of climate sensitivity but do not account for the range of ecological responses that result from changes in environmental conditions (e.g. physical damage resulting from storms). Storms and bleaching events can result in coral mortality caused by sustained loss of symbionts and physical damage (Puotinen *et al.*, 2016; Hughes *et al.*, 2018), leading to a reduction in live hard coral cover. More gradual climatic changes (e.g. ocean warming) can influence coral growth and recovery, and impact competitive interactions between structurally complex hard coral and competing macroalgae (Anthony *et al.*, 2015), which also influences hard coral cover. Measures of hard coral cover can capture ecosystem changes resulting from various stressors and the use of a single response variable allows comparison between different geographic locations. However, neither total nor single genera hard coral cover captures the difference in disturbance tolerance between organisms or changes in community composition following disturbance (Kim *et al.*, 2019). Hard coral cover for the range of species/genera present at a location is necessary to indicate ecological change due to climate exposure. Currently, these responses to multiple climatic disturbances are difficult to quantify because of the lack of long-term data and presence of multiple factors that affect coral reef sensitivity. Even though such detailed data collection is costly and time consuming, long-term datasets are increasingly needed to better understand the response of corals to climate stressors (Van Woesik *et al.*, 2018; Darling *et al.*, 2019; Donner and Carilli, 2019).

When projecting ecological responses to climate stress, a reef's adaptive capacity must also be considered. Coral reefs can acclimate or adapt to climatic changes over time

(Hughes *et al.*, 2017a), but the extent to which (and how) coral reefs can adapt is not well known (Mumby *et al.*, 2011). Thermal adaptation has been linked to various SST characteristics, such as heating rate (Middlebrook *et al.*, 2010), diurnal variability (Safaie *et al.*, 2018), and high historical chronic and acute thermal stress (Mumby *et al.*, 2011). However, these studies do not account for variability in adaptive capacity between species subjected to the same thermal disturbance (Safaie *et al.*, 2018) or external factors affecting a site's adaptive capacity (e.g. supply of coral recruits adapted to warmer environments; Matz *et al.*, 2020). Because adaptation is not guaranteed in locations that have been affected by past bleaching events (Hughes *et al.*, 2017b), thermal regimes alone cannot provide a proxy for adaptive capacity in the identification of low vulnerability areas.

Long-term hard coral cover datasets that track past ecological responses of coral genera to multiple disturbances can facilitate identification of increasing resistance (or the lack thereof) for coral genera over time. Sites subjected to frequent disturbance – for instance, the high thermal stress exposure of the Gilbert Islands in Kiribati (Donner and Carilli, 2019) or coral communities that currently exist under marginal environmental conditions resulting from multiple stressor types, such as macrotidal or upwelling reef environments (Camp *et al.*, 2018) – are ideal candidates for monitoring changes in response to frequent exposure. Utilising palaeoecological data and further extending existing genus-level records for hard coral cover to track responses to consecutive disturbances over multiple locations, habitat types, and disturbance regimes will be vital for informing potential adaptive predictions of future ecological vulnerability.

2.7 Conclusions

The loss in coral reef value with continued ecosystem decline will impact millions of people who rely on the services coral reefs provide for their livelihoods (Hughes *et al.*, 2017a). Our framework identifies low vulnerability areas for conservation using an ecologically sensitive, multi-stressor climate vulnerability measure. We recommend that this framework be implemented in climate vulnerability assessments to improve the use of climate model projections in conservation science. Ecologically informed climate vulnerability estimates can direct local-scale management efforts in identifying protected areas with the highest chance of reef survival and assist international climate policy by quantifying future changes in coral reef ecosystems resulting from multiple interacting climate stressors. In future work, ecologically informed reef vulnerability can be used to predict how reefs might be transformed in terms of total and genera-level cover, and the contribution of adaptive capacity in maintaining coral cover. However, the role of vulnerability in guiding conservation requires a clear understanding of the management actions to be implemented alongside dedicated efforts to curtail global GHG emissions (Hughes *et al.*, 2017a).

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2.10 Supplementary Material

Supplementary Table 2.1: Climate stressors included in coral reef climate vulnerability studies. In publication, Supplementary Table 2.1 is displayed as a WebTable.

Climate stressor	Climate exposure metric	Projections included	Downscaled ~resolution	Spatial scale	Species/ genus/ community	Ecological response	References
Thermal stress	Sea-surface temperature (SST, °C)	**No**	–	Regional	Community	Bleaching	Maina *et al.* (2008)
		No	–	Local	Community	**No**	Licuanan *et al.* (2015)
		Yes	Yes (111 km)	Regional	Community	**No**	Andréfouët *et al.* (2015)
		Yes	Yes (4 km)	Regional	Community	**No**	Magris *et al.* (2015)
		Yes	No (56 km)	Regional	Genus	**No**	Wolff *et al.* (2015)
		Yes	**No**	Local	Community	**No**	Maina *et al.* (2016)
	Warm spell duration index (number of days/warm days) (%)	Yes	**No**	Local	Community	**No**	Maina *et al.* (2016)
	Degree heating weeks/ cumulative weekly SST anomalies (°C weeks)	**No**	–	Global	Community	**No**	Beyer *et al.* (2018)
		Yes	Yes (4 km)	Regional	Community	**No**	McLeod *et al.* (2010); Magris *et al.* (2015); Asaad *et al.* (2018)
		Yes	Yes (4 km)	Regional	Community	**No**	Harris *et al.* (2017)
		No	–	Regional	Community	Bleaching	Maina *et al.* (2008)
	Degree heating months (°C months)	Yes	**No (611 km)**	Global	Community	**No**	Beyer *et al.* (2018)
		Yes	**No (139 km)**	Regional	Community	**No**	Vivekanandan *et al.* (2009)
		Yes	Yes (36 km)	Global	Community	**No**	Donner *et al.* (2005)
		Yes	**No (111 km)**	Global	Species	**No**	Foden *et al.* (2013)
		Yes	**No (200 × 400 km)**	Local	Genus	**No**	Anthony *et al.* (2011)
		Yes	Yes (4 km)	Regional	Genus	Hard coral cover	Wolff *et al.* (2018)
	Hotspots/ SST anomalies (°C)	No	–	Regional	Community	Bleaching	Maina *et al.* (2008)
		Yes	**No (550 km)**	Global	Community	**No**	Beyer *et al.* (2018)
		Yes	Yes (4 km)	Local	Community	**No**	Maina *et al.* (2016)
Storms	Exposure days	**No**	–	Global	Community	**No**	Beyer *et al.* (2018)
	Return time interval (1 day yr^{-1})	**No**	–	Global	Community	**No**	Beyer *et al.* (2018)
	Significant wave height (m)	**No**	–	Regional	Community	**No**	Andréfouët *et al.* (2015); Puotinen *et al.* (2016)
	Frequency/ intensity/ temporal clustering	**No**	–	Regional	Genus	Hard coral cover	Wolff *et al.* (2018)
	Relative wave exposure	**No**	–	Local	Community	**No**	Licuanan *et al.* (2015)
Wind	Wind speed (ms^{-1})	**No**	–	Local	Community	**No**	Maina *et al.* (2016)
		No	–	Regional	Community	**No**	Maina *et al.* (2008)

	Wind stress (Newtons m^{-2})	**Yes**	Yes (111 km)	Regional	Community	**No**	Andréfouët *et al.* (2015)
Precipitation	Extremely wet/very heavy rainfall days/ consecutive dry days (number of days)	Yes	**No**	Local	Community	**No**	Maina *et al.* (2016)
Ocean acidification	Aragonite saturation state	Yes	**No (278 × 416 km)**	Global	Species	**No**	Foden *et al.* (2013)
		Yes	**No (200 × 400 km)**	Local	Genus	**No**	Anthony *et al.* (2011)
		Yes	**No (56 km)**	Regional	Genus	**No**	Wolff *et al.* (2015)
Solar irradiance	Ultraviolet radiation (milliwatts m^{-2}/watts m^{-2})	**No**	–	Regional	Community	Bleaching	Maina *et al.* (2008)
		No	–	Local	Community	**No**	Maina *et al.* (2016)
	Photo-synthetically active radiation (Einsteins m^{-2} $days^{-1}$)	**No**	–	Regional	Community	Bleaching	Maina *et al.* (2008)
Sea-level rise	Sea-surface height change (cm)	**No**	–	Local	Community	**No**	Licuanan *et al.* (2015)

Notes: vulnerability studies are those that use the word "vulnerability/vulnerable" in reference to the study findings. We list only those stressors explicitly included and not those simulated using background mortality, for example. Studies conducted in a lab setting or focusing on reef-associated species only are excluded. SST = sea-surface temperature. For downscaled resolutions, 1.0° is assumed to equal 111 km. No downscaled resolution is given for projected climate data where it is not reported. Ecological responses refer to responses to past climate exposure quantified using field data.

Chapter 3 - Future loss of local-scale thermal refugia in coral reef ecosystems

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3.0 Abstract

Thermal refugia underpin climate-smart management of coral reefs, but whether current thermal refugia will remain so under future warming is uncertain. We use statistical downscaling to provide the highest resolution thermal stress projections (0.01°/1 km, >230,000 reef pixels) currently available for coral reefs and identify future refugia on locally manageable scales. Here, we show that climate change will overwhelm current local-scale refugia, with declines in global thermal refugia from 84% of global coral reef pixels in the present-day climate to 0.2% at 1.5°C, and 0% at 2.0°C of global warming. Local-scale oceanographic features such as upwelling and strong ocean currents only rarely provide future thermal refugia. We confirm that warming of 1.5°C relative to pre-industrial levels will be catastrophic for coral reefs. Focusing management efforts on thermal refugia may only be effective in the short-term. Promoting adaptation to higher temperatures and facilitating migration will instead be needed to secure coral reef survival.

3.1 Introduction

Coral reefs in every region of the world are threatened by climate change, no matter how remote or well protected (Hughes *et al.*, 2017b). Identifying and protecting climate refugia is a popular recommendation for coral reef management (Morelli *et al.*, 2016; Beyer *et al.*, 2018; Mcleod *et al.*, 2019; Wilson *et al.*, 2020). Climate refugia are locations that maintain suitable environmental conditions for a resident species even when surrounding areas become inhospitable (Kavousi and Keppel, 2018). An effective climate refugium is characterised by an ability to provide long-term protection from multiple climate stressors (Kavousi and Keppel, 2018). One of the most pervasive climate threats to coral reefs is ocean warming. Identifying coral reef locations that can buffer the effects of rising ocean temperatures, hereafter "thermal refugia", is a crucial first step to identifying multi-stressor climate refugia. Upwelling areas and reefs with strong ocean currents have been proposed as potential thermal refugia that protect coral reefs from warming conditions (Chollett *et al.*, 2010; Chollett and Mumby, 2013; Perdanahardja and Lionata, 2017; Camp *et al.*, 2018). However, climate projections are often too coarse to capture the smaller scale oceanographic features that characterise thermal refugia (Kavousi and Keppel, 2018). By missing oceanographic features that lower local temperatures, large coral reef declines are projected globally (Frieler *et al.*, 2013; van Hooidonk *et al.*, 2016). Whether smaller scale features will provide hidden refugia in the future remains an open question. As climate change progresses, the number of coral reef refugia is expected to diminish (Hughes *et al.*, 2017a), particularly as global warming of 1.5°C set by the Paris Agreement becomes increasingly ambitious. Success of thermal refugia conservation hinges on the ability of local-scale oceanographic features to maintain environmental conditions suitable for coral reef survival under future warming of at least 2.0°C, generating an urgent need to identify such features at management scales.

Thermal exposure projections using the previous generation of climate models involved in the fifth Coupled Model Intercomparison Project Phase 5 (CMIP5) are available at 4 km resolution (van Hooidonk *et al.*, 2015). The projections were generated using statistical downscaling techniques that use the relationship between fine and coarse-scale climate variables to increase the resolution of coarse climate model projections and capture observed climate variability (Stoner *et al.*, 2013). Here, we use the latest generation of climate model projections (CMIP6) to project future thermal exposure on shallow-water coral reefs globally and identify thermal refugia at the highest spatial resolution available (1 km). We use the Multi-scale Ultra-high Resolution (MUR) Sea Surface Temperature (SST) Analysis observational dataset at 1 km spatial resolution (JPL MUR MEaSUREs Project, 2015) as the training dataset to statistically downscale CMIP6 projections of daily SSTs. In satellite-derived observational datasets, the resolution of the grid is often finer than the resolution of the input data. The MUR dataset uses different sized time windows of night-time SST data to reconstruct small-scale SST features, resulting in a feature resolution up to ten times finer than 5 – 25 km products (Chin *et al.*, 2017). Downscaling using the MUR dataset allows us to identify areas where local oceanographic conditions promote thermal refugia and provide information at an unprecedented scale (1 km) to inform reef management.

The CMIP6 models better simulate climate system features influencing thermal stress on corals than CMIP5 models, including elements of El Niño Southern Oscillation and Indian Ocean Dipole (McKenna *et al.*, 2020). The new models generally have a higher spatial resolution (as high as ~25 km; Held *et al.*, 2019) than their CMIP5 counterparts (typically ~100 km). Some CMIP6 models have a higher equilibrium climate sensitivity (1.8 – 5.6°C; i.e. the temperature change resulting from a doubling of CO_2) than those of CMIP5 (1.5 – 4.5°C; Forster *et al.*, 2020; Sherwood *et al.*, 2020; Zelinka *et al.*, 2020). Most models with an equilibrium climate sensitivity > 4.5°C do not reproduce observed warming trends, suggesting that > 4.5°C values are unlikely (Forster *et al.*, 2020; Sherwood *et al.*, 2020; Tokarska *et al.*, 2020) and ensemble means including these models may be biased high. To avoid this bias, we use the models' response at prescribed future global warming levels (e.g. 1.5 or 2.0°C) in our downscaling approach. Thus, models with high equilibrium climate sensitivity can be included in our model ensembles without our method overestimating future warming. This level-analysis approach uses large ensembles of multiple models and emissions experiments to project local climatic changes associated with each future global warming level (Mitchell *et al.*, 2017). This approach removes most of the uncertainty associated with different climate model sensitivities and displaces the uncertainty due to future emissions trajectories onto an uncertainty as to when a global warming level will be passed (Dixon *et al.*, 2021).

Refugia are defined by their ability to maintain favourable conditions. As such, high thermal stress tolerance of species in a location does not influence whether the area is classified as a refugia (Kavousi and Keppel, 2018). However, various biological and ecological factors can influence the level of impact on corals from thermal exposure. To model the assumption that global coral reefs will adapt to warmer conditions over time, some projections of thermal stress on coral reefs have applied a global increase in the thermal stress threshold (Donner *et al.*, 2005; Frieler *et al.*, 2013; Schleussner *et al.*, 2016; Langlais *et al.*, 2017). Coral reefs living in variable temperature environments have exhibited higher thermal tolerance than those in low variability environments (McClanahan *et al.*, 2007; Donner, 2011; Guest *et al.*, 2012; van Woesik *et al.*, 2012; Barshis *et al.*, 2013; Donner and Carilli, 2019). Reefs with high historical thermal exposure and temporal variability have been used to identify coral reef refugia on the basis that these reefs have been able to acclimate/adapt to thermal stress (Mumby *et al.*, 2011; Magris *et al.*, 2015).

Here, we examine historical and future thermal exposure to present local-scale (1 km) predictions of whether present-day thermal refugia will persist into the future and provide the context of seasonal and inter-annual SST variability as indicators of the susceptibility of reefs to thermal exposure.

3.2 Results and Discussion

3.2.1 Thermal refugia in the future

Coral recovery following extensive thermal stress-induced mortality is spatially variable but on average is thought to require at least 10 years to re-establish coral communities (Baker *et al.*, 2008). To represent sites where coral communities can be maintained and/or re-established, we define thermal refugia as 1 km reef pixels with a probability of thermal stress events less than 0.1 yr^{-1} (one event every 10 years; Figure 3.1). Exposed reefs are defined as 1 km reef pixels with a probability of thermal stress events greater than 0.2 yr^{-1} (one event every five years). A probabilistic frequency of 0.2 yr^{-1} corresponds to an intolerable level of thermal stress (Donner, 2009; Frieler *et al.*, 2013; Schleussner *et al.*, 2016). All other reef pixels are described as intermediate which indicates reefs where the level of thermal stress may be too high to maintain pre-disturbance communities and coral cover, but where species with high recovery rates might proliferate.

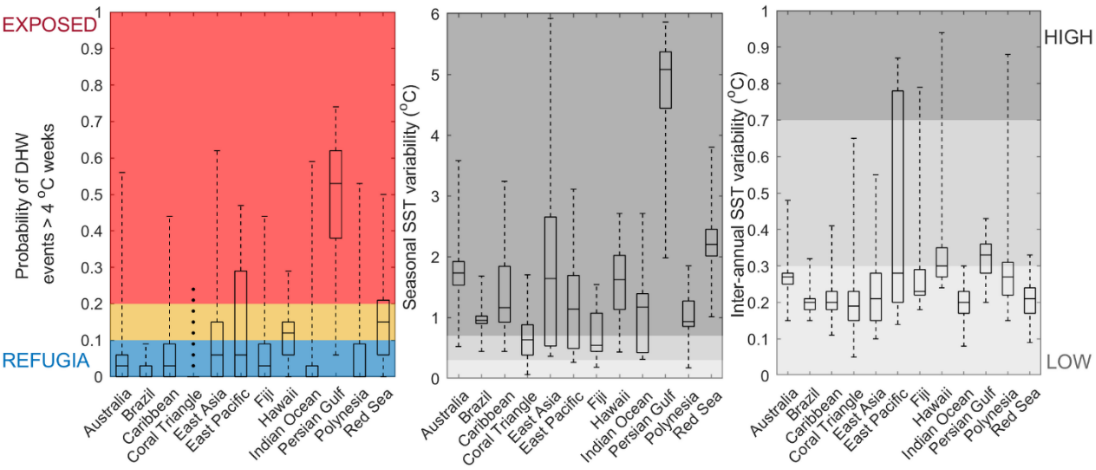

Figure 3.1: Probability of DHW events > 4°C-weeks, seasonal SST variability and inter-annual SST variability in 12 coral reef regions during the period 1986-2019. Outliers (>100 * interquartile range) are shown by the black dots. Thresholds for determining thermal refugia (probability of DHW events > 4°C-weeks less than 0.1 yr^{-1}) and exposed reefs (probability of DHW events > 4°C-weeks greater than 0.2 yr^{-1}) are represented by the blue and red shaded areas, respectively. Thresholds for determining high SST variability (> 0.7°C) and low SST variability (< 0.3°C) are represented by the dark and light grey shaded areas, respectively.

Thermal stress is calculated using the cumulative thermal stress metric Degree Heating Weeks (DHW), which is the rolling 12-week sum of SST anomalies at least 1°C higher than the long-term maximum monthly mean (MMM; Liu *et al.*, 2014). Thermal stress events are identified as those with a DHW value above 4°C-weeks, which is the threshold commonly used to indicate thermal stress high enough to cause significant coral bleaching and some mortality, whereas the 8°C-weeks threshold indicates severe thermal stress leading to broad-scale catastrophic coral mortality (Eakin *et al.*, 2009). The long-term MMM calculated here is slightly higher (up to 1°C) for much of the world's coral reefs than those calculated by previous studies (Supplementary Figure 3.1). We use the European Space Agency (ESA) Climate Change Initiative (CCI) 5 km SST Analysis product (Merchant *et al.*, 2016) for the early part of the time series, instead of the more-commonly used National Oceanic and Atmospheric Administration (NOAA) Coral Reef Watch product, due to its consistency with in situ SST measurements for coral reef regions (Merchant *et al.*, 2019). The 5 km SST is then downscaled to 1 km by replacing the CCI 5 km monthly SST climatology with that of the 1 km MUR dataset (Supplementary Methods 3.1). Together, these factors result in small changes to the MMM which can then lead to larger changes in accumulated thermal stress. The 4°C-weeks threshold we use therefore indicates more severe bleaching than described in previous studies. We define low variability reefs as those with seasonal and inter-annual SST variability less than 0.3°C and high variability reefs as those with seasonal or inter-annual SST variability greater than 0.7°C (Figure 3.1; Langlais *et al.*, 2017).

In the recent era (1986-2019), 84.1% of reef pixels globally are thermal refugia (Figure 3.2). The percentage of global thermal refugia drops to 0.2% (0 – 57.8%) at 1.5°C of warming, relative to pre-industrial levels, and to 0% (0 – 45.2%) at 2.0°C of warming (Figure 3.2). Only 6.8% of reef pixels are exposed in the 1986-2019 period, increasing to 90.6% (12.1 - 100%) and 99.7% (16.3 - 100%) at 1.5°C and 2.0°C of warming, respectively. At 3.0°C and 4.0°C, there are no thermal refugia and all global reef pixels are exposed (Figure 3.3). Coarse resolution (50 km) CMIP3 projections for the global coral reef area estimated that 100% (4 °C-weeks threshold) and 89% (8 °C-weeks threshold) of coral reefs will be exposed (> 0.2 yr^{-1}) at 1.5°C of global warming (Frieler *et al.*, 2013). Our findings provide further support that the Paris Agreement target of limiting warming to 1.5°C will not be enough to save most coral reefs (Frieler *et al.*, 2013; Schleussner *et al.*, 2016; Hoegh-Guldberg *et al.*, 2018). However, by capturing fine-scale SST features that have been known to prevent bleaching mortality in the past, we locate small reef areas where the probability of thermal stress under future warming is lower than in adjacent areas.

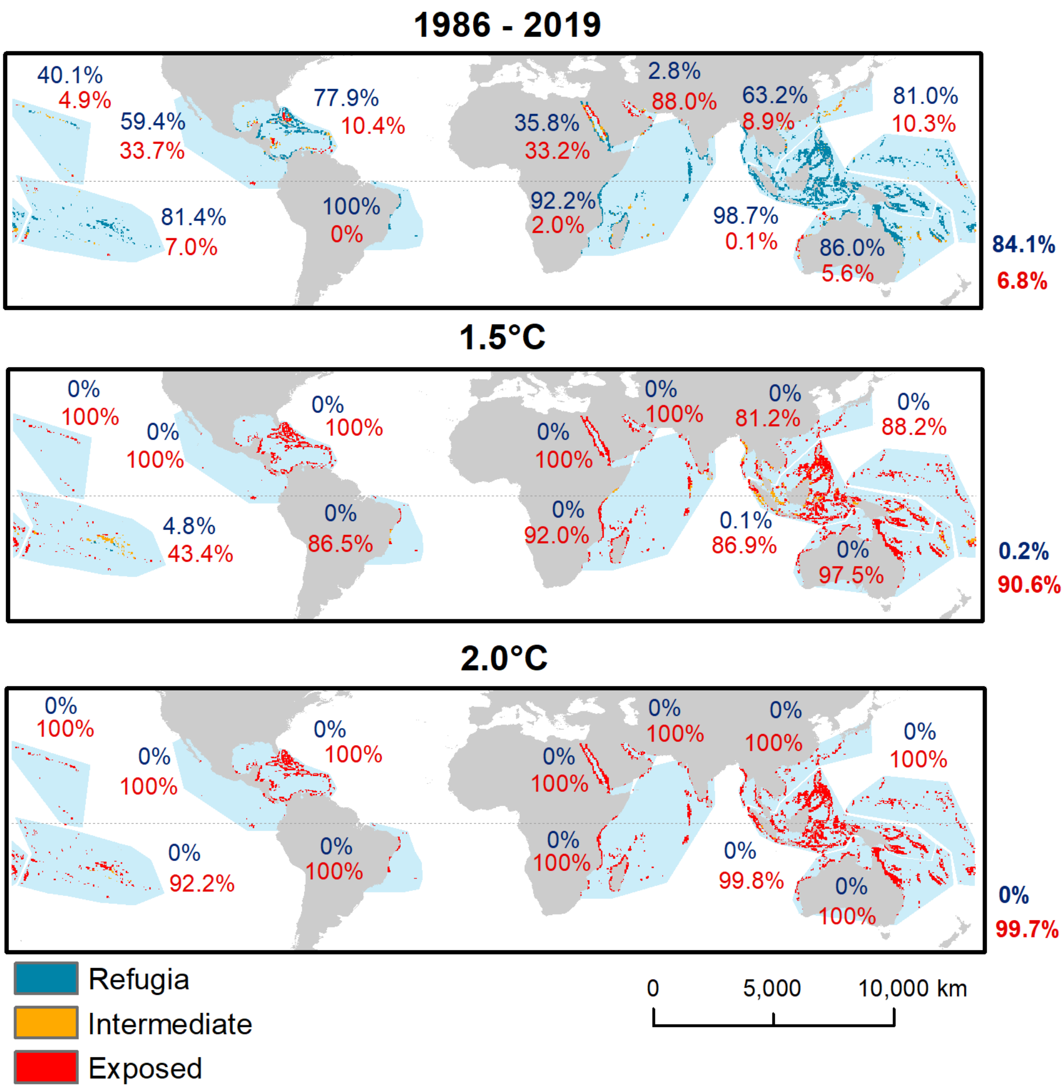

Figure 3.2: Global distribution of exposure categories in the 1986-2019 climate and at 1.5 and 2.0°C of future global warming. Exposure categories are thermal refugia (probability of DHW events > 4°C-weeks less than 0.1 yr^{-1}), intermediate (probability of DHW events > 4°C-weeks from 0.1 – 0.2 yr^{-1}) and exposed (probability of DHW events > 4°C-weeks greater than 0.2 yr^{-1}). Percentages indicate the regional (on map) and

global (right of map) proportion of thermal refugia (blue) and exposed reefs (red). The 12 coral reef regions are outlined in light blue. The base map is made with Natural Earth.

We find thermal refugia in all 12 coral reef regions in the 1986-2019 climate (Figure 3.2). At 1.5°C, thermal refugia are only present in two coral reef regions (Figure 3.2): Polynesia and the Coral Triangle. For most coral reef areas, current thermal refugia are not projected to remain so. Many known upwelling areas in Oman (Schils and Coppejans, 2003; Chollett *et al.*, 2010), Colombia (Chollett *et al.*, 2010), Indonesia (Lesser Sunda; Perdanahardja and Lionata, 2017) and the Caribbean (Chollett and Mumby, 2013) are projected to have no thermal refugia remaining at 1.5°C of warming (Figure 3.2). The exception is in the East Indian Ocean Sumatra-Java upwelling region, which has some thermal refugia remaining at 1.5°C of warming. While upwelling areas can provide respite from coral bleaching and mortality in the present-day climate, local upwelling is only enough to mitigate thermal stress on coral reefs in very rare cases and under the smallest projected change in future warming. Similarly, there are no thermal refugia at 1.5°C of global warming in areas with high currents known to influence bleaching dynamics in the past, such as Panama, Florida (Chollett and Mumby, 2013) and Lesser Sunda, Indonesia (Perdanahardja and Lionata, 2017). Some small reef areas influenced by upwelling or high currents in Lesser Sunda and Oman are rated intermediate for exposure at 1.5°C of warming rather than exposed, but they are not thermal refugia given our refugia criteria. Similar patterns emerge when using an 8°C-weeks threshold to define thermal refugia, with a slightly slower decline to 0% thermal refugia (Supplementary Figure 3.2).

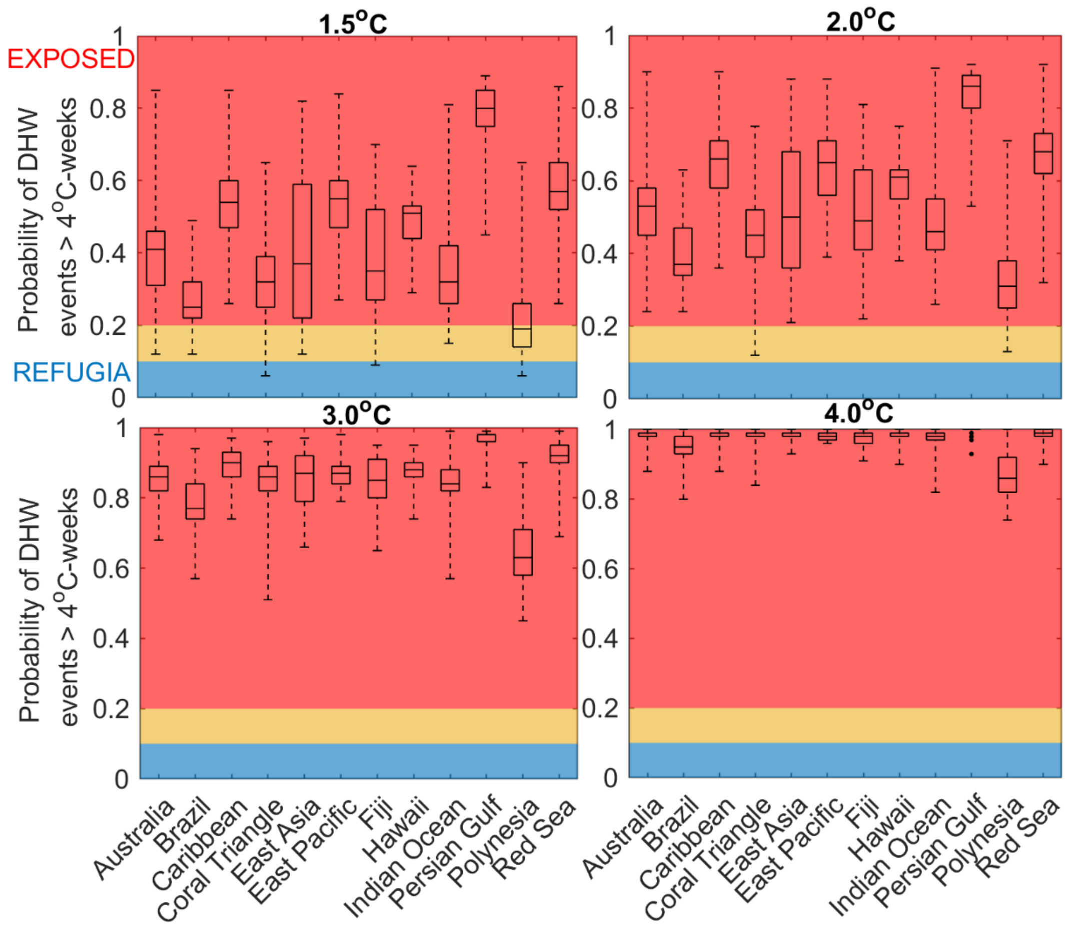

Figure 3.3: Probability of DHW events > 4°C-weeks across 12 coral reef regions under 1.5, 2.0, 3.0 and 4.0°C of global warming relative to pre-industrial levels. Thresholds for determining thermal refugia (probability of DHW events > 4°C-weeks less than 0.1 yr^{-1}) and exposed reefs (probability of DHW events > 4°C-weeks greater than 0.2 yr^{-1}) are represented by the blue and red shaded areas, respectively.

Bleaching risk is heavily influenced by inter-annual and seasonal SST variability (van Hooidonk and Huber, 2012; Langlais *et al.*, 2017). Here, we find that areas with moderate to high inter-annual variability have a lower bleaching risk with future warming (Supplementary Figure 3.3) because cooler years, influenced by natural climate variability, provide respite between thermal stress events (Langlais *et al.*, 2017). For example, the probability of thermal stress events > 4°C-weeks is lower along the Sumatra-Java coast, resulting in small areas of thermal refugia at 1.5°C of warming with some intermediate reefs remaining at 2.0°C of warming in West Sumatra. This pattern most likely arises from positive Indian Ocean Dipole events that drive upwelling that results in cold SST anomalies along the Sumatra-Java coastline (McKenna *et al.*, 2020), which may provide respite from future warming in Sumatra facilitating coral reef recovery. However, some CMIP6 models simulate more regular Indian Ocean Dipole events during the historical period compared to observations, indicating that this cool respite might be less frequent than projected here (McKenna *et al.*, 2020). Furthermore, upwelling is associated with the transport of nutrients to surface waters which can have harmful effects on coral reef ecosystems (Abram *et al.*, 2003). Thermal refugia in South Sumatra are associated with bay areas influenced by river input which also contribute high nutrient loading (Baum *et al.*, 2015), potentially exacerbated by increased extreme rainfall with future warming and land use change (Marhaento *et al.*, 2018).

The probability of thermal stress events > 4°C-weeks is lower in the Polynesia region under future warming than in other coral reef regions (Figure 3.3). The region has the highest number of thermal refugia at 1.5°C of global warming (Figure 3.2). CMIP6 models simulate relatively low rates of future warming in the southern Pacific compared to the rest of the world (Grose *et al.*, 2020; Kwiatkowski *et al.*, 2020). Weakening of equatorial trade winds due to global warming will slow ocean circulation and equatorial upwelling (Collins *et al.*, 2010) causing less warm water being transported away from the equator resulting in higher rates of warming in the equatorial Pacific compared to regions off the equator (e.g. French Polynesia). However, rates of warming in the southern Pacific are uncertain. SST warming rates in the tropical Pacific are affected by long-standing climate model biases in oceanographic SST features (e.g. the equatorial cold tongue bias; Ying *et al.*, 2019) although this bias is reduced in CMIP6 compared to CMIP5 (Grose *et al.*, 2020).

High latitude reefs are among the first areas to lose thermal refugia under future global warming (Figure 3.2). These regions are characterised by high seasonal variability (Figure 3.1). We find that reef pixels with high seasonal SST variability have a larger increase in the probability of thermal stress between the 1986-2019 climate and 1.5°C of warming (Supplementary Figure 3.4). Chronic warming in highly seasonally variable regions results in summer temperatures exceeding thermal stress thresholds annually under small changes in global mean temperature (Langlais *et al.*, 2017). High latitude reefs may therefore provide a thermal refugia for range shifting corals adapted to warmer baseline temperatures (Beger *et al.*, 2014) but are unlikely to provide a thermal refugia for the species currently living there, unless they are able to sufficiently increase their thermal tolerance under the highly variable environmental conditions.

3.2.2 Thermal refugia and variability

Variable environmental conditions are thought to indicate more resistant or adaptable coral reef communities (McClanahan *et al.*, 2007; Donner, 2011; Guest *et al.*, 2012; van Woesik *et al.*, 2012; Barshis *et al.*, 2013; Donner and Carilli, 2019). Seasonal variability is the dominant SST variability (Figure 3.1). A large percentage (68.7%) of the global coral reef area has seasonal variability above the high (> 0.7°C; Langlais *et al.*, 2017) SST variability threshold. Only 0.7% of the global coral reef area has inter-annual variability above the high SST variability threshold. Reefs with the highest inter-annual variability, influenced by El Niño, are located in the tropical East Pacific (Donner, 2011). We divide thermal refugia, intermediate and exposed reefs into high (seasonal or inter-annual variability > 0.7°C), moderate and low (seasonal and inter-annual variability < 0.3°C) SST variability categories (Langlais *et al.*, 2017) to identify locations where high SST variability might lead to more rapid adaptation of species and communities (Figure 3.4 and Supplementary Figure 3.5).

Reef pixels with high SST variability (Figure 3.4) are the most promising candidates for corals surviving through adaptation. In areas of high variability, species are better equipped, both physiologically (Morikawa and Palumbi, 2019) and genetically (Barshis *et al.*, 2013), to cope with thermal stress. However, the variable conditions that increase thermal tolerance also drive bleaching risk (Langlais *et al.*, 2017). Regions with high inter-annual variability are already some of the most thermally stressed due to periodic high temperatures associated with El Niño (Donner and Carilli, 2019). High latitude regions with high seasonal variability experience frequent thermal stress with relatively low background warming (e.g. the Northern Caribbean, Figure 3.5). As a result, thermal refugia with high variability are rare at 1.5°C of warming (407 global coral reef pixels, 0.17%), and are mostly located in French Polynesia, likely due to lower rates of warming.

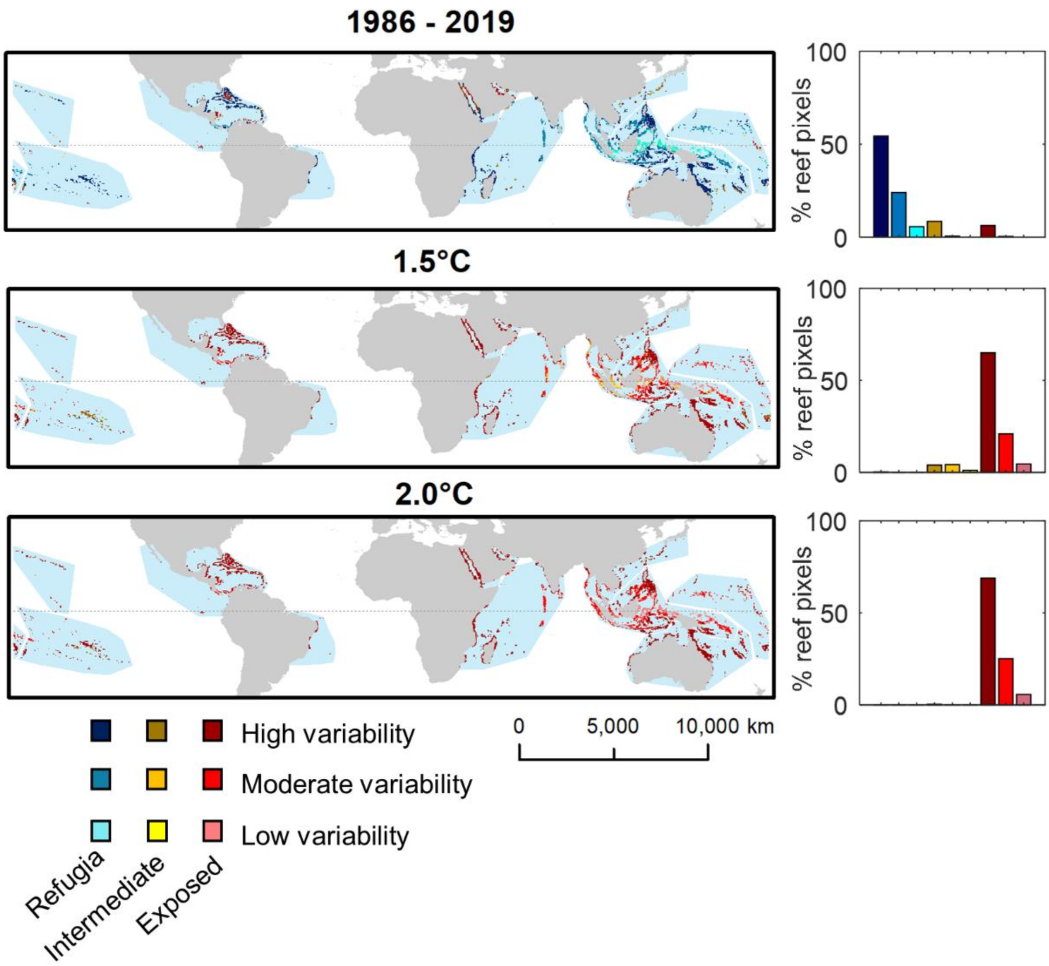

Figure 3.4: Global distribution of exposure categories and SST variability level in the 1986-2019 climate and at 1.5 and 2.0°C of future global warming relative to pre-industrial levels. Exposure categories are thermal refugia (probability of DHW events > 4°C-weeks less than 0.1 yr^{-1}), intermediate (probability of DHW events > 4°C-weeks from 0.1 – 0.2 yr^{-1}) and exposed (probability of DHW events > 4°C-weeks greater than 0.2 yr^{-1}). Exposure categories are split by the level of SST variability (high = seasonal OR inter-annual variability > 0.7°C, low = seasonal AND inter-annual variability < 0.3°C, moderate = all others). The 12 coral reef regions are outlined in light blue. Bars indicate the

percentage of 1 km reef pixels in each exposure category. The base map is made with Natural Earth.

Low variability reef areas have a low bleaching risk under low levels of background warming, but as global warming increases, these regions rapidly transition to experiencing very frequent thermal stress that leads to bleaching (Langlais *et al.*, 2017). This is the case in much of the equatorial Coral Triangle (Figure 3.4); where thermal refugia in the 1986-2019 climate transition to exposed at 1.5°C. Despite having high susceptibility to future thermal stress, low variability thermal refugia in South Sumatra and intermediate reefs in Sulawesi (Figure 3.5) may act as very short-term thermal refuges. Less exposed reefs in Central Sulawesi occur where river input influences local SST (Sulistiawati *et al.*, 2019, 2020). Reefs in these thermal refugia are in poor health (Moore and Ndobe, 2008). River input and nearby coastal developments result in high levels of marine pollution and sedimentation (Sulistiawati *et al.*, 2019, 2020), alongside overfishing and destructive fishing practices (Moore and Ndobe, 2008). Management of anthropogenic pressures in low variability, less exposed reefs may however allow these areas to reseed in the short term and facilitate the recovery of the thermally exposed surrounding areas (Beyer *et al.*, 2018).

Higher thermal tolerance of corals in more variable regions facilitates the notion of a higher thermal threshold (Donner, 2011). We sum SST > 1°C above the maximum monthly mean to calculate DHWs, following the commonly used NOAA Coral Reef Watch metric (Liu *et al.*, 2014). Donner (2011) developed an offset to replace the 1°C threshold with a spatially varying value determined by the variability in summer maximum SST. Using this thermal stress metric lowers the thermal exposure in regions where summer SST is highly variable, for example in the Persian Gulf that experiences wind-driven variability in summer SST (Paparella *et al.*, 2019), and in tropical East Pacific regions affected by El Niño (Donner and Carilli, 2019). Here, we use the standard (constant) 1°C thermal threshold as the variability offset underestimates the observed thermal stress in these high maximum SST variability regions (Donner, 2011). For example, we find no thermal stress events > 4°C-weeks in 1986-2019 in the Persian Gulf when thermal stress is calculated using the variability offset (Supplementary Figure 3.6), yet Persian Gulf reefs have experienced high thermal stress leading to bleaching in multiple years (Paparella *et al.*, 2019). Our projections for these regions are therefore likely to be conservative.

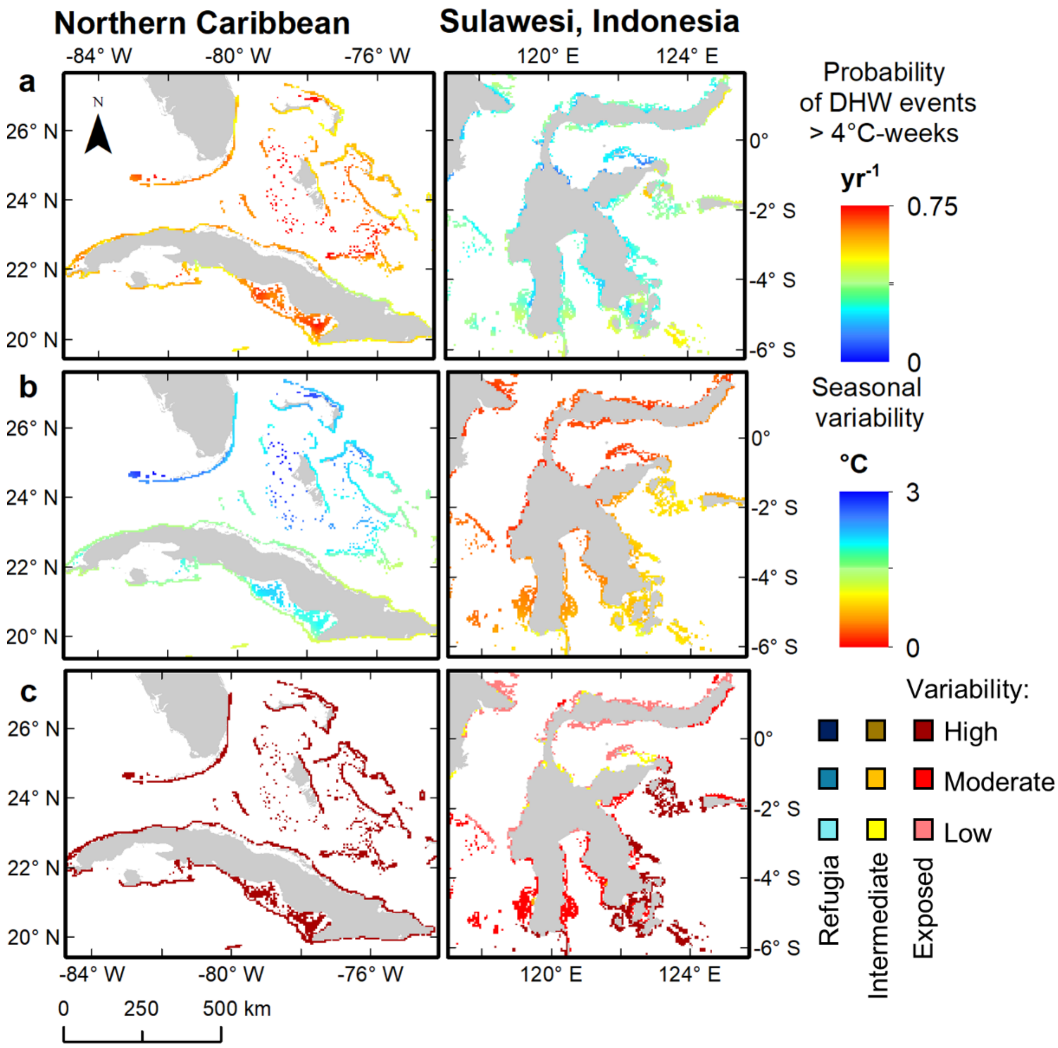

Figure 3.5: Probability of DHW events > 4°C-weeks (a), seasonal SST variability (b) and exposure category (c) in the Northern Caribbean and Sulawesi, Indonesia at 1.5°C of global warming. Exposure categories are thermal refugia (probability of DHW events > 4°C-weeks less than 0.1 yr^{-1}), intermediate (probability of DHW events > 4°C-weeks from 0.1 – 0.2 yr^{-1}) and exposed (probability of DHW events > 4°C-weeks greater than 0.2 yr^{-1}). Exposure categories are split by the level of SST variability (high = seasonal OR inter-

annual variability > 0.7°C, low = seasonal AND inter-annual variability < 0.3°C, moderate = all others). The base map is made with Natural Earth.

3.2.3 Thermal refugia in coral conservation

Future warming will quickly result in thermal stress events that are, without adaptation by corals, too frequent for the persistence of corals currently living in thermal refugia (Figure 3.6). Thermal refugia at 1.5°C of global warming are very rare, and non-existent for 2.0°C. We demonstrate that thermal refugia in upwelling areas (e.g. Sumatra-Java) are not widespread, and clearly not enough to save contemporary coral reef ecosystems. Many known upwelling and high-current areas previously identified as refugia are not thermal refugia under future warming. Future thermal refugia in existing coral locations are predicted for a very limited number of coral reef areas.

Our projections of future thermal refugia are dependent on the refugia criteria. We use an ecologically relevant threshold based on the capacity of coral communities to recover following bleaching in the past (Baker *et al.*, 2008). However, there will likely be regional and local-scale differences in the recovery rate of coral reef ecosystems. Micro-refugia may exist on smaller spatial scales than those projected here (< 100 m; Kavousi and Keppel, 2018), e.g. in unique environments such as lagoons, not well represented by global SST observations (Van Wynsberge *et al.*, 2017). In addition, corals have found refugia at depth during past thermal stress events (Frade *et al.*, 2018). However, deep refugia are not guaranteed as high thermal stress and significant bleaching can still occur (Frade *et al.*, 2018; Venegas *et al.*, 2019). High frequency temporal variability in SST can decrease coral bleaching (Ainsworth *et al.*, 2016; Safaie *et al.*, 2018) but higher than daily temporal resolution for global observational SST is lacking. Turbid reefs may act as potential refuges from thermal stress-induced coral bleaching due to reduced irradiance (Mies *et al.*, 2020). Our projected probability of thermal stress is calculated using a minimum 30-year period so indicates where long-term thermal refugia might exist under future warming. These projections can then be used alongside other environmental variables, such as water clarity and irradiance, to identify multi-stressor climate refugia.

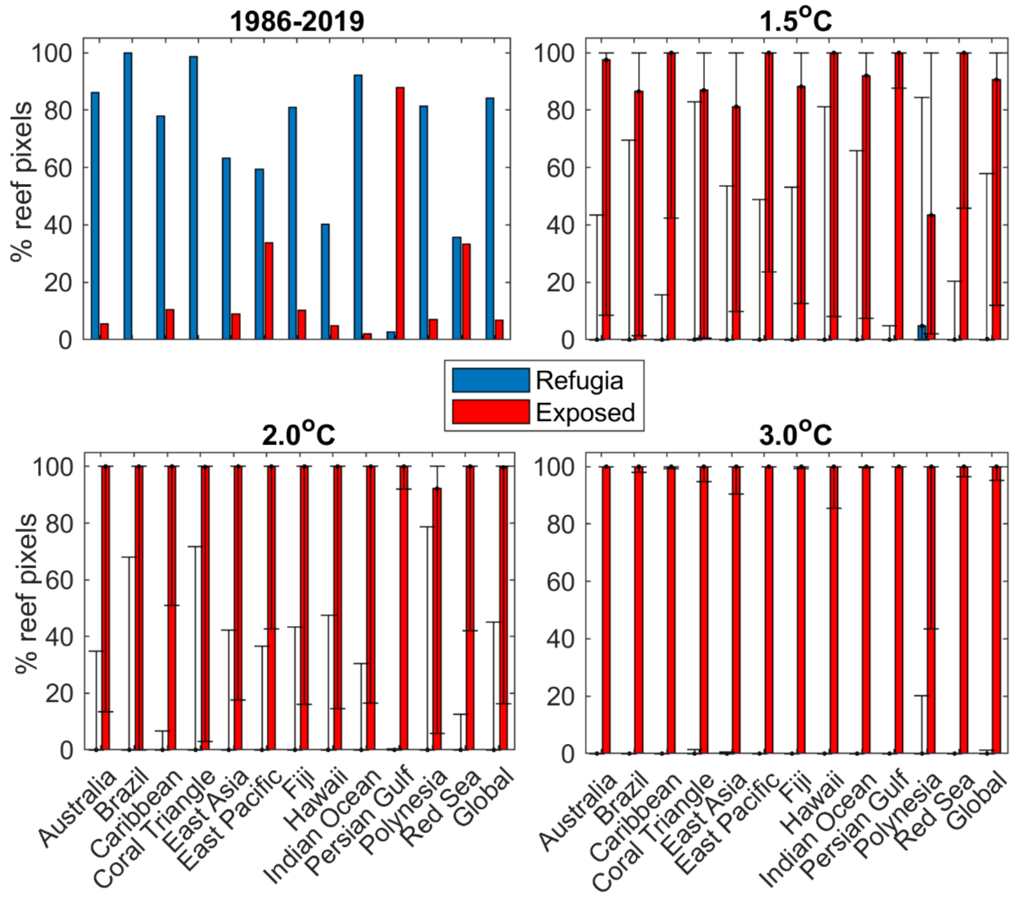

Figure 3.6: Percentage of thermal refugia and exposed reef pixels in 12 coral reef regions and globally in the 1986-2019 climate and at 1.5, 2.0 and 3.0°C of global warming. As with 3.0°C, there are 0% thermal refugia and 100% exposed reefs at 4.0°C of global warming. Error bars are the percentage of thermal refugia and exposed reefs identified using the maximum and minimum probability of DHW events > 4°C-weeks simulated by the 57 sets of CMIP6 climate projections (15 models and four SSP emissions scenarios: two climate models, GFDL-CM4 and NESM3, had only two and three SSP runs available, respectively).

Corals vary in their bleaching susceptibility depending on species, geographic location and presence of thermally tolerant symbiont clades (Mies *et al.*, 2020). While high tolerance to thermal stress does not identify an area as a refugium, knowing which species and locations will be better able to cope with ocean warming can aid conservation decision making (Kavousi and Keppel, 2018). Corals will need to adapt in order to persist in their current locations, but whether they'll be able to do this fast enough is unclear. Refugia have been suggested as “slow lanes” which may allow time for genetic adaptation to warmer conditions (Morelli *et al.*, 2020) but species living in refugia may also have low adaptation potential as it is the inhospitable conditions that drive adaptation (Kavousi, 2020). High SST variability reefs are promising candidates for adaptation as variable environments can promote thermal tolerance (Guest *et al.*, 2012). Low variability thermal refugia and high variability exposed reefs may be useful in multi-objective management approaches. By supplying coral larval recruits and reef-associated species (Beyer *et al.*, 2018), low variability thermal refugia may promote the recovery of high variability exposed reefs in the next decade as they undergo more frequent thermal stress. As climate change progresses, high variability exposed reefs may be better able to facilitate the recovery of the low variability thermal refugia once they become exposed by supplying more thermally tolerant larval recruits. This approach requires connectivity between the low variability thermal refugia and high variability exposed reefs. Prior exposure can lead to shifts in community composition to more stress-tolerant species rather than adaptation (Côté and Darling, 2010). In some cases, promoting the conservation of high variability reefs may succeed in conserving the most thermally-tolerant coral species but not maintain ecosystems in their present state. Furthermore, prior thermal stress exposure in 1998 and 2002 did not lessen bleaching severity on the Great Barrier Reef in 2016 (Hughes *et al.*, 2017b). As such, prior thermal exposure does not guarantee adaptation.

The rapid increase in the frequency of thermal stress events on corals in their current locations reinforces the need for alternative management approaches (van Oppen *et al.*, 2015; Tittensor *et al.*, 2019), alongside the implementation of marine protected areas. Coral reefs are shifting their range to locations with more favourable climate conditions (Yara *et al.*, 2011). High latitude reefs may provide a crucial habitat for migrating corals adapted to tropical SST (Beger *et al.*, 2014). Corals and their associated species have expanded their ranges poleward in Australia (Baird *et al.*, 2012; Wernberg *et al.*, 2016) and Japan (Yamano *et al.*, 2011), in a process known as tropicalisation. Dynamic management approaches may facilitate the movement of coral populations over time (Tittensor *et al.*, 2019). Prioritising present thermal refugia in management strategies may provide stepping stones for migrating corals to more favourable habitats (Morelli *et al.*, 2020). However, concomitant ocean acidification is likely to limit the poleward extent of reef-accreting corals due to reductions in aragonite saturation state (van Hooidonk *et al.*, 2014). In future research, our projections can be used to estimate future thermal stress at high latitudes for corals adapted to tropical baseline temperatures in different locations around the world. Assisted evolution and the translocation of heat-tolerant corals also require further exploration, especially for the coral reef regions projected to lose all thermal refugia by 1.5°C of warming. The projections presented here are a valuable tool to be considered alongside other sources of climate exposure, non-climate related stressors, ecological processes and socioeconomic factors for effective coral reef management in the face of future climate change (Mcleod *et al.*, 2019; Dixon *et al.*, 2021).

3.3 Materials and Methods

3.3.1 Coral reef area

We obtained the latitudinal and longitudinal coordinates for the global coral reef area at 1 km resolution from the UNEP World Conservation Monitoring Centre dataset (UNEP-WCMC *et al.*, 2010). The dataset includes tropical and subtropical coral reefs and spans a latitudinal range of approximately -35 to 35 °N. We divided the global coral reef area into 12 biogeographically distinct regions described by McWilliam *et al.* (2018). These regions vary in their functional redundancy and so indicate susceptibility to ecological changes with climate change (McWilliam *et al.*, 2018). There are 232,828 1 km reef pixels included in the analysis.

3.3.2 Increasing the resolution of climate model projections

We applied statistical downscaling by linear regression that relates fine and coarse-scale climate variables (Fowler *et al.*, 2007). The fine-scale local climate conditions are represented by observational historical SST data obtained from two global datasets: the

5 km resolution ESA CCI SST Analysis daily dataset (Merchant *et al.*, 2016) from 1985-2006 and the 1 km MUR SST Analysis dataset (JPL MUR MEaSUREs Project, 2015) from 2006-2019. SST is an estimate of the upper ocean (1-20+ m) temperature in the absence of diurnal temperature variability (Donlon *et al.*, 2007). We combined these two observational datasets to provide daily SST data from 1985-2019 for each reef pixel (Supplementary Methods 3.1). We downscaled the 5 km CCI dataset to 1 km using the change factor technique (Tabor and Williams, 2010; Kumagai and Yamano, 2018). The 1 km MUR dataset is bias adjusted to the 1 km downscaled CCI dataset. For locations where CCI data demonstrably used climatological values, they were replaced by CoralTemp SST data (NOAA Coral Reef Watch, 2018) downscaled using the same approach.

The coarse-scale SST refers to the larger-scale atmospheric predictor that is simulated by the CMIP6 climate models (Stoner *et al.*, 2013), downloaded from ESGF-CoG (https://esgf-node.llnl.gov/projects/cmip6/). We obtained simulated daily SST data from 1985 to 2100 for historical and four Shared Socioeconomic Pathway (SSP) experiments (SSP1 2.6, SSP2 4.5, SSP3 7.0 and SSP5 8.5) for 15 CMIP6 models with a spatial resolution of less than 100 km (Supplementary Methods 3.2). SST data is linearly interpolated longitudinally to fill grid points missing data as in Van Hooidonk *et al.* (2015). Climate model daily SST is converted to 1 km resolution by bilinear interpolation and the SST data extracted for each 1 km reef pixel.

Linear models are generated based on the relationship between observed and simulated historical (1985-2019) daily SST (Supplementary Methods 3.3). We generated four separate linear models to reflect SST variability by season (Jan-Mar, Apr-Jun, Jul-Sept and Oct-Dec) for each 1 km reef pixel. Observational SST is not well correlated with climate model output because model runs cannot provide correspondence in time between reality and the climate model (Stoner *et al.*, 2013). The observational and simulated data were therefore ranked in ascending order according to the asynchronous piecewise linear regression technique used by Stoner *et al.* (2013). The approach uses a piecewise linear regression technique to find the relationship between the spread of simulated output and observed data whereby the highest observed SST corresponds to the highest simulated SST. The simple linear regression is suitable for this study due to the relatively low day-to-day, seasonal and inter-annual SST variability in the tropics (Stoner *et al.*, 2013). We applied these seasonal linear models to the climate model daily ensemble mean projections to modulate local-scale SST projections.

A key assumption of statistical downscaling is that the relationship between large and local scale SST will be unchanged in the future (Fowler *et al.*, 2007). Our projections capture present-climate local-scale SST features, for example where seasonal upwelling lowers summer SST. However, local-scale features may be altered under future climate change, for example upwelling may be reduced or enhanced. Such changes will not be captured by statistically downscaled projections (van Hooidonk *et al.*, 2015). Further, we maintain the coarse resolution model-simulated long-term warming trend in our downscaled projections and so may not capture local-scale spatial variation in warming, for example where upwelling areas do not warm as rapidly as non-upwelling reefs nearby (Randall *et al.*, 2020).

3.3.3 Identifying thermal refugia

Thermal refugia are reef pixels with a low probability of a thermal stress event occurring in a given year. We calculated the probability of thermal stress events of DHW values greater than 4°C-weeks (Supplementary Figure 3.7 and Supplementary Dataset 3.1). DHW is the sum of SST anomalies 1°C higher than the long-term MMM over a 12-week period (Liu *et al.*, 2014). We calculated the long-term (1985-2012) MMM following the NOAA Coral Reef Watch approach by re-centring the monthly mean SST to the 1985-1990 + 1993 period (Skirving *et al.*, 2020). This approach allows a sufficient (28-year) time period to be used to capture inter-annual variability in the climatology while minimising the effect of chronic warming over the 1985-2012 time period (Heron *et al.*, 2014). The 4°C-week thermal stress threshold is useful for estimating bleaching occurrence (Eakin *et al.*, 2009). Observed bleaching is likely to vary on less than 1 km scales due to varying tolerances to thermal stress between coral species and other factors influencing bleaching susceptibility such as nutrient input (Donovan *et al.*, 2020), light exposure (Skirving *et al.*, 2018) and diurnal and intra-seasonal temperature variability (Ainsworth *et al.*, 2016; Safaie *et al.*, 2018). The 4°C-week threshold is not necessarily a predictor of bleaching at the 1 km scale but is useful for comparing thermal exposure between reefs now and in the future.

We calculated seasonal and inter-annual SST variability (Supplementary Dataset 3.2) as indicators of acclimation or adaptation potential (Heron *et al.*, 2016). Previous studies have indicated that past elevations in temperature associated with seasonal and inter-annual temperature variability have lowered the bleaching susceptibility of corals (Carilli *et al.*, 2012; Castillo *et al.*, 2012; Guest *et al.*, 2012). We transformed monthly SST into frequency bands using Fourier transform and calculated the root mean square (RMS) of spectral energy in the seasonal (0.5-1 year) and inter-annual (3-8 year) bands (Langlais *et al.*, 2017). Changes in seasonal and inter-annual variability with increased global warming are not robust across climate models and emissions scenarios for all global coral reef pixels (Supplementary Table 3.1). The change in inter-annual variability is not robust for reef pixels with the highest inter-annual variability, indicating uncertainty in future changes to El Niño Southern Oscillation. We therefore used observed seasonal and inter-annual variability to identify high variability reef pixels under increased levels of global warming.

Model uncertainty in SST projections is reduced by downscaling all models and SSP experiments separately and creating large ensembles including different models and emissions pathways in each of four global mean temperature change scenarios (1.5, 2.0, 3.0 and 4.0°C). The global mean temperature change is defined as the change in decadal global mean surface temperature from a pre-industrial baseline (1861-1901). We used a pre-industrial baseline rather than a century-scale baseline due to the greater availability of climate model output for the historical experiments compared to the historical natural climate experiments. All model years in which the decadal global mean surface temperature change is within 0.2°C of the global warming level (e.g. 1.3-1.7°C for the 1.5°C level; King *et al.*, 2017) are included in the calculation of the ensemble mean probability of DHW events greater than 4°C-weeks (Supplementary Figure 3.8).

Coral recovery following bleaching mortality varies spatially but is limited in the first five years and possible in 10 years (Baker *et al.*, 2008). We identified thermal refugia as reef pixels with a probability of DHW events > 4°C-weeks less than 0.1 yr^{-1}. Exposed reef pixels have a probability of DHW events > 4°C-weeks greater than 0.2 yr^{-1}. Reef pixels with a probability of DHW events > 4°C-weeks from 0.1 – 0.2 yr^{-1} are described as intermediate. The probability is the number of events during a present-day or future time period divided by the length of the period. A probability of 0.1 yr^{-1} corresponds to thermal stress events occurring every 10 years and 0.2 yr^{-1} every five years. A probability of 1.0 yr^{-1} corresponds to annual thermal stress. We calculated the minimum and maximum simulated probability of thermal stress per pixel to calculate the uncertainty in the percentage of reef pixels in each exposure category (refugia, intermediate or exposed).

We defined low variability reefs as those with seasonal and inter-annual variability less than 0.3°C and high variability reefs as those with seasonal or inter-annual variability greater than 0.7°C (Langlais *et al.*, 2017). We lowered the threshold for inter-annual variability from 0.9°C in Langlais *et al.* (2017) to 0.7°C to incorporate reefs heavily influenced by El Nino across the tropical Pacific (Donner and Carilli, 2019). We compared regional thermal refugia and exposed reefs in the present-day climate (1986-2019) and at 1.5, 2.0, 3.0 and 4.0°C global mean temperature change between 12 coral reef regions.

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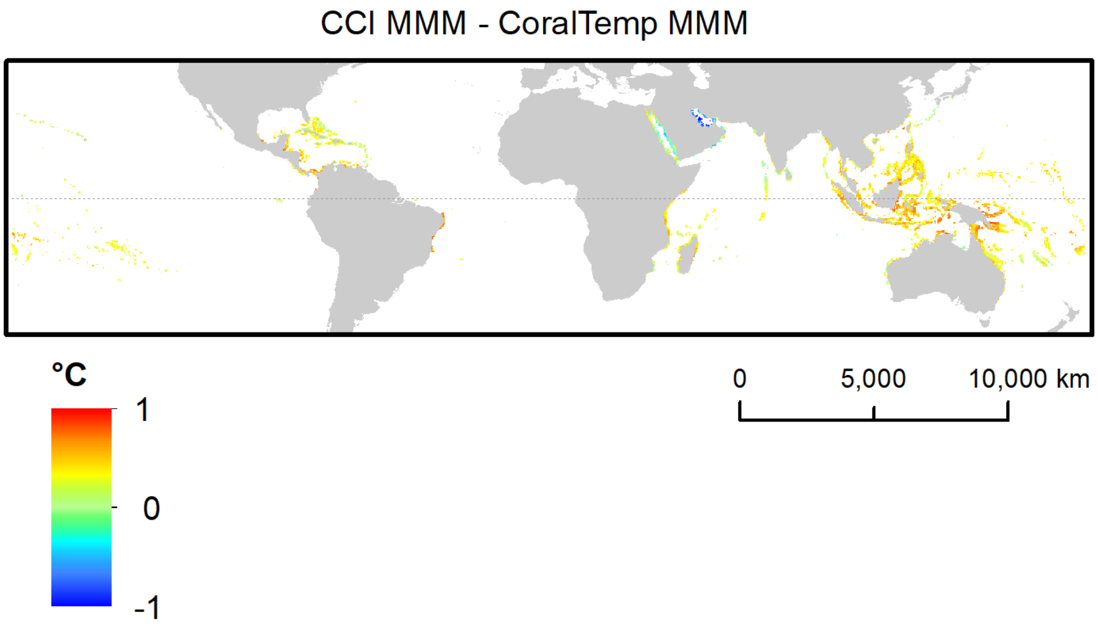
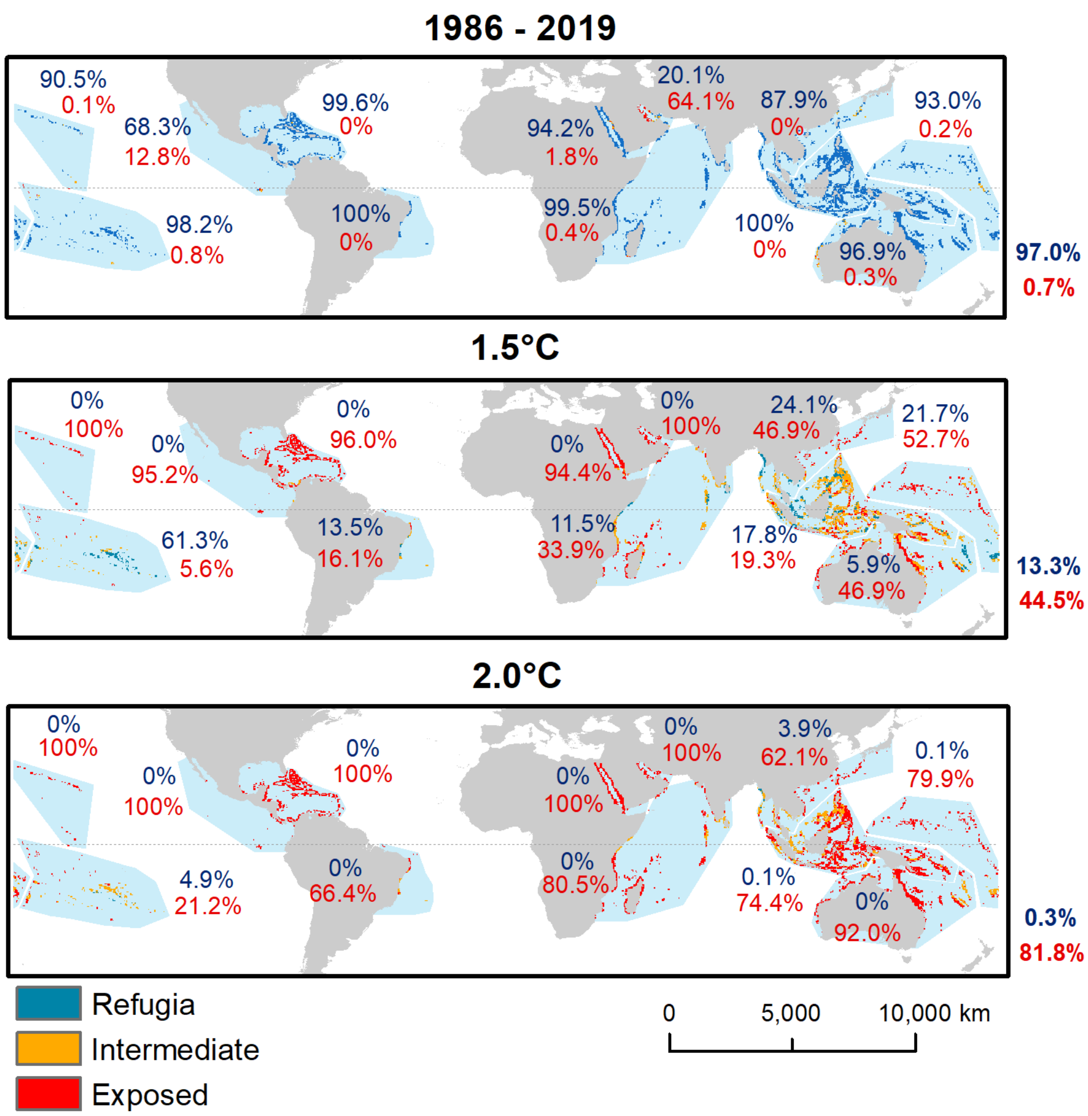
Ziehn, T. *et al.* (2020) ‘The Australian Earth System Model: ACCESS-ESM1.5’, *Journal of Southern Hemisphere Earth Systems Science*, 70, pp. 193–214. doi: 10.1071/ES19035.

3.6 Supplementary Material

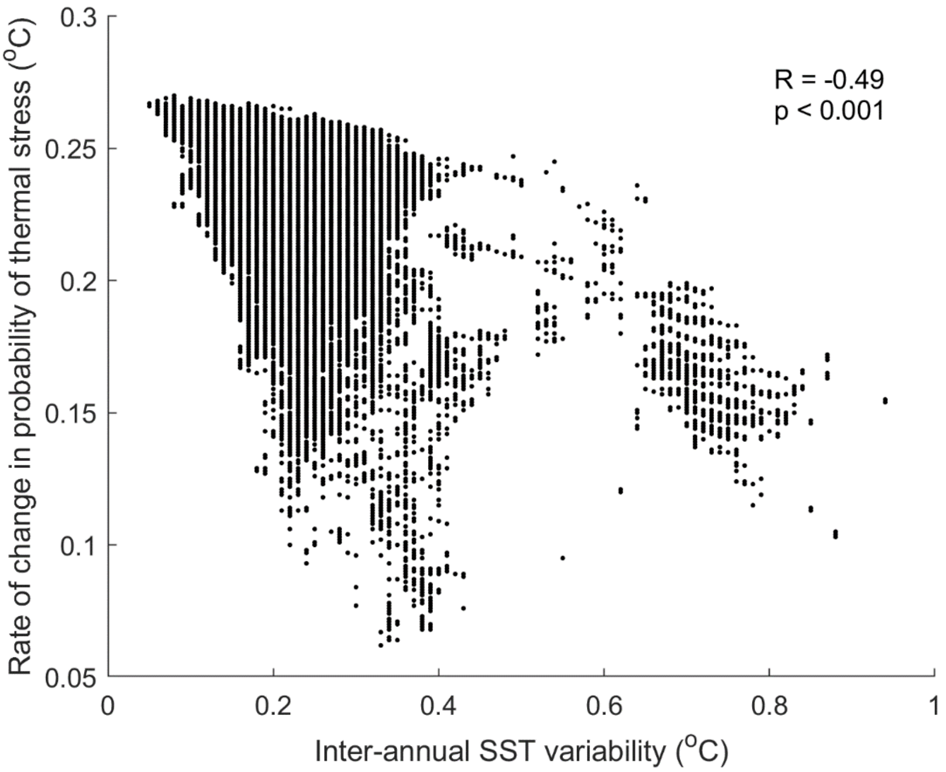
3.6.1 Supplementary Figures



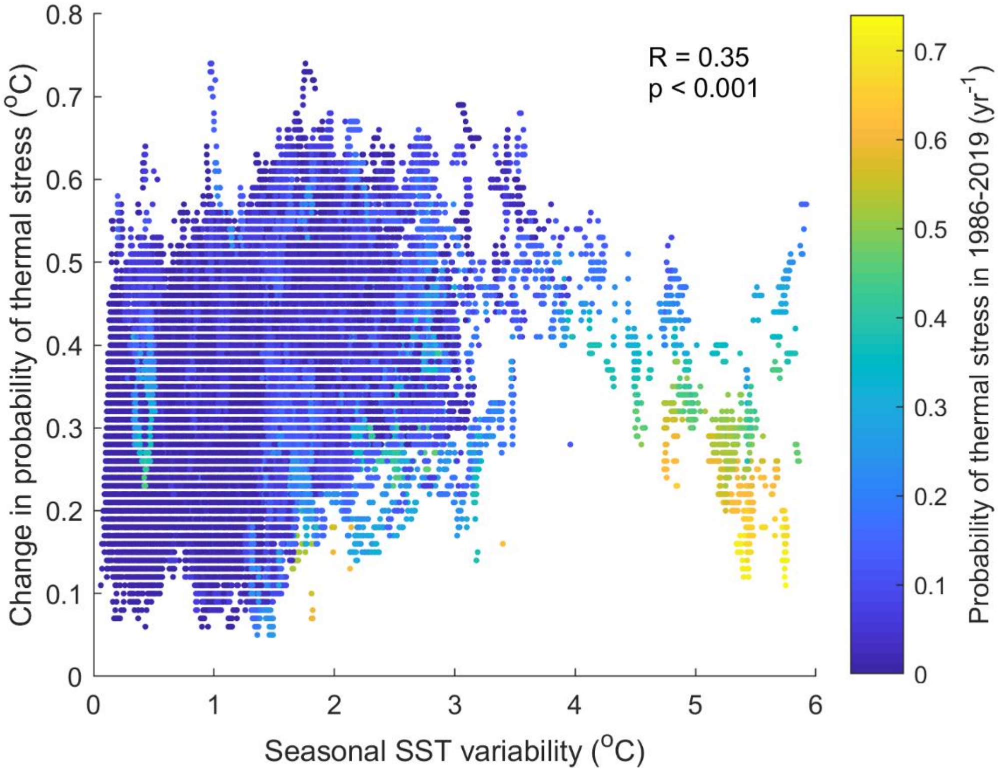
Supplementary Figure 3.1: The difference between the maximum monthly mean (MMM) calculated using the Coral Reef Watch (CRW) CoralTemp product and the MMM calculated using the bias corrected and downscaled Climate Change Initiative (CCI) dataset. The difference is calculated as the CCI MMM minus the CoralTemp MMM, therefore values from 0 to 1°C indicate where the CCI MMM is higher than CoralTemp and values from -1 to 0°C indicate where the CoralTemp MMM is higher than CCI. The 5 km MMM was calculated from the CoralTemp SST and hotspot products and converted to 1 km resolution using bilinear interpolation. The CCI dataset was downscaled and bias corrected to the 1 km Multi-scale Ultra-high Resolution (MUR) dataset and then the MMM calculated. Both MMMs were calculated using the NOAA CRW approach; the monthly mean climatologies were calculated using data from 1985-2012 and re-centered on the period 1985-1990+1993. The hottest monthly mean was then selected as the MMM. The observed Degree Heating Weeks (DHW) calculated using the combined bias corrected CCI and MUR datasets are lower than previously reported for most of the world's coral reefs because the MMM is higher. The base map is made with Natural Earth.



Supplementary Figure 3.2: Global distribution of exposure categories in the 1986-2019 climate and at 1.5 and 2.0°C of future global warming using the 8°C-weeks thermal stress threshold. Exposure categories are thermal refugia (probability of DHW events > 8°C-weeks less than 0.1 yr^{-1}), intermediate (probability of DHW events > 8°C-weeks from 0.1 – 0.2 yr^{-1}) and exposed (probability of DHW events > 8°C-weeks greater than 0.2 yr^{-1}). There are no thermal refugia and all reef pixels are exposed at 3.0 and 4.0°C of global warming. Percentages indicate the regional (on map) and global (right of map) proportion of thermal refugia (blue) and exposed reefs (red). The 12 coral reef regions are outlined in light blue. The base map is made with Natural Earth.

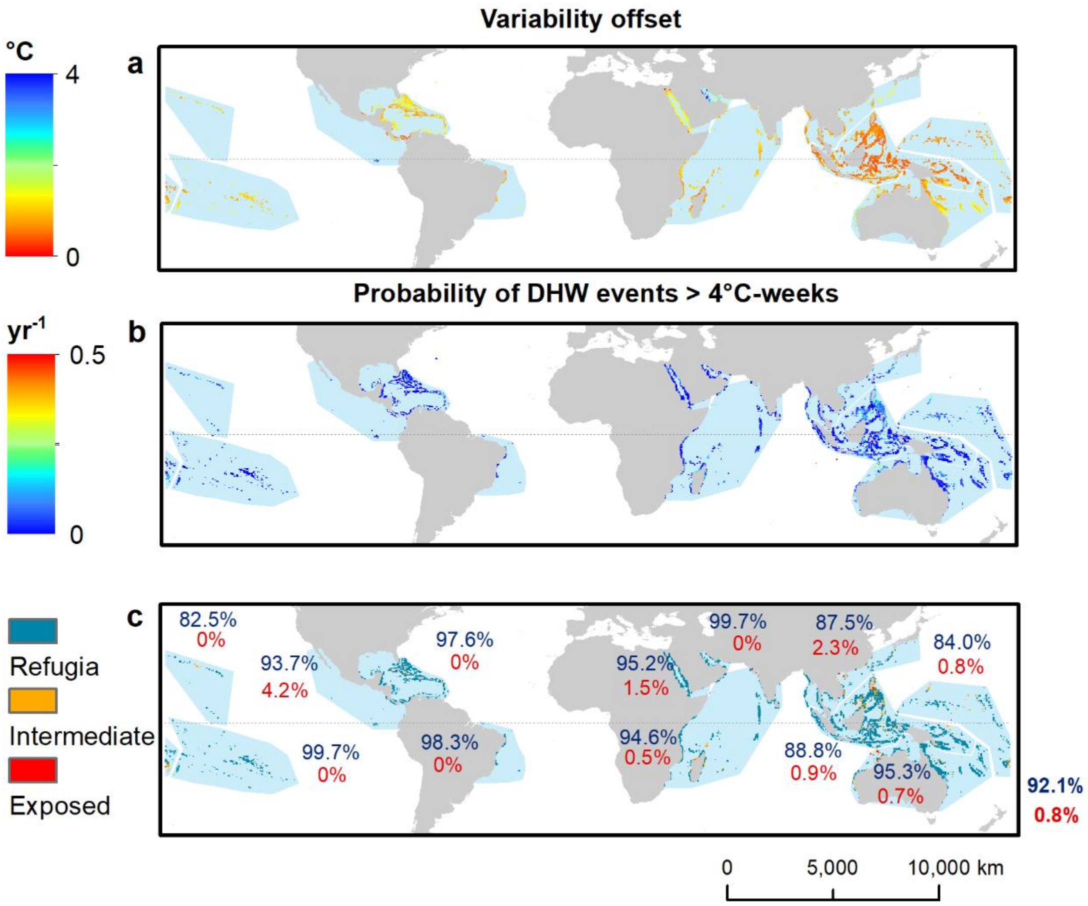


Supplementary Figure 3.3: Correlation between the rate of change in the probability of thermal stress and inter-annual SST variability. The rate of change in the probability of thermal stress is the linear slope in the probability of thermal stress events > 4°C-weeks from the 1986-2019 climate to 1.5, 2.0, 3.0 and 4.0°C. There is a significant negative correlation between the rate of change in the probability of thermal stress and inter-annual SST variability.

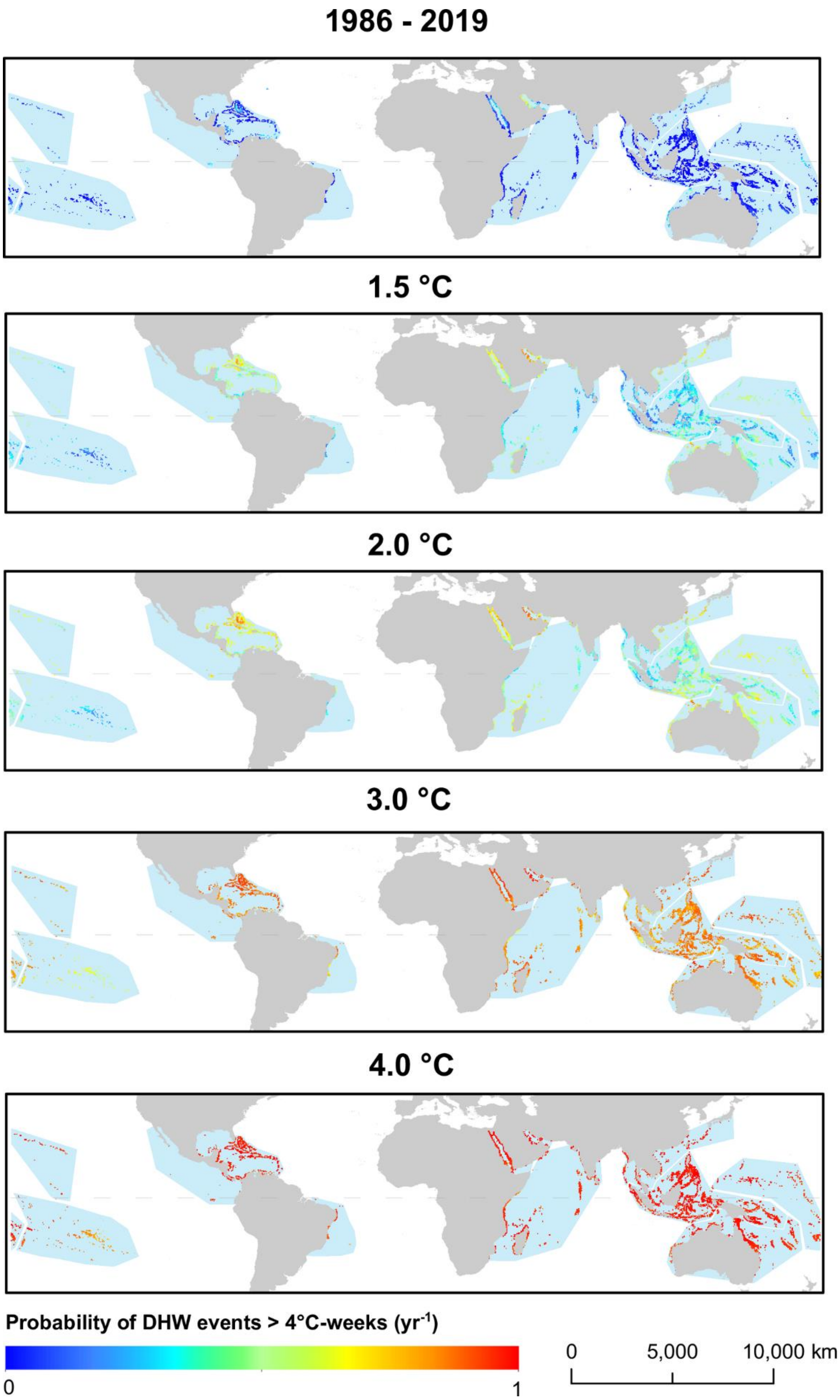


Supplementary Figure 3.4: Correlation between the change in the probability of thermal stress and seasonal SST variability. The change in the probability of thermal stress is the difference between the probability of thermal stress events > 4°C-weeks in the 1986-2019 climate and 1.5°C of global warming relative to pre-industrial levels. The colour indicates the probability of thermal stress events > 4°C-weeks in the 1986-2019 climate. There is a significant positive correlation between the change in the probability of thermal stress and seasonal SST variability. This relationship breaks down where reef pixels have high seasonal SST variability and the probability of thermal stress is already high in the 1986-2019 climate (e.g. in the Persian Gulf).

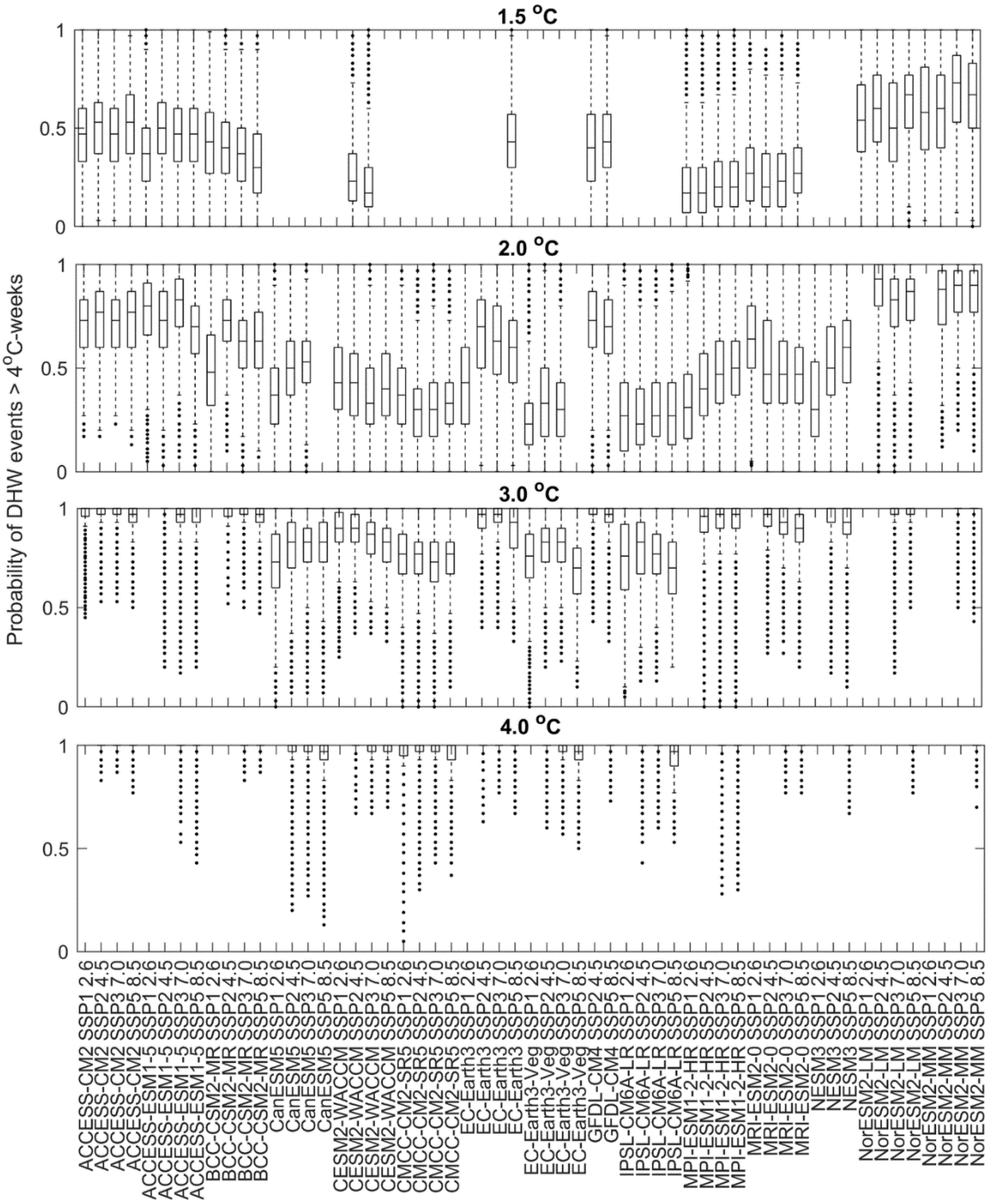
Supplementary Figure 3.5: (Note: The figure can be accessed through the link. The figure is not included in the thesis due to the large file size.) High resolution image (3,000 dpi) of the global distribution of exposure category and SST variability level in the 1986-2019 climate and at 1.5, 2.0 and 3.0°C of future global warming relative to pre-industrial levels. Exposure categories are thermal refugia (probability of DHW events > 4°C-weeks less than 0.1 yr^{-1}), intermediate (probability of DHW events > 4°C-weeks from 0.1 – 0.2 yr^{-1}) and exposed (probability of DHW events > 4°C-weeks greater than 0.2 yr^{-1}). Exposure categories are split by the level of SST variability (high = seasonal OR inter-annual variability > 0.7°C, low = seasonal AND inter-annual variability < 0.3°C, moderate = all others). The 12 coral reef regions are outlined in blue. The base map is made with Natural Earth.



Supplementary Figure 3.6: Thermal exposure calculated using the variability offset. a) Global distribution of the variability offset in 12 coral reef regions during the period 1986-2019. The variability offset is the normalised standard deviation in the annual maximum monthly SST. b) Global distribution of the probability of DHW events > 4°C-weeks. c) Global distribution of the 1986-2019 exposure category: thermal refugia (probability of DHW events > 4°C-weeks less than 0.1 yr^{-1}), intermediate (probability of DHW events > 4°C-weeks from 0.1 – 0.2 yr^{-1}) and exposed (probability of DHW events > 4°C-weeks greater than 0.2 yr^{-1}). Percentages indicate the regional proportion of thermal refugia (blue) and exposed reefs (red). The base map is made with Natural Earth.



Supplementary Figure 3.7: Probability of DHW events > 4°C-weeks in 12 coral reef regions in 1986-2019 and at 1.5, 2.0, 3.0 and 4.0°C of global warming relative to pre-industrial levels. The base map is made with Natural Earth.



Supplementary Figure 3.8: Probability of DHW events > 4°C-weeks for global coral reef pixels simulated by 15 CMIP6 models and four Shared Socioeconomic Pathways (SSPs) under 1.5, 2.0, 3.0 and 4.0°C of global warming relative to pre-industrial levels. Outliers (>1.5 * interquartile range) are shown by the black dots.

3.6.2 Supplementary Tables

Supplementary Table 3.1: Percentage of global coral reef pixels with a robust (positive: > 0.01°C or negative: < -0.01°C) SST variability trend from observed (1985-2019) to future global warming scenario. A trend is considered robust if simulated by 75% of models. Of those reef pixels with a robust change in inter-annual SST variability, none are those pixels most heavily influenced by El Niño Southern Oscillation in the observed climate (tropical Pacific).

Scenario	Global coral reef pixels with a robust change in SST variability (%)	
	Seasonal	Inter-annual
1.5 °C	33.81	30.03
2.0 °C	31.97	30.51
3.0 °C	37.56	28.60
4.0 °C	54.31	38.53

3.6.3 Supplementary Methods 3.1: Combining 5 km and 1 km observational sea surface temperature datasets

The Multi-scale Ultra-high Resolution (MUR) Sea Surface Temperature (SST) Analysis (Table i) is a daily 1 km observational dataset with global coverage from June 2002-present (JPL MUR MEaSUREs Project, 2015). In satellite-derived observational datasets, the resolution of the grid is typically finer than the resolution of the actual data. The MUR dataset addresses this by reconstructing small to large spatial scale SST features using different sized time windows of night-time SST data (Chin *et al.*, 2017). The approach assumes that small-scale SST features evolve over a period of a few hours while large scale features evolve over days. All night-time SST data of high enough quality are used to reconstruct these features. This process results in an actual data resolution of ~10 km as opposed to other 5 – 25 km datasets, including the Operational SST and Sea Ice Analysis (OSTIA) dataset, where the actual data resolution can be as much as 100 km (Chin *et al.*, 2017). Though the data have a daily temporal resolution, and SST can vary over a day impacting coral bleaching dynamics, MUR has the highest resolution grid and data resolution available. Datasets with a higher temporal resolution are not yet available for global coral reefs.

Table i: Observational SST datasets.

Dataset	**Year**	**Spatial Resolution**	**Adjustment**	**Source**	**Downloaded from**
MUR SST Analysis daily version 4.1	Feb 2006 - Dec 2019	1 km	Bias adjusted to CCI	Group for High Resolution Sea Surface Temperature at NASA Jet Propulsion Laboratory (JPL MUR MEaSUREs Project, 2015)	https://podaac.jpl.nasa.gov
CCI daily SST version 2.1	Jan 1985 - Feb 2006	5 km	Downscaled to 1 km	ESA SST CCI (Merchant *et al.*, 2016, 2019)	https://anon-ftp.ceda.ac.uk
CoralTemp daily SST version 3.1	Jan 1985 – Feb 2006	5 km	Downscaled to 1 km Bias adjusted to CCI	NOAA Coral Reef Watch (NOAA Coral Reef Watch, 2018)	https://ftp.star.nesdis.noaa.gov

MUR combines various types of input data: High (1 km) and medium (4 – 10 km) resolution infra-red satellite retrievals, microwave satellite retrievals (25 km) and in-situ measurements (Chin *et al.*, 2017). Input datasets are accompanied by single sensor error statistics (SSES) used, alongside in-situ measurements, to estimate bulk SST from the skin measurements obtained by the satellite retrievals. Inter-sensor bias correction is performed for every input dataset. MUR uses the Advanced Very High Resolution Radiometer (AVHRR) Pathfinder 4 km dataset in the early years (1 June 2002 – 9 February 2006). The Pathfinder dataset has no SSES values. Instead, a constant bulk-SST bias of 0°C is assumed, as the dataset is tuned to bulk SST. This, alongside known biases in the Pathfinder dataset, results in large root mean square (residuals) when the data are compared to independent data sources. The dataset is due to be replaced in later versions of MUR. Due to the large biases and lack of consistency between the Pathfinder dataset and other MUR inputs, we used the MUR dataset from February 2006 to December 2019, therefore excluding the Pathfinder-derived data.

The MUR dataset, excluding the Pathfinder years, is only available from 2006-2019. To extend the observational SST dataset for calculating long-term maximum monthly mean (MMM) SST used in coral reef thermal stress metrics and for providing a 30+ year climatology for statistical downscaling of projected SST, we combined MUR with another observational dataset. Observed SST datasets are not available at 1 km resolution prior to 2002, so we combined MUR with the European Space Agency (ESA) Climate Change Initiative (CCI) SST Analysis daily 5 km (Table i) dataset (Merchant *et al.*, 2016, 2019). The CCI dataset has better feature resolution than other long-term SST products and agrees with near-coral loggers at 3-6 m depth in two coral reef locations: Florida and Belize (Beggs, 2020) and with mooring measurements in Australian seas (Merchant *et al.*, 2019). In areas where CCI SST data are missing, and so are given the climatology values, we replaced the CCI dataset with the CoralTemp 5 km daily SST (Table i) dataset (NOAA Coral Reef Watch, 2018). The OSTIA dataset is the input for the 1985-2002 period of CoralTemp, which is bias corrected against in-situ data measured by ships and buoys. Beyond 2002, CoralTemp uses the Geo-Polar Blended SST (Maturi *et al.*, 2017), which is at present bias-corrected using the OSTIA product.

We extracted the SST for the exact 1 km reef pixel from the MUR SST Analysis dataset. If a reef pixel is missing SST data (Figure ia), e.g. the pixel is considered land, the next pixel longitudinally (Figure ib) was used. If longitudinal pixels either side of the reef pixel are missing data, one of the next latitudinal pixels (Figure ic), then one of those to the north-east, south-east, north-west or south-west (Figure id), was used. If SST data is still missing, the reef pixel was discarded (Figure ie), which occurred for 219 reef pixels (0.09%).

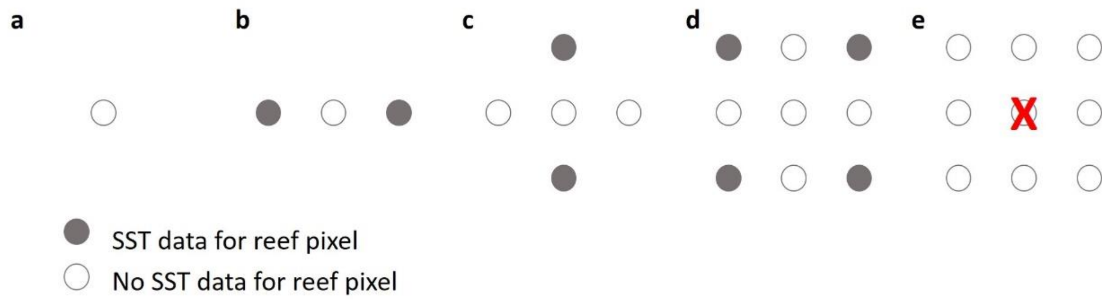


Figure i: Procedure for reef pixels missing data in the MUR SST Analysis dataset. Data from adjacent reef pixels were used up to one pixel away from the original pixel in all directions. If data are missing from all adjacent pixels, the reef pixel was excluded.

We downscaled CCI from 5 km to the 1 km MUR dataset using the change factor downscaling technique (Tabor and Williams, 2010; Kumagai and Yamano, 2018). The 5 km monthly CCI climatology 2006-2016 was subtracted from the daily 5 km CCI SST 1985-2016 to produce a CCI anomaly. The 5 km daily CCI anomaly data were then converted to 1 km resolution by bilinear interpolation (van Hooidonk *et al.*, 2015). The 1 km CCI anomaly was produced for the global coral reef area. The 1 km CCI anomalies were then added to the 1 km monthly mean MUR climatology 2006-2016. We then bias corrected MUR to the 1 km CCI data using linear regression of monthly SST during the overlapping period (2006-2016). We blended the CCI and MUR datasets together for February 2006. In the 28 days of February 2006, the CCI dataset was transitioned to

MUR using the linear approach used by NOAA Coral Reef Watch for combining datasets (NOAA Coral Reef Watch, 2020).

We detrended the combined CCI and MUR 1 km time series for the global coral reef pixels by removing the ordinary least squares trend (1985-2019). We compared the detrended mean SST and standard deviation, seasonal and inter-annual variability, and variability in winter minimum and summer maximum SST between CCI (Jan 1985 – Jan 2006) and MUR (Mar 2006 – Dec 2019) for the global 1 km coral reef pixels (Figure ii). February 2006 was excluded as it is a blend of the two datasets. The seasonal and inter-annual variability is the square root of the sum of the power spectral density in the 0.5-1 year and 3-8 year frequency bands for seasonal and inter-annual variability, respectively (Langlais *et al.*, 2017). The winter minimum and summer maximum SST variability is the standard deviation in the annual minimum and maximum monthly SST.

The change factor approach is suitable for combining the 5 km CCI and 1 km MUR datasets for the majority of the global coral reef pixels. There are examples where the 5 km CCI dataset uses a climatology to represent SST in areas missing sufficient data which is then carried through following downscaling and bias adjustment (Figure iiia and Figure iiic). These pixels were identified as those with a winter minimum and summer maximum CCI SST variability < 0.10°C indicating a regular climatology and a difference between CCI and MUR in winter minimum and summer maximum SST variability > 0.10°C indicating a difference in SST cycles between the datasets. Where CCI SST data for reef pixels use a climatology and MUR data do not, we replaced the SST data for these pixels with downscaled 1 km CoralTemp data (Figure iiib and Figure iiid). The CoralTemp data were downscaled in the same way as the 5 km CCI data. The 1 km downscaled CoralTemp data were bias adjusted to the 1 km downscaled CCI data using linear regression of monthly mean SST for the overlapping period (1985-2016). In total, 429 reef pixels were replaced with CoralTemp data.

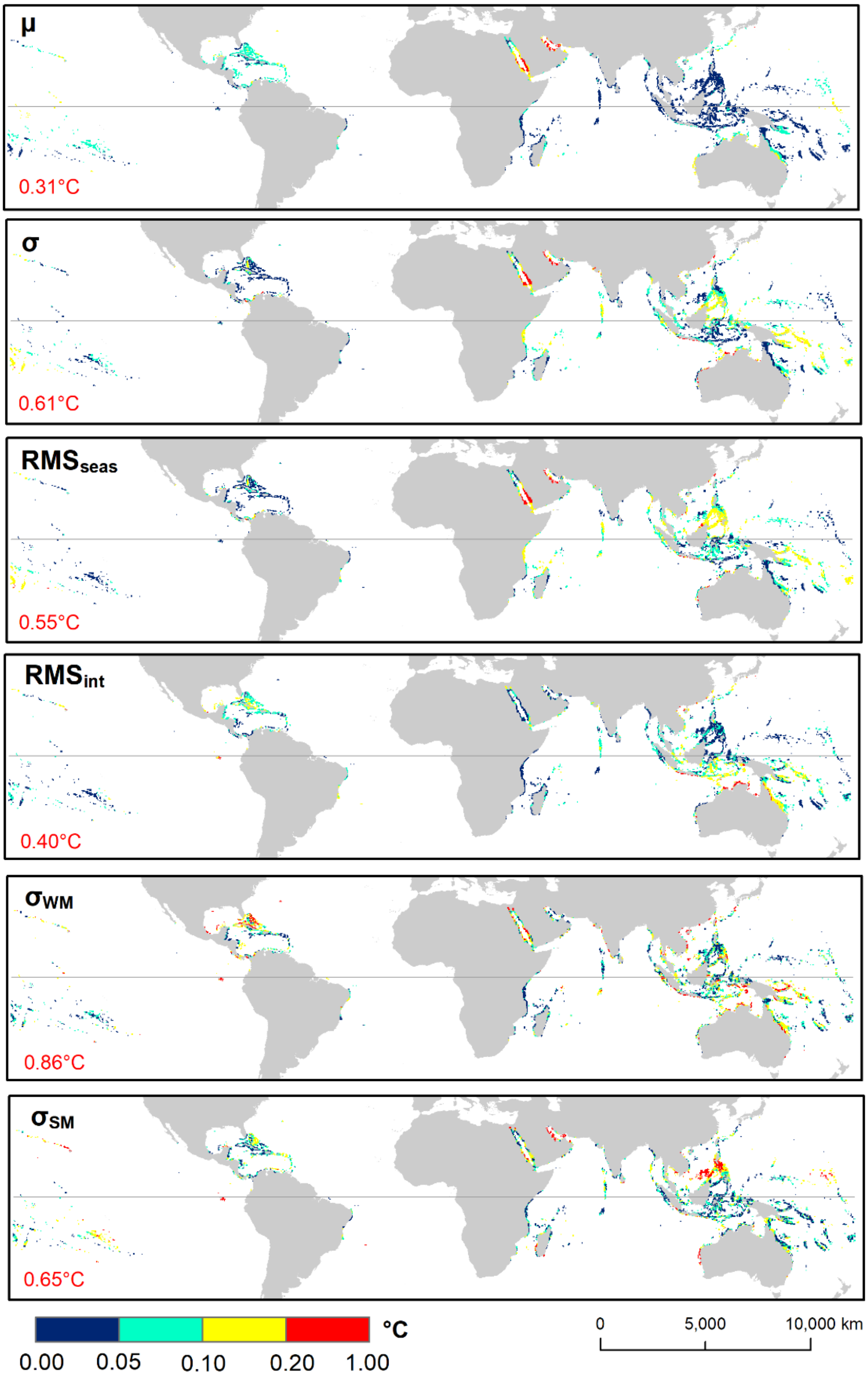


Figure ii: Difference between detrended downscaled 1 km CCI (1985-Jan 2006) and bias adjusted 1 km MUR (Mar 2006-2019) in mean (μ), standard deviation (σ), seasonal (RMS_{seas}) and inter-annual (RMS_{int}) variability, and winter minimum (σ_{WM}) and summer maximum (σ_{SM}) variability. Maximum values are in red in the bottom left of each panel. The base map is made with Natural Earth.

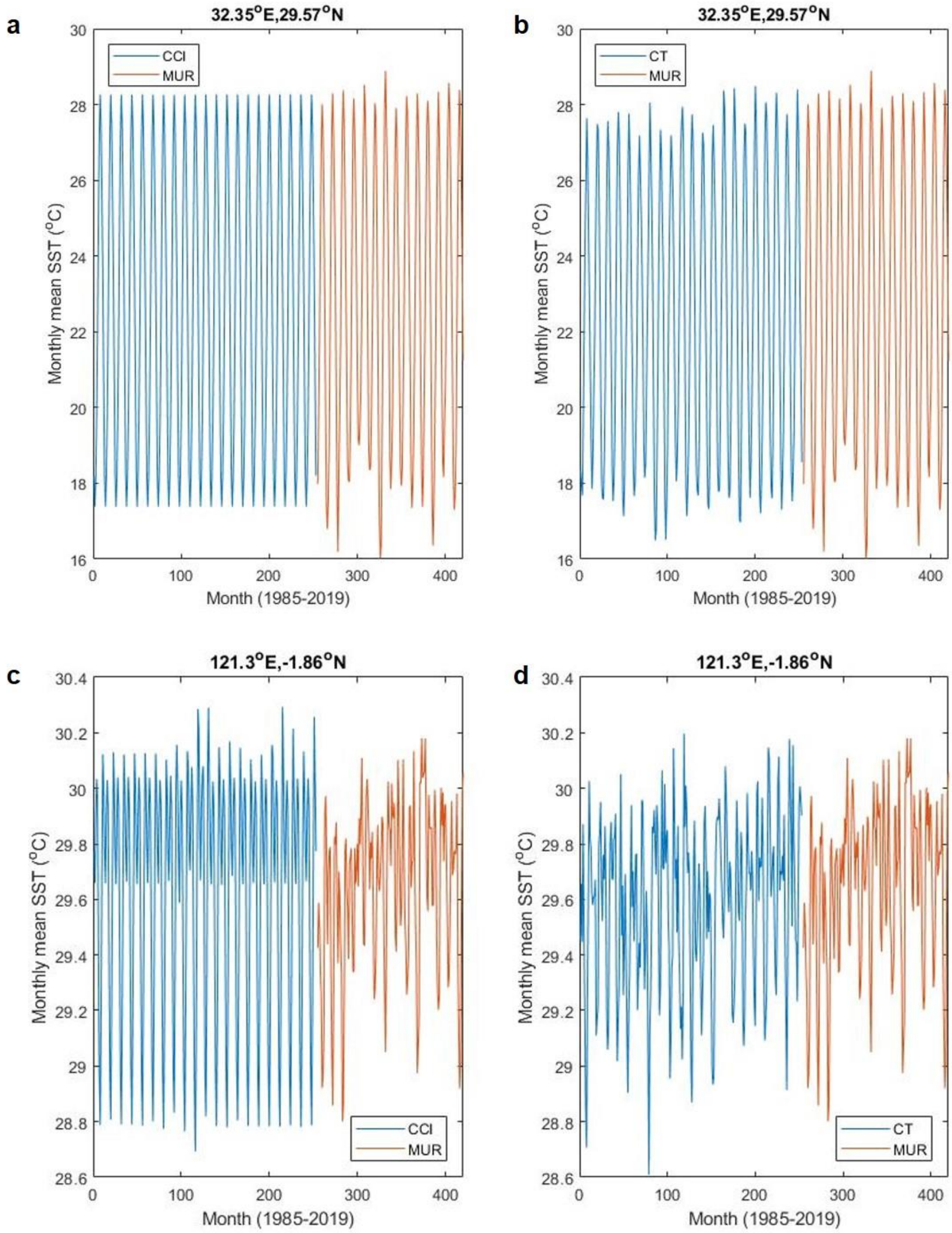


Figure iii: Monthly mean SST for the combined CCI (a and c) and MUR datasets and combined CoralTemp (b and d) and MUR datasets. Examples are for a Northern Red Sea pixel (a and b) and a Sulawesi, Indonesia pixel (c and d).

3.6.4 Supplementary Methods 3.2: Simulated SST data used in statistical downscaling

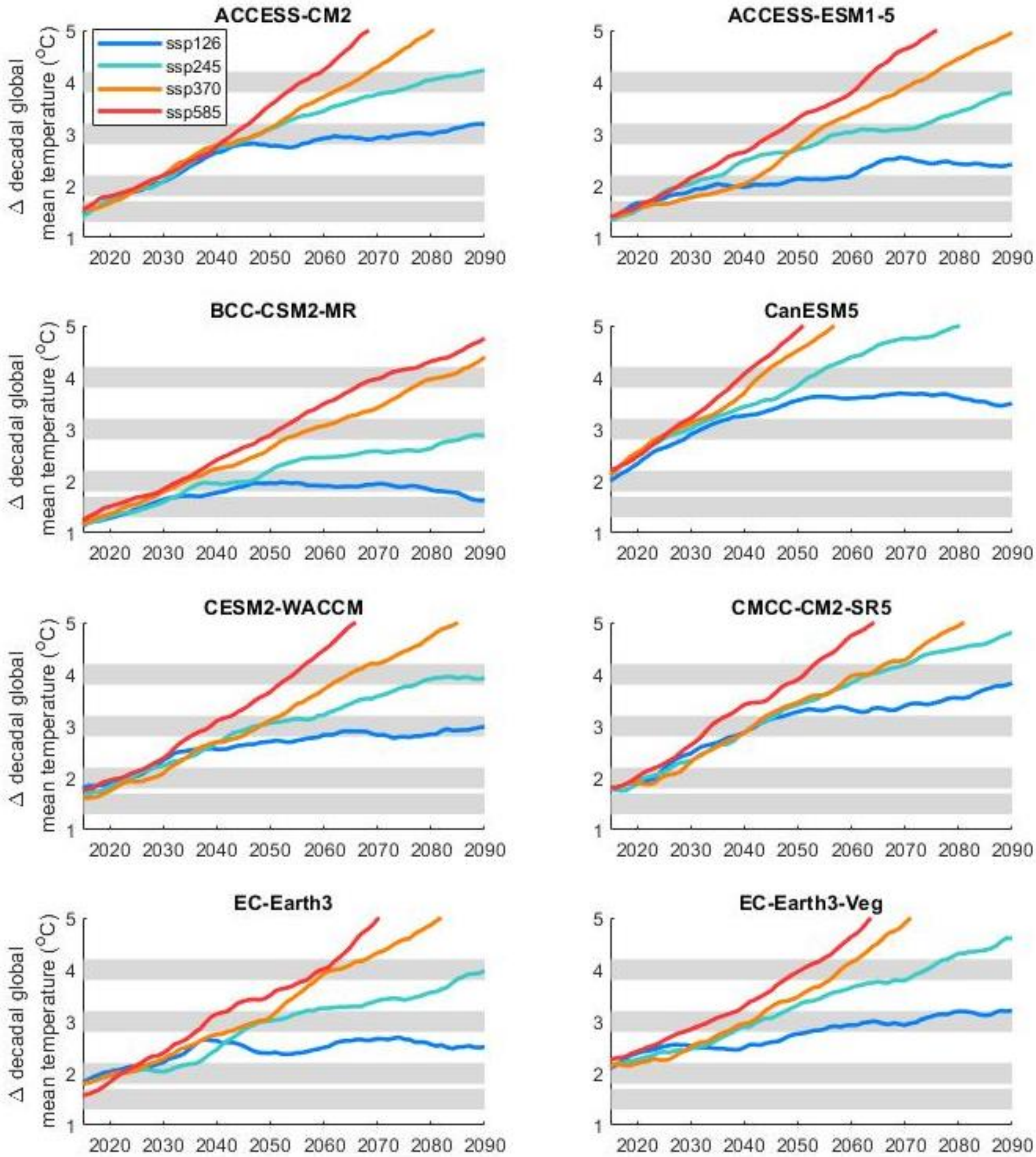
We extracted ‘tos’ output for four emissions scenarios (SSP1 2.6, SSP2 4.5, SSP3 7.0 and SSP5 8.5) and 15 CMIP6 (Eyring *et al.*, 2016) general circulation models (GCMs) with an ocean grid resolution < 100 km (Table i). The climate model output was interpolated longitudinally to fill missing data points (van Hooidonk *et al.*, 2015). The climate model grid was then converted to 1 km resolution using bilinear interpolation and the SST for the global coral reef pixels extracted. All model years (Table ii and Figure i) with a decadal global mean surface temperature change within 0.2°C of four global warming scenarios (1.5, 2.0, 3.0 and 4.0°C), determined using ‘tas’ output, were included in the calculation of the ensemble mean probability of DHW events > 4°C-weeks (King *et al.*, 2017). A minimum of 30 years was used to calculate the probability. If there were fewer than 30 years within the global warming range, the 30-year period was centred on these years with additional years included before and after.

Table i: CMIP6 climate model output. ‘tos’ and ‘tas’ outputs were downloaded for each model and experiment.

Model and reference	**Institution ID**	**Simulations**
ACCESS-CM2 (Bi *et al.*, 2020)	CSIRO	Historical, SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5
ACCESS-ESM1-5 (Ziehn *et al.*, 2020)	CSIRO	Historical, SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5
BCC-CSM2-MR (Wu *et al.*, 2019)	BCC	Historical, SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5
CanESM5 (Swart *et al.*, 2019)	CCCma	Historical, SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5
CESM2-WACCM (Danabasoglu *et al.*, 2020)	NCAR	Historical, SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5
CMCC-CM2-SR5 (Cherchi *et al.*, 2019)	CMCC	Historical, SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5
EC-Earth3 (Döscher *et al.*, 2021)	EC-Earth-Consortium	Historical, SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5
EC-Earth3-Veg (Wyser *et al.*, 2020)	EC-Earth-Consortium	Historical, SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5
GFDL-CM4 (Held *et al.*, 2019)	NOAA-GFDL	Historical, SSP2-4.5, SSP5-8.5
IPSL-CM6A-LR (Boucher *et al.*, 2020)	IPSL	Historical, SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5
MPI-ESM1-2-HR (Müller *et al.*, 2018)	MPI-M	Historical, SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5
MRI-ESM2-0 (Yukimoto *et al.*, 2019)	MRI	Historical, SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5
NESM3 (Cao *et al.*, 2018)	NUIST	Historical, SSP1-2.6, SSP2-4.5, SSP5-8.5
NorESM2-LM (Seland *et al.*, 2020)	NCC	Historical, SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5
NorESM2-MM (Seland *et al.*, 2020)	NCC	Historical, SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5

Table ii: The number of model years in four emissions experiments for 15 CMIP6 climate models included in the calculation of the ensemble mean probability of DHW events > 4°C-weeks for each of four global warming scenarios. A dash indicates no model years within +/- 0.2°C of the global warming level.

Model	**Emissions scenario**	**Number of model years**			
		1.5 °C	**2.0 °C**	**3.0 °C**	**4.0 °C**
ACCESS-CM2	SSP1 2.6	14	19	55	-
	SSP2 4.5	14	19	18	26
	SSP3 7.0	15	15	20	16
	SSP5 8.5	12	19	15	15
ACCESS-ESM1-5	SSP1 2.6	17	44	-	-
	SSP2 4.5	17	21	30	-
	SSP3 7.0	22	20	14	16
	SSP5 8.5	17	15	15	13
BCC-CSM2-MR	SSP1 2.6	34	50	-	-
	SSP2 4.5	22	24	14	-
	SSP3 7.0	20	17	20	19
	SSP5 8.5	20	16	16	21
CanESM5	SSP1 2.6	-	13	18	-
	SSP2 4.5	-	11	18	15
	SSP3 7.0	-	10	17	13
	SSP5 8.5	-	-	14	13
CESM2-WACCM	SSP1 2.6	-	23	40	-
	SSP2 4.5	11	18	25	22
	SSP3 7.0	14	20	16	16
	SSP5 8.5	-	19	16	14
CMCC-CM2-SR5	SSP1 2.6	-	16	19	10
	SSP2 4.5	-	17	16	20
	SSP3 7.0	-	23	15	17
	SSP5 8.5	-	18	13	15
EC-Earth3	SSP1 2.6	-	24	-	-
	SSP2 4.5	-	30	21	15
	SSP3 7.0	-	22	19	18
	SSP5 8.5	13	15	15	15
EC-Earth3-Veg	SSP1 2.6	-	11	46	-
	SSP2 4.5	-	12	18	19
	SSP3 7.0	-	15	16	15
	SSP5 8.5	-	-	40	16
GFDL-CM4	SSP2 4.5	17	21	24	-
	SSP5 8.5	17	18	15	16
IPSL-CM6A-LR	SSP1 2.6	-	22	59	-
	SSP2 4.5	-	17	18	18
	SSP3 7.0	-	19	16	16
	SSP5 8.5	-	20	13	16
MPI-ESM1-2-HR	SSP1 2.6	26	64	-	-
	SSP2 4.5	20	23	17	-
	SSP3 7.0	20	22	17	16
	SSP5 8.5	21	22	18	16
MRI-ESM2-0	SSP1 2.6	13	44	-	-
	SSP2 4.5	14	18	33	-
	SSP3 7.0	16	19	23	19
	SSP5 8.5	10	18	22	15
NESM3	SSP1 2.6	-	21	-	-
	SSP2 4.5	-	24	24	-
	SSP5 8.5	-	19	16	15
NorESM2-LM	SSP1 2.6	68	-	-	-
	SSP2 4.5	28	28	-	-
	SSP3 7.0	29	22	14	-
	SSP5 8.5	23	19	15	14
NorESM2-MM	SSP1 2.6	67	-	-	-
	SSP2 4.5	18	34	-	-
	SSP3 7.0	18	20	16	-
	SSP5 8.5	18	22	16	15
Ensemble size		**705**	**1152**	**995**	**555**


ACCESS-CM2
ACCESS-ESM1-5
BCC-CSM2-MR
CanESM5
CESM2-WACCM
CMCC-CM2-SR5
EC-Earth3
EC-Earth3-Veg
ssp126
ssp245
ssp370
ssp585
Δ decadal global mean temperature (°C)
2020 2030 2040 2050 2060 2070 2080 2090

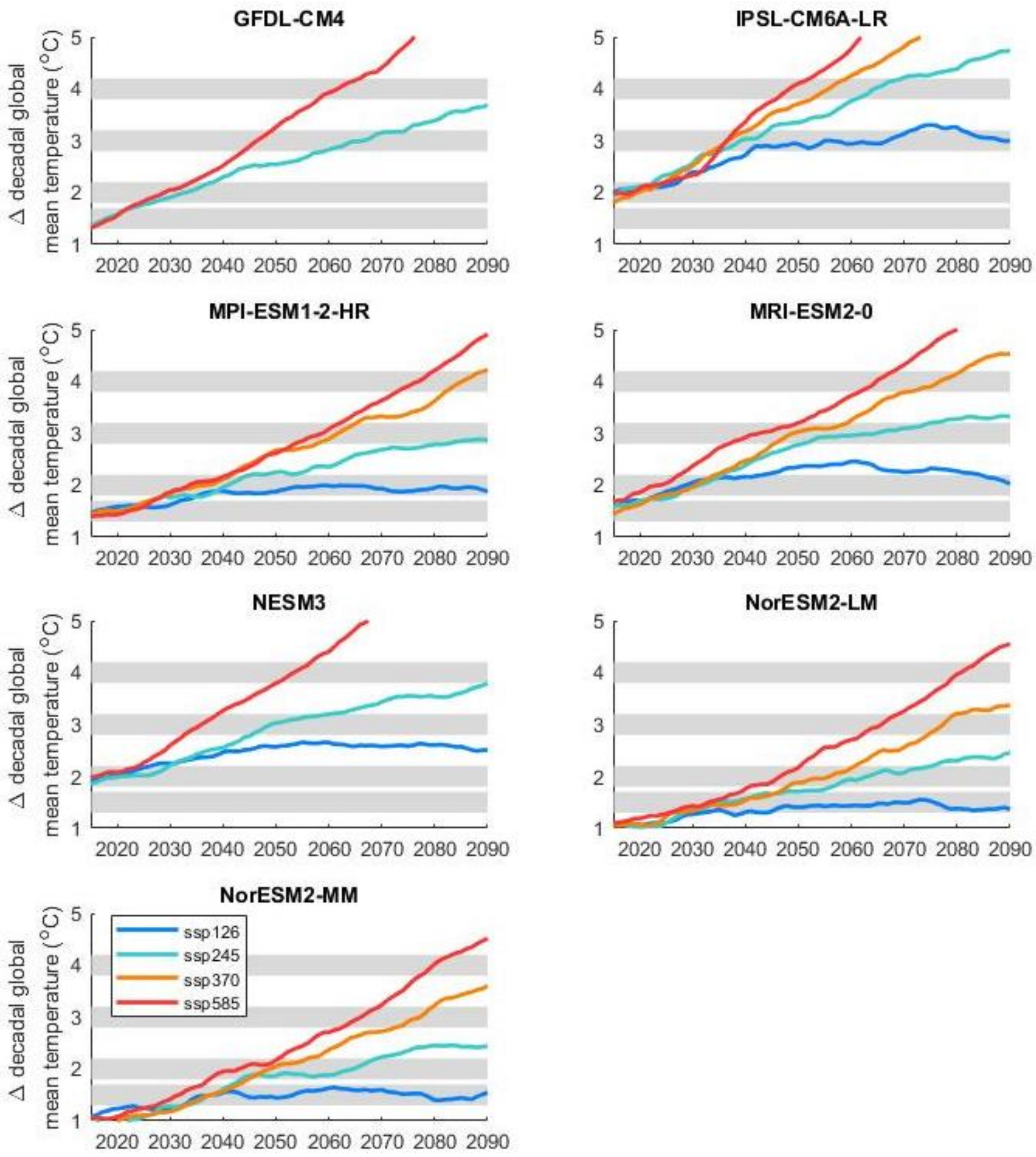


Figure i: Change in decadal global mean surface temperature from a pre-industrial period (1861-1900) under four emissions pathways (2015-2090) projected by 15 CMIP6 models. Shaded areas indicate the four global warming scenarios (+/- 0.2°C).

3.6.5 Supplementary Methods 3.3: Statistical downscaling of SST

The observational SST is not well correlated with the general circulation model (GCM) SST as the chaotic evolution of the model runs result in no correspondence in time between reality and the GCM (Stoner *et al.*, 2013). The observational and simulated data were therefore ranked in ascending order according to the asynchronous piecewise linear regression technique used by Stoner *et al.* (2013). The approach analyses the linear relationship between the spread of simulated and observed data whereby the highest observed SST corresponds to the highest simulated SST. A simple linear regression was calculated for the ranked and detrended datasets resulting in a stronger linear correlation. The simple linear regression is suitable for this study due to the relatively low day-to-day variability in tropical SST. A piecewise regression may be more advantageous when applying the method to regions with higher SST variability e.g. temperate regions (Stoner *et al.*, 2013). The linear model for each seasonal period was then applied to the GCM daily ensemble mean projections.

We trained the statistical models on the even years (training period) in the historical period (1985-2019) and evaluated the downscaled output using the odd years (testing period). SST data were detrended prior to downscaling and the trend added back in after. The statistical downscaling was run six times removing different combinations of 1st, 2nd, and 3rd order polynomial trends from the observational and simulated SST training periods (Figure i). The root mean square error (RMSE) was compared between ranked GCM and downscaled SST testing periods relative to the ranked observed testing period. The combination of trends in the run with the lowest downscaled RMSE was selected.

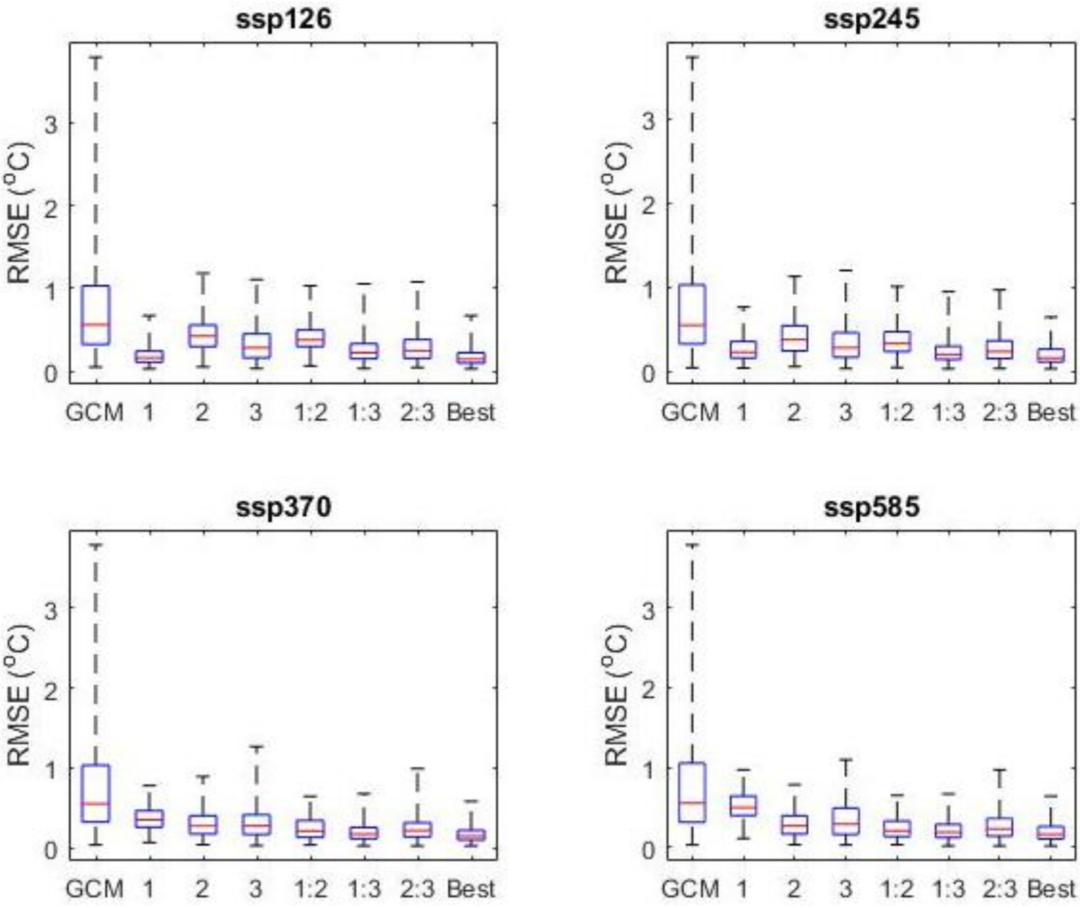


Figure i: Ranked GCM and downscaled root mean square error (RMSE) relative to ranked observations for the model testing period (odd years) for the CMIP6 GCM ACCESS-CM2. Downscaled models were trained on even years. The downscaling was run six times removing (prior to downscaling) and adding back in (after downscaling): (1) 1st order polynomial trends for both the observations and GCM; (2) 2nd order polynomial trends for both the observations and GCM; (3) 3rd order polynomial trends for both the observations and GCM; (1:2) 1st order polynomial trend for the observations and 2nd order polynomial trend for the GCM; (1:3) 1st order polynomial trend for the observations and 3rd order polynomial trend for the GCM; and (2:3) 2nd order polynomial trend for the observations and 3rd order polynomial trend for the GCM. The lowest RMSE of the six runs was selected as the "Best" option.

Statistical downscaling reduces the RMSE relative to observations for the testing period for 85.86-99.86% of reef pixels depending on model and SSP (Figure ii). There are reef pixels (Table i) where the downscaled RMSE is larger than for the original GCM for the testing period. This can occur for two reasons: 1. Removing the long-term trend prior to downscaling and adding it in afterwards causes the downscaled SST to be tilted higher than the observations (e.g. where the mean detrended GCM SST is lower than the observations, the mean downscaled SST is shifted up to the mean observed SST. When the steeper long term GCM trend is added to the downscaled SST, it is tilted higher than the observed SST). Detrending prior to downscaling is necessary to maintain the GCM long-term trend in the downscaled projections. 2. There is a difference in observed SST between even and odd years (e.g. the mean observed SST in the even years is lower than the GCM SST in the even years while the mean observed SST in the odd years is higher than the GCM in odd years). To account for this, the statistical downscaling applied to the projected period (2020-2100) used the entire historical period (even and odd years) to train the models. The previously selected combination of trends removed prior to downscaling were added back in after. The higher downscaled RMSE occurs when the GCM SST is already similar to the observations. The maximum increase in downscaled RMSE compared to the GCM RMSE is 0.34 +/- 0.11°C.

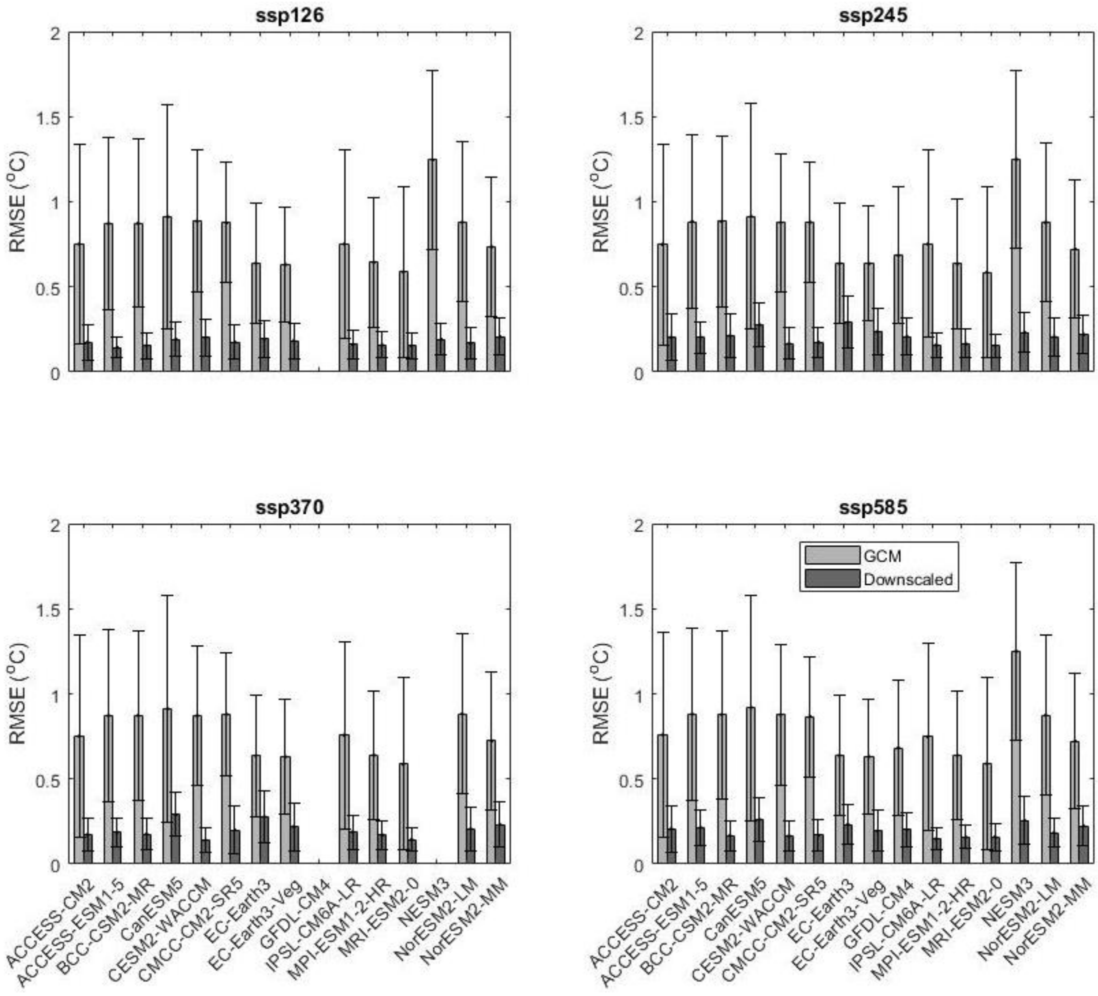


Figure ii: Ranked GCM and lowest downscaled root mean square error (RMSE) relative to ranked observations for the model testing period (odd years) for the 15 CMIP6 models. Downscaled models are trained on even years.

Table i: The percentage of global coral reef pixels (N = 232,828) with a higher downscaled RMSE than GCM RMSE relative to observations for the test period (odd years 1985-2019).

Model	**% reef pixels with a higher RMSE after downscaling**			
	SSP1 2.6	**SSP2 4.5**	**SSP3 7.0**	**SSP 5.8.5**
ACCESS-CM2	9.06	12.90	9.61	13.78
ACCESS-ESM1-5	0.85	1.36	0.69	2.65
BCC-CSM2-MR	0.72	1.71	1.05	0.86
CanESM5	2.26	7.02	8.12	5.54
CESM2-WACCM	2.14	1.77	1.55	1.94
CMCC-CM2-SR5	0.49	0.52	0.95	0.51
EC-Earth3	5.38	14.14	12.65	9.17
EC-Earth3-Veg	5.05	8.67	8.72	6.44
GFDL-CM4	-	10.32	-	8.99
IPSL-CM6A-LR	2.06	2.40	3.55	1.88
MPI-ESM1-2-HR	1.07	2.48	2.20	1.33
MRI-ESM2-0	8.15	7.14	6.92	9.15
NESM3	0.14	1.45	-	1.40
NorESM2-LM	2.68	4.43	4.55	2.67
NorESM2-MM	3.06	4.10	4.69	3.25

3.6.6 Supplementary Datasets

Supplementary Dataset 3.1: Probability of thermal stress > 4°C-weeks in the 1986-2019 climate and at 1.5, 2.0, 3.0 and 4.0°C of global warming.

Supplementary Dataset 3.2: Seasonal and inter-annual SST variability in the 1986-2019 climate.

Chapter 4 - Coral reef exposure to damaging tropical cyclone waves in a warming climate

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4.0 Key Points

- Wave damage to coral communities from tropical cyclones depends on their intensity, size and duration while tracking near coral reefs.
- Downscaled tracks capture observed cyclone characteristics impacting the Great Barrier Reef with mixed to poor performance in other regions.
- Projections vary by region and cyclone characteristic with some models projecting increases and others decreases in future reef damage.

4.1 Abstract

Tropical cyclones generate large waves that physically damage coral communities and are commonly cited as a worsening threat to coral reefs under climate change. However, beyond projections of ocean basin-scale changes in cyclone intensity, the other determinants of future coral reef damage such as cyclone size and duration remain uncertain. Here, we determine the extent to which downscaled cyclones represent observed cyclone characteristics that influence wave damage to Australian coral reef regions. We then investigate mid-century (2040-2060) and end of century (2080-2100) downscaled tracks to assess whether cyclone characteristics will change with future warming under a high-emissions scenario. We find that spatial uncertainties in

downscaled cyclogenesis and track positions limit estimates of reef damage for individual coral reefs and regions. Further, the models are unable to reproduce the most reef-damaging cyclones for any of the regions. The downscaled tracks capture observed cyclone characteristics, such as size, impacting the Great Barrier Reef well, but perform poorly for the Northern Territory, with mixed performance for the Coral Sea and Western Australia. We find no clear evidence that cyclones will cause more damage to Australian coral reef regions in the future, at least based on the climate models and downscaling approach examined here. There is increasing interest in using tropical cyclone projections to assess future coral reef exposure to damaging waves. We recommend caution when interpreting such projections due to large uncertainty in the mechanisms that influence reef-damaging tropical cyclone characteristics and how these will change with future warming.

4.2 Plain Language Summary

Tropical cyclone intensity, size and duration together determine the extent to which their waves damage coral reefs. Increased tropical cyclone intensity with climate change is often cited as evidence that tropical cyclones will cause more damage to coral reefs in the future but changes to size and duration remain uncertain. Here, we determine whether tropical cyclones simulated from climate models can represent the observed tropical cyclone characteristics that are important for estimating wave damage to coral reefs and assess how these characteristics might change in the future. We find that the tropical cyclones simulated from climate models capture the observed cyclone characteristics well for those impacting the Great Barrier Reef (with the exception of the most damaging cyclones) with mixed to poor performance for other regions. The projections of future reef damage are uncertain with some models projecting increases and others decreases. Tropical cyclone projections are used in conservation planning to identify and protect the coral reefs least exposed to future tropical cyclones. However, we find that the simulated tropical cyclone tracks explored here are unlikely to represent future reef-damaging tropical cyclone characteristics well if used in conservation decision making.

4.3 Introduction

Tropical cyclones are often a key driver of coral reef condition where they commonly occur (De'ath *et al.*, 2012; Zinke *et al.*, 2018), potentially thwarting conservation success if not considered in management decisions. For example, protecting sites least exposed to thermal stress and able to provide larval recruits to other vulnerable reefs as a strategy for enhancing coral reef survival (Beyer *et al.*, 2018) will fail if such sites are subjected to frequent and severe wave damage from tropical cyclones. The threat of tropical cyclones is rising as the increased severity and spatial extent of other stressors impedes recovery from storm damage (Blackwood *et al.*, 2011; Dietzel *et al.*, 2021). Conservation plans need to consider multiple environmental dimensions of climate change (Groves *et al.*, 2012; Dixon *et al.*, 2021) because climate change can lead to ecosystem collapse (Newton *et al.*, 2021). For coral reefs, a key part of this is to identify the management areas experiencing the most damaging tropical cyclones now and in the future. Thus, there is increasing interest in the use of future simulated tracks in coral reef vulnerability assessments and conservation planning, though there has been no assessment of their suitability nor their ability to project robust changes in reef damage at the coral reef region scale. Here, we examined to what degree simulated historical cyclone tracks likely capture the key characteristics that underpin a cyclone's ability to damage reefs, assuming vulnerable colonies are present. Secondly, we determined whether robust changes in reef-damaging tropical cyclone characteristics are projected at the scale of coral reef regions in tropical Australia.

Despite being localised short-term individual events, repeated tropical cyclones can cause long-term damage to coral reefs across broad scales. Recovery from this can take decades to centuries (Harmelin-Vivien, 1994), especially if damage affects the physical structure of the reef (Hughes and Connell, 1999) or recovery is impeded by other disturbances (Hughes, 1994). Yet, spatial variability in coral reef exposure to tropical cyclone waves at both local and regional scales means that damage is patchy (Maynard *et al.*, 2016; Puotinen *et al.*, 2016; Wolff *et al.*, 2016; Beyer *et al.*, 2018; Zinke *et al.*, 2018; Gilmour *et al.*, 2019), not least because equatorial coral reefs are outside the geographic range where tropical cyclones track (Puotinen *et al.*, 2020). Tropical cyclones degrade coral reef ecosystems in various ways (Harmelin-Vivien, 1994). Heavy rainfall and flooding lowers salinity and increases nutrient concentration and terrestrial sediment influx, and large waves cause sediment resuspension and physical damage. Physical damage to coral communities ranges from breakage of branches in the most vulnerable and delicate species to the removal of entire sections of the reef structure (Harmelin-Vivien, 1994; Beeden *et al.*, 2015; Puotinen *et al.*, 2016).

The severity of physical damage from waves is dependent on storm characteristics such as intensity, size, duration and translation speed (Puotinen *et al.*, 2020) as well as local-scale reef characteristics such as depth, structural complexity, community type and disturbance history (Harmelin-Vivien, 1994; Blackwood *et al.*, 2011). At the coral colony scale, damage is always patchy because the individual characteristics (morphology, size) and spatial arrangement of colonies determine the extent to which physical damage from a potentially damaging wave climate actually occurs (Madin and Connolly, 2006). The worst possible wave damage can be expected from cyclones that are intense, large, and slow-moving with long-lived tracks that persist near reefs. This damage is most fully realised for vulnerable colonies within reef communities that are compromised by other stressors or are not routinely exposed to a high energy wave regime (Madin and Connolly, 2006). Tropical cyclone-induced wave damage can be exacerbated by other climate stressors, for example where ocean acidification weakens coral skeletons and thus increases their vulnerability to physical damage (Madin *et al.*, 2012).

Global climate models project increases in the frequency and severity of thermal stress events in coral reef regions in the future (Dixon *et al.*, 2022). Though tropical cyclone projections have existed for coral reef regions for many years, they have focused on global and ocean basin-scale trends in tropical cyclone frequency and intensity (Emanuel *et al.*, 2008; Knutson *et al.*, 2013). At the global scale, there is medium to high confidence that the average tropical cyclone peak intensity and the proportion of storms that reach high intensity will increase in the future with climate change, but trends in the remaining tropical cyclone characteristics that influence wave-induced reef damage are less certain (Knutson *et al.*, 2020). Future changes to translation speed are equivocal; one study has projected a significant decrease (Gutmann *et al.*, 2018), while others project no change (Knutson *et al.*, 2013; Kim *et al.*, 2014; Wu *et al.*, 2014). Projected changes in tropical cyclone size are also highly variable between studies: some studies project increases in some basins (Kim *et al.*, 2014; Knutson *et al.*, 2015; Yamada *et al.*, 2017), and decreases in others (Knutson *et al.*, 2015; Yamada *et al.*, 2017), while other studies project no change (Gutmann *et al.*, 2018).

The projected global and basin-scale increases in tropical cyclone intensity are often cited as evidence of greater tropical cyclone-induced coral reef damage with future climate change (Cheal *et al.*, 2017; Harvey *et al.*, 2018; Gilmour *et al.*, 2019; França *et al.*, 2020), but there are two key gaps in knowledge undermining this statement. First, global and basin-scale changes in tropical cyclone characteristics do not capture spatial variation in future tropical cyclone exposure within and between coral reef regions. For example, whether the projected increase in intensity differs between the coral reef regions within an ocean basin is unknown, much less between individual reefs. Second, a projected increase in intensity alone does not provide a complete picture of the future potential for coral reef damage as size, duration and location of tropical cyclone tracks also determine the coral reef wave damage severity and extent. For example, tropical cyclones may be more intense in the future but no longer track as close to coral reefs, be as large in size or move as slowly.

Vital for assessing damage potential to coral reefs is understanding where cyclones are likely to form and track. Numerous factors influence tropical cyclone formation including sea surface temperature, vertical wind shear, mid-level moisture and the Coriolis parameter (Emanuel, 2003). The link between tropical cyclone formation and climate is not fully understood, making projected changes in tropical cyclone formation with future climate change uncertain (Walsh *et al.*, 2016; Sobel *et al.*, 2021). Where a tropical cyclone tracks, and how quickly, is influenced by synoptic-scale atmospheric circulations, including major subtropical high pressure systems (Chan and Gray, 1982; Chu *et al.*, 2012; Camp *et al.*, 2019). Where a tropical cyclone tracks can affect its intensity and lifetime, as high sea surface temperature can cause a cyclone to intensify while low sea surface temperature, high wind shear and landfall can cause tropical cyclones to weaken and dissipate (Emanuel, 2003). Hence, the ability of climate models to project future changes in tropical cyclone characteristics hinges on the accurate simulation of the many mechanisms affecting the tropical cyclone life cycle.

Future changes to tropical cyclone characteristics are commonly estimated at global or ocean basin (e.g. South Pacific Ocean) scales. Only once have any projections of future changes for individual coral reef regions been undertaken (Great Barrier Reef, where Callaghan *et al.* (2020) used the HADGEM model to assess the extent to which reefs prevent coastal erosion from cyclones). We build upon that work by assessing the current and future potential for cyclone waves to damage reefs based on a suite of six Coupled Model Intercomparison Project Phase 5 (CMIP5) climate models and extending the study region to all of tropical northern Australia. Ideally, a numerical wave model would be used to simulate nearshore wave climates for future cyclones using high resolution bathymetry as per Callaghan *et al.* (2020) for the full suite of climate models and for all regions. However, running numerical wave analysis for large sets (thousands) of historical and future simulated tracks is computationally and time intensive, the requisite bathymetry data does not yet exist for Western Australia nor the Northern Territory, and model performance for the full suite of climate models has not yet been assessed. We therefore examined whether downscaled tropical cyclones (Emanuel *et al.*, 2006, 2008) derived from historical climate model output can capture observed regional variability in individual potential reef-damaging tropical cyclone characteristics such as intensity, size and duration near reefs. We used tropical Australia as a case study, as its northern coastlines are frequently exposed to tropical cyclone impacts (Chand *et al.*, 2019) and there is regional variability in coral reef exposure to cyclone generated waves (Great Barrier Reef – Maynard *et al.* 2016; Puotinen *et al.* 2016; Western Australia – Gilmour *et al.* 2019; all tropical Australia – Puotinen *et al.* 2020). We then compared regional tropical cyclone reef-damaging characteristics between the past and future climates under the high-emissions Representative Concentration Pathway (RCP) 8.5 scenario.

4.4 Materials and Methods

4.4.1 Calculating observed reef-damaging tropical cyclone metrics

We identified tropical cyclones with the potential to have generated waves capable of damaging tropical coral reefs, henceforth called 'reef-damaging' cyclones, as those where the cyclone circulation (defined as maximum radius to gale force winds (~17 m/s) in any sector mapped around the cyclone track position each hour) intersects a 100 km boundary around any of three regional coral reef regions (Coral Sea, Great Barrier Reef and Western Australia; Figure 4.1) – termed the track position's spatial 'footprint'. This extends work done previously for the Great Barrier Reef (Wolff *et al.*, 2018) by explicitly mapping how the size of the cyclone (the spatial footprint) varies along the track and intersecting that with the coral reef regions instead of assuming damage is possible at any reef within a uniform zone around each cyclone track. The 100 km zone was added to conservatively account for positional uncertainty in recorded cyclone track positions. In the satellite era (post 1970), such uncertainty is less than 150 km, and less than 50 km where the tropical cyclone has a clearly defined eye (D. Herndon, personal communication). We included a fourth region, Northern Territory, but due to uncertainty regarding the location of coral reefs in the Northern Territory we used the entire region rather than a 100 km buffer around the reef area (Figure 4.1).

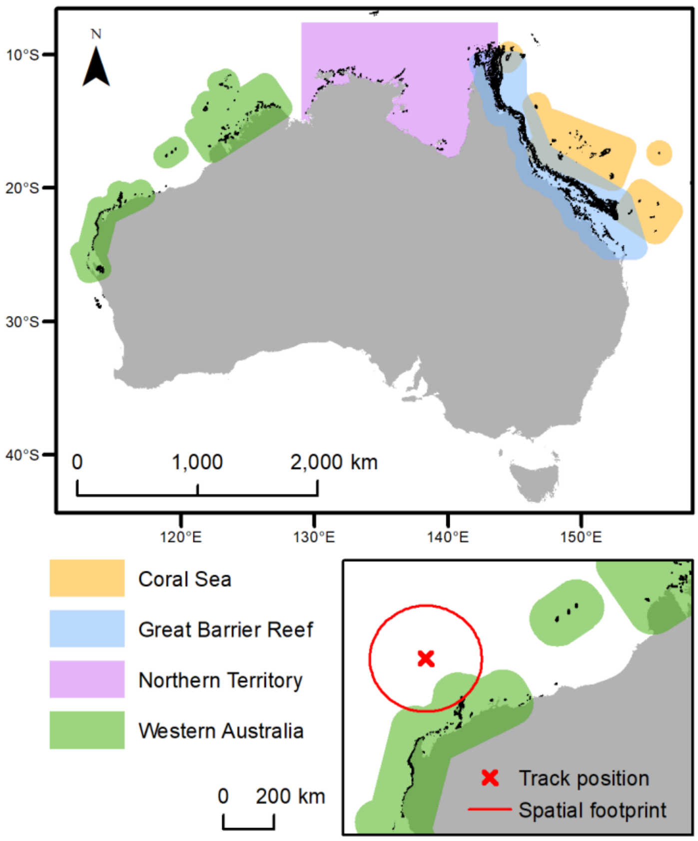

Figure 4.1: Map of Australia showing 100 km boundaries around the Coral Sea, Great Barrier Reef and Western Australia coral reef areas and the entire Northern Territory region. Coral reef areas are shown in black. The bottom panel shows a track position with its spatial footprint (maximum radius to gales) intersecting with the Western Australia region.

Though cyclones can generate freshwater flood plumes whose lowered salinity and light-blocking turbidity can adversely affect coral communities (Brodie *et al.*, 2012), here we limited our consideration to physical damage to corals from cyclone generated waves. As the magnitude of a given sea state depends on the combination of wind speed, duration and fetch (distance over which winds can blow consistently unobstructed), three key characteristics of cyclones contribute most to their potential to generate seas capable of damaging reefs: intensity, size of circulation, and duration near reefs (Puotinen *et al.*, 2020). For each incidence of a tropical cyclone's spatial footprint intersecting a coral reef region between 1985 and 2020, the following three reef-damaging tropical cyclone characteristics were calculated: maximum intensity, maximum radius to gales and duration of gales. Best track data prior to the early 1980s has a high number of missing records and tends to underestimate intensity (Ramsay *et al.*, 2012). We further applied a reef damage index that uses all three characteristics to estimate damage potential based on field data of past cyclone damage of reefs predominantly in the Great Barrier Reef (Supplementary Table 4.1).

The three metrics were calculated only for the cyclone track positions located along the section of tracks whose spatial footprint intersects with the reef regions. The maximum intensity was calculated using the maximum 10-minute wind speed extracted from the International Best Track Archive for Climate Stewardship (IBTrACS; Knapp *et al.*, 2010, 2018). The maximum radius to gales was calculated using the maximum distance from the cyclone eye to gale force winds at 17 m/s in any of the four geographic quadrants, reported in IBTrACS. Where the radius to gales was missing in IBTrACS, the maximum radius to gales from the Bureau of Meteorology database was used. Where the radius to gales was missing in both data sources, the basin average (210 km) was used (Chavas and Emanuel, 2010). Using a basin rather than a regional average avoids the modifiable areal unit problem where the average radius to gales may change depending on where the regional boundaries are drawn. The duration of gales is the number of days a tropical cyclone's spatial footprint intersects with a reef region while the maximum wind speed is greater than 17 m/s.

The reef damage index (*RDI*) was used to estimate the overall potential for reef damage from waves (assuming vulnerable corals are present) for each tropical cyclone track while impacting a region. The index is calculated by:

$$RDI = \left(\frac{MI}{MI_{max}}\right) * \left(\frac{RG}{RG_{max}}\right) * \left(\frac{DG}{DG_{max}}\right) * 100$$

where MI is the maximum intensity, RG is the maximum radius to gales and DG is the duration of gales. The reef damage index is a reasonable estimate of the reef damage potential of a tropical cyclone when compared to field data for nine cyclones from the Great Barrier Reef and Western Australia (Supplementary Table 4.1).

The greatest potential for wave damage comes from a cyclone that is simultaneously intense, slow moving, large and generates gales for a long time within a reef region. No recorded cyclone in any of the Australian coral reef provinces has met all of these criteria. Cyclone Yasi in 2011 on the Great Barrier Reef (Beeden *et al.*, 2015) and Cyclone Lua in 2012 in Western Australia (Puotinen *et al.*, 2020) were simultaneously both intense and large, but not slow-moving. Cyclone Hamish in 2009 on the Great Barrier Reef generated gales near an unprecedented number of reefs due to its unusual track while it maintained high intensity, but it was not large (Puotinen *et al.*, 2016). We categorised the tropical cyclone track position spatial footprints that intersect with the four Australian coral reef regions into four very damaging categories (Table 4.1) and one category containing all others. The translation speed was calculated using the distance between consecutive track positions (length of great circle arc between coordinates of track positions) divided by the time between the recorded track positions.

Table 4.1: The four reef-damaging categories of track positions.

Category	Name	Description
1	Intense and large	Maximum wind speed > 33 m/s and radius to gales > 275 km
2	Intense and slow-moving	Maximum wind speed > 33 m/s and translation speed < 5 m/s
3	Large and slow-moving	Radius to gales > 275 km and translation speed < 5 m/s
4	Intense, large and slow-moving	Maximum wind speed > 33 m/s, radius to gales > 275 km and translation speed < 5 m/s

4.4.2 Calculating downscaled reef-damaging tropical cyclone metrics

Tropical cyclone intensity is measured by maximum wind speeds, which occur over a relatively small area at the boundary of the cyclone eye. As most cyclone eye radii in the Australian region range between 10-40 km, accurately identifying and assessing cyclones from a global climate model requires relatively high spatial resolution (~20 km or less). This requirement combined with the fact that many tropical cyclones are short-lived, makes their simulation by relatively coarse scale global climate models difficult (Knutson *et al.*, 2010). The high spatial resolution necessary to simulate intense tropical cyclones can be obtained by dynamical and statistical-dynamical downscaling. Downscaling is thus commonly used to simulate observed tropical cyclones and examine basin-scale trends in tropical cyclone frequency and intensity (Emanuel, 2006; Camargo *et al.*, 2008; Emanuel *et al.*, 2008; Villarini *et al.*, 2011; Knutson *et al.*, 2013, 2015).

Here, we obtained downscaled tropical cyclone tracks (commonly referred to as "synthetic tracks") derived from six CMIP5 climate models (Supplementary Table 4.2) from K. Emanuel (Emanuel, 2013) for the simulated historical (1985-2005), mid-century (2040-2060) and end of century (2080-2100) time periods under the RCP8.5 high-emission scenario. The tracks were downscaled using a statistical-dynamical technique. Detail on how the tracks were generated is described in Emanuel *et al.* (2006) and Emanuel *et al.* (2008). These simulations were used here due to the large number of downscaled tracks (n = 3000) for historical, mid-century and end of century. These tracks provide robust statistics for predicting changes in tropical cyclone characteristics, especially for the less common but most destructive storms (Emanuel *et al.*, 2006). Further, the tracks have demonstrated applicability to the Australia region (Ramsay *et al.*, 2018) and mid-century tracks are available. Mid-century tracks are more relevant for coral reef timescales than the commonly used 2080-2100 future tracks, given the expected near-term decline of coral reefs due to climate warming (Hughes *et al.*, 2017; Dixon *et al.*, 2022). Finally, the downscaled tracks respond to the physics of climate change, for example responding to changes in atmospheric water vapour, sea surface temperature and wind shear. The evolution of these large-scale, tropical cyclone-relevant parameters in CMIP5 models will therefore be reflected in the future tracks (Emanuel, 2006; Emanuel *et al.*, 2008). Natural climate variability modes, such as El Niño Southern Oscillation (ENSO), can affect reef-damaging tropical cyclone characteristics such as intensity and duration as well as where they form and track in the

Australia region (Ramsay *et al.*, 2012). Changes to ENSO patterns under future climate change are simulated by the climate models that drive the downscaled tropical cyclone tracks and so are considered in the projected changes in tropical cyclone characteristics presented here. However, there is known uncertainty in projected changes to ENSO under future climates (Taschetto *et al.*, 2014).

The reef-damaging tropical cyclone characteristics were calculated for tracks whose spatial footprint intersects the coral reef regions for the downscaled historical, mid-century and end of century tracks. We converted the 1-minute maximum wind speed provided by K. Emanuel to 10-minute maximum wind speed (1-minute maximum wind speed * 0.88; Harper *et al.*, 2010; Ramsay *et al.*, 2018) in order to calculate maximum intensity. The radius to gales is not explicitly simulated but can be estimated by constructing radial wind profiles using the maximum wind speed and radius to maximum wind. The historical radius to gales at each track position was calculated three times, each time constructing radial wind profiles using a different method: Holland (2010), Emanuel (2010) and Emanuel and Rotunno (2011). We then compared the downscaled maximum radius to gales to the observed maximum radius to gales for each model and wind profile method using two-sided Mann-Whitney-Wilcoxon to test the null hypothesis that the observed and downscaled maximum radius to gales are from continuous distributions with equal medians. The wind profile method that produced maximum radius to gales that were not significantly different from observed at the 0.01 significance level was selected as the 'best' method for each model. The selected wind profile was then used to calculate the radius to gales for the mid-century and end of century downscaled tracks. Scripts for calculating the radius to gales using the three wind profiles were provided by K. Emanuel. We calculated the duration of gales and the reef damage index in the same way as for the observed tracks and categorised the most damaging track positions in the same way as the observed tracks. Both observed and downscaled tracks were linearly interpolated to 1 hourly time steps.

4.4.3 Statistical Analysis

We compared the spatial distributions of the observed and downscaled tracks at two spatial scales for the period 1985-2005: regional and reef. At the regional scale, we compared the number of tracks whose spatial footprint intersects each of the coral reef regions between simulated past and observed tropical cyclones. At the reef scale, we compared the number of tracks intersecting each of the reef areas within the coral reef regions between simulated past and observed. This analysis assessed the suitability of the downscaled tracks in representing future changes to tropical cyclones for finer than regional scales (e.g. within the Great Barrier Reef). Both were compared using a Chi Squared test to test whether the distribution of observed and downscaled tracks whose spatial footprints intersect each of the regions/reefs were different. We then visually compared kernel density estimates (KDE) of the tropical cyclone hourly track positions, and the median genesis (formation) positions and track positions for the first 10 days between observed and downscaled tracks (Ramsay *et al.*, 2018) for tropical cyclones whose spatial footprint intersects with each of the coral reef regions between 1985 and 2005.

The observed reef-damaging tropical cyclone characteristics were compared to the downscaled historical metrics for each model and region separately based on a two-sided Mann-Whitney-Wilcoxon test. This analysis tested the null hypothesis that the observed and downscaled metrics for tropical cyclones intersecting each region are from continuous distributions with equal medians. P-values greater than 0.01 indicated that the model was not significantly different from the observed regional reef-damaging tropical cyclone metrics and indicated that models capture observed cyclone characteristics. One-sided Mann-Whitney-Wilcoxon was used to test the direction of differences. Observed and downscaled maximum intensity and duration of gales were compared for the period 1985-2005. For the maximum radius to gales, we compared the longer observed 1985-2020 period to the simulated past 1985-2005 period and assumed stationarity for the periods before and after 2005. The most reliable wind radii data has been recorded in best track databases for the Australian region since 2003, with some opportunity-based surface observations included earlier in the record (Courtney *et al.*, 2021). We also used the 1985-2020 observed period to compare the reef damage index and number of tracks in each damage category as both require reliable radius to gales data. The number of track positions in each of the damage categories was compared between the observed (1985-2020) and simulated past (1985-2005) periods using a Chi Squared test to compare the distributions of the two populations (observed and downscaled) of categorical data.

Changes in reef-damaging tropical cyclone characteristics with future climate change were determined by bootstrapping the difference in means following Ramsay *et al.* (2018). The mean change in reef-damaging metric (e.g. maximum intensity) and 95% confidence intervals were calculated from 10,000 replicates using the bias-corrected and accelerated technique. If the confidence intervals did not cross zero, the projected change was considered statistically significant. Bootstrapped changes in means were analysed for all tropical cyclones in the Southern Hemisphere ocean basins (South Indian Ocean and South Pacific Ocean) and for tropical cyclones impacting each of the coral reef regions for both the mid-century and end of century periods.

4.5 Results

4.5.1 Comparing observed and downscaled past tropical cyclones

The maximum radius to gales calculated using the Emanuel (2010) wind profile correctly captured past cyclone size observations for four out of six of the models ($p > 0.01$; GFDL, HADGEM, MIROC and MPI; Supplementary Figure 4.1). For CCSM and IPSL, the maximum radius to gales was correctly represented using the Holland (2010) wind profile ($p > 0.01$). The maximum radius to gales calculated using the Emanuel and Rotunno (2011) wind profile was significantly higher than observed for all models ($p < 0.0001$). For the rest of the analysis, the Emanuel (2010) wind profile was thus used to calculate the radius to gales for GFDL, HADGEM, MIROC and MPI and the Holland (2010) wind profile for CCSM and IPSL for the historical and future downscaled tracks.

4.5.1.1 Spatial distribution of tracks and cyclogenesis

The number of observed tracks whose spatial footprints intersect with each region was significantly different ($p < 0.01$) to the number of downscaled historical tracks for all but HADGEM ($\chi^2 = 2.39$, $p = 0.495$) and IPSL ($\chi^2 = 5.88$, $p = 0.117$). In the downscaled tracks, there was a greater proportion of tracks impacting the Coral Sea and Great Barrier Reef than observed and a smaller proportion of tracks impacting Western Australia (Figure 4.2).

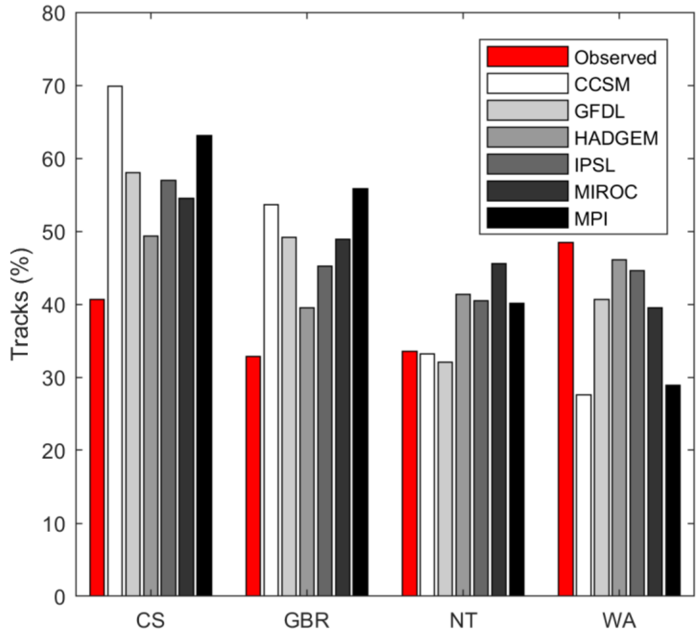

Figure 4.2: Percentage of tropical cyclone tracks whose spatial footprints intersect with each coral reef region out of the total number of tracks intersecting any region in the observed (1985-2005) and simulated past (1985-2005) periods. CS – Coral Sea, GBR – Great Barrier Reef, NT – Northern Territory, WA – Western Australia.

The number of tracks impacting the reefs within the Coral Sea was captured by CCSM, GFDL, HADGEM, MIROC and MPI (i.e. there was no significant difference between the observed and downscaled past distribution of tracks). There was a greater proportion of downscaled tracks impacting the Northern reef area (1 in Figure 4.3a) than observed and fewer tracks impacting the central sections (2-4 in Figure 4.3a) than observed. The number of observed tracks whose spatial footprints intersect with reefs within the Great Barrier Reef was correctly represented by all models ($p > 0.01$; Supplementary Table 4.3; Figure 4.3b). The number of observed tracks that impact reefs within Western Australia was captured by CCSM, GFDL, HADGEM, IPSL and MPI. There was a greater proportion of downscaled tracks impacting Ashmore (1 in Figure 4.3c) and Scott Reef (2 in Figure 4.3c) in the north of the region than observed. The downscaled tracks in some of the models had a smaller proportion impacting the Kimberly (3 in Figure 4.3c) and Montebellos (5 in Figure 4.3c) on the Western Australian coastline than observed. This finding highlights how uncertainty increases at finer spatial scales, making it problematic to use these data at increasingly finer scales.

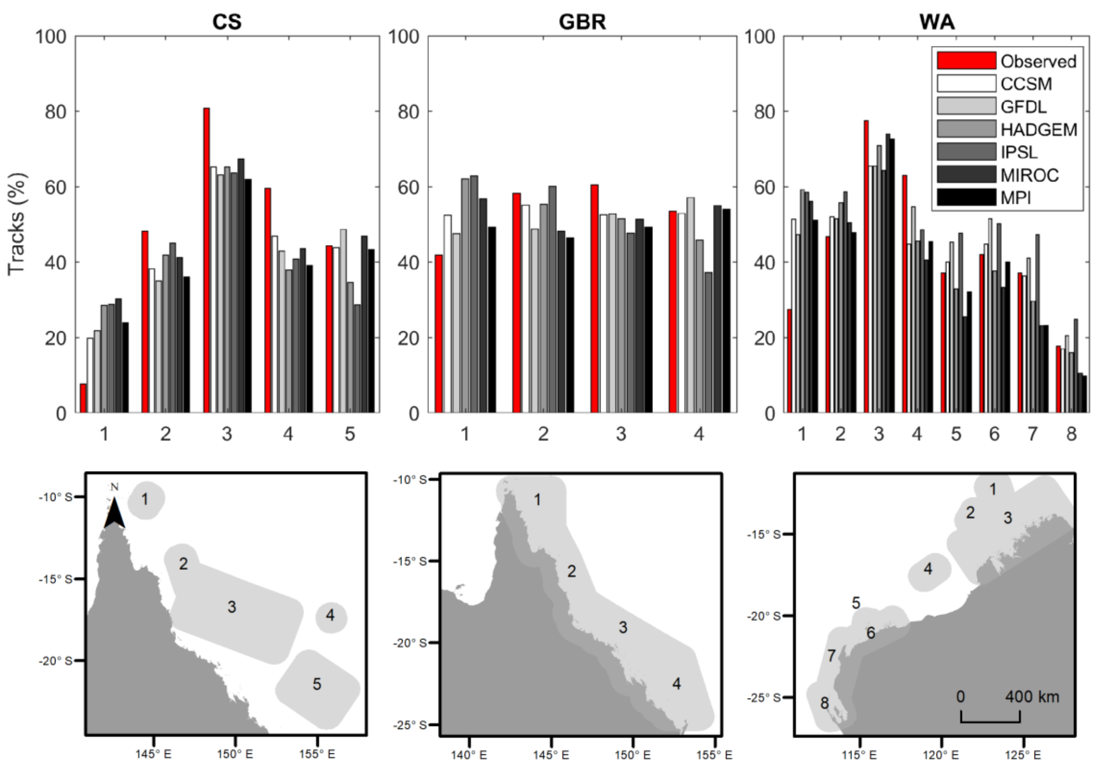

Figure 4.3: Percentage of tropical cyclone tracks whose spatial footprints intersect with each coral reef within the Coral Sea (a), Great Barrier Reef (b) and Western Australia (c) in the observed (1985-2005) and simulated past (1985-2005) periods. The Northern

Territory is not included because it is not divided into coral reef areas due to uncertainty regarding the location of coral reefs within the region. In Western Australia, the reefs are 1 – Ashmore, 2 – Scott Reef, 3 – Kimberly, 4 – Rowley Shoals, 5 – Montebello, 6 – Pilbara, 7 – Ningaloo, 8 – Shark Bay.

The observed median track for tropical cyclones impacting Western Australia initially followed the Western Australian coastline, and therefore a single tropical cyclone had the potential to impact many reefs during its track (Figure 4.4). The median downscaled tracks and track positions extended further west than observed. The downscaled tracks in CCSM, GFDL, HADGEM, IPSL and MPI captured the observed median track direction travelling east to west for tropical cyclones impacting the Northern Territory, though CCSM, GFDL and IPSL had genesis positions further east than observed. The observed median track for tropical cyclones impacting the Coral Sea and Great Barrier Reef tracked north to south while the downscaled median tracks started further east and tracked east to west before curving south. Downscaled track positions also extended further east in the north of the regions than observed. The median cyclone genesis positions in the models were at a lower latitude than observed for all coral reef regions (Supplementary Figure 4.2).

4.5.1.2 Reef-damaging tropical cyclone characteristics

The maximum intensity (Supplementary Figure 4.3) was best captured for tracks whose spatial footprints intersect the Coral Sea and Great Barrier Reef, followed by Western Australia (five and four out of six models were not significantly different to observed, respectively). The maximum intensity was poorly represented for the Northern Territory (all six models were significantly different to observed). The maximum radius to gales (Supplementary Figure 4.4) was captured for tracks whose spatial footprints intersect the Great Barrier Reef, Western Australia and the Coral Sea by six, five and three out of six models, respectively. All six models had significantly higher maximum radius to gales of tracks impacting the Northern Territory. The duration of gales (Supplementary Figure

4.5) was best represented for tracks whose spatial footprints intersect the Great Barrier Reef and Northern Territory followed by Western Australia as six, five and two models were not significantly different to observed, respectively. None of the models captured the observed duration of gales for tracks impacting the Coral Sea. The observed reef damage index (Supplementary Figure 4.6) was correctly represented for tracks whose spatial footprints intersect the Great Barrier Reef and Western Australia by all six models, and the Coral Sea by four models. All six models had significantly higher reef damage indices of tracks impacting the Northern Territory.

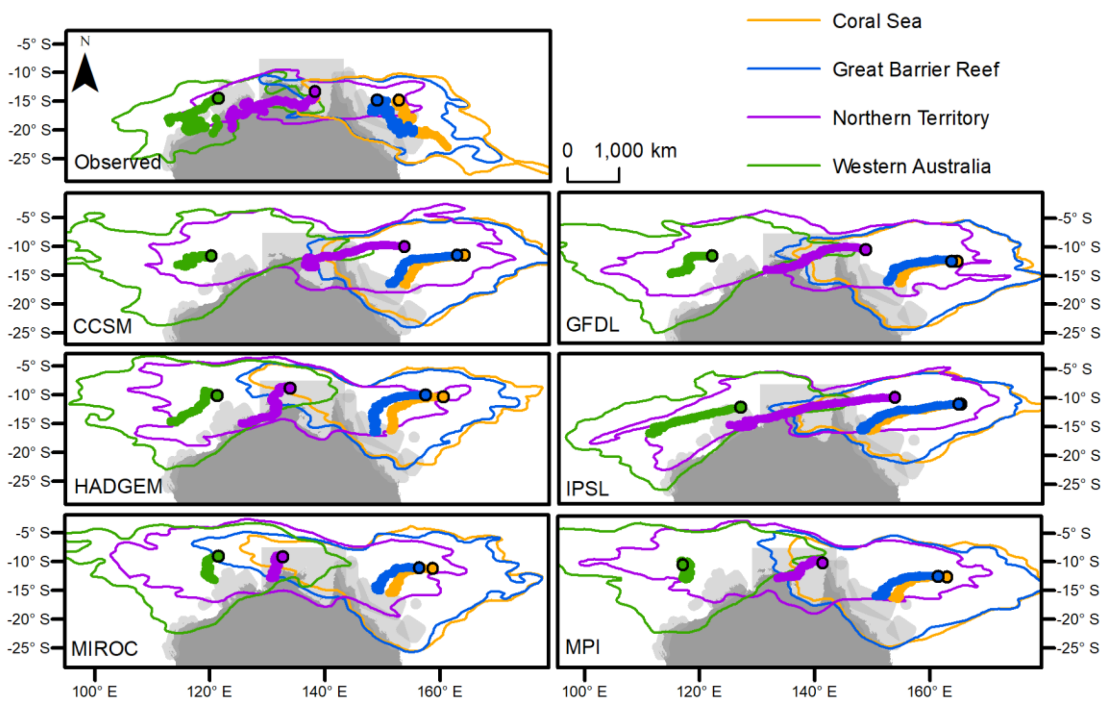

Figure 4.4: Kernel density estimates (KDE) of observed (1985-2005) and downscaled past (1985-2005) tropical cyclone track positions for tropical cyclones whose spatial footprints intersect with each of the four coral reef regions. The median hourly track positions for the first 10 days are shown by the circles and the 75% KDE contours are shown by the lines. The median genesis positions are shown by the black outlined circles.

We found that CCSM and IPSL were the best performing models, as they were not significantly different from observed on 11 and 12 out of 16 occasions, respectively

(Table 4.2). The Great Barrier Reef was the best represented region, as downscaled metrics were not significantly different from observed on 23 out of 24 occasions, followed by Western Australia (17/24) and then the Coral Sea (12/24). The Northern Territory was poorly represented by all six models for every metric but the duration of gales (5/24).

Table 4.2: p-values for two-sided Mann-Whitney-Wilcoxon test to test the null hypothesis that the following observed and downscaled metrics for tropical cyclones whose spatial footprints intersect each region are from continuous distributions with equal medians: maximum intensity, maximum radius to gales, duration of gales and reef damage index. The full results (medians, sample sizes, U test statistics and p values) are reported in Supplementary Table 4.4.

Metric	Region	CCSM	GFDL	HADGEM	IPSL	MIROC	MPI	Region performance (out of 24)[c]
Maximum intensity (m/s)	CS	**0.888**[a]	**0.099**	**0.894**	**0.586**	0.002	**0.439**	5
	GBR	**0.308**	**0.064**	**0.156**	**0.256**	0.001	**0.058**	5
	NT	0.000	0.000	0.000	0.000	0.000	0.000	0
	WA	**0.055**	0.008	0.001	**0.732**	**0.016**	**0.040**	4
Maximum radius to gales (km)	CS	**0.353**	0.000	0.000	**0.103**	**0.059**	0.000	3
	GBR	**0.033**	**0.661**	**0.934**	**0.127**	**0.384**	**0.184**	6
	NT	0.000	0.000	0.000	0.000	0.000	0.000	0
	WA	**0.863**	**0.385**	0.003	**0.397**	**0.058**	**0.234**	5
Duration of gales (days)	CS	0.003	0.004	0.000	0.001	0.009	0.000	0
	GBR	**0.346**	**0.356**	**0.313**	**0.226**	**0.638**	**0.345**	6
	NT	**0.801**	**0.070**	0.002	**0.993**	**0.031**	**0.021**	5
	WA	0.000	**0.087**	0.004	**0.015**	0.001	0.007	2
Reef damage index	CS	**0.193**	**0.081**	0.003	**0.087**	**0.690**	0.003	4
	GBR	**0.445**	**0.807**	**0.843**	**0.646**	**0.127**	**0.994**	6
	NT	0.000	0.000	0.000	0.000	0.000	0.000	0
	WA	**0.057**	**0.109**	**0.068**	**0.901**	**0.788**	**0.477**	6
Regional model performance (out of 4)	CS	3	2	1	3	2	1	**12**
	GBR	4	4	4	4	3	4	**23**
	NT	1	1	0	1	1	1	**5**
	WA	3	3	1	4	3	3	**17**
Model performance (out of 16)[b]		**11**	**10**	**6**	**12**	**9**	**9**	

[a] Bold values indicate where the test hypothesis cannot be rejected ($p > 0.01$); i.e. the model simulates a similar distribution to observed.

[b] Model performance is the number of times a model succeeds in simulating the observed distribution ($p > 0.01$). Model performance is out of 16 (four metrics * four regions).

[c] Region performance is out of 24 (four metrics * six models).

4.5.1.3 Damaging track positions

There were no observed or downscaled track positions in the most damaging category (intense, large and slow-moving) whose spatial footprints intersect with coral reef regions (Supplementary Figure 4.7). Observations in the Coral Sea and Great Barrier Reef regions showed similar distributions across the categories, with lower percentages of intense and large cyclones compared to intense and slow and large and slow. In contrast, observations in the Northern Territory and Western Australia both showed by far the greatest percentage in the intense and slow category with relatively few in the other categories.

The downscaled tracks simulated track positions in every damage category represented by the observed tracks, indicating that the downscaled tracks are able to simulate reef-damaging tropical cyclones (Supplementary Figure 4.7). However, the number of downscaled historical tracks in each of the damage categories was not correctly represented by any of the models for any region ($p < 0.01$; Supplementary Table 4.5). For the Great Barrier Reef and Coral Sea, all six models had more intense and large track positions and fewer large and slow-moving track positions than observed (Supplementary Figure 4.7). For Western Australia and the Northern Territory, the models captured the low occurrence of large and slow-moving track positions impacting the region but had more intense and large track positions than observed in both regions. For the Northern Territory, many models had more intense and slow-moving track positions than observed, while in Western Australia many models had fewer than observed of these track positions. Projections of the number of track positions in each of the damage categories in the future are not included here due to the downscaled tracks' inability to capture the observed distribution of damaging track positions.

4.5.2 Projected changes in reef-damaging tropical cyclone characteristics

The downscaled tracks exhibited a significant increase in the maximum intensity of tropical cyclones during the mid-century period (2040-2060; Supplementary Figure 4.8) in the CCSM, GFDL and MIROC models for the Southern Hemisphere ocean basins (South Indian Ocean and South Pacific Ocean). By the end of the century (2080-2100), five models exhibited a significant increase in maximum intensity (CCSM, GFDL, HADGEM, MIROC and MPI). The downscaled tracks in the IPSL model decreased significantly in their maximum intensity in the end of century period. Five models (CCSM, GFDL, IPSL, MIROC and MPI) exhibited a significant increase in the maximum radius to gales in the mid-century extending to all six models in the end of century (Supplementary Figure 4.8). The projected change in the duration of gales showed opposite tendencies between the mid and end of century periods, with four models displaying a significant decrease (GFDL, HADGEM, IPSL and MIROC) and increase (CCSM, GFDL, HADGEM and MPI) during the mid and end of century periods, respectively. CCSM and IPSL were best able to reproduce the observed reef-damaging tropical cyclone characteristics for the historical period (Table 4.2) but had opposite projections to each other for maximum intensity and duration of gales. Both models exhibited a significant increase in maximum radius to gales.

4.5.2.1 Cyclone projections for the mid-century (2040-2060)

Projected changes in the reef-damaging tropical cyclone characteristics varied in sign in the mid-century. The tracks driven by the MIROC model exhibited a significant increase in maximum intensity (Figure 4.5) for tropical cyclones impacting all four regions. The tracks in CCSM exhibited significant increases in the maximum intensity of tropical cyclones impacting the Coral Sea and Western Australia. Tracks impacting the Coral Sea, the Great Barrier Reef and the Northern Territory exhibited significant decreases in maximum intensity in a third of models (IPSL and MPI for the Great Barrier Reef and the Northern Territory, and GFDL and IPSL for the Coral Sea). For the maximum radius to gales, a significant increase was projected in four models for Western Australia and the Coral Sea, three models for the Great Barrier Reef and two models for the Northern Territory. The only model with a significant decrease in the maximum radius to gales was HADGEM (for tracks impacting the Northern Territory and Western Australia). For the duration of gales, only MIROC and CCSM exhibited significant increases for cyclones impacting the Coral Sea and Western Australia, respectively. A significant decrease in the duration of gales was projected for tracks impacting the Great Barrier Reef when driven by IPSL, GFDL and MPI, for the Northern Territory in the IPSL and MPI models, and for Western Australia in the GFDL and MPI models. The reef damage index exhibited mixed projections, with MIROC tracks displaying a significant increase for all four regions, and CCSM producing a significant increase for the Western Australia region only. The IPSL tracks exhibited a significant decrease in the reef damage index in three regions, while the tracks driven by HADGEM and MPI exhibited a significant decrease in two regions each.

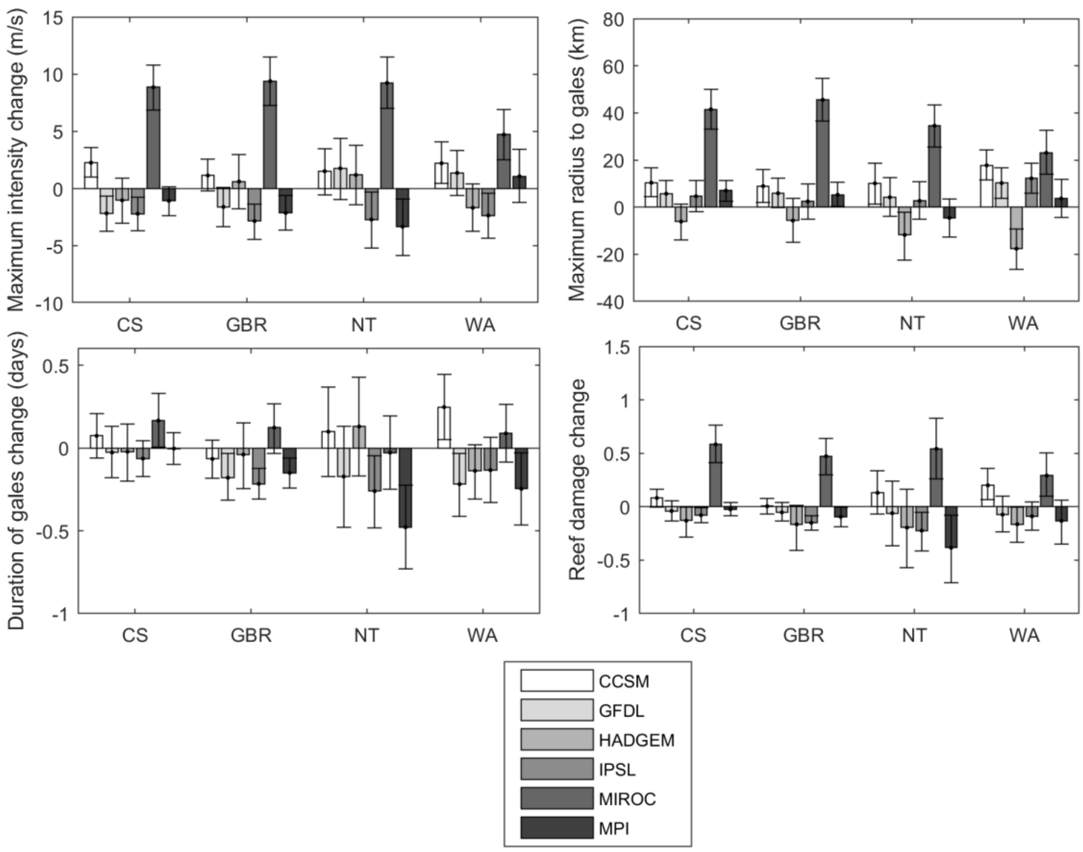

Figure 4.5: Mean projected change from the simulated past (1985-2005) to simulated mid-century (2040-2060) period in reef-damaging tropical cyclone metrics of 10,000 replicates. The error bars depict 95% confidence intervals.

4.5.2.2 Cyclone projections for the end of the century (2080-2100)

The MIROC model tracks exhibited a significant increase in maximum intensity during the end of century period for tropical cyclones impacting every region (Figure 4.6), although the projected increase was lower than for the mid-century for cyclones impacting the Coral Sea and Great Barrier Reef. Other models with significant increases in maximum intensity at the end of the century included CCSM for three regions (Coral Sea, Great Barrier Reef and Western Australia), and GFDL for two regions (Northern Territory and Western Australia). On the other hand, a significant decrease in maximum intensity was found for tropical cyclones impacting the Coral Sea, Great Barrier Reef and Northern Territory when driven by IPSL. For the maximum radius to gales, many models exhibited significant increases, including for tropical cyclones impacting the Coral Sea (five out of six models), the Great Barrier Reef, Northern Territory and Western Australia (four models each). The tracks driven by HADGEM were the only tracks to exhibit a significant decrease in maximum radius to gales in the end of the century, which was for tropical cyclones impacting the Great Barrier Reef and Northern Territory. For the duration of gales, the downscaled tracks exhibited a significant increase for tropical cyclones impacting the Coral Sea and Western Australia for three models each and two models each for the Great Barrier Reef. Conversely, the MPI tracks exhibited a significant decrease in the duration of gales in the Northern Territory. Finally, assessment of the reef damage index revealed that three out of six models yielded a significant increase in this metric for tropical cyclones impacting Western Australia, as did two models for the Coral Sea, Great Barrier Reef and Northern Territory. The tracks driven by MPI exhibited a significant decrease in the reef damage index for tropical cyclones impacting Western Australia.

The projected changes in coral reef-damaging tropical cyclone characteristics for both the mid-century and end of century are dependent on projected changes in where tropical cyclones will track (Supplementary Figures 4.9 and 4.10). Spatial uncertainties in downscaled track trajectories for the historical period highlight uncertainty in the projected changes to the characteristics presented here.

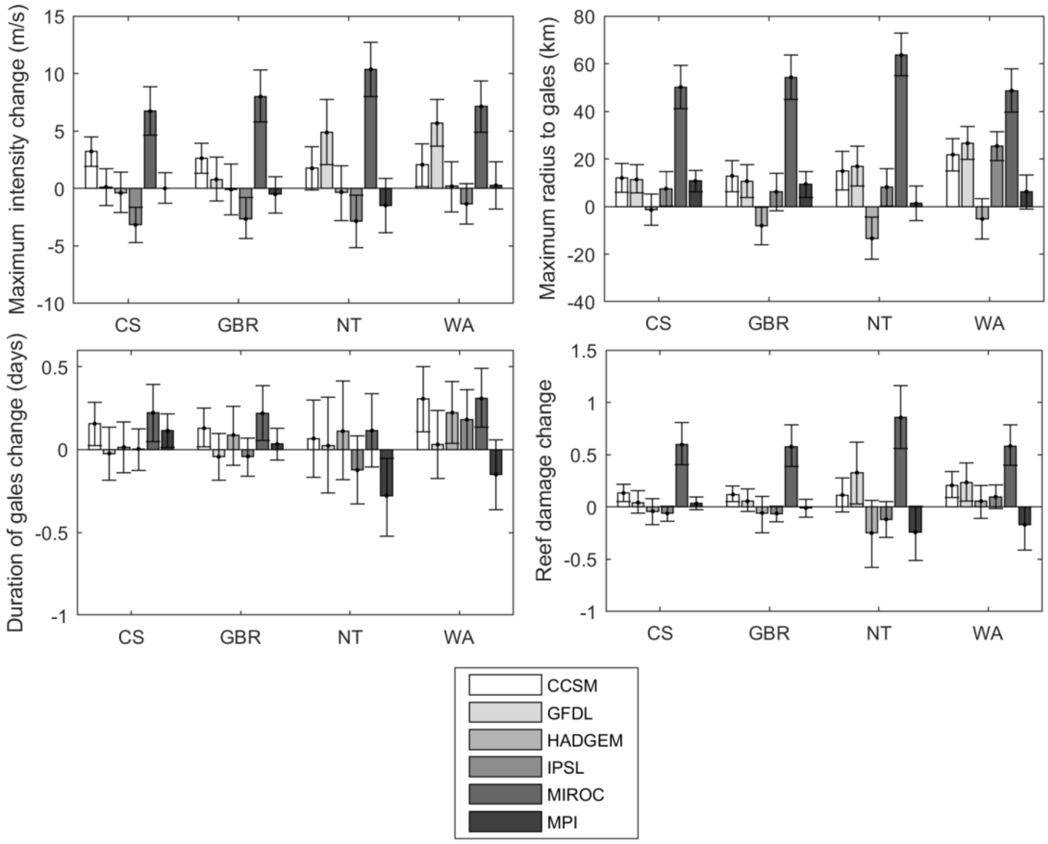

Figure 4.6: Mean projected change from the simulated past (1985-2005) to simulated end of century (2080-2100) period in reef-damaging tropical cyclone metrics of 10,000 replicates. The error bars depict 95% confidence intervals.

4.6 Discussion

Increased tropical cyclone peak intensities under future climate change are a well-established climate change signal at global and ocean-basin scales (Knutson *et al.*, 2020) and are commonly cited as a threat to coral reefs (Cheal *et al.*, 2017; Harvey *et al.*, 2018; Gilmour *et al.*, 2019; França *et al.*, 2020). However, the extent to which future tropical cyclones will damage coral reefs more than in the recent historical climate has been unknown. Here, we found that model projections of future reef damage in the mid-century and end of century are uncertain, with some models projecting increases in future reef damage and reef-damaging characteristics (e.g. intensity) and others decreases. Perhaps this is to be expected given the considerable uncertainty in the projections presented here, in part due to a limited understanding of the mechanisms that influence the reef-damaging characteristics of tropical cyclones (e.g. size and translation speed) and how these will change in the future. It should also be noted that the observations themselves carry uncertainty due to the limited observational period, changes in tropical cyclone observing practices over time (Courtney *et al.*, 2021), and the fine-scale spatial nature of the tracks examined which also limits their sample size. The similarity of tropical cyclone characteristics between the simulated and observed historical tracks was closest for the Great Barrier Reef. This finding may indicate that downscaled future tropical cyclone tracks could be credible in some instances, but nevertheless we recommend caution given the spatial uncertainties in track behaviour, particularly when making predictions at the sub-regional scale, and the poor representation of the most damaging tropical cyclones for coral reefs.

4.6.1 Spatial distribution of tracks and cyclogenesis

The formation locations and trajectories of the downscaled tracks exhibited pronounced differences in some instances compared with the observed tracks. There is therefore some uncertainty in where they will generate seas capable of damaging coral reefs. The median genesis position of downscaled tropical cyclones impacting all four coral reef regions was at lower latitudes than observed (Ramsay *et al.*, 2018). This finding is likely due to the random seeding technique used to generate the downscaled tracks where tropical cyclones can form anywhere south of 2°S (Emanuel *et al.*, 2008). The lower latitude of cyclogenesis positions in the downscaled tracks influenced the subsequent track trajectories, causing more of the northern reef areas to be projected to be impacted in the past than was observed in the Coral Sea and Western Australia. The models underestimated the proportion of tropical cyclones impacting Western Australian reefs and overestimated the proportion of tropical cyclones impacting reefs in the Coral Sea and Great Barrier Reef. The median track for the first 10 days for tropical cyclones impacting Western Australia was further west than observed resulting in the outer reefs being more frequently impacted than observed. Differences in track direction between the models and observations may be due to misrepresentations of the large-scale steering flow which predominantly influences downscaled storm movement (Ramsay *et al.*, 2018). The spatial uncertainties in cyclogenesis and track trajectory, shown by the median genesis and track positions, impact all subsequent metrics (intensity, size, etc.) as they determine which sections of a tropical cyclone track impacts a coral reef region. That said, there was still considerable overlap in the observed and downscaled KDE areas for both the cyclogenesis and track positions, and therefore the exposure to tropical cyclones, at the reef region scale supporting their use in comparisons of observed and downscaled tropical cyclone characteristics and projections of future change. However, the spatial uncertainty limits the suitability of future downscaled tracks for projecting changes at the scale of coral reefs within regions.

4.6.2 Reef-damaging tropical cyclone characteristics

Only one out of six models exhibited a significant increase in the reef damage index in the mid-century, and two models in the end of century, for the Coral Sea, Great Barrier Reef and Northern Territory. For Western Australia, two and three models exhibited a significant increase in the reef damage index in the mid and end of the century periods, respectively. The significant increase was predominantly due to increases in two of the three components of the reef damage index: intensity and size. When considering the entire Southern Hemisphere region, we found that half of the models projected a significant increase in maximum intensity in the mid-century, expanding to the majority (five out of six models) by the end of the century. Previous studies reported a significant increase in the intensity of South Indian Ocean tropical cyclones (Murakami *et al.*, 2012; Knutson *et al.*, 2015; Yamada *et al.*, 2017; Yoshida *et al.*, 2017), but no significant change in the intensity of Southwest Pacific tropical cyclones in the future (Oouchi *et al.*, 2006; Emanuel *et al.*, 2008; Knutson *et al.*, 2015; Yamada *et al.*, 2017; Yoshida *et al.*, 2017; Emanuel, 2021). Regional differences in tropical cyclone intensity projections, including the physical mechanisms behind such differences, is currently a topic of active research. This hemisphere-scale increase in intensity was not as robust when examined at coral reef scales. A significant increase in the maximum intensity was only projected by two and three out of six models in the mid-century and end of the century periods, respectively. The large increase in intensity projected by MIROC downscaled tropical cyclones may be an outlier as it was not projected by the other models, especially those that represent the observed characteristics well. This disagreement in projected changes between models highlights the importance of considering projections from a model ensemble rather than a single model. In addition, even if more of the cyclones that form in the future are more intense, the overall frequency of cyclones is most often predicted to stay the same or drop (Sobel *et al.*, 2021). This means that the absolute frequency of intense cyclones may not rise, depending on how much overall cyclone frequency changes.

Tropical cyclone size is a key determinant of the coral reef damage extent, as demonstrated for tropical cyclone Lua in Western Australia in 2012 which caused major coral loss 800 km away from its track (Puotinen *et al.*, 2020). Four to five out of six models projected a significant increase in the maximum radius to gales of tropical cyclones impacting all four regions by the end of century indicating a robust change in tropical cyclone size in the future. However, there is uncertainty in the mechanisms that determine tropical cyclone size and therefore how these will change in the future limiting robust projections of size at the coral reef region scale and even more so at the within reef scale. Knutson *et al*. (2015) and Yamada *et al*. (2017) found significant increases in tropical cyclone size with future warming in both the South Indian and South Pacific oceans. Kim *et al*., (2014) found significant increases in tropical cyclone size from a doubling of CO_2 in every ocean basin except the South Indian Ocean. Intensity is suggested to influence changes in tropical cyclone size because size metrics are often based on wind speed (e.g. radius to 17 m/s winds; Kim *et al.*, 2014). Here, radius to gales is estimated by constructing wind profiles based on maximum wind speed so projected changes in tropical cyclone size are influenced by changes in intensity. However, Chavas *et al*. (2016) find that relative sea surface temperature (i.e. local surface temperature minus the tropical-mean value) is the better determinant of tropical cyclone size. Without a better understanding of these mechanisms, there will be large uncertainty in the magnitude and spatial distribution of projected coral reef damage as intensity is not the only driver of reef damage.

4.6.3 Damaging track positions

The ability of downscaled cyclone tracks to capture observed cyclone characteristics differs by geographic region. The downscaled tracks generally captured the observed characteristics of tropical cyclones that generate reef-damaging wave climates (intensity, size and duration) for the Great Barrier Reef, but not the Northern Territory, and only partially for the Coral Sea and Western Australia. The distribution of downscaled tropical cyclones whose spatial footprints intersect with reef areas within the regions in most models (five to six out of six models depending on the region) was not significantly different to observed, indicating that the downscaled tracks are suitable for projecting within region changes to reef-damaging tropical cyclone characteristics. However, the models do not capture the frequency of track positions in the most damaging categories which are the most important for determining severe or large-scale reef damage. Cheal *et al.* (2017) report that three tropical cyclones were the biggest drivers of coral decline on the Great Barrier Reef from 1985 to 2012 as shown by De'ath *et al.* (2012): Cyclone Hamish (2009), Cyclone Yasi (2011) and Cyclone Ita (2014). Hamish and Ita were both intense and slow-moving, and Yasi was intense and large while their spatial footprints intersected with the Great Barrier Reef. Accurately simulating these 'most damaging' tropical cyclones is crucial for estimating future reef damage severity and extent. However, comparing the most reef-damaging tropical cyclones between observed and downscaled historical tracks is complex because reef-damaging tropical cyclones are relatively rare in the observed record. Thus, the observed past represents just one realisation of possible past tropical cyclone tracks while the downscaled tracks provide a large sample of track positions. Caution is therefore recommended when interpreting projected changes to tropical cyclone-induced reef damage at the regional scale in the future in all coral reef regions.

4.6.4 Future research

We focus here on physical damage to coral reefs caused by tropical cyclone-induced waves, and found considerable uncertainty in projections of the reef damage index in the mid-century (2040-2060) and the end of century (2080-2100) based on a commonly-used tropical cyclone downscaling approach (Emanuel *et al.*, 2006). Examinations of other cyclone-related drivers of coral reef damage, such as rainfall and flooding (Van Woesik *et al.*, 1995), should be considered alongside wave damage in future to provide a holistic view of tropical cyclone impacts to coral reefs with climate change. An alternative investigation of explicitly-simulated tropical cyclones in climate models is also recommended as recent studies have shown that such projections are sensitive to the approach used to simulate tropical cyclones (i.e. explicitly-simulated vs. downscaled) in addition to the downscaling method applied (Jing *et al.*, 2021). Further, temporal clustering can impact coral reef degradation as successive tropical cyclone events mean that tropical cyclones following a very damaging first strike may cause relatively little further damage compared to a random regime where corals have had time to recover in between strikes (Mumby *et al.*, 2011; Wolff *et al.*, 2016). However, clustered tropical cyclones may also destabilise the substrate preventing the survival of coral larval recruits and inhibiting recovery (Ceccarelli *et al.*, 2020).

Tropical cyclones interact with other anthropogenic stressors exacerbating (i.e. ocean acidification) or reducing coral reef damage. Tropical cyclones generate a cooling wake through mixing of cooler deeper waters and enhanced surface fluxes which can provide respite to coral reefs experiencing thermal stress-induced coral bleaching (Carrigan and Puotinen, 2014). Both the intensity and spatial extent of the cool wake are maximized for tropical cyclones that are both intense and slow-moving, assuming favourable ocean conditions (Mei and Pasquero, 2013). Coral reef damage risk is also dependent on the coral species present, and the depth and exposure of a site (Harmelin-Vivien, 1994; Blackwood *et al.*, 2011). We set thresholds for damaging track positions here that are assumed to have the potential to cause coral reef damage to vulnerable colonies that are present, recognising that coral reef damage is likely to be patchy at local scales within broadly defined risk zones (Puotinen *et al.*, 2016).

ENSO is known to impact tropical cyclone frequency, genesis, track, intensity and duration in the Southern Hemisphere causing changes in tropical cyclone activity in different parts of the region during different phases (Lin *et al.*, 2021). For example, tropical cyclone activity in the Australia region is enhanced during La Niña years (Ramsay *et al.*, 2012). Changes to ENSO patterns under future climate change are therefore likely to affect reef-damaging tropical cyclone characteristics. However, uncertainty in how ENSO will change with climate change limits projections of the influence of ENSO on tropical cyclones in the future.

Incorporating additional factors affecting coral reef damage risk from tropical cyclones such as rainfall, temporal patterns of tropical cyclones, interacting stressors, local-scale ecological data and improved estimates of natural climate variability into future research will contribute to a holistic picture of the future tropical cyclone threat to coral reefs.

4.7 Acknowledgements

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development of software infrastructure in partnership with the Global Organization for Earth System Science Portals.

4.8 Open Research

The observed tropical cyclone tracks for the period 1985-2020 used in this analysis are publicly available online from the International Best Track Archive for Climate Stewardship (IBTrACS) at: https://www.ncei.noaa.gov/products/international-best-track-archive?name=ib-v4-access. The downscaled historical (1985-2005) and RCP8.5 mid-century (2040-2060) and end of the century (2080-2100) tropical cyclone tracks were provided by Kerry Emanuel. The tracks are to be used for non-profit research only and so are not openly available but they can be requested for research purposes from K. Emanuel (emanuel@mit.edu). Researchers using these tracks are asked to sign a data agreement stating that the tracks will not be redistributed to ensure that the data is used only for non-profit research.

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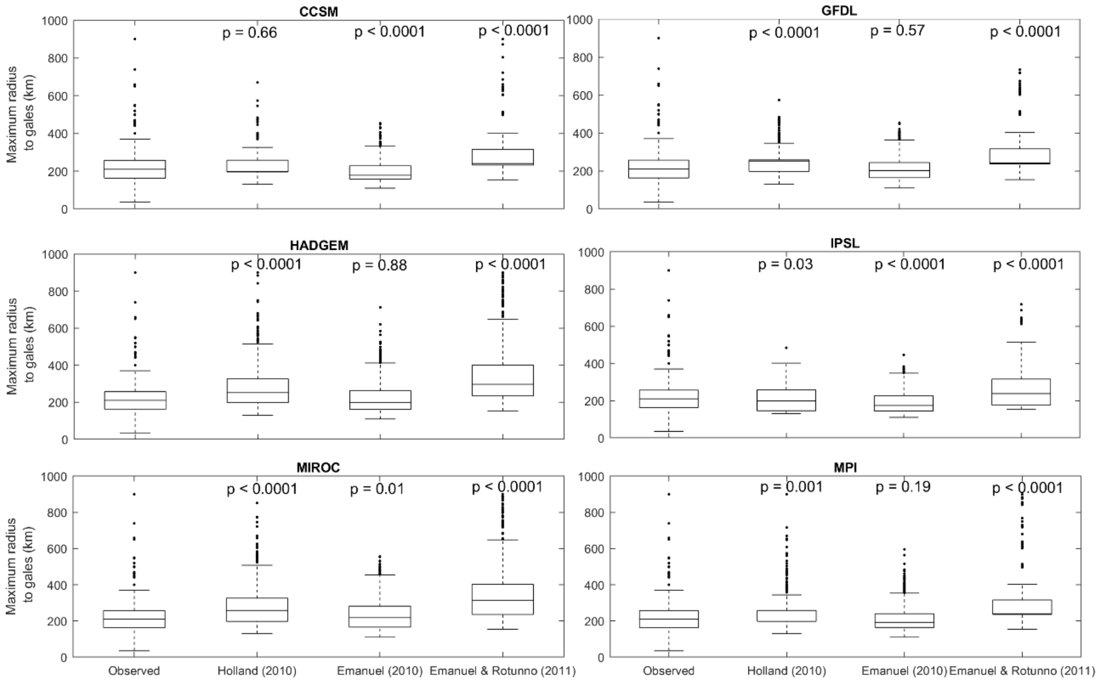
4.10 Supplementary Material

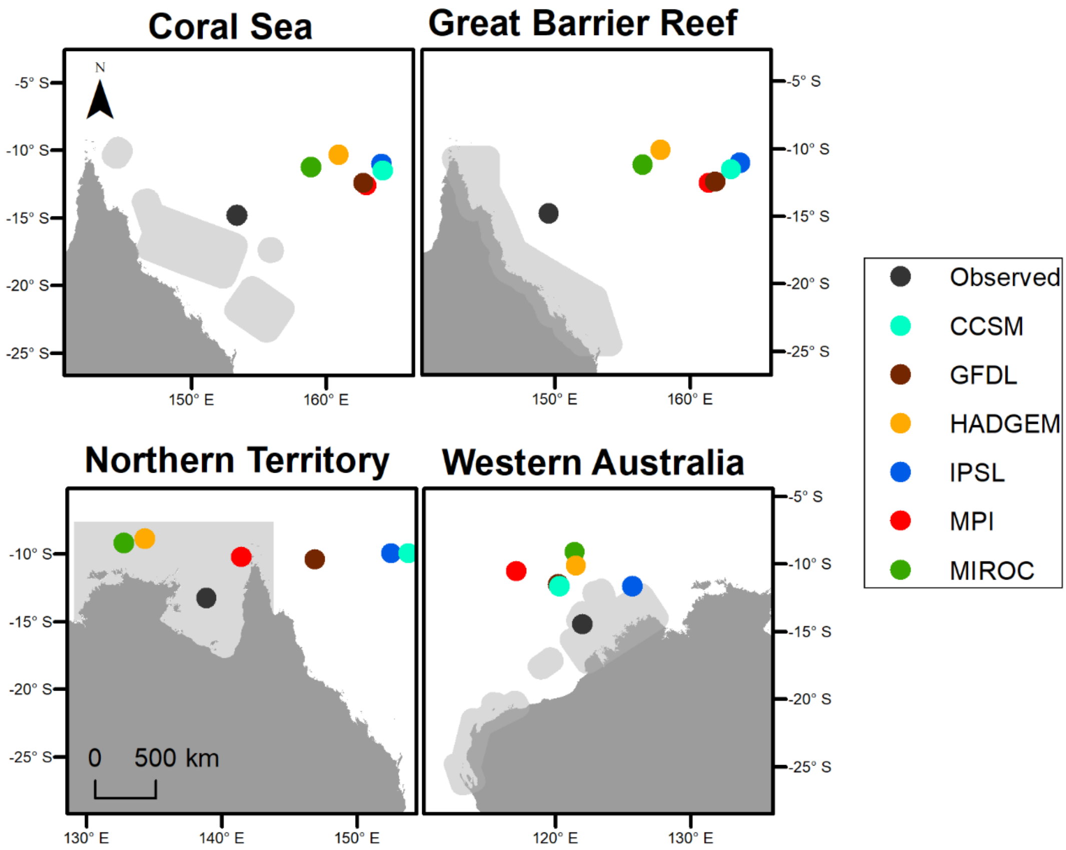
4.10.1 Introduction

Supporting information includes additional figures comparing the downscaled historical tropical cyclone characteristics to observed including the maximum radius to gales (Supplementary Figure 4.1), median cyclogenesis positions (Supplementary Figure 4.2), reef-damaging tropical cyclone characteristics (Supplementary Figures 4.3-4.6) and track positions in the most damaging categories (Supplementary Figure 4.7). Supplementary Figure 4.8 shows the projected change in hemisphere-wide reef-damaging characteristics and Supplementary Figures 4.9 and 4.10 show projected changes in cyclogenesis and track positions. Supplementary Table 4.1 shows the comparison between the reef damage index and the observed coral reef damage zone. Supplementary Table 4.2 lists the CMIP5 models used in the study. Supplementary Tables 4.3-4.5 display the results of statistical analyses detailed in section 4.4.3 of the main text including comparisons between observed and simulated past spatial distribution of tracks (Supplementary Table 4.3), reef-damaging characteristics (Supplementary Table 4.4) and track positions in the most damaging categories (Supplementary Table 4.5).

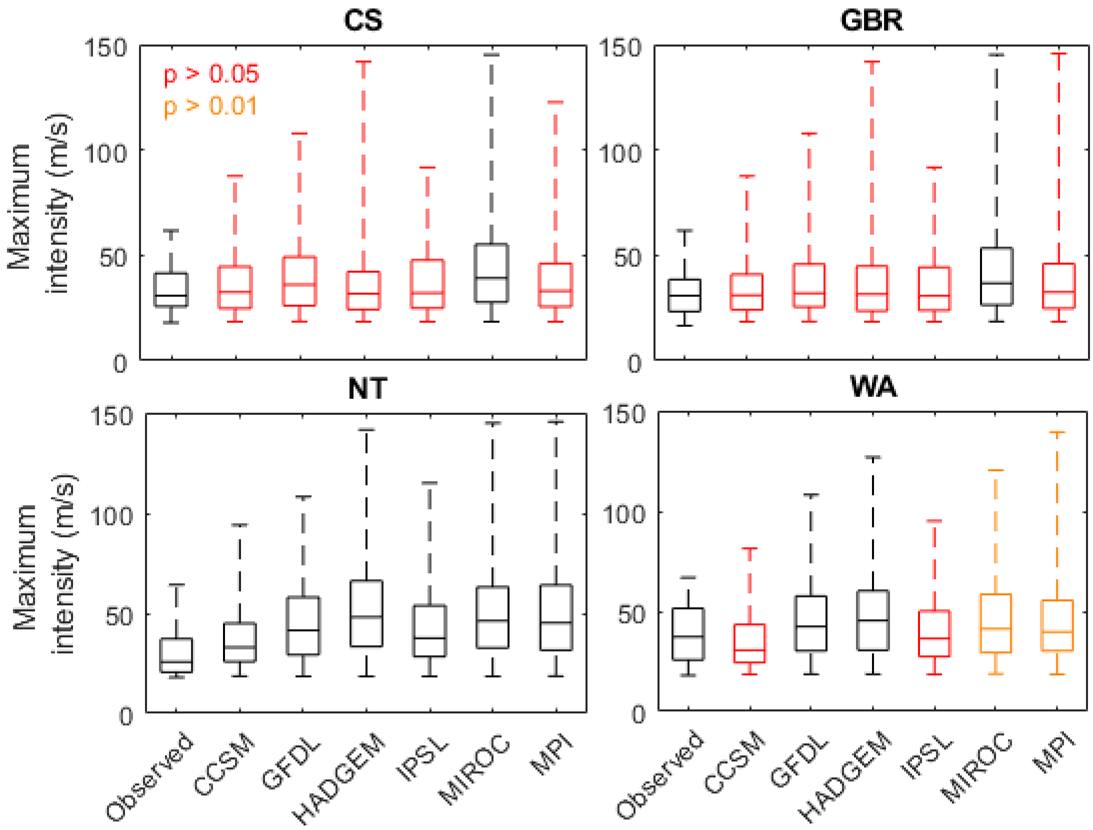
4.10.2 Supplementary Figures



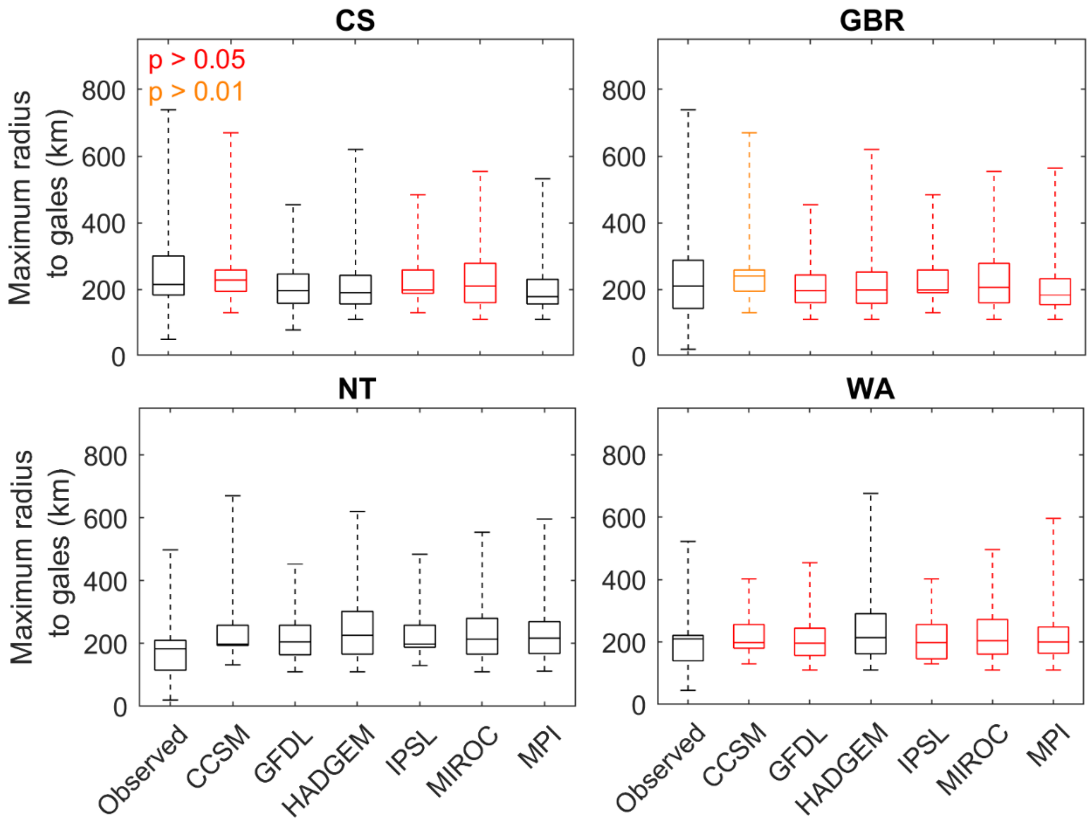
Supplementary Figure 4.1: Maximum radius to gales of the full tropical cyclone track for all observed tracks (n = 381) and downscaled historical tracks (n = 3000) calculated by constructing radial wind profiles using three different methods: Holland (2010), Emanuel (2010) and Emanuel and Rotunno (2011). Each of the distributions of maximum radius to gales calculated using the three different methods are compared to the observed distribution using two-sided Mann-Whitney-Wilcoxon.



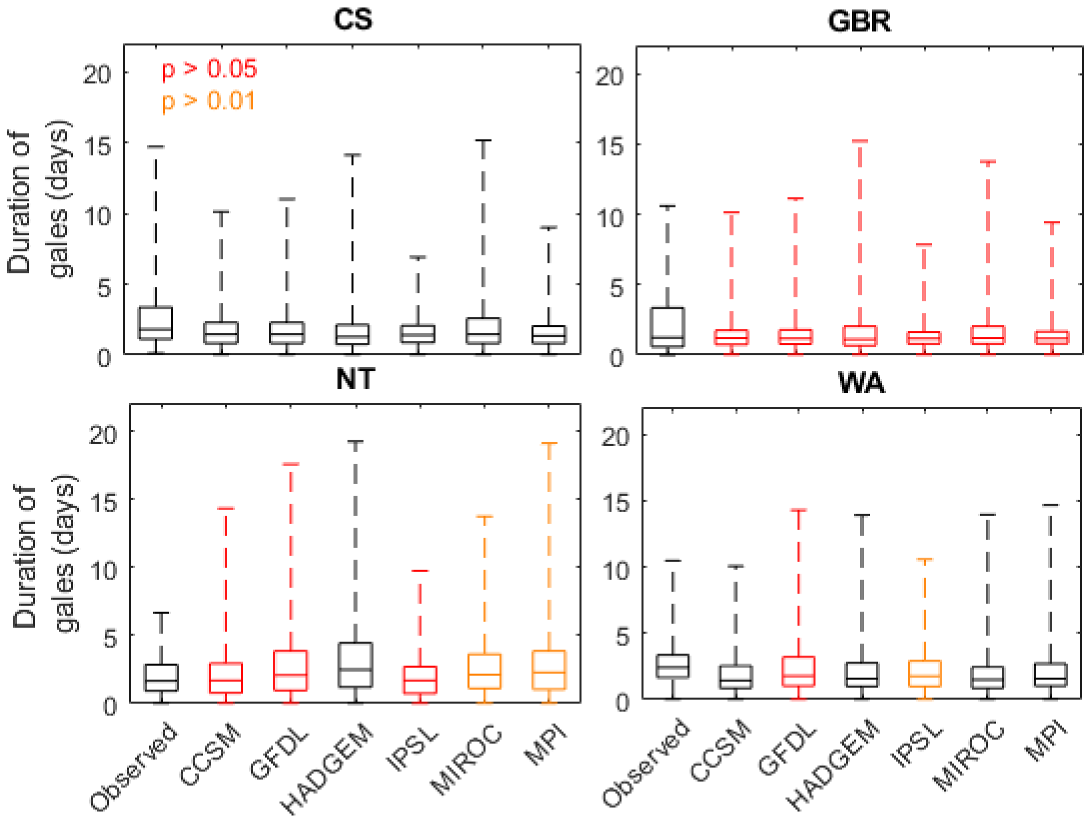
Supplementary Figure 4.2: Median tropical cyclone genesis positions of observed (1985-2005) and downscaled past (1985-2005) tropical cyclones impacting each of the four coral reef regions.



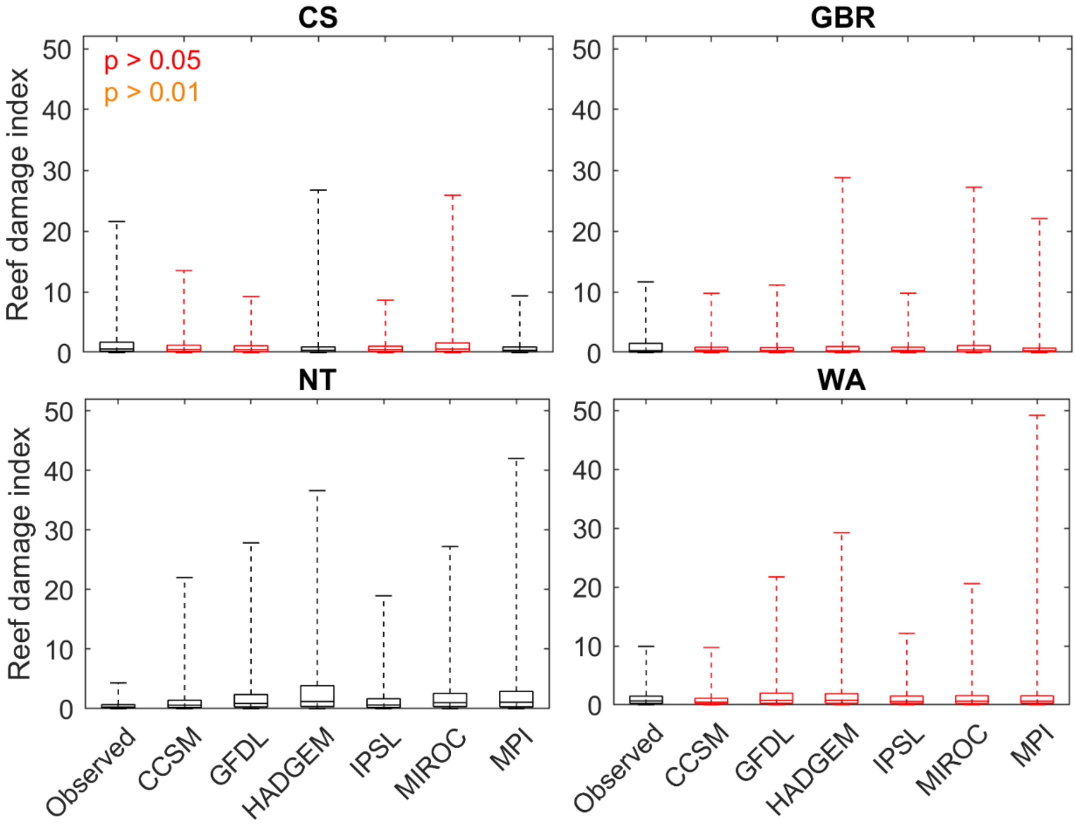
Supplementary Figure 4.3: Observed (1985-2005) and downscaled past (1985-2005) maximum intensity of tropical cyclone tracks intersecting four coral reef regions. The downscaled past maximum intensity is compared to the observed maximum intensity for each region and model separately using a two-sided Mann-Whitney-Wilcoxon test. P values greater than 0.05 (red) and 0.01 (yellow) indicate the models where the downscaled maximum intensity is not significantly different to observed.



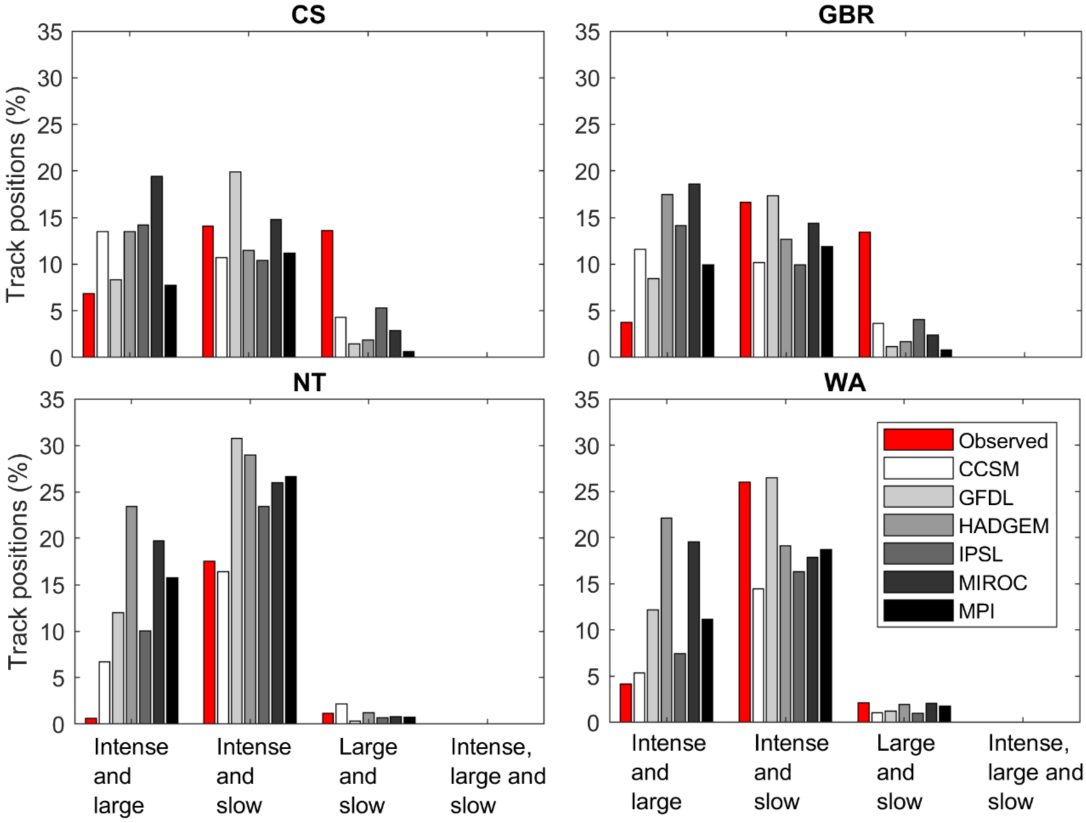
Supplementary Figure 4.4: Observed (1985-2020) and downscaled past (1985-2005) maximum radius to gales of tropical cyclone tracks intersecting four coral reef regions. The downscaled past maximum radius to gales is compared to the observed maximum radius to gales for each region and model separately using a two-sided Mann-Whitney-Wilcoxon test. P values greater than 0.05 (red) and 0.01 (yellow) indicate the models where the downscaled maximum radius to gales is not significantly different to observed.



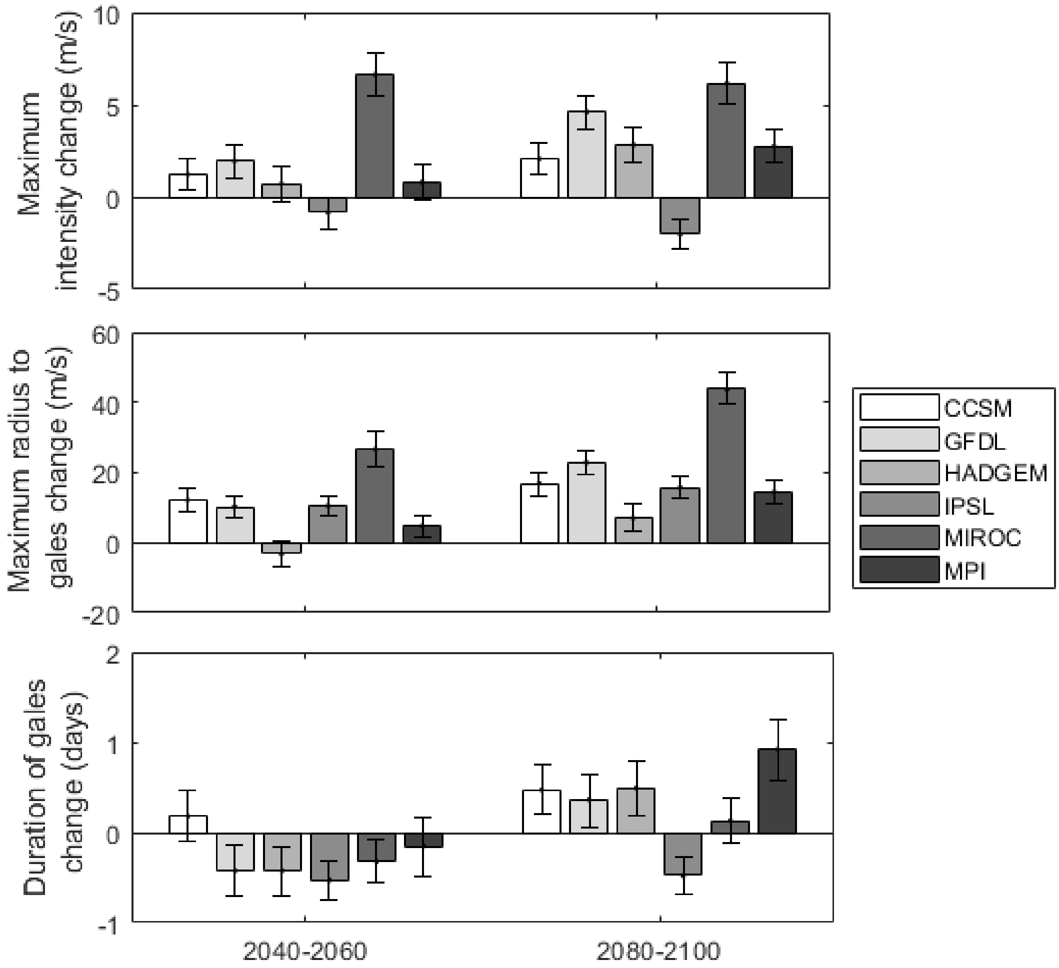
Supplementary Figure 4.5: Observed (1985-2005) and downscaled past (1985-2005) duration of gales of tropical cyclone tracks intersecting four coral reef regions. The downscaled past duration of gales is compared to the observed duration of gales for each region and model separately using a two-sided Mann-Whitney-Wilcoxon test. P values greater than 0.05 (red) and 0.01 (yellow) indicate the models where the downscaled duration of gales is not significantly different to observed.



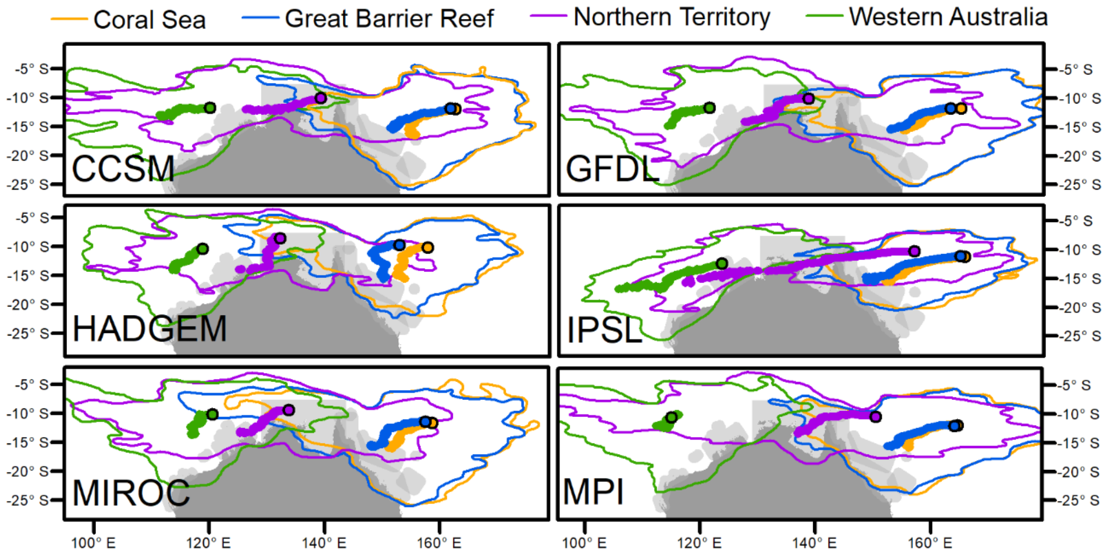
Supplementary Figure 4.6: Observed (1985-2020) and downscaled past (1985-2005) reef damage index of tropical cyclone tracks intersecting four coral reef regions. The downscaled past reef damage index is compared to the observed reef damage index for each region and model separately using a two-sided Mann-Whitney-Wilcoxon test. P values greater than 0.05 (red) and 0.01 (yellow) indicate the models where the downscaled reef damage index is not significantly different to observed.



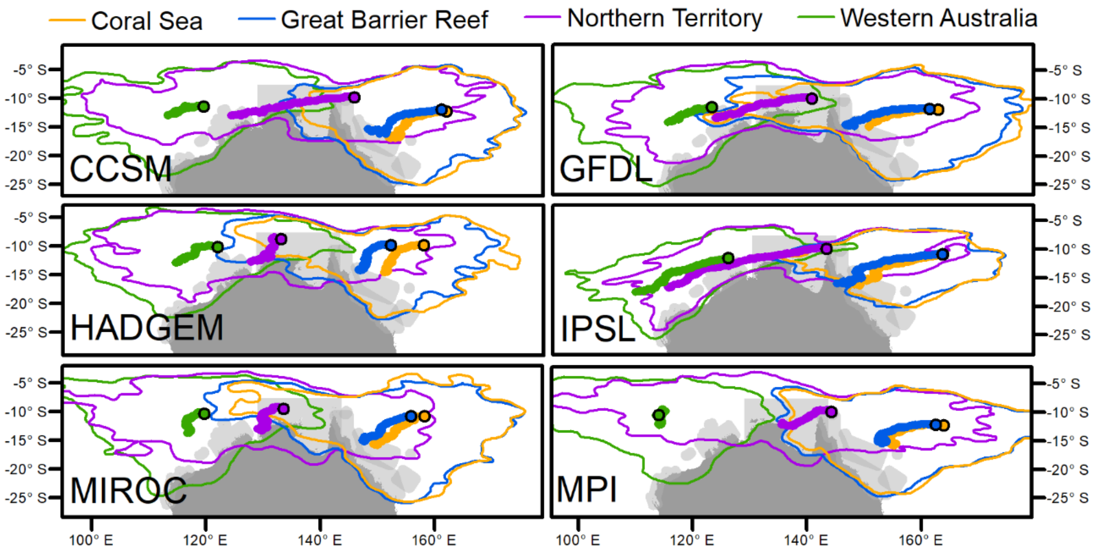
Supplementary Figure 4.7: Percentage of observed (1985-2020) and downscaled past (1985-2005) track positions in the most damaging categories: Intense (> 33 m/s), large (> 275 km) and slow (< 5 m/s), of all the track positions whose spatial footprints intersect with the region.



Supplementary Figure 4.8: Mean projected change from the simulated past (1985-2005) to simulated mid-century (2040-2060) and simulated end of century (2080-2100) in reef-damaging tropical cyclone metrics of 10,000 replicates for the Southern Hemisphere ocean basins. The error bars show the 95% confidence intervals.



Supplementary Figure 4.9: Kernel density estimates (KDE) of downscaled mid-century (2040-2060) tropical cyclone track positions for tropical cyclones whose spatial footprints intersect with each of four coral reef regions. The median hourly track positions for the first 10 days are shown by the circles and the 75% KDE contours are shown by the lines. The median genesis positions are shown by the black outlined circles.



Supplementary Figure 4.10: Kernel density estimates (KDE) of downscaled end of century (2080-2100) tropical cyclone track positions for tropical cyclones whose spatial footprints intersect with each of four coral reef regions. The median hourly track positions for the first 10 days are shown by the circles and the 75% KDE contours are shown by the lines. The median genesis positions are shown by the black outlined circles.

4.10.3 Supplementary Tables

Supplementary Table 4.1: Comparison of the reef damage index (RDI) to records of damage from field data and the percentage of the Great Barrier Reef World Heritage Area (GBRWHA) in the tropical cyclone damage zone predicted using 4MW (the latter excludes cyclone Lua).

Cyclone name	Region	Season	RDI	% of GBRWHA in predicted damage zone using 4MW[a]	Field data establishing damage severity & extent	Reference
Lua	WA	2012	46.50	NA	Major coral loss recorded at two clusters of field sites up to 800 km away from the cyclone track.	Puotinen et al. (2020)
Joy	GBR	1990	31.82	27.31	Severe damage patchily distributed	Puotinen et al. (2016)
Debbie	GBR	2017	24.17	27.80	400 tonnes of 1-3 metre sized reef displaced	McLeod et al. (2019)
Justin	GBR	1997	16.88	21.15	Limited field surveys document severe damage 100s of km from the track	Puotinen et al. (2016)
Ita[b]	GBR	2014	15.87	5.59	Severe damage rare and close to the track	Castro-Sanguino et al. (2022)
Yasi	GBR	2011	11.67	16.58	15% of GBRWA estimated damaged	Beeden et al. (2015)
Ivor	GBR	1990	10.89	12.30	Severe damage patchily distributed	Done (1992)
Ingrid	GBR	2005	4.98	8.50	Severe damage patchily distributed	Fabricius et al. (2008)
Larry	GBR	2006	3.78	7.02	Severe damage very rare and close to the track	Puotinen et al. (2016)

[a] 4MW is a model developed by Puotinen et al. (2016) to predict where rough sea states (significant wave height ≥ 4 m) that may damage coral reefs are possible.

[b] Ita showed the least match between RDI and the percentage of the predicted damage zone, where field data show more damage than predicted, probably because important parameters (e.g. near-bed orbital velocity) were not modelled in 4MW (Castro-Sanguino *et al.*, 2022). Otherwise, both RDI and the percentage area in the damage zone generally decline in the same order, with slight differences between Joy and Debbie.

Supplementary Table 4.2: CMIP5 models used to generate the past (historical) and future (high-emissions RCP8.5 scenario) downscaled tropical cyclone tracks.

Institution	Model
National Center for Atmospheric Research (NCAR)	CCSM4
NOAA Geophysical Fluid Dynamics Laboratory (GFDL)	GFDL-CM3
Met Office Hadley Centre (MOHC)	HADGEM2-ES
Institut Pierre-Simon Laplace (IPSL)	IPSL-CM5A-LR
Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies (NIES), and Japan Agency for Marine-Earth Science and Technology (JAMEST)	MIROC5
Max Planck Institute for Meteorology (MPI-M)	MPI-ESM-MR

Supplementary Table 4.3: Results of chi squared test to infer whether the number of tropical cyclones intersecting each of the reefs within the coral reef regions is significantly different between observed (1985-2005) and simulated past (1985-2005).

Model	Region		
	CS	GBR	WA
CCSM	**χ^2 = 6.25**[a] **p = 0.181**	**χ^2 = 1.43** **p = 0.699**	**χ^2 = 12.12** **p = 0.097**
GFDL	**χ^2 = 9.67** **p = 0.046**	**χ^2 = 1.39** **p = 0.708**	**χ^2 = 8.70** **p = 0.275**
HADGEM	**χ^2 = 13.05** **p = 0.011**	**χ^2 = 3.88** **p = 0.275**	**χ^2 = 16.67** **p = 0.020**
IPSL	χ^2 = 13.78 p = 0.008	**χ^2 = 6.75** **p = 0.080**	**χ^2 = 17.57** **p = 0.014**
MIROC	**χ^2 = 12.65** **p = 0.013**	**χ^2 = 3.06** **p = 0.382**	χ^2 =22.80 p = 0.002
MPI	**χ^2 = 10.83** **p = 0.029**	**χ^2 = 2.11** **p = 0.549**	**χ^2 = 16.20** **p = 0.023**

[a] Bold values indicate where $p > 0.01$ indicating that the simulated past is not significantly different from observed at the 0.01 significance level.

Supplementary Table 4.4: Results of two-sided Mann-Whitney-Wilcoxon test to test the null hypothesis that observed and downscaled metrics for tropical cyclones intersecting each region are from continuous distributions with equal medians.

Metric	Region	Observed	CCSM	GFDL	HADGEM	IPSL	MIROC	MPI
Maximum intensity (m/s)	CS	M = 30.87 S = 52	**M = 32.52** **U = 30248** **S = 1177** **p = 0.888**[a,b]	**M = 36.03** **U = 21142** **S = 941** **p = 0.099**	**M = 31.84** **U = 19689** **S = 749** **p = 0.894**	**M = 32.22** **U = 18869** **S = 760** **p = 0.586**	M = 39.11 U = 18461 S = 955 p = 0.002	**M = 33.16** **U = 29859** **S = 1226** **p = 0.439**
	GBR	M = 30.87 S = 42	**M = 31.10** **U = 17628** **S = 903** **p = 0.308**	**M = 32.04** **U = 14268** **S = 797** **p = 0.064**	**M = 31.62** **U = 11230** **S = 600** **p = 0.156**	**M = 30.74** **U = 11639** **S = 604** **p = 0.256**	M = 36.81 U = 12898 S = 856 p = 0.001	**M = 32.48** **U = 19351** **S = 1085** **p = 0.058**
	NT	M = 25.72 S = 43	M = 33.05 U = 7798 S = 559 p = 0.000	M = 41.48 U = 5262 S = 520 p = 0.000	M = 48.15 U = 5125 S = 628 p = 0.000	M = 37.66 U = 6214 S = 541 p = 0.000	M = 46.26 U = 6669 S = 798 p = 0.000	M = 45.30 U = 6780 S = 779 p = 0.000
	WA	M = 37.30 S = 62	**M = 30.66** **U = 16580** **S = 465** **p = 0.055**	M = 42.32 U = 16308 S = 660 p = 0.008	M = 45.32 U = 16239 S = 700 p = 0.001	**M = 36.33** **U = 17988** **S = 596** **p = 0.732**	**M = 41.26** **U = 17528** **S = 693** **p = 0.016**	**M = 39.77** **U = 14626** **S = 561** **p = 0.040**
Maximum radius to gales (km)	CS	M = 215	**M = 228** **U = 58478** **p = 0.353**	M = 196 U = 54309 p = 0.000	M = 190 U = 43720 p = 0.000	**M = 198** **U = 39381** **p = 0.103**	**M = 210** **U = 50171** **p = 0.059**	M = 178 U = 75233 p = 0.000
	GBR	M = 210	**M = 240** **U = 29703** **p = 0.033**	**M = 196** **U = 31614** **p = 0.661**	**M = 198** **U = 22967** **p = 0.934**	**M = 198** **U = 20784** **p = 0.128**	**M = 206** **U = 30984** **p = 0.384**	**M = 184** **U = 45553** **p = 0.184**
	NT	M = 183	M = 198 U = 14127 p = 0.000	M = 205 U = 14268 p = 0.000	M = 226 U = 15176 p = 0.000	M = 198 U = 20952 p = 0.000	M = 214 U = 20952 p = 0.000	M = 217 U = 19731 p = 0.000
	WA	M = 210	**M = 198** **U = 27248** **p = 0.863**	**M = 196** **U = 36347** **p = 0.385**	M = 214 U = 33529 p = 0.003	**M = 198** **U = 36272** **p = 0.397**	**M = 204** **U = 35780** **p = 0.058**	**M = 200** **U = 30257** **p = 0.234**
Duration of gales (days)	CS	M = 1.81	M = 1.46 U = 38071 p = 0.003	M = 1.46 U = 30301 p = 0.004	M = 1.29 U = 27533 p = 0.000	M = 1.42 U = 25441 p = 0.001	M = 1.46 U = 30151 p = 0.009	M = 1.35 U = 41463 p = 0.000
	GBR	M = 1.25	**M = 1.21** **U = 21065** **p = 0.346**	**M = 1.17** **U = 18567** **p = 0.356**	**M = 1.13** **U = 25369** **p = 0.313**	**M = 1.17** **U = 14422** **p = 0.226**	**M = 1.21** **U = 19187** **p = 0.638**	**M = 1.17** **U = 25306** **p = 0.345**
	NT	M = 1.67	**M = 1.71** **U = 11741** **p = 0.801**	**M = 2.08** **U = 9323** **p = 0.070**	M = 2.50 U = 14088 p = 0.002	**M = 1.71** **U = 11621** **p = 0.993**	**M = 2.13** **U = 13801** **p = 0.031**	**M = 2.29** **U = 13254** **p = 0.021**
	WA	M = 2.44	M = 1.46 U = 18470 p = 0.000	**M = 1.79** **U = 23149** **p = 0.087**	M = 1.58 U = 26532 p = 0.004	**M = 1.77** **U = 21938** **p = 0.015**	M = 1.50 U = 27772 p = 0.001	M = 1.58 U = 21012 p = 0.007
Reef damage index	CS	M = 0.62	**M = 0.54** **U = 59780** **p = 0.193**	**M = 0.51** **U = 49055** **p = 0.081**	M = 0.39 U = 41805 p = 0.003	**M = 0.52** **U = 39584** **p = 0.087**	**M = 0.60** **U = 46002** **p = 0.690**	M = 0.41 U = 68381 p = 0.003
	GBR	M = 0.34	**M = 0.44** **U = 32943** **p = 0.445**	**M = 0.38** **U = 30166** **p = 0.807**	**M = 0.34** **U = 22779** **p = 0.843**	**M = 0.39** **U = 22507** **p = 0.646**	**M = 0.48** **U = 29496** **p = 0.127**	**M = 0.34** **U = 41749** **p = 0.994**
	NT	M = 0.26	M = 0.58 U = 16241 p = 0.000	M = 0.87 U = 13093 p = 0.000	M = 1.21 U = 13176 p = 0.000	M = 0.60 U = 15342 p = 0.000	M = 1.00 U = 17891 p = 0.000	M = 1.08 U = 17738 p = 0.000
	WA	M = 0.67	**M = 0.46** **U = 30055** **p = 0.057**	**M = 0.78** **U = 34708** **p = 0.109**	**M = 0.79** **U = 36305** **p = 0.068**	**M = 0.58** **U = 34820** **p = 0.901**	**M = 0.63** **U = 39567** **p = 0.788**	**M = 0.63** **U = 31175** **p = 0.477**

[a]Bold values indicate where the test hypothesis cannot be rejected (p > 0.01).

[b]M is the median, U is the U test statistic and S is the sample size.

Supplementary Table 4.5: Results of chi squared test to infer whether the number of track positions in each of the most damaging categories, and those not in the most damaging categories, is significantly different between observed (1985-2020) and simulated past (1985-2005).

Model	Region			
	CS	GBR	NT	WA
CCSM	$\chi^2 = 1814$ $p < 0.0001$	$\chi^2 = 1046$ $p < 0.0001$	$\chi^2 = 235$ $p < 0.0001$	$\chi^2 = 540$ $p < 0.0001$
GFDL	$\chi^2 = 2784$ $p < 0.0001$	$\chi^2 = 2069$ $p < 0.0001$	$\chi^2 = 976$ $p < 0.0001$	$\chi^2 = 429$ $p < 0.0001$
HADGEM	$\chi^2 = 2111$ $p < 0.0001$	$\chi^2 = 1752$ $p < 0.0001$	$\chi^2 = 1814$ $p < 0.0001$	$\chi^2 = 1208$ $p < 0.0001$
IPSL	$\chi^2 = 821$ $p < 0.0001$	$\chi^2 = 907$ $p < 0.0001$	$\chi^2 = 493$ $p < 0.0001$	$\chi^2 = 485$ $p < 0.0001$
MIROC	$\chi^2 = 2004$ $p < 0.0001$	$\chi^2 = 1621$ $p < 0.0001$	$\chi^2 = 1254$ $p < 0.0001$	$\chi^2 = 1032$ $p < 0.0001$
MPI	$\chi^2 = 4518$ $p < 0.0001$	$\chi^2 = 3018$ $p < 0.0001$	$\chi^2 = 995$ $p < 0.0001$	$\chi^2 = 431$ $p < 0.0001$

Chapter 5 - The influence of spatial resolution and source of climate data on marine spatial conservation priorities

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5.0 Abstract

Ocean warming threatens coral reef ecosystems, but exposure to thermal stress can vary on small spatial scales. This spatial heterogeneity can inform how priority sites are selected for management actions. Observed thermal stress datasets from a variety of sources range from 1 to 100 km in resolution, however the influence of climate data source and resolution on spatial planning priorities is unclear. Typical conservation objectives to address climate change include protecting refugia (Climate Refugia), protecting a range of thermal regimes (Multiple Regimes) or protecting reefs that experienced high past temperature variability (Variable Reefs). Using these objectives, we assessed how conservation priorities varied when evaluated with four climate datasets at two spatial resolutions, 1 km and 5 km, derived from two source datasets, CoralTemp (Coral Reef Watch) and CCI (European Space Agency). We found that both the data source and resolution altered spatial planning solutions. The Climate Refugia objective had the greatest difference, and the Variable Reefs objective the greatest overlap, between solutions. Along with carefully specifying conservation objectives, our analysis shows that selecting an appropriate climate dataset requires detailed

consideration. In future, this decision should ideally be supported by quantitative validation with local observations of ecological responses to climate stress.

5.1 Introduction

Ocean warming due to climate change is causing increasing frequency and severity of coral bleaching events (Heron *et al.*, 2016; Hughes *et al.*, 2018). Even limiting global warming to the Paris Agreement's ambitious target of 1.5°C is projected to render 90% of the global coral reef area exposed to an intolerable frequency of thermal stress (Dixon *et al.*, 2022). Coral reefs are economically and ecologically valuable ecosystems (Costanza *et al.*, 2014), but their high sensitivity to thermal stress threatens their future and that of coastal populations and species that rely on them (Heron *et al.*, 2017; Hoegh-Guldberg *et al.*, 2018; Dixon *et al.*, 2021). While local management of thermal stress is not possible, mitigation of local anthropogenic stressors that interact synergistically with climate stressors, such as pollution, may mitigate climate change impacts on ecosystems (Ghedini *et al.*, 2013). Spatial heterogeneity in warming patterns has led to the inclusion of thermal stress in marine spatial planning for climate-relevant coral reef management (Mumby *et al.*, 2011; Mcleod *et al.*, 2012; Levy and Ban, 2013; Makino *et al.*, 2014; Beger *et al.*, 2015; Magris *et al.*, 2015; García Molinos *et al.*, 2017; Harris *et al.*, 2017; Asaad *et al.*, 2018; Beyer *et al.*, 2018; Chollett *et al.*, 2022). Marine spatial planning involves the allocation of three-dimensional marine space for specific uses that satisfy ecological, economic and social objectives (Douvere, 2008). Climate-relevant spatial planning studies have used thermal stress datasets from various sources ranging from 4 to 100 km spatial resolution (Magris *et al.*, 2015; Harris *et al.*, 2017; Asaad *et al.*, 2018), but thermal stress can vary on scales smaller than 4 km (Safaie *et al.*, 2018). In 2022, a historical and projected thermal stress dataset was developed at 1 km spatial resolution (Dixon *et al.*, 2022), but whether higher resolution climate data adds value to spatial planning prioritisations is unclear.

Reef-building corals depend on the mutualistic relationship between microscopic dinoflagellate algae and coral hosts (Heron *et al.*, 2016; Swain *et al.*, 2016). Thermal stress disrupts this partnership rendering corals energetically compromised, more susceptible to disease and less able to compete with other benthic colonisers (Anthony *et al.*, 2015; Hughes *et al.*, 2018; Safaie *et al.*, 2018). Here, thermal stress refers to acute stress due to accumulated exposure to high temperatures over a specified time period (Mumby *et al.*, 2011). Thermal stress varies on local scales as oceanographic features such as upwelling, strong currents and tropical cyclone-associated cold wakes can lower ocean temperatures and alleviate thermal stress on coral reefs (Chollett *et al.*, 2010; Chollett and Mumby, 2013; Carrigan and Puotinen, 2014; Perdanahardja and Lionata, 2017; Camp *et al.*, 2018).

Remotely sensed sea surface temperature (SST) can indicate the thermal conditions that coral reefs are exposed to (Levy and Ban, 2013; Makino *et al.*, 2014; Magris *et al.*, 2015; Heron *et al.*, 2016; van Hooidonk *et al.*, 2016, 2020; Beyer *et al.*, 2018). The National Oceanic and Atmospheric Administration (NOAA) Coral Reef Watch (CRW) 5 km resolution products, such as the CoralTemp daily SST dataset, have tracked coral bleaching probability and extent globally since 2014 (Liu *et al.*, 2014). In 2016, a similar SST dataset was released: the European Space Agency Climate Change Initiative (CCI) daily 5 km product (Merchant *et al.*, 2016, 2019). Both CCI and CoralTemp compare well with in situ temperature measurements at the depth of shallow water (3-6 m) coral reefs in Florida and Belize, but the estimates of thermal stress differ because the products exhibit diverging trends (Rayner *et al.*, 2019). Daily SST data is available for CCI and CoralTemp from 1985 to 2016 and 1985 to present, respectively. The coarser resolution CCI and CoralTemp data were downscaled to a 1 km SST time series from 1985 to 2019 using the Multi-scale Ultra-high Resolution (MUR) daily 1 km SST analysis dataset (2002 to present; JPL MUR MEaSUREs Project, 2015) in Dixon *et al.* (2022). This 1 km resolution SST time series was then used to increase the spatial resolution of coarse (25-100 km) climate model projections creating a 1 km resolution SST dataset for the global coral area (Dixon *et al.*, 2022). Given the availability of these SST datasets that differ in resolution and trend, it is unclear how the choice of data influences which reef areas will be prioritised for management when climate change objectives are applied.

Spatial heterogeneity in climate change impacts is a crucial factor when selecting areas for management, but fundamentally different conservation objectives can underpin such decisions. These objectives often prioritise reefs with the lowest exposure to future climate change (Levy and Ban, 2013; Harris *et al.*, 2017; Asaad *et al.*, 2018; Beyer *et al.*, 2018). Other studies prioritise a range of reefs with varying thermal regimes to facilitate species range shifts with increasing SST (Makino *et al.*, 2014) or account for varying thermal tolerance between reefs subjected to past or future thermal stress (Mumby *et al.*, 2011; Magris *et al.*, 2015). Adaptation of corals to increasing thermal stress is considered a crucial component of priority area selection (Donner and Carilli, 2019), but ecological or genomic spatial data is generally not available (Mumby *et al.*, 2011; Mcleod *et al.*, 2012) nor is the estimation of adaptive potential reliable (Riginos and Beger, 2022). Therefore, coral reef conservation prioritisations often apply historical SST variability as a proxy for adaptation/acclimation (Boylan and Kleypas, 2008; Chollett *et al.*, 2014). In addition, prioritisations rarely consider climate-related conservation objectives only – other objectives such as the protection of particular species and habitats, the representation of reef biodiversity, the maximisation of larval connectivity between reefs and minimising socio-economic burdens are also important (Beger *et al.*, 2015; Asaad *et al.*, 2018). As different conservation objectives change where priority areas are selected, it is rare to achieve win-win areas where multiple objectives are met (Boon and Beger, 2016; Hargreaves-Allen *et al.*, 2017; Chollett *et al.*, 2022). Thus, the differences between different spatial resolutions and source datasets are also likely influenced by conservation objectives.

Here, we compare the priority areas selected in marine spatial planning between 1 km and 5 km resolution thermal stress datasets derived from two different source datasets (CCI and CoralTemp) for three different climate-relevant conservation objectives (1. Prioritising thermal refugia with low thermal stress (Climate refugia), 2. Prioritising a range of thermal exposures (Multiple Regimes) and 3. Prioritising high SST variability (Variable Reefs)), using Southeast Sulawesi province in Indonesia as a case study. The priority areas selected do not represent implementable conservation plans, as we omit important factors in decision making here, such as larval connectivity, spatial aggregation, reef health, existing protected areas and stakeholder input. Instead, this analysis will inform the selection of climate datasets used in spatial planning, which will be crucial for the conservation of vulnerable marine ecosystems such as coral reefs.

5.2 Methods

Southeast Sulawesi is located in the centre of the Coral Triangle, the most biodiverse coral reef region in the world and one of the global priority areas for climate-smart reef conservation (Beyer *et al.*, 2018). The region experiences widespread anthropogenic pressures from overfishing and destructive fishing, sedimentation from land-runoff and coral mortality due to thermal stress (Burke *et al.*, 2012). However, both national-level and local-level marine management is being implemented in the area (Wiadnya *et al.*, 2011).

We used the spatial conservation planning software Marxan to compare priority areas selected for different conservation objectives. Marxan is a decision support tool that implements quantifiable conservation objectives to select areas that meet targets of conservation features (e.g. area of habitats or species ranges), while minimising the cost of the reserve system (Ball *et al.*, 2009). We divided the Southeast Sulawesi study area into 11,047 1 km^2 planning units (Figure 5.1a). Each planning unit overlaps with the benthic classes dataset (Figure 5.1b), developed using remote sensing at 3.7 m resolution (Roelfsema *et al.*, 2013; Allen Coral Atlas, 2020), as such the area of habitat varies between planning units. We identified suites of areas for protection based on the area in km^2 of two feature habitats within the planning units: coral/algae and seagrass as proxies for reef biodiversity (Boon and Beger, 2016). Here, biodiversity conservation involved the protection of 20% of the total area of the two desired habitat types as conservation features in Marxan. This value is a commonly used proportion of habitat area target in spatial prioritisation studies and matches the 20% target set by the Coral Triangle Initiative on Coral Reefs, Fisheries and Food Security (Mumby *et al.*, 2011; Makino *et al.*, 2014; White *et al.*, 2014; Beger *et al.*, 2015; Boon and Beger, 2016). Protection of 20% of each habitat type was the baseline prioritisation criteria common to all conservation objectives.

To represent the feasibility of protecting areas, we estimated the anthropogenic pressure on each planning unit using the Gridded Population of the World Version 4 (GPWv4): Population Count, Revision 11 dataset (Center for International Earth Science Information Network (CIESIN) Columbia University, 2018) to assign each planning unit a cost (Figure 5.1c; Ball et al. 2009). The cost describes the effect of conservation management on users of the planning area, for example through restriction of fishing practices. We used the sum of the population within 10 km of the centre of the planning unit as the cost to indicate the number of people that might access the planning unit for fishing. Population-based cost metrics assume that population is correlated with human use of the marine area (i.e. fishing effort; Ban *et al.*, 2009). There is evidence for this at large spatial scales (e.g. provinces) but not at finer scale, where a greater number of people in small rural communities rely on fishing as their main livelihood compared to urban centres (Weeks *et al.*, 2010). However, in the absence of other socioeconomic data such as fishing effort, population data are commonly used in spatial planning (Harris *et al.*, 2014; Makino *et al.*, 2014, 2015; Beger *et al.*, 2015; Boon and Beger, 2016; Cheok *et al.*, 2016; Vercammen *et al.*, 2019). Where the population within 10 km of a planning unit was zero, a minimum cost of 100 people was assigned (Ban *et al.*, 2009). The cost was then scaled between zero and one. Marxan algorithms minimise the cost, therefore avoiding planning units with high interaction between humans and reefs and minimising the effect of conservation on users. Minimising the cost leads to the prioritisation of cheaper planning units (Cheok *et al.*, 2016). To disentangle the influence of cost data relative to climate data, we repeated the analysis using a universal cost of one to examine the difference in Marxan solutions if only the climate dataset and habitat area influence the output. Whether or not an area is currently protected was not considered in the analysis, as the goal was to compare the priority areas selected when using different climate datasets rather than to select priority areas for conservation decision making.

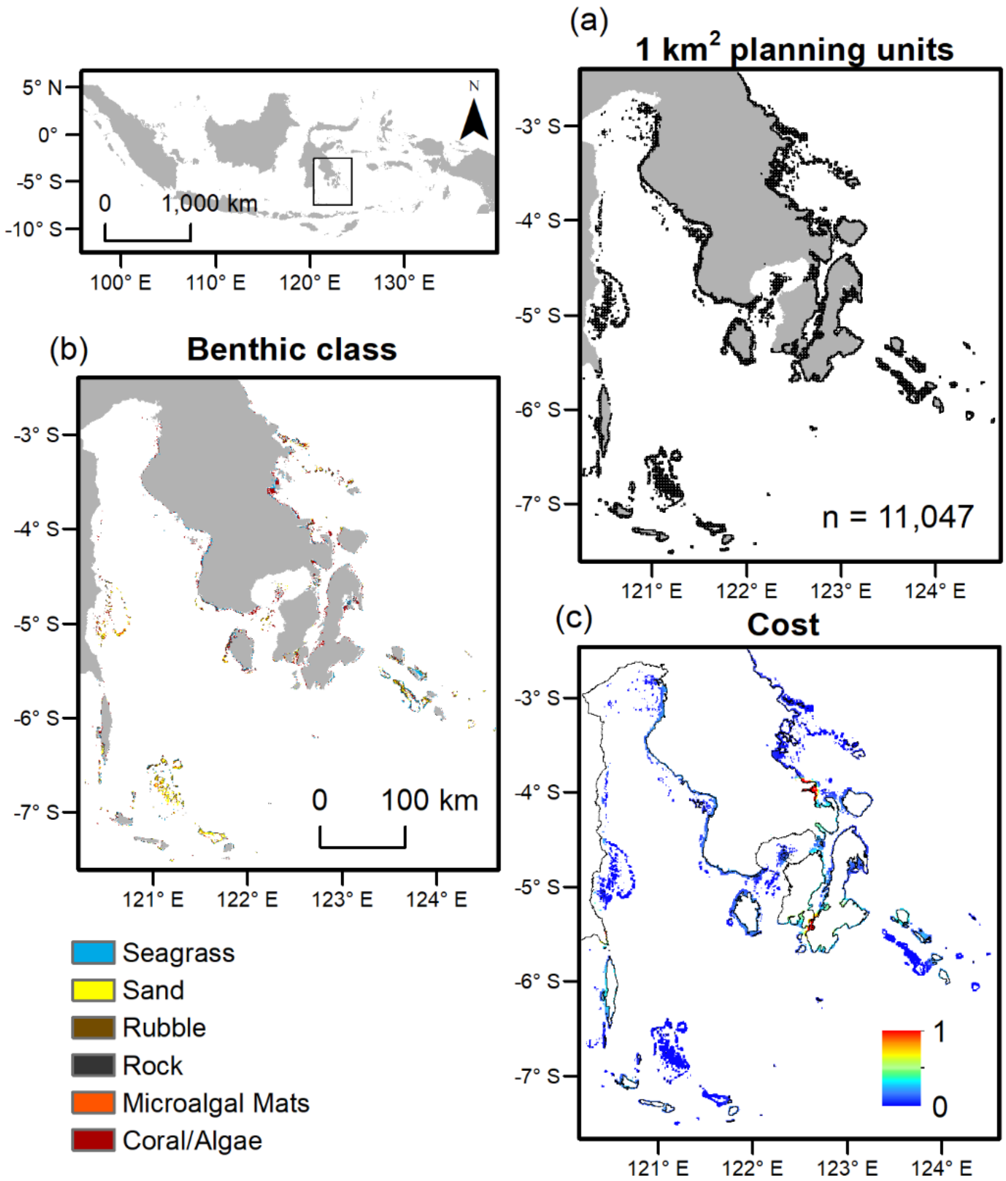

Figure 5.1: Southeast Sulawesi study region divided into: a) 1 km^2 planning units. b) The Allen Coral Atlas benthic classes (Allen Coral Atlas, 2020) used to create the planning units. c) The cost of protection based on the population of Southeast Sulawesi from the Gridded Population of the World Version 4 (GPWv4): Population Count, Revision 11 (Center for International Earth Science Information Network (CIESIN) Columbia University, 2018).

5.2.1 Setting conservation objectives

We tested the influence of different data resolutions and sources on achieving the persistence of coral reef systems under climate change with a climate-smart approach to spatial management (Figure 5.2). Given the overarching goal of reef persistence, specific conservation objectives illustrate different ecological interpretations of the effect of thermal stress on reefs and how management might support reef persistence. We set climate change-specific objectives that describe three management scenarios: Climate Refugia, Multiple Regimes and Variable Reefs. These objectives encompass three major approaches to climate-relevant coral reef management: prioritising climate refugia which are then able to reseed damaged reefs (Levy and Ban, 2013; Harris *et al.*, 2017; Asaad *et al.*, 2018; Beyer *et al.*, 2018), prioritising reefs experiencing a range of regimes to spread the risk of uncertain predictions and allow for adaptation/acclimation (Mumby *et al.*, 2011; Magris *et al.*, 2015) and prioritising reefs that have experienced highly variable environmental conditions in the past increasing thermal tolerance (Donner and Carilli, 2019). Each objective can be represented with multiple, and sometimes overlapping, criteria that are quantified by different metrics. For example, both the Climate Refugia and Multiple Regimes objectives were represented by past and future thermal stress metrics with different levels of global warming relative to pre-industrial levels (1.5, 2.0 and 3.0°C).

The Climate Refugia objective included reefs that have experienced low past thermal stress indicating that the reefs have likely not been severely damaged by past warming, and low future thermal stress indicating that environmental conditions remain more suitable for resident species even when surrounding areas become inhospitable (Kavousi and Keppel, 2018). Very few refugia that maintain suitable conditions for corals are projected to remain under future warming (Dixon *et al.*, 2022) so refugia here refer to areas where the projected thermal stress is lower than surrounding areas. The Multiple Regimes objective accounted for uncertainty in future climate change projections and the ecological responses of corals to future warming by prioritising reefs experiencing a range of past and future thermal stress. The Variable Reefs objective included reefs with high seasonal and inter-annual SST variability, indicating that the reefs have experienced fluctuations in SST and thermal stress events in the past, and may be less vulnerable to thermal stress (Guest *et al.*, 2012; Donner and Carilli, 2019). Past exposure to thermal stress on relatively short timescales serves as a proxy for adaptive potential, so here the term predominantly refers to phenotypic adjustment (e.g. shift to more thermally tolerant algal symbionts; Berkelmans and Van Oppen, 2006) and changes in community composition (e.g. shifts to more thermally tolerant species; Darling *et al.*, 2013) rather than genetic adaptation due to natural selection.

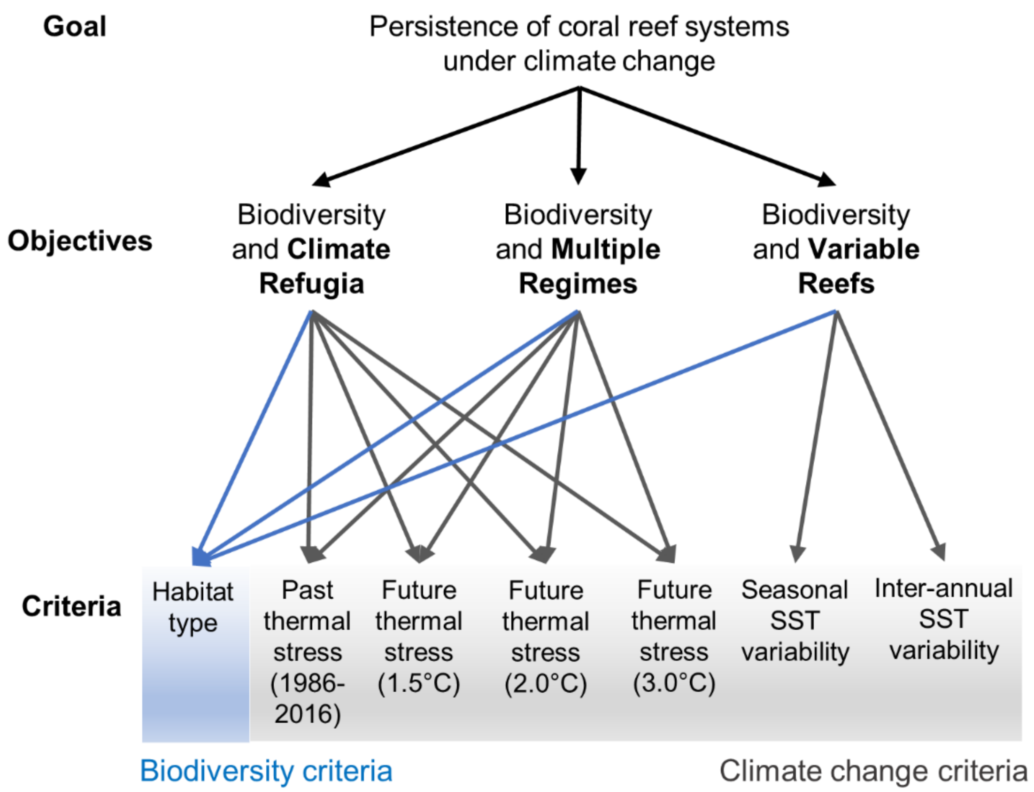

Figure 5.2: Framework for climate-relevant coral reef conservation planning showing how conservation goals translate to different conservation objectives and planning criteria.

The percentage of planning units to protect for each conservation feature was arbitrarily set but represented the aims of each conservation objective. For planning units in the most desired thermal categories (low for Climate Refugia and high for Variable Reefs), 70% were prioritised. In the medium categories, 20% were prioritised to allow inclusion of planning units with moderate thermal conditions and potentially high biodiversity and/or low cost (Supplementary Table 5.1). In the Multiple Regimes objective, the proportion of planning units to protect was equal for every thermal stress category.

5.2.2 Calculating thermal stress metrics

We used the maximum degree heating week (DHW) value (Supplementary Methods) to indicate past (1985-2016) and future (1.5, 2.0 and 3.0°C of global warming relative to pre-industrial levels) thermal stress exposure for each coral reef planning unit (Dixon *et al.*, 2022). DHW values are the accumulated SST anomalies more than 1°C greater than the long-term maximum monthly mean over the past 12 weeks (Liu *et al.*, 2014). The maximum monthly mean is calculated by re-centring the monthly mean climatology for each month for the period 1985-2012 to the 1985-1990 + 1993 period and then selecting the maximum monthly value from the 12 months. The years 1991 and 1992 are excluded due to the eruption of Mount Pinatubo that reduced satellite data reliability (Heron *et al.*, 2014).

Past thermal stress was calculated at 5 km spatial resolution for two observational SST datasets (Supplementary Figure 5.1): CCI (Merchant *et al.*, 2016), and CoralTemp (NOAA Coral Reef Watch, 2018) from 1985-2016. We used the 1 km MUR dataset (JPL MUR MEaSUREs Project, 2015) to calculate past thermal stress at 1 km spatial resolution. As SST data at 1 km resolution is only available from June 2002, we downscaled the 5 km CCI and CoralTemp SST datasets to 1 km for the period 1985-2006 following the change factor technique detailed in Dixon *et al.* (2022). This approach involved subtracting the monthly climatology from the 5 km data, interpolating the SST anomaly to 1 km and adding the monthly climatology from the MUR dataset to generate a time series of 1 km SST that had sufficient length for estimating past thermal stress. We calculated four past thermal stress metrics to determine the extent to which the spatial resolution and/or source dataset affect which planning units are prioritised: 5 km

CCI, 5 km CoralTemp, 1 km downscaled CCI and MUR and 1 km downscaled CoralTemp and MUR.

Future thermal stress was estimated for three levels of global warming: global warming of 1.5, 2.0 and 3.0°C relative to pre-industrial levels (Supplementary Figure 5.1). We calculated the future maximum DHW using daily SST projections from 15 Coupled Model Intercomparison Project Phase 6 (CMIP6) models and four Shared Socio-economic Pathways (SSP): SSP1 2.6, SSP2 4.5, SSP3 7.0 and SSP5 8.5 (Eyring *et al.*, 2016). For each model and SSP, we calculated the maximum DHW for all model years within 0.2°C of each of the global warming levels and then calculated the ensemble mean (Dixon *et al.*, 2022). The SST projections for each model and SSP were downscaled from their native resolution (25-100 km) to 5 km and 1 km using the asynchronous regression statistical downscaling method by Stoner *et al.* (2013), detailed for coral reefs in Dixon *et al.* (2022). This technique involved the generation of seasonal linear models of ranked observed and climate model simulated SST for the historical period to quantify the relationship between fine (1 km) and coarse (model resolution) SST. This relationship was then applied to the projected SST data.

Chronic thermal stress metrics, such as the trend in SST, have previously been used in conservation planning (Magris *et al.*, 2015). We did not use a measure of chronic thermal stress here due to the statistical downscaling approach used, where the long-term projected warming trend in the SST projections were removed prior to downscaling and added back in after (Dixon *et al.*, 2022). As such, the trend in SST has the coarse climate model spatial resolution and not the 1 km and 5 km resolution examined here.

To examine the variability in SST that the reefs routinely experience, we calculated two further thermal exposure metrics: seasonal and inter-annual SST variability. Coral reefs that have experienced high SST variability have demonstrated higher tolerance to thermal stress events. For example, reefs in Kiribati in the Central Pacific that experience high inter-annual SST variability and frequent thermal stress events associated with El Niño show growing resistance to heat stress (Donner and Carilli, 2019). We calculated seasonal and inter-annual SST variability for the past period (1986-2016) only, as changes to SST variability under future global warming are not robust across models (Dixon *et al.*, 2022). We used Fourier transformations to transform time series of monthly mean SST for each planning unit into temporal frequency bands to find the amplitude of the seasonal and inter-annual signals (Langlais *et al.*, 2017). We then calculated the root mean square of the signal in the 0.5-1 year frequency band for seasonal SST variability and in the 3-8 year band for inter-annual SST variability (Langlais *et al.*, 2017). If the amplitude of the signal in the seasonal frequency band is high, the planning unit has high seasonal SST variability.

We compared the past and future thermal stress exposure and SST variability between the four climate datasets using Spearman's rank correlation to test the correlation between the different climate datasets. We assigned the 5 km^2 resolution thermal stress and SST variability data to the 1 km^2 planning units so that the Marxan output for the 1 km and 5 km climate data could be statistically compared. The cost and area of coral/algae and seagrass features were the same in both the 1 km and 5 km runs. The past and future thermal stress and seasonal and inter-annual SST variability were categorised as high, medium, or low by dividing the metrics into terciles. The planning units in the low category were assigned a one and all others were assigned a zero. This approach was repeated for the medium and high categories and all three (low, medium and high) were input to Marxan as conservation features for each thermal metric (Supplementary Table 5.1).

5.2.3 Comparing spatial planning solutions

The cost and conservation features were input to Marxan and run 100 times for each conservation objective. We compared the selection frequency to determine the extent to which the different spatial resolutions and datasets used influence which planning units are prioritised, that is to say how robust planning unit priority is to the data source and resolution. To measure the overlap in the selection frequencies between the four datasets, removing the overlap due to chance (Wilson *et al.*, 2005), we calculated the

Kappa statistic (Cohen, 1960). Following Ruiz-Frau et al. (2015), we divided the selection frequencies into five categories: 1 = 0, 2 = 1-25, 3 = 26-50, 4 = 51-75, 5 = 76-100. The Kappa statistic ranges from -1 to 1 and indicates the level of agreement between the selection frequencies for the four datasets from complete disagreement to perfect agreement (Wilson *et al.*, 2005). We then calculated the number of planning units selected by all four of the climate datasets and the percentage selection frequency (e.g. planning units that were selected 400 times over the 100 Marxan runs with the four climate datasets had a percentage selection frequency of 100%).

5.3 Results

5.3.1 Comparing thermal exposure of planning units

Comparisons of the past and projected maximum DHW (Supplementary Table 5.2) and seasonal and inter-annual SST variability (Supplementary Table 5.3) between the four climate datasets show significant positive correlation in all but two cases. In the observed period, there was no correlation between the CCI 5 km and CoralTemp 5 km datasets and weak negative correlation between the CCI 1 km and CoralTemp 5 km datasets.

The maximum DHW varied between datasets during 1986-2016 with the highest maximum DHW (8.74°C-weeks) recorded by the CoralTemp 5 km dataset (Figure 5.3). The higher maximum monthly mean calculated for the CCI dataset resulted in lower DHW values, and a proportion of the area having experienced no thermal stress (7 and 913 planning units in the 1 km and 5 km datasets, respectively, compared with zero planning units in the CoralTemp datasets). The maximum DHW increased with projected increases in global mean temperature change for all spatial resolutions and datasets.

There was spatial heterogeneity in past and projected thermal stress (Supplementary Figure 5.2). The spatial distribution of thermal stress varied between datasets, spatial resolutions, and global warming levels. The difference in the maximum DHW between the CCI and CoralTemp datasets for the 1986-2016 period was greatest in the south-western and south-eastern part of the region (Supplementary Figure 5.3). For the future warming periods, the difference between the two datasets was reduced. The greatest difference in maximum DHW in the future was in the north and central eastern area of the study region.

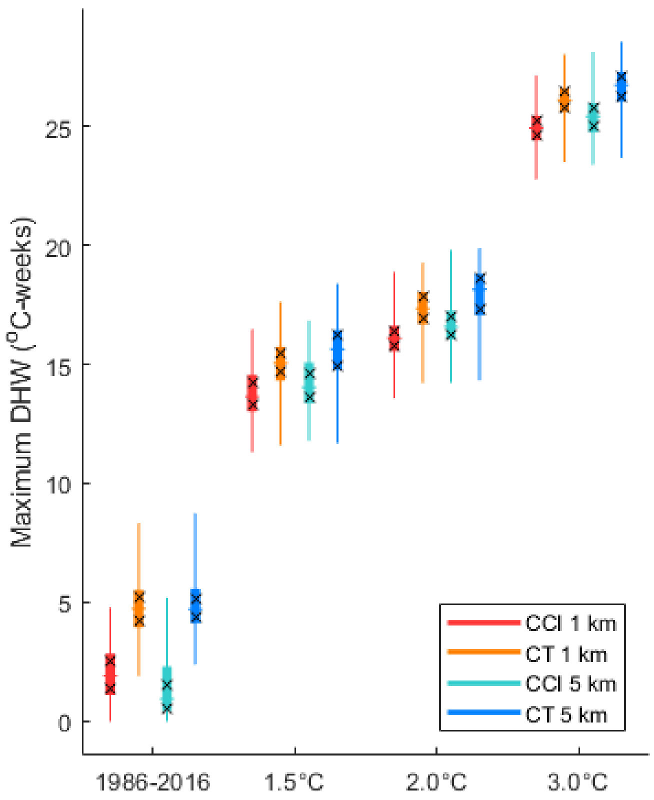

Figure 5.3: Past (1986-2016) and future (1.5, 2.0 and 3.0°C of global warming relative to pre-industrial levels) maximum degree heating weeks (DHW) calculated using four observational and downscaled projected sea surface temperature (SST) datasets: 1 km resolution downscaled CCI and MUR (CCI 1 km), 1 km resolution downscaled CoralTemp and MUR (CT 1 km), 5 km resolution CCI (CCI 5 km), 5 km resolution CoralTemp (CT 5 km). The black crosses indicate the terciles used to create discrete high, medium, and low conservation features.

The seasonal and inter-annual SST variability ranged from 0.29-1.2°C and 0.07-0.26°C, respectively (Figure 5.4), and were both greatest in the southern part of the study area at higher latitude. Seasonal SST variability was also high on the eastern coast (Supplementary Figure 5.4). The CCI datasets had a higher median and a greater range in seasonal and inter-annual SST variability than CoralTemp. The greatest differences in seasonal SST variability between the datasets were in the central eastern part of the study area where CCI records higher seasonal variability than CoralTemp (Supplementary Figure 5.5). The greatest differences in the inter-annual SST variability between the two datasets were in the north and central east where CCI records lower inter-annual SST variability than CoralTemp.

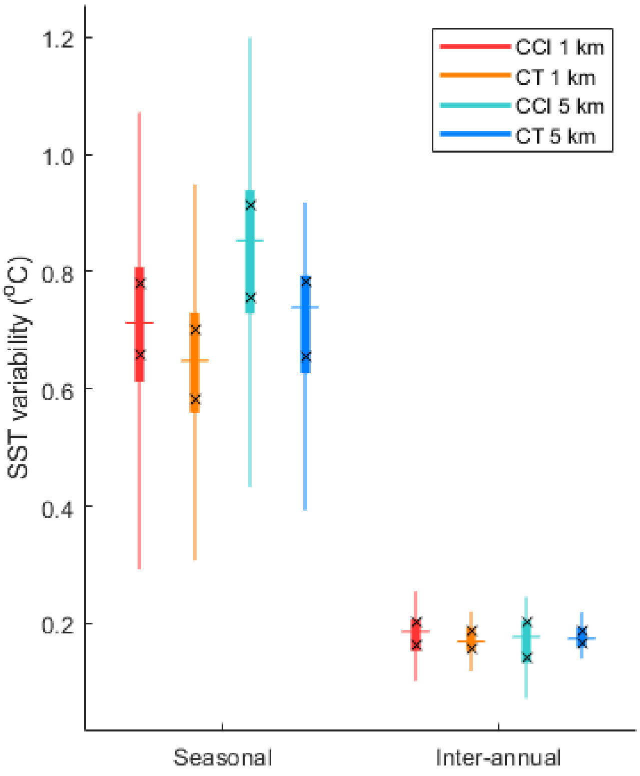

Figure 5.4: Seasonal and inter-annual sea surface temperature (SST) variability for the period 1986-2016 calculated using four observational SST datasets: 1 km resolution downscaled CCI and MUR (CCI 1 km), 1 km resolution downscaled CoralTemp and MUR (CT 1 km), 5 km resolution CCI (CCI 5 km), 5 km resolution CoralTemp (CT 5 km). The black crosses indicate the terciles used to create discrete high, medium, and low conservation features.

5.3.2 Comparing spatial planning solutions

Kappa statistics, indicating the overlap in selection frequency (Supplementary Figures 5.6 and 5.7) and thus robustness of priority assignments, were different for the three climate objectives both when using a universal and spatially varying cost (Figure 5.5). When using a universal cost, Kappa statistics were between -0.04 and 0.53, indicating poor (κ = -0.2 – 0.0) to moderate (κ = 0.4 – 0.6) agreement in the selection frequency of planning units between the datasets (Figure 5.5a-c).

When using a spatially varying cost, Kappa statistics were higher for every climate objective. Kappa statistics were between 0.20 and 0.76, indicating fair (κ = 0.2-0.4) to substantial (κ = 0.6 – 0.8) agreement in the selection frequency of planning units between the datasets (Figure 5.5d-f). For both the universal and spatially varying cost, the lowest Kappa statistics were observed in the Climate Refugia objective and the highest in the Variable Reefs objective.

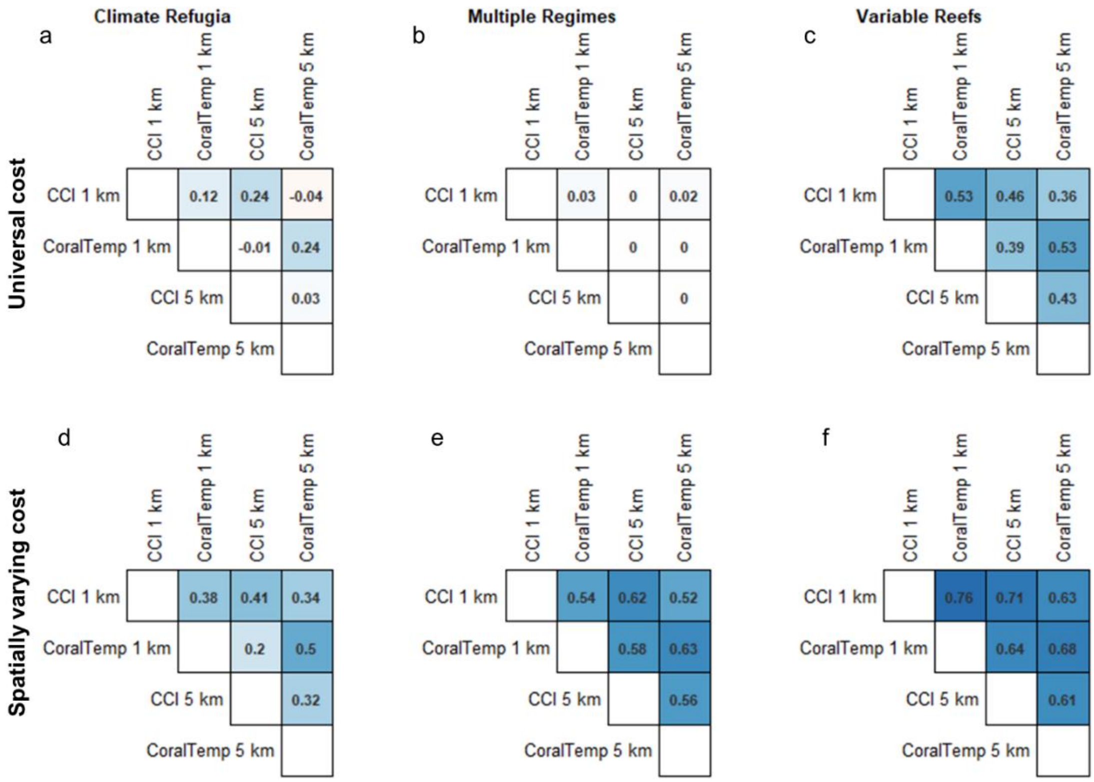

Figure 5.5: The overlap of planning unit selection frequencies for the four datasets assessed using Kappa statistics for a universal cost of one (a-c) and a spatially varying cost based on the population within 10 km of each planning unit (d-f). Kappa statistics were divided into the following six categories (García-Barón *et al.*, 2021): poor agreement κ = -0.2 – 0.0; slight agreement κ = 0.0 – 0.2; fair agreement κ = 0.2 – 0.4; moderate agreement κ = 0.4 – 0.6; substantial agreement κ = 0.6 – 0.8; almost perfect agreement κ = 0.8 – 1.0.

When using a spatially varying cost as typically needed in a real-world marine spatial prioritisation, the number of planning units selected in the best solution, no matter which climate dataset was used, varied by conservation objective (Figure 5.6). A total of 1701 (15.40%), 1797 (16.27%) and 2913 (26.37%) planning units were selected in the best solution for all four climate datasets in the Climate Refugia, Multiple Regimes and Variable Reefs objectives, respectively. Of these planning units, 396 (23.28%; Climate Refugia), 854 (47.52%; Multiple Regimes) and 1871 (64.23%; Variable Reefs) had a percentage selection frequency of 100% (i.e. they were selected all 400 times in 100 runs for four climate datasets; Figure 5.6) indicating that the best solution for the Variable Reefs objective was the most stable over the 100 runs.

5.4 Discussion

Climate projections are increasingly being used in marine spatial planning to design reserve systems for coral reefs that account for changing environmental conditions in the future. A novel fine-scale 1 km thermal stress dataset with downscaled past and projected SST (Dixon *et al.*, 2022) introduces questions as to whether the data resolution and source datasets alter potential marine spatial conservation priorities. Here, we found that both the data resolution and source dataset altered which planning units are selected, with the extent of these differences depending on the conservation objectives. Agreement between solutions in the Variable Reefs objective was high, indicating that using SST variability is the most robust approach to incorporating climate data in marine conservation planning in terms of minimising error/noise from data sources. However, protecting reefs with high variability may not be a viable conservation strategy as these reefs may still be highly exposed to thermal stress. In the Climate Refugia objective, the data source and resolution used altered the spatial planning solutions. If adopting this objective, the climate datasets used in spatial planning require careful consideration, based on the source dataset's ability to represent the spatial variation in thermal stress within the study area. There was high flexibility for the Multiple Regimes objective, as there were many combinations of planning units selected that would meet conservation targets. In this case, the high agreement between datasets was driven by the cost.

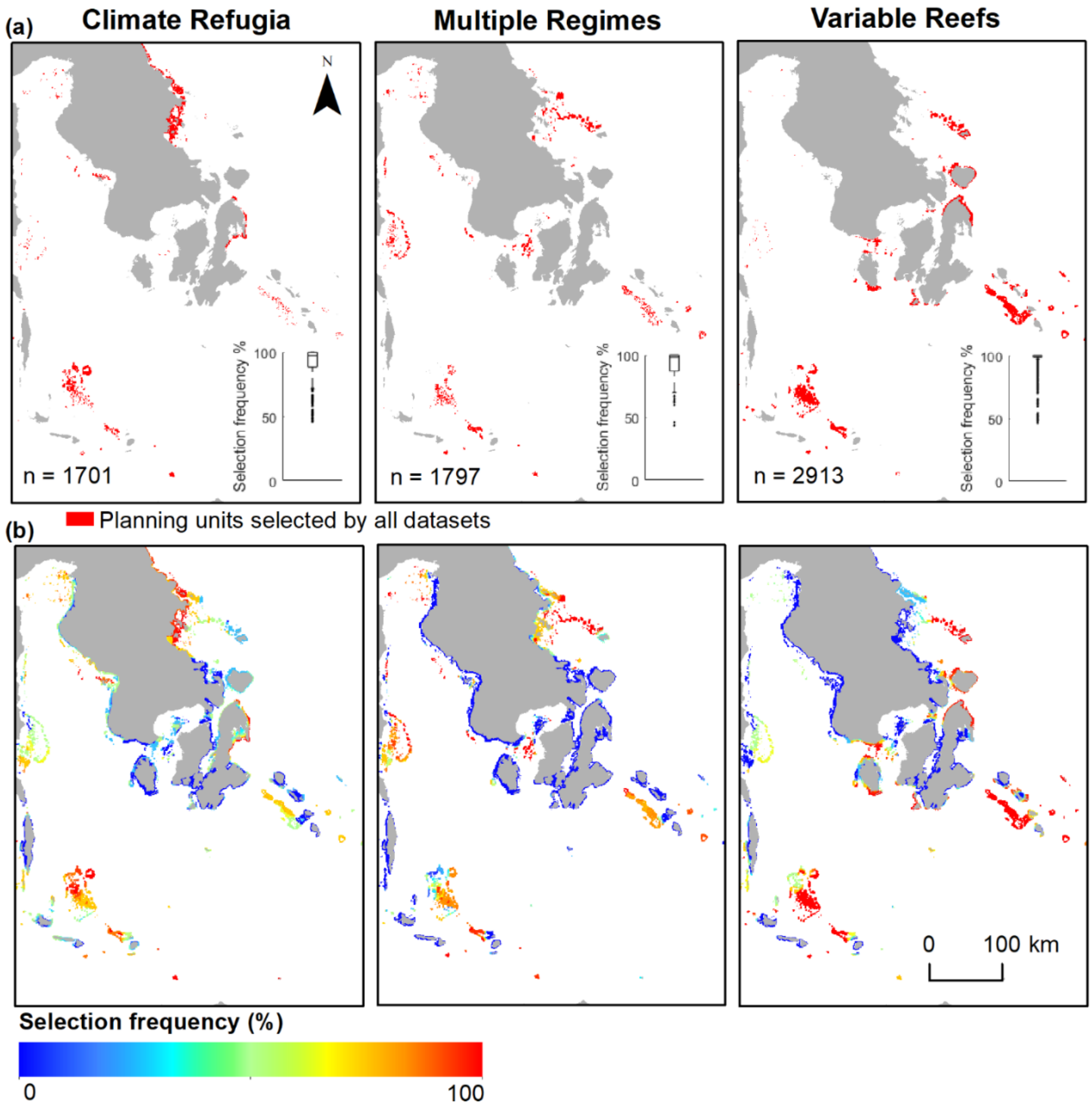

Figure 5.6: a) Planning units selected in the best solution by all climate datasets (1 km resolution downscaled CCI and MUR, 1 km resolution downscaled CoralTemp and MUR, 5 km resolution CCI and 5 km resolution CoralTemp) for three conservation objectives. Planning units are selected using a spatially varying cost based on the population within 10 km of each planning unit. Boxplots show the percentage selection frequency of the planning units where a value of 100% indicates planning units selected 400 times (i.e. in all 100 Marxan runs for the four climate datasets). b) Percentage selection frequency of planning units for the three conservation objectives when Marxan is run 100 times each with the four climate datasets and resolutions (100% = selected 400 times).

There was poor (κ = -0.2 – 0.0) to moderate (κ = 0.4 – 0.6) robustness in priority assignment among datasets when using a universal cost and slight (κ = 0.0 – 0.2) to substantial (κ = 0.6 – 0.8) agreement when using a spatially varying cost. The agreement was highest for the Variable Reefs objective, which did not use the accumulative DHW thermal stress metric in the conservation features but instead used variability in SST. In the DHW calculation, small differences in the SST anomalies are summed over a 12-week period which magnifies differences between datasets. The difference in trends between the datasets identified by Rayner *et al.* (2019) may have little effect on the SST variability, which may be constant over time, but a large effect on the DHW which is calculated relative to a baseline temperature. As such, there may be greater differences in the maximum DHW between datasets, compared to the SST variability. This finding highlights a problem for conservation objectives informed by accumulated thermal stress metrics (Mumby *et al.*, 2011; Chollett *et al.*, 2014; Beger *et al.*, 2015; Magris *et al.*, 2015; Harris *et al.*, 2017), as DHW metrics make spatial prioritisations and subsequently the conservation plans more sensitive to differences in source datasets.

The source dataset had a greater effect on the differences in selection frequency between the datasets in the Climate Refugia objective than the data resolution. This was evidenced in the lower Kappa statistic between the CCI 5 km and CoralTemp 5 km datasets and higher Kappa statistics between CCI 1 km and CCI 5 km datasets and CoralTemp 1 km and CoralTemp 5 km datasets observed both when using a universal and a spatially varying cost. By downscaling the 5 km datasets to 1 km, the differences between the datasets were reduced as the monthly climatology for the MUR dataset was used in the early (1985-2006) part of the time series altering the baseline temperature used to calculate the DHW (Dixon *et al.*, 2022). In contrast to the Climate Refugia objective, the overlap in the spatial planning output in the Variable Reefs objective was highest between the CCI 1 km and CoralTemp 1 km datasets. This finding is likely due to the downscaling process which captures the SST variability estimated by the MUR dataset (Dixon *et al.*, 2022). Seasonal and inter-annual SST variability in Indonesian

Seas is affected by local-scale monsoonal winds, solar radiation, atmospheric temperature and humidity (Kida and Richards, 2009). These local-scale features may be better resolved in the 1 km MUR dataset because the reconstruction of small-scale processes, through the use of different sized time windows of night-time SST, has improved feature resolution ten-fold compared with other 5-25 km products (Chin *et al.*, 2017). Additionally, the two 5 km SST datasets are predominantly composed of infrared measurements of SST taken by satellite sensors (Roberts-Jones *et al.*, 2012; Maturi *et al.*, 2017; Merchant *et al.*, 2019). Infrared measurements are not able to accurately measure SST in areas covered by cloud resulting in data voids (Chin *et al.*, 2017). The microwave measurements included alongside infrared measurements in the estimated SST in the MUR dataset allow observed SST to be measured in areas commonly covered by clouds (Chin *et al.*, 2017). At present, the two 5 km resolution datasets do not incorporate microwave measurements in the estimated SST, though they may be included in future versions of CoralTemp (Roberts-Jones *et al.*, 2012; Maturi *et al.*, 2017; Merchant *et al.*, 2019).

Seasonal and inter-annual SST variability and thermal stress are closely linked (Dixon *et al.*, 2022). Small increases in global mean temperature result in summer SST frequently exceeding thermal stress thresholds in reefs with high seasonal variability (Langlais *et al.*, 2017). Conversely, reefs with high inter-annual variability experience less frequent thermal stress under future warming due to the respite provided during cooler periods (Langlais *et al.*, 2017). Projections of thermal stress by coarse resolution climate models are the most sensitive to seasonal and inter-annual SST variability and have previously underestimated coral bleaching by not correctly simulating the observed seasonal cycle (van Hooidonk and Huber, 2012). Accurately representing seasonal and inter-annual SST cycles is therefore crucial for monitoring past and projecting future thermal stress events. Using 1 km SST data likely better represents the SST variability and therefore thermal stress experienced by coral reefs in a conservation planning area, adding value to marine spatial plans.

When using a universal cost, the selection frequencies slightly agreed in the Multiple Regimes objective and there was little difference between the Kappa statistics. The Multiple Regimes objective represents a bet-hedging approach whereby 30% of each thermal category (high, medium, and low thermal stress) was prioritised. Without the influence of a spatially varying cost preferentially selecting cheaper planning units, there was flexibility in which planning units may be prioritised resulting in an overlap between solutions expected due to chance indicated by Kappa statistics close to zero (Wilson *et al.*, 2005). When using a spatially varying cost, there was moderate to substantial agreement in spatial planning solutions between datasets. As cheaper planning units were favoured and those that were prohibitively expensive avoided, the choice of planning units was reduced resulting in greater agreement between solutions. The high level of flexibility afforded by the bet-hedging approach means that the conservation objectives can be met in a variety of configurations while selecting the cheapest planning units reducing differences between solutions. Bet-hedging conservation objectives are implemented to reduce the effect of uncertainty in coral responses to future thermal stress on spatial planning solutions (Mumby *et al.*, 2011; Magris *et al.*, 2015). Our finding indicates that a bet-hedging approach reduces differences between the climate datasets used in spatial planning solutions compared with the Climate Refugia approach, though overlap between solutions is driven by cost and not climate data in the Southeast Sulawesi region.

Climate datasets can have uncertainty, both in observations and especially in future climate projections. DHW-based thermal stress metrics were particularly sensitive to differences between datasets. There was no correlation in the maximum DHW between the 5 km resolution datasets in the past period. Positive correlation in maximum DHW between datasets was higher in the projected climate data than observed. As such, the choice of climate dataset was less important for model projections than for observed data. Long-term and geographically extensive coral bleaching observations are required to determine which dataset best captures the in situ thermal stress experienced by coral reefs.

Climate-relevant conservation planning is widely understood to be crucial for safeguarding coral reefs under future climate change (Mcleod *et al.*, 2012; Chollett *et al.*, 2014; Green *et al.*, 2014; Beyer *et al.*, 2018). We demonstrated that the resolution and climate data source used alters spatial planning solutions, but whether there is a “best” dataset to use is unknown. The most robust approach may be to use more than one climate dataset, as we have here, and prioritise areas selected when using both datasets. However, calculating thermal stress for multiple climate datasets is computationally intensive and may be impractical for conservation planners. The differences in spatial planning solutions between datasets were minimised by using a spatially varying cost and non-accumulative temperature metrics such as SST variability. Including other factors used to inform spatial planning such as larval connectivity, cultural aspects, genomic diversity and fishing effort alongside cost may further increase overlap between spatial planning solutions. Further research should determine whether the climate data underpinning conservation plans accurately captures the environmental conditions experienced by coral reefs at an appropriate scale for coral reef management. Coral reef survival in a rapidly changing climate will rely on the implementation of climate-smart management developed using the best available resources.

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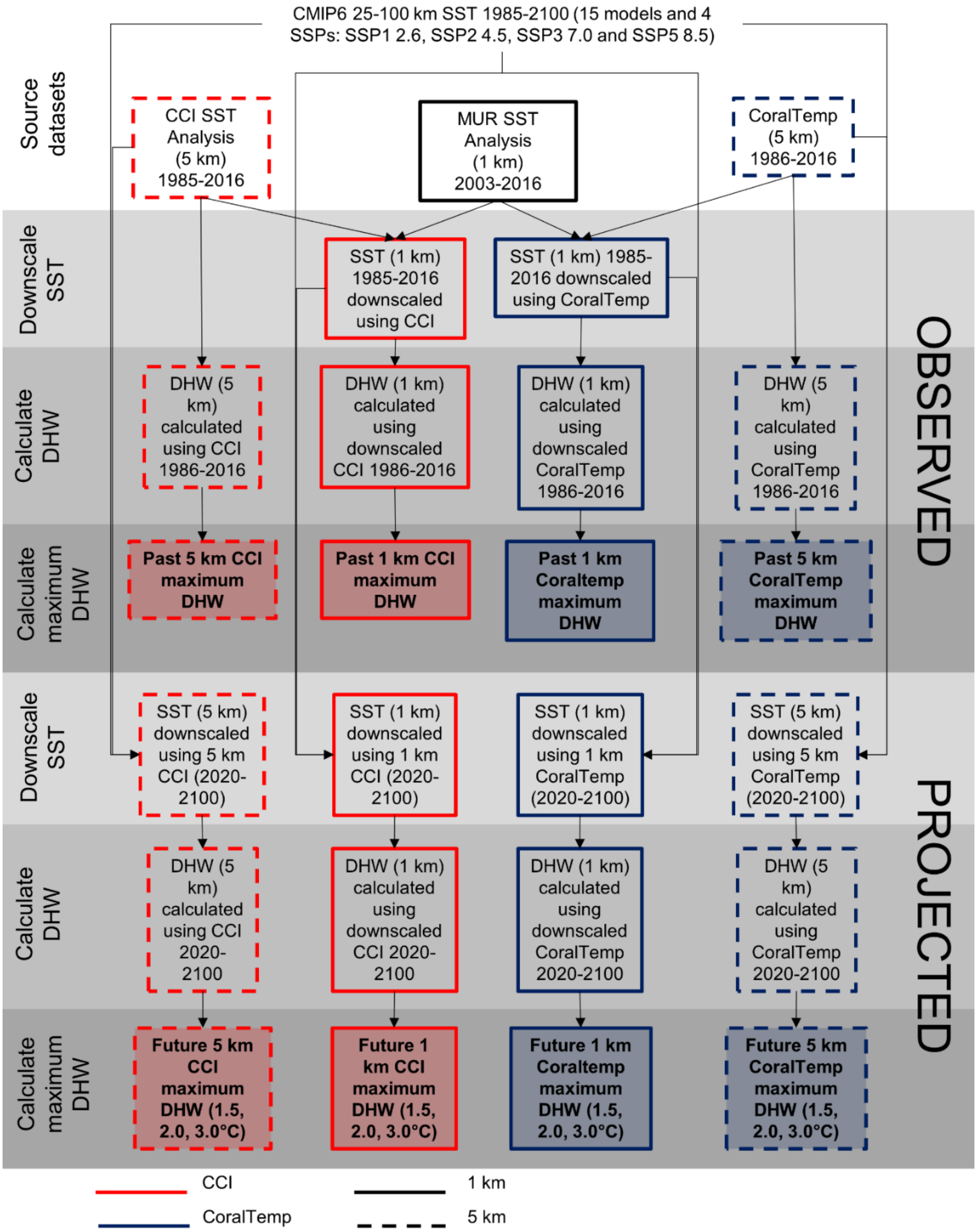
5.7 Supplementary Material

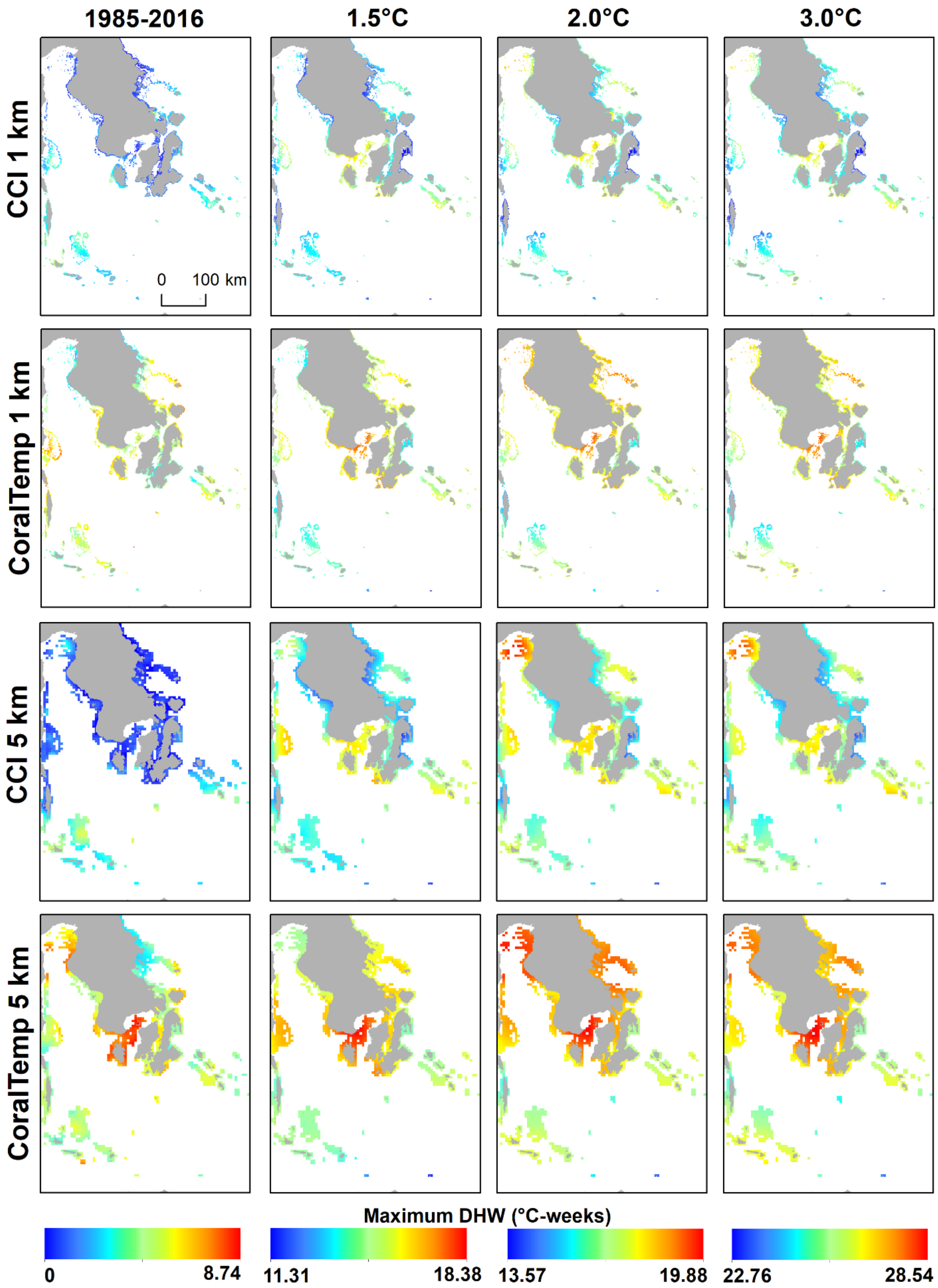
5.7.1 Supplementary Methods

The maximum DHW metric captures the maximum thermal stress each planning unit is exposed to during a given time period or period of global warming but does not indicate the frequency with which a planning unit is exposed. Despite this, we chose to use the maximum DHW here as it avoids reliance on thermal stress thresholds such as the 4°C-weeks threshold which is typically used to indicate significant coral bleaching, with 8°C-weeks indicating severe bleaching and mortality (Eakin *et al.*, 2009). These thresholds are derived from NOAA CRW products such as CoralTemp but are not appropriate for DHW values calculated using CCI. The maximum monthly mean that underlies DHW values differs between the two products, with CCI being warmer and thus producing lower DHW values as SST must be higher to exceed the warmer baseline (Dixon *et al.*, 2022). Furthermore, coral bleaching varies on small spatial scales due to differing environmental conditions (e.g. nutrient input; Donovan *et al.*, 2020) and thermal tolerance between species (Guest *et al.*, 2012; Kim *et al.*, 2019), influencing bleaching severity. As such, we chose to use the maximum DHW over the full time period here over threshold-based metrics such as the probability of thermal stress events (Dixon *et al.*, 2022) or the sum of DHW values (Chollett *et al.*, 2022) greater than 4°C-weeks.

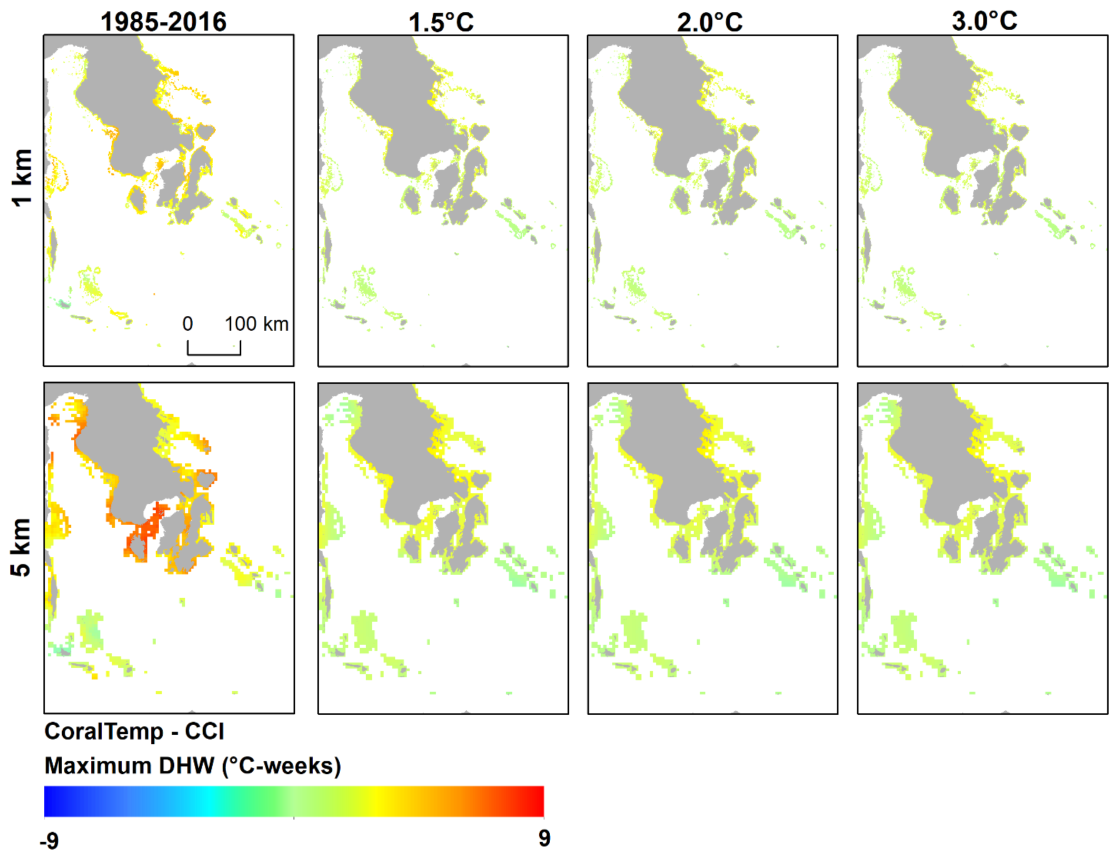
5.7.2 Supplementary Figures



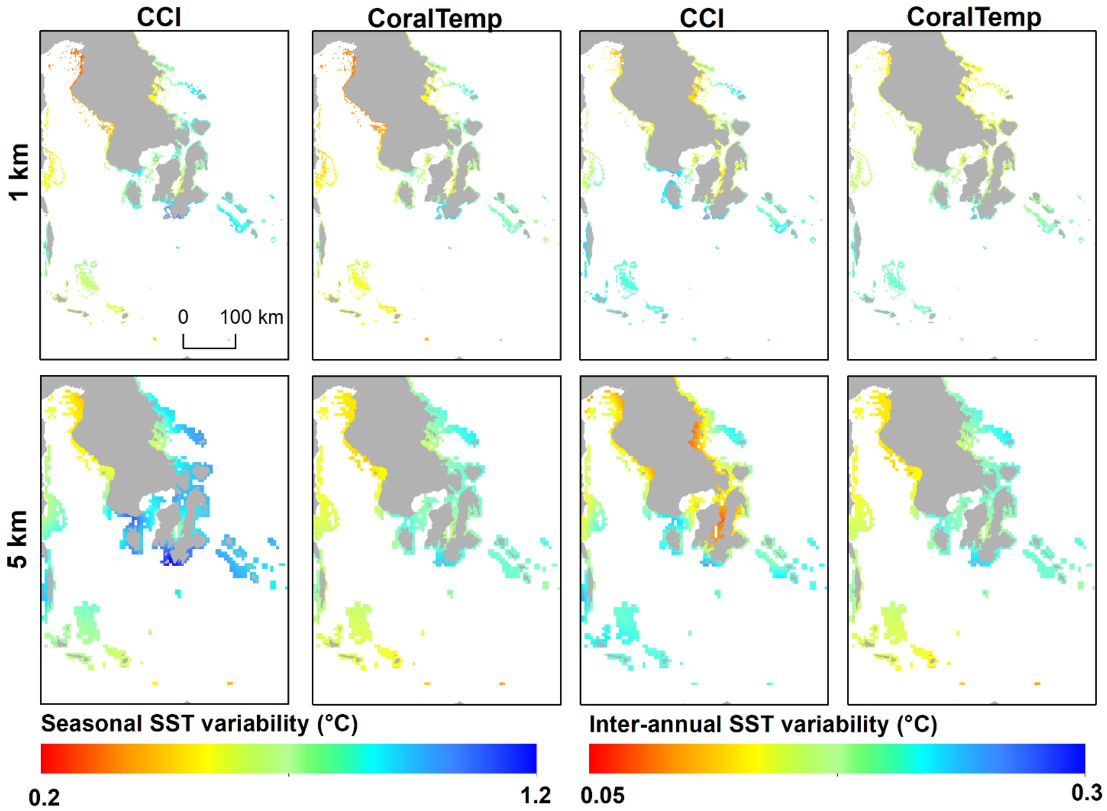
Supplementary Figure 5.1: Process for calculating the four past and four future thermal stress metrics (in shaded boxes) downscaled to 1 km and 5 km spatial resolution using CCI and CoralTemp SST datasets.



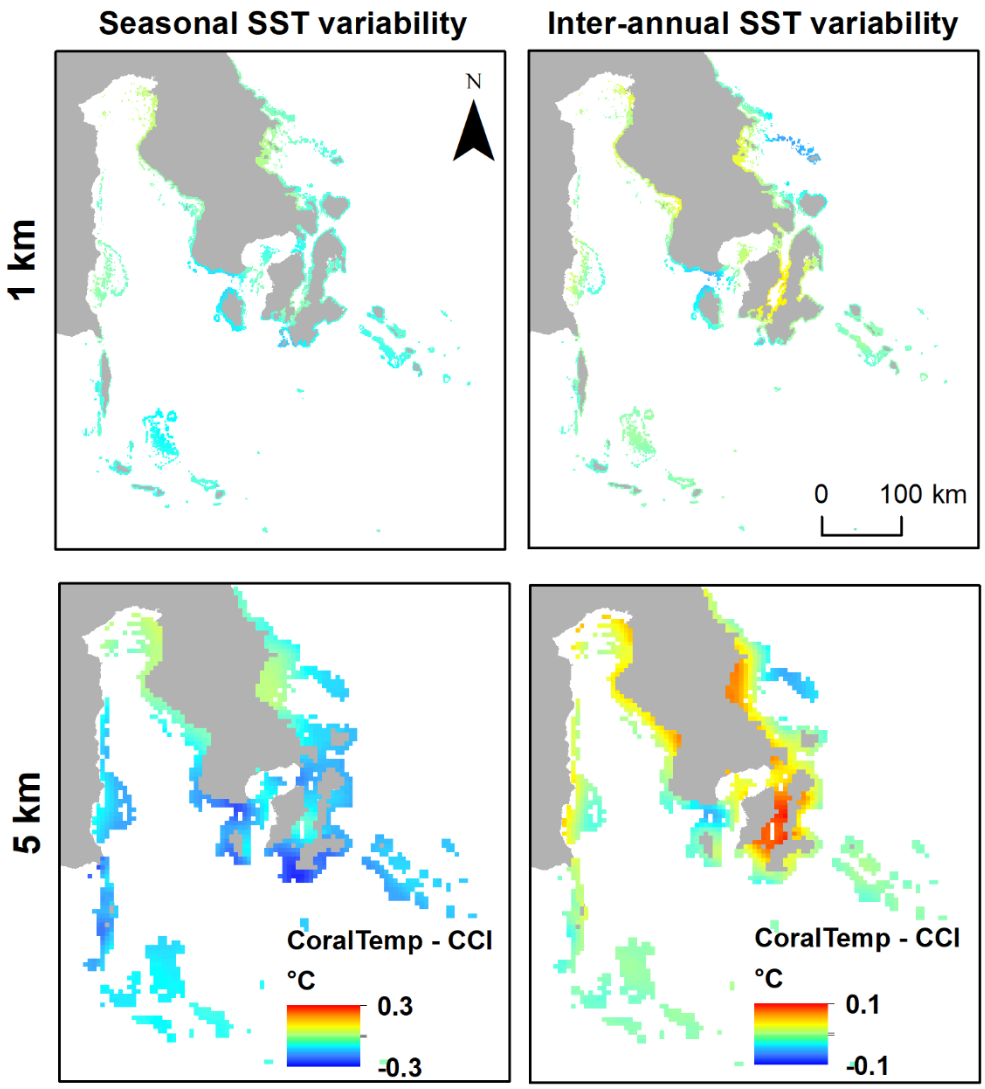
Supplementary Figure 5.2: Past and future maximum degree heating weeks (DHW) calculated using four observational and downscaled projected sea surface temperature (SST) datasets: 1 km downscaled CCI and MUR, 1 km downscaled CoralTemp and MUR, 5 km CCI, 5 km CoralTemp.



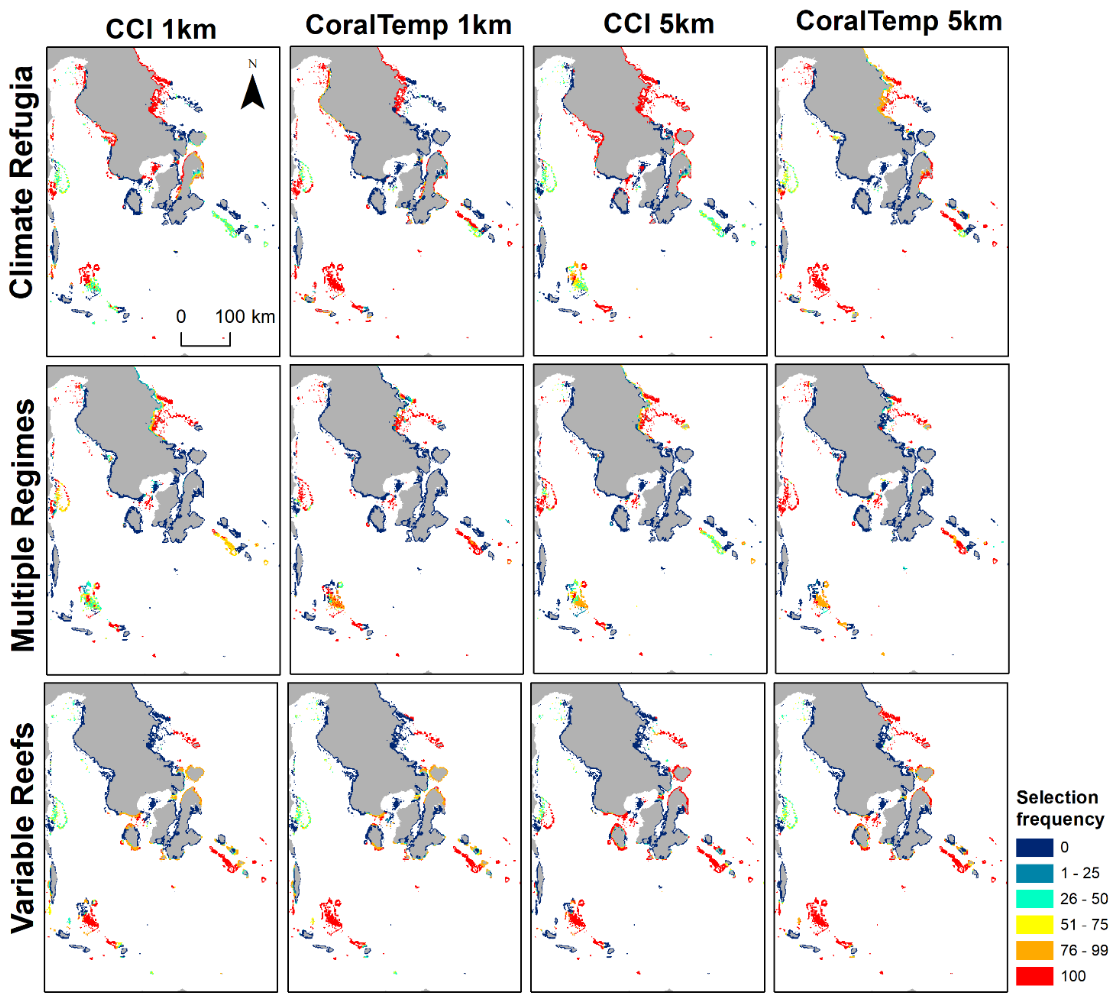
Supplementary Figure 5.3: Difference between the maximum degree heating weeks (DHW) calculated using the CoralTemp and CCI datasets for the past (1986-2016) and future (1.5, 2.0 and 3.0°C of global warming relative to pre-industrial levels) at 1 km and 5 km spatial resolution.



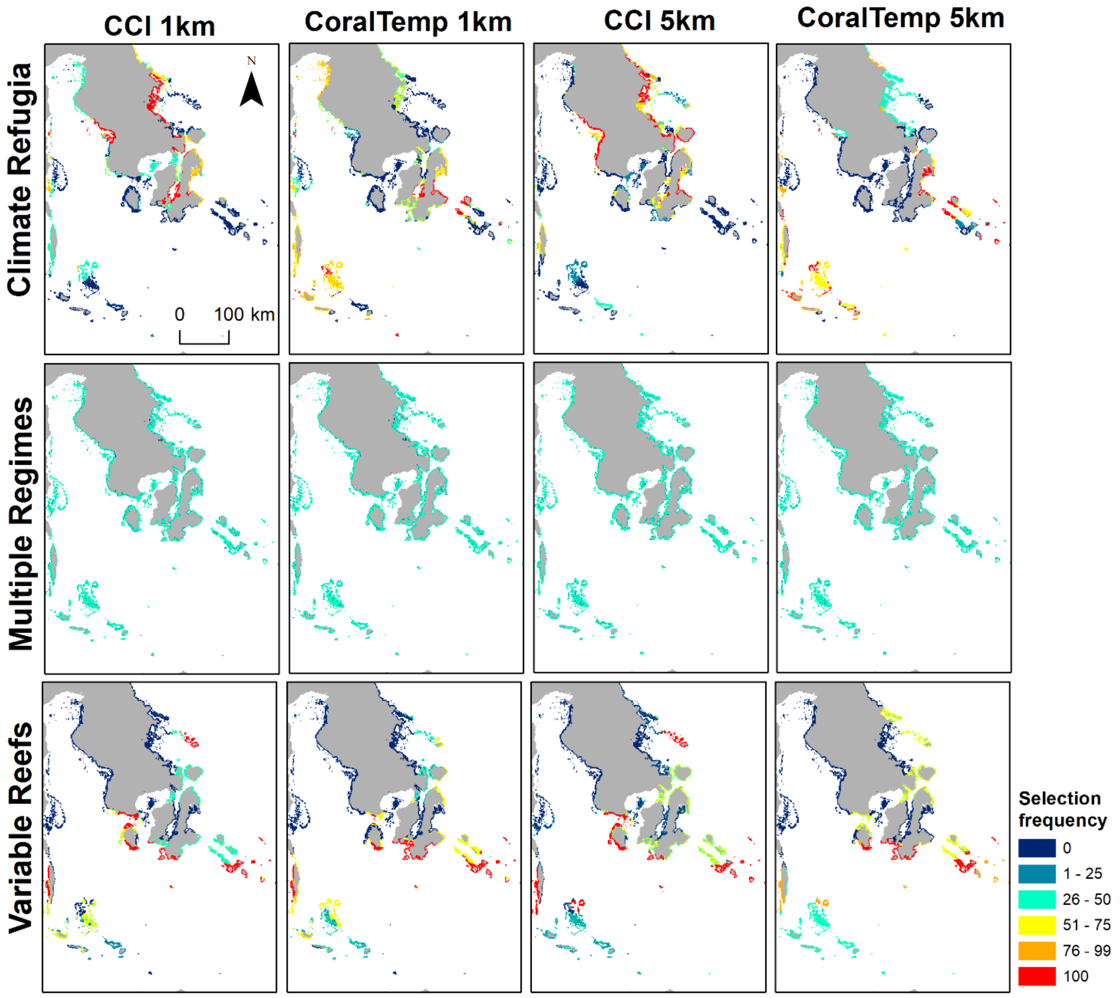
Supplementary Figure 5.4: Seasonal and inter-annual sea surface temperature (SST) variability (1986-2016) calculated using four observational SST datasets: 1 km resolution downscaled CCI and MUR, 1 km resolution downscaled CoralTemp and MUR, 5 km resolution CCI, 5 km resolution CoralTemp. The seasonal and inter-annual SST variability is shown for the past period only (1986-2016). SST variability under future levels of global warming is not used due to the model uncertainty in projected changes to SST variability.



Supplementary Figure 5.5: Difference between the seasonal and inter-annual sea surface temperature (SST) variability calculated using the CoralTemp and CCI datasets at 1 km and 5 km spatial resolution.



Supplementary Figure 5.6: Selection frequency of planning units when Marxan is run using a spatially varying cost and four different climate datasets (CCI 1 km - 1 km resolution downscaled CCI and MUR, CoralTemp 1 km - 1 km resolution downscaled CoralTemp and MUR, CCI 5 km - 5 km resolution CCI and CoralTemp 5 km - 5 km resolution CoralTemp) for three different conservation objectives.



Supplementary Figure 5.7: Selection frequency of planning units when Marxan is run using a universal cost and four different climate datasets (CCI 1 km - 1 km resolution downscaled CCI and MUR, CoralTemp 1 km - 1 km resolution downscaled CoralTemp and MUR, CCI 5 km - 5 km resolution CCI and CoralTemp 5 km - 5 km resolution CoralTemp) for three different conservation objectives.

5.7.3 Supplementary Tables

Supplementary Table 5.1: Conservation features and the percentage of each protected for each conservation objective.

Scenario*	Conservation features	Protect (%)
Climate Refugia	Low past thermal stress	70
	Medium past thermal stress	20
	Low 1.5°C thermal stress	70
	Medium 1.5°C thermal stress	20
	Low 2.0°C thermal stress	70
	Medium 2.0°C thermal stress	20
	Low 3.0°C thermal stress	70
	Medium 3.0°C thermal stress	20
Multiple Regimes	Low past thermal stress	30
	Medium past thermal stress	30
	High past thermal stress	30
	Low 1.5°C thermal stress	30
	Medium 1.5°C thermal stress	30
	High 1.5°C thermal stress	30
	Low 2.0°C thermal stress	30
	Medium 2.0°C thermal stress	30
	High 2.0°C thermal stress	30
	Low 3.0°C thermal stress	30
	Medium 3.0°C thermal stress	30
	High 3.0°C thermal stress	30
Variable Reefs	High seasonal SST variability	70
	Medium seasonal SST variability	20
	High inter-annual SST variability	70
	Medium inter-annual SST variability	20

*For every objective the area of coral/algae and seagrass are also input as conservation features with the target of protecting 20% of each habitat type.

Supplementary Table 5.2: Comparison of maximum DHW between four climate datasets from two sources (CCI and CoralTemp - CT) and at two spatial resolutions (1 km and 5 km) using Spearman's rank correlation. Datasets that are significantly positively correlated ($p < 0.05$) are in blue, datasets that are significantly negatively correlated ($p < 0.05$) are in red and datasets with no correlation ($p > 0.05$) are in black.

Observed				
	CCI 1 km	CT 1 km	CCI 5 km	CT 5 km
CCI 1 km				
CT 1 km	r = 0.43 p < 0.0001			
CCI 5 km	r = 0.67 p < 0.0001	r = 0.04 p < 0.0001		
CT 5 km	r = -0.02 p = 0.0125	r = 0.21 p < 0.0001	r = 0.01 p = 0.3490	
1.5°C				
CCI 1 km				
CT 1 km	r = 0.68 p < 0.0001			
CCI 5 km	r = 0.89 p < 0.0001	r = 0.53 p < 0.0001		
CT 5 km	r = 0.54 p < 0.0001	r = 0.89 p < 0.0001	r = 0.52 p < 0.0001	
2.0°C				
CCI 1 km				
CT 1 km	r = 0.65 p < 0.0001			
CCI 5 km	r = 0.85 p < 0.0001	r = 0.44 p < 0.0001		
CT 5 km	r = 0.52 p < 0.0001	r = 0.90 p < 0.0001	r = 0.45 p < 0.0001	
3.0°C				
CCI 1 km				
CT 1 km	r = 0.68 p < 0.0001			
CCI 5 km	r = 0.86 p < 0.0001	r = 0.42 p < 0.0001		
CT 5 km	r = 0.52 p < 0.0001	r = 0.87 p < 0.0001	r = 0.38 p < 0.0001	

Supplementary Table 5.3: Comparison of seasonal and inter-annual SST variability between four climate datasets from two sources (CCI and CoralTemp - CT) and at two spatial resolutions (1 km and 5 km) using Spearman's rank correlation. Datasets that are significantly positively correlated ($p < 0.05$) are in blue, datasets that are significantly negatively correlated ($p < 0.05$) are in red and datasets with no correlation ($p > 0.05$) are in black.

Seasonal				
	CCI 1 km	CT 1 km	CCI 5 km	CT 5 km
CCI 1 km				
CT 1 km	r = 0.98 p < 0.0001			
CCI 5 km	r = 0.94 p < 0.0001	r = 0.93 p < 0.0001		
CT 5 km	r = 0.90 p < 0.0001	r = 0.92 p < 0.0001	r = 0.93 p < 0.0001	
Inter-annual				
CCI 1 km				
CT 1 km	r = 0.82 p < 0.0001			
CCI 5 km	r = 0.96 p < 0.0001	r = 0.76 p < 0.0001		
CT 5 km	r = 0.78 p < 0.0001	r = 0.97 p < 0.0001	r = 0.75 p < 0.0001	

Chapter 6 - Discussion

6.1 Research Summary

Climate change is already impacting coral reefs around the world and, as the global temperature continues to rise, climate change impacts on vulnerable coral reef ecosystems are projected to worsen causing widespread degradation (Cooley *et al.*, 2022). Low exposure coral reefs have been proposed as conservation targets due to their higher likelihood of survival (Beyer *et al.*, 2018; Chollett *et al.*, 2022). In this thesis, I have examined the capabilities of climate models in identifying low climate exposure coral reefs and informing conservation plans. I have explored the uncertainty in observed and climate model data when applied to coral reef conservation and highlighted where climate model projections are unsuitable for informing conservation plans.

In the Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report (AR6), there is high certainty that the frequency of extreme heat stress causing mass coral bleaching has increased ("virtually certain") and will continue to increase in the future ("very high confidence") due to anthropogenic climate change (Cooley *et al.*, 2022). The report highlights that just 1.5°C of global warming will put coral reefs at high risk ("high confidence"). Several global scale analyses of future thermal stress exposure impacting coral reef areas support this statement (Frieler *et al.*, 2013; Schleussner *et al.*, 2016; Kalmus *et al.*, 2022). My research further supports these findings as I projected that >90% of the global coral reef area will experience intolerable levels of thermal stress with just 1.5°C of warming and >99% with 2.0°C (Dixon *et al.*, 2022b). I found that suitable conditions for coral reef survival in the future were projected to be rare with 1.5°C of global warming relative to pre-industrial levels and ceased to exist with 2.0°C of warming.

Increasing storm intensity is identified in the IPCC AR6 as another climate change driver impacting coral reefs in the future ("high confidence"; Cooley *et al.*, 2022). Other studies commonly cite increased risk of storm damage to coral reefs in the future as a climate change impact based on projections of global and ocean basin-scale increases in tropical cyclone intensity with future warming (Cheal *et al.*, 2017; Harvey *et al.*, 2018; Gilmour *et al.*, 2019; França *et al.*, 2020). My findings contradict this assumption. I found that future changes in coral reef damage resulting from tropical cyclones were not possible to determine with any certainty as the models disagreed on whether reef damage would increase, decrease or be unchanged with future climate change (Dixon *et al.*, 2022a). In addition, there were spatial uncertainties in where tropical cyclones will track in the future and uncertainty in how the tropical cyclone characteristics important for determining coral reef damage will be altered by climate change. Further research on the tropical cyclone characteristics that influence coral reef damage (intensity, size and duration) and how these might change on local scales in the future is necessary before scientists can say with high confidence that coral reefs will be more at risk of tropical cyclone damage in the future.

Various observed and projected climate datasets at different spatial resolutions and from different sources have been used to prioritise coral reefs for protection (Mumby *et al.*, 2011; Mcleod *et al.*, 2012; Levy and Ban, 2013; Makino *et al.*, 2014; Beger *et al.*, 2015; Magris *et al.*, 2015; García Molinos *et al.*, 2017; Harris *et al.*, 2017; Asaad *et al.*, 2018; Beyer *et al.*, 2018; Chollett *et al.*, 2022). By applying climate data at different resolutions in marine spatial planning, I found that using finer resolution data can alter planning solutions. Given the improved resolution of sea surface temperature (SST) features that affect thermal stress, such as upwelling and strong currents, using 1 km data can better resolve differences between planning units and aid in identifying the lowest exposure coral reefs. The differences in solutions between climate datasets from different sources, driven by the differences between the observed datasets, highlight the need to account for uncertainty in both projected and observed climate datasets in conservation planning.

6.2 Chapter Overview

In Chapter 2, I explored current gaps in climate vulnerability assessments for coral reefs and made four recommendations for improving the identification of low climate vulnerability coral reefs (Dixon *et al.*, 2021). Firstly, current assessments of future climate exposure on coral reefs are often based on emissions scenarios (e.g. Andréfouët *et al.*, 2015; Magris *et al.*, 2015; Wolff *et al.*, 2015; Maina *et al.*, 2016; Beyer *et al.*, 2018). Model and scenario uncertainty can be reduced by using changes in global mean temperature, such as 1.5 and 2.0°C, as future warming scenarios in place of emissions scenarios. This approach is particularly important when using the latest generation of climate models, Coupled Model Intercomparison Project Phase 6 (CMIP6), as some of the models have higher than likely equilibrium climate sensitivities (Forster *et al.*, 2020; Sherwood *et al.*, 2020; Zelinka *et al.*, 2020). I implemented this recommendation in both Chapters 3 and 5. However, I used an emissions scenario in Chapter 4 as the climate model projections were provided by an external contributor and were only available for emissions scenarios. Secondly, thermal stress projections are often the only projections of future climate used in climate exposure assessments and conservation prioritisation studies for coral reefs (e.g. Mcleod *et al.*, 2010; Magris *et al.*, 2015; Harris *et al.*, 2017; Asaad *et al.*, 2018; Beyer *et al.*, 2018) and the applicability of tropical cyclone projections for use in coral reef studies had not yet been tested. I implemented this recommendation in Chapter 4, examining the extent to which downscaled tropical cyclones represent the cyclone characteristics that determine coral reef damage extent. The third and fourth recommendations of combining projected stressors and incorporating ecological sensitivity and adaptive capacity are the subject of ongoing research and are discussed further in the Future Work section below.

In Chapter 3, I advanced thermal stress projections for coral reefs by generating the first 1 km resolution statistically downscaled thermal stress dataset (Dixon *et al.*, 2022b). I showed that thermal refugia, reefs that experience bleaching-level thermal stress every 10 years or more, rapidly decline with future warming. Only 0.2% of the global coral reef area were refugia with 1.5°C of global warming and 0% remain with 2.0°C. This finding is in line with other coarse resolution thermal stress projections for coral reefs (Frieler *et al.*, 2013; Schleussner *et al.*, 2016) and a high resolution study published after my Chapter 3 work (Kalmus *et al.*, 2022). The major advance is in the high resolution of the projections. Areas with fine-scale oceanographic features that lower ocean temperatures, such as upwelling and strong currents, have been proposed as future thermal refugia for coral reefs but these features are not captured by coarse resolution climate projections. By capturing finer-scale features with my 1 km thermal projections, I show that many of these areas are still unable to maintain suitable conditions for coral persistence with future warming.

In Chapter 4, I tested the suitability of downscaled tropical cyclones for simulating the observed cyclone characteristics important for determining physical damage to coral reefs resulting from wind-induced waves (Dixon *et al.*, 2022a). I showed that tropical cyclone projections are currently unsuitable for informing coral reef management for two main reasons. Firstly, the downscaled tracks did not replicate the spatial patterns of tropical cyclones as the genesis positions were further north and the median track differed to observed. Identifying the coral reefs least likely to be impacted by tropical cyclones is key to coral reef conservation planning (Beyer *et al.*, 2018), but the spatial uncertainties indicate that these low exposure reefs cannot be identified with sufficient certainty to drive conservation decisions. Secondly, the projected changes in reef-damaging characteristics were uncertain as some models projected increases in intensity, size and duration and others projected decreases. The underlying mechanisms driving changes to tropical cyclone characteristics with climate change, such as size, are currently poorly understood limiting our ability to project changes in reef damage in the future.

In Chapter 5, I examined the impact of using climate datasets from different sources and at different spatial resolutions on spatial planning solutions. I used the same statistical downscaling approach described in Chapter 3 to downscale SST projections to 1 km and

5 km using two different observed 5 km SST datasets: CoralTemp (NOAA Coral Reef Watch, 2018) and Climate Change Initiative (CCI; Merchant *et al.*, 2016, 2019). I showed that the climate dataset and resolution used in spatial planning can affect solutions. The extent of differences between solutions varied between the three conservation objectives tested. The objective that prioritised climate refugia (low exposure areas), had the greatest difference between solutions due to the differing trends between the two 5 km datasets and large impact this difference has on the accumulative thermal stress metric used. The objective that prioritised reefs with high historical SST variability had the smallest difference between datasets as the SST variability metrics used were less affected by the difference in trends between the 5 km datasets. When using accumulative thermal stress metrics (e.g. metrics based on degree heating weeks) to prioritise low climate exposure coral reefs, choosing the most appropriate climate dataset is an important step in the conservation planning process. Climate datasets should be compared to coral bleaching and mortality observations in the study location to select the climate dataset that best represents local thermal stress.

6.3 Climate model suitability for projecting coral reef climate exposure

Future changes in temperature were projected with greater certainty than changes in tropical cyclone characteristics. All 57 model and Shared Socioeconomic Pathway (SSP) runs in the ensemble mean calculated in Chapter 3, hereafter referred to as Dixon *et al.* (2022b), agreed that the probability of degree heating week (DHW) events greater than 4°C-weeks will increase with each increase in global mean temperature change, though the magnitude of increases varied between models. In contrast, the six models in Chapter 4, hereafter referred to as Dixon *et al.* (2022a), used to project changes in tropical cyclone characteristics with warming disagreed on whether reef damage would increase, decrease or be unchanged with future warming. The occurrence of extreme climatic events is driven by changes in mean climate and in climate variability (Schaeffer *et al.*, 2005). Mean climate warming contributes more to marine heatwave probability than SST variance (Oliver *et al.*, 2018; Oliver, 2019) and as mean climate is better understood, temperature extremes can be projected with greater certainty than for precipitation for example, where climate variability is a major driver (van der Wiel and Bintanja, 2021).

The statistical downscaling approach used in Dixon *et al.* (2022b) and Chapter 5 captures finer-scale oceanographic processes influencing coral bleaching and mortality and advances previous downscaled projections which have been informing coral reef conservation for the last five years (van Hooidonk *et al.*, 2016; Harris *et al.*, 2017). These projections can be useful in conservation decision making by allowing managers to target low exposure coral reefs for management actions (van Hooidonk *et al.*, 2015). Low exposure reefs may continue to provide goods and services for longer and support the recovery of surrounding areas. However, there are three main factors limiting the identification of low exposure reefs using my statistically downscaled data. Firstly, the daily SST is detrended prior to downscaling to maintain the climate model simulated warming trend. However, this approach does not account for smaller-scale variability in long-term warming trends, for example where upwelling areas are warming more slowly than their surroundings (Randall *et al.*, 2020). Secondly, statistical downscaling techniques assume that the relationship between the fine and coarse scale climate will be unchanged in the future (Fowler *et al.*, 2007). As a result, any changes to oceanographic features impacting bleaching dynamics such as upwelling and ocean circulation will not be captured. Finally, SST is known to vary on less than 1 km scales (Safaie *et al.*, 2018). Microrefugia on <100 m scales are not captured by the 1 km thermal stress dataset generated here (Kavousi and Keppel, 2018). Despite the limitations presented here, the 1 km thermal stress dataset that I have generated represents the highest resolution climate projections for the global coral reef area currently available for coral reef managers to use in practical conservation decisions.

Projecting tropical cyclones using climate models presents a great many challenges due to the rarity of tropical cyclones and lack of consistent, long-term observed data (Knutson *et al.*, 2019). This makes it harder to detect a climate change signal in the historical record than for temperature for which there are longer-term and more consistent time series. Projecting changes in tropical cyclone characteristics requires the accurate simulation of a range of environmental factors that drive tropical cyclone activity (Knutson *et al.*, 2020). While there is a good understanding in the physical mechanisms underlying some tropical cyclone characteristics such as intensity, there are significant knowledge gaps for others such as size. Due to the difficulties in projecting tropical cyclones, current assessments indicate the direction of projected changes at very broad scales (i.e. global and ocean basins). The projections are not yet suitable for projecting changes at scales relevant for coral reef management and so are unsuitable for informing conservation decisions at present.

6.4 Future climate exposure of coral reef ecosystems

The probability of thermal stress greater than 4°C-weeks is projected to increase with future increases in global mean temperature (Dixon *et al.*, 2022b). With 1.5°C of global warming relative to pre-industrial levels, I projected that 90.6% of the 1 km pixels containing coral reefs will be exposed to intolerable levels of thermal stress and 99.7% with 2.0°C of global warming (Table 6.1). At 1.5°C of global warming, this finding is slightly higher than coarse resolution CMIP3 projections (Frieler *et al.*, 2013; Schleussner *et al.*, 2016) and lower than another 1 km resolution CMIP6 study (Kalmus *et al.*, 2022). There is good agreement between all four studies with 2.0°C of global warming where 99-100% of coral reefs globally are projected to be exposed. The three studies used the same definition of intolerable thermal stress as I used in Dixon et al. (2022b) to identify “exposed” coral reef pixels; probability of bleaching-level thermal stress greater than 0.2 yr^{-1} or one event every five years. However, projections are still difficult to compare between studies because the 4 and 8°C-weeks bleaching thresholds are based on different baseline temperatures. The baseline used to calculate the maximum monthly mean (MMM) and DHW in Dixon *et al.* (2022b) is based on remotely sensed CCI SST data. The 4 and 8°C-week thresholds have been applied to the National Oceanic and Atmospheric Administration (NOAA) Coral Reef Watch datasets (Liu *et al.*, 2006) but their applicability to CCI have not yet been tested. In Dixon *et al.* (2022b), I demonstrated that the higher baseline temperatures in the CCI dataset compared to the NOAA Coral Reef Watch CoralTemp dataset, likely mean that the 4°C-week threshold I used indicates higher thermal stress than previous studies. Thus, my 4°C-week projections are more comparable to the 8°C-week projections used by other studies than my 8°C-week projections. However, setting thermal stress thresholds for my 1 km projections is urgently needed as thermal stress projections are highly dependent on the thermal stress threshold used, as noted by Kalmus *et al.* (2022).

Table 6.1: Percentage of the global coral reef area projected to experience probability of bleaching-level thermal stress greater than 0.2 yr^{-1} with 1.5 and 2.0°C of global warming.

Study	Model projections	Coral reef pixel size (km)	Bleaching threshold (°C-weeks) and climatological reference period	Coral reef pixels exposed to intolerable thermal stress (%)	
				1.5°C	2.0°C
Frieler et al. (2013)	CMIP3	50	8 (1980-1999)	89	100
Schleussner et al. (2016)	CMIP3	~30-500	8 (1980-2000)	70-90	99
Dixon et al. (2022b)	CMIP6	1	4 (1985-1990 + 1993)	90.6	99.7
Kalmus et al. (2022)	CMIP6	1	8 (1985-1990 + 1993)	95-98	99.7

Other thermal stress projections for the global coral reef area include those by Donner *et al.* (2005), Donner (2009), van Hooidonk *et al.* (2016) and van Hooidonk *et al.* (2020). Using downscaled (36 km) projections of two models, Donner *et al.* (2005) projected that severe bleaching will occur every 3-5 years in the 2030s and biannually in the 2050s under A2 (higher emissions path) and B2 (lower emission path) emissions scenarios. Based on an ensemble of two GFDL climate models, Donner (2009) projected that 80% of the global coral reef area will be exposed to thermal stress every five years by 2030, 2025 and 2020 in the B1 (“mitigation scenario”), A2 (“fossil fuel dependence”) and A1b (“business as usual”) emissions scenarios, respectively. Higher resolution 4 km CMIP5 projections by van Hooidonk *et al.* (2016) projected an average year of annual thermal stress greater than 8°C-weeks (termed annual severe bleaching) of 2043 (2006-2089) under RCP8.5 (high emissions scenario). Using coarser 25 km CMIP6 projections, van Hooidonk *et al.* (2020) projected that the year of annual severe bleaching will be nine years earlier than in their CMIP5 study under the higher emissions SSP5-8.5.

Higher resolution thermal stress projections (≤ 36 km) identify regional variability in the probability of thermal stress in the future. In agreement with Dixon *et al.* (2022b), the northern Caribbean, Micronesia and parts of Melanesia were identified as high exposure areas and reefs in Polynesia had the lowest projected climate exposure (Donner *et al.*, 2005). In contrast to Dixon *et al.* (2022b), Donner *et al.* (2005) projected high thermal stress in Indonesia and Malaysia. The average year of annual severe bleaching is shown at country and sub-country level in van Hooidonk *et al.* (2016) and (2020). In contrast to Dixon *et al.* (2022b) and Donner *et al.* (2005), French Polynesia did not exhibit the lowest future climate exposure; the year of annual severe bleaching was only slightly later than the global average (van Hooidonk *et al.*, 2016, 2020). In addition, the Persian Gulf had low future thermal stress exposure in van Hooidonk *et al.* (2020) but high exposure in Dixon *et al.* (2022b). This difference may be due to the lower baseline SST for the Persian Gulf in the CCI dataset resulting in higher thermal exposure calculated for the region in Dixon *et al.* (2022b). The Caribbean was identified as a high climate exposure region in all studies. Spatial patterns of thermal stress agreed in some cases (e.g. Sulawesi, Indonesia and Red Sea) and differed in others (e.g. northern Great Barrier Reef and Cuba) between Dixon *et al.* (2022b) and van Hooidonk *et al.* (2016, 2020), although these studies are difficult to compare due to the different metrics of thermal stress used and the different observational SST datasets on which the downscaling is based.

Despite the differences in the methodologies and the magnitude and spatial variation in projected thermal stress, all the studies described in this section agreed that continued global warming will have a devastating effect on coral reefs globally. Rapidly reducing global emissions is paramount to minimise the global mean temperature change and secure a future for coral reef ecosystems. The latest and highest resolution thermal stress projections demonstrate that relying on a small proportion of thermal refugia to maintain suitable conditions for coral reefs is not a viable conservation strategy as these areas will be rare with just 1.5°C of global warming (Dixon *et al.*, 2022b; Kalmus *et al.*, 2022). Instead, promoting coral adaptation to warmer conditions and aiding migration to higher latitudes may better secure coral reef survival than focusing efforts on protecting climate refugia. The IPCC AR6 indicates that many coral reefs may be unable to adapt under high rates of global warming exceeding those in RCP4.5 (Cooley *et al.*, 2022). Identifying lower climate exposure reefs can aid adaptation as these reefs may have more time to adapt than more exposed surrounding areas.

Regional patterns of future tropical cyclone exposure on Australian coral reefs have not been possible to quantify with any certainty as the downscaled tracks were unsuitable for representing coral reef damage at the reef region scale (Dixon *et al.*, 2022a). One and two out of six models projected a significant increase in reef damage for the Coral Sea, Great Barrier Reef and Northern Territory and two and three models for Western Australia in the mid-century and end of century, respectively. Two models projected a significant decrease in reef damage for the Coral Sea, Great Barrier Reef and Northern Territory in mid-century and one model for Western Australia in both mid-century and end of century. These projections indicate slightly higher certainty in an increase in reef damage in Western Australia compared to other regions. However, there was high spatial uncertainty in where tropical cyclones will track and how the three components of reef damage (intensity, size and duration) will change in the future with climate change. This uncertainty in projections prevents the identification of low tropical cyclone exposure coral reefs under future climate change.

6.5 Applicability of local-scale climate projections in conservation planning

I identified differences in spatial planning solutions when using 1 km and 5 km climate datasets. The 1 km resolution Multi-scale Ultra-high Resolution (MUR) SST dataset used to generate the 1 km observed and projected thermal stress has a feature resolution an order of magnitude higher than other remote sensing SST datasets such as Operational SST and Sea Ice Analysis (OSTIA) used in the 5 km CoralTemp dataset (Chin *et al.*, 2017). As MUR is able to resolve both mesoscale (~100 km) and small-scale SST features (as fine as 1 km), the 1 km MUR dataset likely better captures SST features important for determining thermal stress such as upwelling and strong currents. Furthermore, SST datasets based only on infrared data, such as the 5 km CCI and CoralTemp datasets, are affected by seasonal cloud cover preventing high resolution analysis during cloudy months, for example in the northern Indian Ocean summer (Reynolds *et al.*, 2013). Including microwave data in SST analyses increases the monthly variability, better representing seasonal cycles (Reynolds *et al.*, 2007), which is important for calculating thermal stress. Using 1 km climate data in conservation planning may add value by better resolving differences between datasets and better identifying lower climate exposure coral reefs.

Although there may be benefits in using 1 km climate data to inform spatial planning, the differences in spatial planning solutions between the two 1 km datasets from different sources, particularly in the Climate Refugia objective, is a concern, raising questions as to which datasets spatial planners should use. Ocean warming is just one of many considerations in conservation decision making. Socio-economic factors such as reducing impacts on fishing income (Ban *et al.*, 2009), ecological factors such as accurately representing biodiversity and maximising larval connectivity between planning areas (Beger *et al.*, 2010) and other environmental factors such as avoiding areas exposed to tropical cyclones (Beyer *et al.*, 2018) are important considerations. While differences between solutions are reduced by considering other factors that feed into conservation decisions, determining which dataset best represents the thermal stress for a location requires further research. Relating the different climate datasets to observed bleaching and mortality responses can be used to determine the best fit locally. This approach is necessary because there needs to be greater certainty in climate datasets before they can be used to inform spatial planning.

There is increasing interest in using tropical cyclone projections to inform conservation decisions, for example as part of the Reef Restoration and Adaptation Program (https://gbrrestoration.org/), but my research indicates that tropical cyclone projections are not yet suitable for this purpose (Dixon *et al.*, 2022a). Tropical cyclone projections are often made for the end of century (e.g. 2080-2100) or for a doubling in atmospheric CO_2 as climate change signals can be difficult to detect on shorter timescales (Knutson *et al.*, 2020). Conservation decisions are not made this far in advance. Given the uncertainty in the projected change in tropical cyclone characteristics in the mid-century (2040-2060), using observed tropical cyclone data to represent near future tropical cyclone exposure is the most appropriate approach.

6.6 Implications for climate-relevant coral reef management

I have demonstrated that thermal refugia, where suitable conditions for corals are maintained, are rare with 1.5°C of global warming and no longer exist with 2.0°C (Dixon *et al.*, 2022b). While “low” thermal stress exposure reefs are unlikely to persist in the future as no coral pixels are able to escape the impacts of rising ocean temperatures, “lower” thermal stress exposure coral reefs may be identified and used to inform conservation plans. These reefs may have more time to acclimate and adapt to rising temperatures than surrounding areas and may play an important role in repopulating damaged reefs (Beyer *et al.*, 2018; Chollett *et al.*, 2022). Using my high resolution 1 km thermal stress dataset to identify low thermal exposure coral reefs requires two considerations. Firstly, the suitability of the observed data in representing the thermal exposure of the coral reefs in the study location needs to be tested. This can be achieved by comparing the historical thermal stress to bleaching observations. Secondly, uncertainty in the climate model projections needs to be factored into conservation decisions.

Climate models carry uncertainties and biases, but conclusions can still be drawn from their projections providing the associated uncertainty is considered. Chollet *et al.* (2022) used the 1 km resolution thermal stress dataset developed in Dixon *et al.* (2022b) to identify low exposure coral reefs in the northern Caribbean. I calculated historical and projected acute (sum of DHW > 4 and 8°C-weeks) and chronic (trend in SST) thermal stress metrics which were used alongside data on observed hurricane impacts and larval connectivity to identify low climate exposure reefs with high connectivity for repopulating damaged areas, called Climate Priority sites. Robustness of the thermal stress projections was quantified using a novel version of the mean/variance metric to simultaneously account for both model and scenario uncertainty. The mean/variance metric assumes that a low climate exposure reef will have a low average with low variability around it and it can be summarised as the mean divided by the standard deviation (Hamarat *et al.*, 2014). The mean/variance metric was then used alongside the tropical cyclone and connectivity information to identify the Climate Priority sites. Using this approach allowed the most robust low thermal stress exposure sites to be identified factoring uncertainty in climate projections into spatial prioritisation. The work in Chollet *et al.* (2022) is a pilot study that will result in the eventual designation of marine protected areas in the northern Caribbean.

The 1 km resolution thermal stress dataset by Dixon *et al.* (2022b), called HighResCoralStress, is freely available to visualise and download via the data portal at https://highrescoralstress.org/. I have calculated and uploaded eight thermal stress metrics: probability of thermal stress greater than 4 and 8°C-weeks, the number of days greater than 4 and 8°C-weeks, the historical MMM, the trend in annual SST, and the seasonal and inter-annual SST variability. All metrics are available for the observed period (1985-2019) and four projected periods (2021-2040, 2041-2060, 2061-2080 and 2081-2100) except for the seasonal and inter-annual SST variability and the MMM which are available for the observed period only. For each projected time period, metrics are available for four SSPs: SSP1 2.6, SSP2 4.5, SSP3 7.0 and SSP5 8.5 reflecting four future pathways with different peaks in emissions and temperature changes. While the model ensemble mean for each SSP and time period is plotted on the data portal, the projected metrics for each individual model are provided in the files available to download allowing users to account for model uncertainty in their conservation plans. This data is available for 420,334 1 km coral reef pixels, almost twice as many pixels as were analysed in Dixon *et al.* (2022b) providing greater coverage for use in conservation efforts. By making this data publicly available in a user-friendly format, I hope to further research into the inclusion of climate data in spatial planning and support conservation decision making.

6.7 Future Work

6.7.1 Evaluating downscaled thermal stress projections

Differences between both the observed SST data highlighted in Chapter 5 and the different CMIP6 projections of future thermal stress in Dixon *et al.* (2022b), Kalmus *et al.* (2022) and van Hooidonk *et al.* (2020) highlight the need for further evaluation of observed and projected SST datasets. Differences between the data sources are driven by differences in the baseline SST used to calculate DHW-based metrics and likely also drive some of the differences between the projected thermal stress datasets. In situ data for the baseline period (1985-1990 + 1993) used to calculate the MMM for comparing to the remote sensing datasets is not available. The suitability of the climate datasets for a particular location may be evaluated by comparing the remote sensing thermal stress data to bleaching observations to determine which remote sensing dataset best describes observed bleaching responses. Differences between the downscaled thermal stress projections may also be driven by differences in the downscaling methods used (Diaz-Nieto and Wilby, 2005; Wang *et al.*, 2016). Further research is needed to evaluate observed and projected thermal stress datasets to aid conservation decision makers in selecting an appropriate dataset for their needs.

6.7.2 Improving ecological relevance of thermal stress projections

Many of the DHW-based thermal stress metrics used in conservation planning are based on the 4 and 8°C-week thresholds for severe bleaching and catastrophic bleaching and mortality, for example: the number of days above 4 and 8°C-weeks (Beyer *et al.*, 2018), sum of DHW above 4 and 8°C-weeks (Chollett *et al.*, 2022), number of bleaching events above 4°C-weeks (Magris *et al.*, 2015) and the decade in which the DHW exceeds 8°C-weeks every year (Harris *et al.*, 2017). However, many factors alongside thermal stress determine bleaching responses of corals. Some coral species are more thermally tolerant than others (Guest *et al.*, 2012; Kim *et al.*, 2019). Corals that have experienced frequent fluctuations in thermal conditions due to natural climate variability (e.g. El Niño Southern Oscillation) have demonstrated increasing thermal tolerance over time (Donner and Carilli, 2019). Similarly, corals that experienced elevated thermal stress at sub-lethal levels in the days prior to the onset of bleaching-level stress (Ainsworth *et al.*, 2016) or have a high daily SST range (Safaie *et al.*, 2018) experienced reduced bleaching severity and mortality. Local pressures such as nutrient pollution can reduce thermal tolerance (Donovan *et al.*, 2020), while high turbidity can reduce irradiance preventing bleaching (Sully and van Woesik, 2020). Single thresholds of 4 and 8°C-weeks for corals globally do not capture the observed variability in bleaching responses. In addition, the 4 and 8°C-week thresholds have not been tested for the CCI-based 1 km thermal stress projections in Dixon *et al.* (2022b). As such, more ecologically relevant thermal stress metrics are needed to characterise historical and projected bleaching risk. This issue will be explored in future research where revised region-specific bleaching thresholds will be set for my 1 km resolution thermal stress dataset using a large database of bleaching observations (>20,000 observations). Other environmental stressors may be incorporated into this research to examine the impact of stressor interactions on the bleaching response.

6.8 Final Conclusions

The IPCC AR6 identifies tropical coral reefs as the ecosystems most at risk from rising temperatures highlighting that they are already experiencing widespread decline (Cooley *et al.*, 2022). Climate-relevant coral reef management is essential to ensure that conservation plans remain viable under changing environmental conditions. As environmental conditions become more inhospitable for coral reef ecosystems, interest in prioritising the areas with the lowest climate exposure and thus the highest chance of survival is increasing (Beyer *et al.*, 2018; Chollett *et al.*, 2022). My research identifies where climate model projections are suitable for identifying low exposure coral reefs to inform conservation plans and where they are not yet appropriate. High resolution observed and climate model projected thermal stress data can be used to identify coral reefs with lower thermal exposure than surrounding areas informing climate-relevant conservation planning. However, uncertainty in thermal stress data needs to be properly accounted for. Evaluating the suitability of observed data for representing thermal stress in a study location and accounting for uncertainty in climate model projections are important steps in the climate-relevant coral reef management process. My high-resolution thermal stress dataset is a novel freely available tool that can support climate-relevant coral reef management alongside socioeconomic, ecological and other environmental information. By projecting future thermal exposure at high spatial resolution and using the latest generation of climate models, I demonstrate that local-scale thermal refugia will quickly disappear (Dixon *et al.*, 2022b), supporting the IPCC AR6 findings that just 1.5°C will cause widespread decline of coral reefs (Cooley *et al.*, 2022). In contrast, I found that tropical cyclone projections at the coral reef region scale are currently too uncertain for informing conservation decisions (Dixon *et al.*, 2022a) contradicting the high confidence in an increase in storm intensity in the future stated in the IPCC AR6. Understanding when climate data can be applied in conservation planning will result in more robust decision making and ultimately aid coral reef survival in the future.

6.9 References

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