Predicting coral trends and attributing drivers of change from local to global scales

Julie Vercelloni*[1, 2], Murray Logan[1], Andrew Zammit-Mangion[3, 4], Matthew Sainsbury-Dale[5], Kerrie Mengersen[2, 3], and Manuel González-Rivero[1]

[1]Australian Institute of Marine Science, Townsville, Cape Cleveland, QLD 4810, Australia
[2]Centre for Data Science, Queensland University of Technology, Brisbane, QLD 4000, Australia
[3]School of Mathematics and Applied Statistics, University of Wollongong, Wollongong, New South Wales, Australia
[4]Securing Antarctica's Environmental Future, University of Wollongong, Wollongong, New South Wales, Australia
[5]Statistics Program, Computer, Electrical and Mathematical Sciences and Engineering Division, King Abdullah University of Science and Technology (KAUST), Thuwal, Saudi Arabia
[6]School of Mathematical Sciences, Science and Engineering Faculty, Queensland University of Technology, Brisbane, QLD 4000, Australia

Abstract

Modern biodiversity monitoring programs are designed to assess abundance trends of keystone taxa and deliver scientific insights to inform decision-making and policy development. An important consideration when using these evidence-based frameworks is the quantification of uncertainty from trends, which determines the robustness of data-driven methods in detecting and attributing changes across habitats and regions. In coral reefs, sparse and fragmented monitoring programs challenge the assessment of long-term reef habitat changes, despite the need for actionable insights to reduce the loss of coral cover. We introduce a new predictive modelling framework, which combines machine learning for the extraction of ecological data with a statistical model to predict trends in hard coral cover and propagate uncertainty across multiple spatial scales. The model estimates the spatio-temporal variability of coral cover at monitoring locations and integrates information on marine heatwaves and cyclones to predict coral cover across entire marine ecoregions, thereby filling the spatial and temporal observational gaps inherent in coral reef monitoring programs. It also quantifies the effects of known regional drivers on coral cover loss and allows the exploration on how specific disturbances influence coral cover spatially across regions. We demonstrate the framework's capability using case studies from the northern Great Barrier Reef and in simulation experiments. Together, these illustrate the importance of incorporating the spatial dimension to capture

*Corresponding author - Electronic address: j.vercelloni@aims.gov.au; ORCiD: 0000-0001-5227-014X

the variability in coral cover and attribute drivers of coral cover change with greater confidence. This modelling framework is designed for integration into the ReefCloud platform, where it can automatically combine data from monitoring programs worldwide and support evidence-based decision-making for the management and conservation of coral reefs from local to global scales.

Introduction

At the heart of addressing the biodiversity crisis, global efforts focus on obtaining reliable trends of biological components across multiple spatial scales (Dornelas et al., 2023). Used as an indicator, a trend change in the abundance or distribution of keystone taxa supports management plans and policy interventions to maintain biodiversity and ecosystem functions (Eddy et al., 2021; Tekwa et al., 2023; Gonzalez et al., 2023). The main challenge remains the confident detection of increasing and decreasing trends due to the sparsity of monitoring data, sampling biases, and statistical deficiencies to address uncertainty and sources of non-independence across space and time (Hughes et al., 2021; Dornelas et al., 2023; Tekwa et al., 2023; Johnson et al., 2024). Additional monitoring data can alleviate some of the above challenges by improving the confidence in trend detections and enabling more effective data-driven management actions (Leung and Gonzalez, 2024), and future projections (Edmunds, 2024). However, the scale of habitat deterioration is sometimes so substantial that simply increasing the volume of monitoring data is unlikely to be sufficient to improve change detection, which remains constrained by cost and time (King and Halpern, 2025). Methodologies that can extract deeper insights from existing datasets, optimise data interpretation, attribute changes to specific drivers, and enhance predictive capabilities are urgently needed.

Automating biodiversity assessments is essential for providing timely evidence to decision makers (Keitt and Abelson, 2021). The Global Biodiversity Information Facility (GBIF) exemplifies how digital platform engineering through the automation of data processing workflows and the integration of diverse data sources provides greater global coverage (Moritz et al., 2011). Open data supports international biodiversity frameworks such as the Kunming-Montreal Global Biodiversity Framework and drives advances in the detection of population trend changes (Dornelas et al., 2023; Leung and Gonzalez, 2024). Despite an increasing number of digital platforms across regions, additional work is needed to address persistent geographic and taxonomic gaps (Caldwell et al., 2024; King and Halpern, 2025), particularly in biodiversity-rich countries (Stephenson, 2020), and to tackle the unique challenges of marine ecosystems (Fisher et al., 2011; Borja et al., 2024; McClanahan et al., 2024).

A major challenge in assessing changes in the conditions of coral reef ecosystems is the limited availability of long-term trends in monitoring data due to the slow growth of keystone habitat-builders, Scleractinian hard corals, and their complex responses to environmental disturbances (Obura et al., 2019; Eddy et al., 2021; Donovan et al., 2023; Edmunds, 2024; Emslie et al., 2024b). Despite representing 26% of the global coral reef area and being highly susceptible to climate change impacts, including marine heatwaves, monitoring sites in the Pacific region remain limited (Wicquart et al., 2025). When excluding the Australian region, only 50 monitoring locations qualify as long-term (i.e., more than

15 years of data), representing 8.5% of the global dataset that was used to assess the Status of Coral Reefs as part of the Global Coral Reef Monitoring Network (Souter et al., 2021). When the Australian region is included, the number of long-term locations increases to 207, with 89.8% of these surveys conducted along the Great Barrier Reef (GBR) (Souter et al., 2021). Despite their significant scientific value (Obura et al., 2019), many of these long-term datasets are sparse and irregularly sampled, in the sense that yearly inferences are often not based on observations from the same reef locations. These data gaps can increase the uncertainty in trend detection, given the fine-scale spatial variability of decline and recovery dynamics of coral communities (Vercelloni et al., 2023; Donovan et al., 2023; Cresswell et al., 2024) and the heterogeneous impacts of disturbances (Vercelloni et al., 2020; Edmunds, 2024; Emslie et al., 2024b).

Automating assessments of reef habitat conditions facilitates the creation of larger and more consistent datasets over time (Obura et al., 2019; Gonzalez-Rivero et al., 2020; Wicquart et al., 2022). Improved access to these data, along with new quantitative methods to capture patterns of variability in coral cover, is expected to accelerate our ability to detect changes in coral cover trends (as the key indicator of coral reef habitat condition) and advance our knowledge on regional drivers of reef habitat patterns with greater confidence. ReefCloud is a digital platform designed to support decision making for the management and conservation of coral reefs using data-driven products. The project uses machine learning algorithms to analyse underwater reef images of the seafloor (Gonzalez-Rivero et al., 2020; Wyatt et al., 2025) and assesses changes in reef habitat conditions using a predictive model. Data generated from image analysis are automatically integrated into the predictive model, along with remote sensing products, to predict coral cover trends from local to global spatial scales and to attribute loss in habitat extent to key disturbances including marine heatwaves and cyclones. In this paper, we introduce the predictive model designed for integration into the ReefCloud platform. We demonstrate the framework's capability to capture coral cover trends at multiple spatial scales and quantify the effects of known regional drivers of coral loss using case studies from the northern Great Barrier Reef and simulation experiments.

The modelling framework

Machine learning

Coral cover is estimated from underwater images using a convolutional neural network and point-sampling methodology (Gonzalez-Rivero et al., 2020; Wyatt et al., 2025). The neural network classifies a total of 50 points, and these classifications are used to estimate the coverage of benthic communities on the image scale. Underwater images are taken along a transect. We define coral cover along a given transect as the total number of points classified as containing hard coral across all images taken along that transect.

Spatial scales

In this paper, we predict changes in coral cover at two spatial scales defined from global datasets. The first scale of predictions is at the biogeographic regions delineated by the Marine Ecoregions of the World (MEOWs) (Spalding et al., 2007). The second scale, the tier-level, comprises a surface tessellation of 5×5 km hexagonal units and enables fine-scale spatial gridded prediction. Tiers were delineated based on the Tropical Coral Reefs of the World global map (Burke et al., 2011), using reef locations to define their boundaries. Reef area per tier was calculated by summing the proportion of reef area within each tier. This information was then used to weight coral cover predictions at the MEOW scale.

Disturbances

The statistical modelling framework considers two types of disturbances, cyclone and heat stress exposure. They were selected because of their global data availability and their well-documented direct impacts on coral cover. The first, cyclone exposure, defines the spatial distribution of likely cyclone impacts estimated using the 4MW model (Puotinen et al., 2016). Cyclone exposure is defined as the duration of damaging waves (in hours) from cyclones in any given year, and is obtained using the duration and speed of modelled cyclonic winds. Destructive waves are measured as the average of the highest third of wave heights during a period of strong winds, with wave heights of four meters or more. The longest annual duration of damaging wave conditions is treated as the disturbance metric for any given year.

The metric for the second disturbance, Degree Heating Weeks (DHW), is used to estimate the exposure to marine heatwaves that may lead to mass coral bleaching. DHW is derived from the Coral Bleaching HotSpot product that provides an instantaneous estimate of heat stress over a 12-week window (Liu et al., 2018). The maximum DHW per year was used as an indicator of a heat stress event in the model.

Cyclone exposure and DHW values are available at the tier-level across the entire MEOWs. When the annual maximum occurs after the field observations in a given year, the observation in that year is assigned to the following year to ensure temporal consistency. Disturbance values are also considered at different temporal lags (1 and 2 years) to assess their long-term impacts on coral cover.

Predictive model

We developed a hierarchical spatio-temporal model to: (1) predict changes in coral cover across the two spatial scales defined above; (2) propagate model uncertainty from the tier-level to the ecoregion-level; (3) attribute the coral cover loss to disturbances; and (4) enable efficient model deployment across multiple ecoregions with minimal computing resources. We modelled monitoring data using a Fixed-Rank Kriging (FRK) approach (Cressie and Johannesson, 2008; Zammit-Mangion and Cressie, 2021; Sainsbury-Dale et al., 2024). FRK represents spatial and temporal patterns using a basis functions and random effects. The basis functions are represented using a low-rank approximation, characterized by a fixed number of pre-defined basis functions. Because this number remains constant regardless of the size of the dataset, the method allows for efficient computation with large datasets (Cressie and Johannesson, 2008). The random effects are assumed to be correlated, and induce spatial correlation and temporal dependencies. This approach is ideal for capturing the variability of coral dynamics spatially and for detecting trends across multiple spatial scales.

It also naturally handles sampling inconsistencies in reef datasets and predicts coral cover at unobserved space-time locations, like unmonitored reefs, or at additional time points. The model is included within a regression framework to account for additional dependencies, such as disturbances, to improve coral cover predictions and quantify the effects of known regional drivers of coral cover change.

Uncertainty associated with predicted coral cover is quantified through Monte Carlo sampling from predictive distributions, and this can be done at both observed and unobserved locations. Model parameters are estimated as the posterior mode; these estimates are analogous to maximum likelihood estimates in a Frequentist framework.

In this study, our response variable is coral count at the tier level, obtained by summing the coral count in all transects that fall into the respective tier. Z_i denotes the coral count in a year t_i at the tier location s_i, where $i = 1,...,n$, and n is the number of data points. The predictive model is given by;

$$Z_i \sim \text{Binomial}\big(N_i, Y(s_i,t_i)\big) \tag{1}$$

$$\text{logit}(Y(s_i,t_i)) = x(s_i,t_i)^\top \alpha + v(s_i,t_i) + \zeta(s_i,t_i) + V(s_i) \tag{2}$$

Here, $Y(s,t)$ is a non-linear function that represents the underlying spatio-temporal process influencing the proportion of coral cover at tier i, and N_i is the total count. $\mathrm{Y}(s_\mathrm{i},\mathrm{t}_\mathrm{i})$ is related to the observed count Z_i via a logit transformation. Changes in coral cover are modelled using four different sources of spatio-temporal variability attributed to: 1) spatially referenced heat stress and cyclone exposure disturbances at lag of 0 years, 1 year and 2 years in $x(s_i,t_i)$, with associated effect, α to capture long-term effects of disturbances, 2) medium-scale variation associated with spatio-temporal basis functions across the whole area, $v(s_i,t_i)$, 3) fine-scale variation at the tier scale, $\zeta(s_i,t_i)$, and 4) independent and identically distributed random effects at the reef scale, $\mathrm{V}(s_\mathrm{i})$. Coral reefs are identified within each tier using the open-access Tropical Coral Reefs of the World global map (Burke et al., 2011). The predictive model is fitted using the FRK package version 2.3.1 (Sainsbury-Dale et al., 2024) on the R statistical software version 4.4.1 (R Core Team, 2024).

The model was assessed using visual and statistical diagnostics, including model fit, and residual patterns using the DHARMa R package (Hartig, 2024). In addition, we developed a "leave-out data" approach to assess the predictive performance of the model. We used four performance measures to evaluate model predictions with the exclusion of data in two configurations (randomly and by blocks; (Roberts et al., 2017)). We also explored the influences of the basis functions in the detection of coral trends. Results of these analyses are shown in Appendix A.

In the ReefCloud platform, predictive models are fitted at the MEOW level, which we define here as the regional scale. The models generate predictions of coral cover at the tier level within each MEOW. Other spatial layers, such as custom sub-regional classifications, can easily be incorporated into the modelling framework for estimating trends in coral cover at custom spatial scales. The distributions of predicted coral cover at the tier-level within each MEOW are aggregated to estimate regional trends in a statistically sound manner that propagates uncertainty across space. Prior to the aggregation, the predictions are weighted by the reef area within each tier to account for differences in reef extent. Weighted predictions are then summed across region and divided by the total reef area within that region to estimate coral cover at the regional level. The same process is used to predict coral trends at broader spatial scales, including national levels. Significant year-to-year trend changes in coral cover are identified using the predictive distributions and represented with arrows. In the plateform, an upward arrow indicates at least a 90% probability of increase, a downward arrow indicates at least a 90% probability of decrease, and a flat arrow denotes no detectable change.

The attribution of changes in coral cover is explored using different outputs of the model. The effect sizes correspond to the α parameters and are used to assess the significance of disturbance effects (heat stress and cyclone exposure disturbances at lags of 0, 1, and 2 years) on coral cover. Model parameters and observed disturbance values can be used to predict coral cover values under increasing disturbance intensity to explore how much a specific disturbance contributes to changes in coral cover. The model outputs can also be used to predict the individual disturbance's contribution to coral cover. In particular, coral cover changes to one disturbance can be analysed by fixing all other disturbances to some fixed values. Predictions under both low (2 DHWs) and high (14 DHWs) heat stress intensities at lag 0 are generated to explore spatial patterns of coral cover, aggregated across all years.

Case-study 1: Australia

Monitoring data

Publicly available data from the Wet Tropics, one of the five Natural Resource Management (NRM) regions of Australia's Great Barrier Reef (GBR) and a marine ecoregion, are used to fit the predictive model (Figure 1). In the ReefCloud platform, data are considered public when stakeholders have consented to display them on the online dashboard and to include them in analytical processes, including modelling studies. The regional GBR data were extracted from the database on 30 July 2025. They include a total of 763 transects from 171 reefs collected between 2006 and 2024, across four monitoring programs. Ninety-eight per cent of the coral data come from two long-standing monitoring programs led by the Australian Institute of Marine Science: the Long-Term Monitoring Program and the AIMS, Marine Monitoring Program Inshore https://www.aims.gov.au/research-topics/monitoring-and-discovery/monitoring-great-barrier-reef. These programs have surveyed permanent reef locations along the Great Barrier Reef for more than 30 years, with image-based data collection beginning in 2006. Other programs include observations from the Coral Sea Foundation and the XL Catlin Seaview Survey (Rodriguez-Ramirez et al., 2020). Although these datasets are more temporally limited, they provide valuable observations that help expand the spatial coverage of coral data.

Tiers represent the spatial grid on which coral cover is predicted (Figure 1). Observed values in coral cover at data-tiers are used to fit the model, while predictions at prediction-tiers are generated based on the fitted model and cyclone exposure and heat stress values (at lags 0, 1 and 2) at those locations.

The contribution of each disturbance to changes in coral trends across all-tiers (data-tiers and prediction-tiers) is quantified directly by the model. In the Wet Tropics, data-tiers represent 7.1% (77 tiers) of all-tiers (1067 tiers). Observed trajectories of coral cover varied from 2.21% to 74.6% with a median coral cover values estimated at 23.76% between 2006 to 2024 (Figure 2).

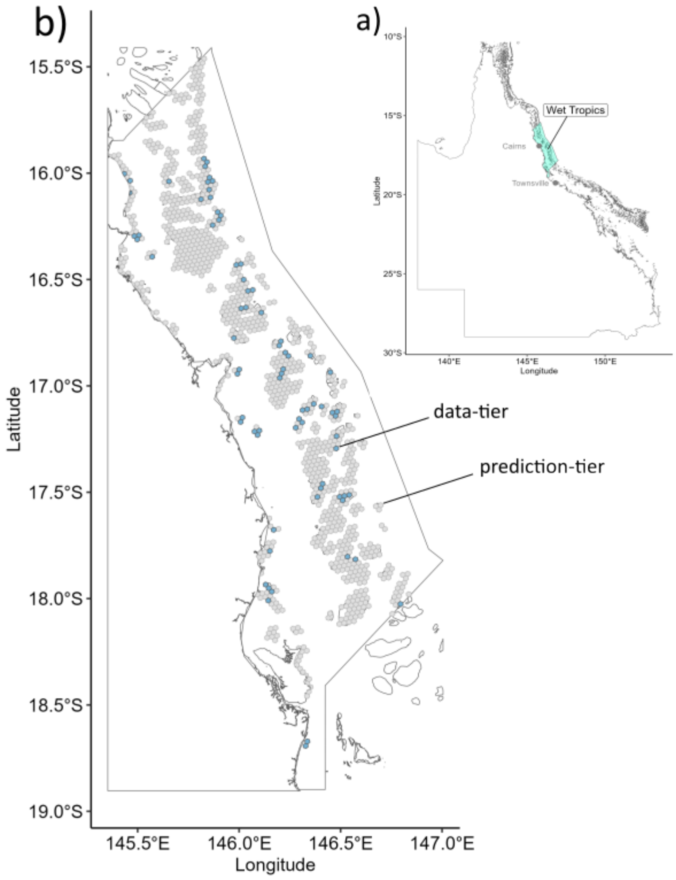

Figure 1: a) Locations of the Wet Tropics along the GBR. b) Visualizations of data- and prediction-tiers within the region showing the spatial distributions of the coral data.

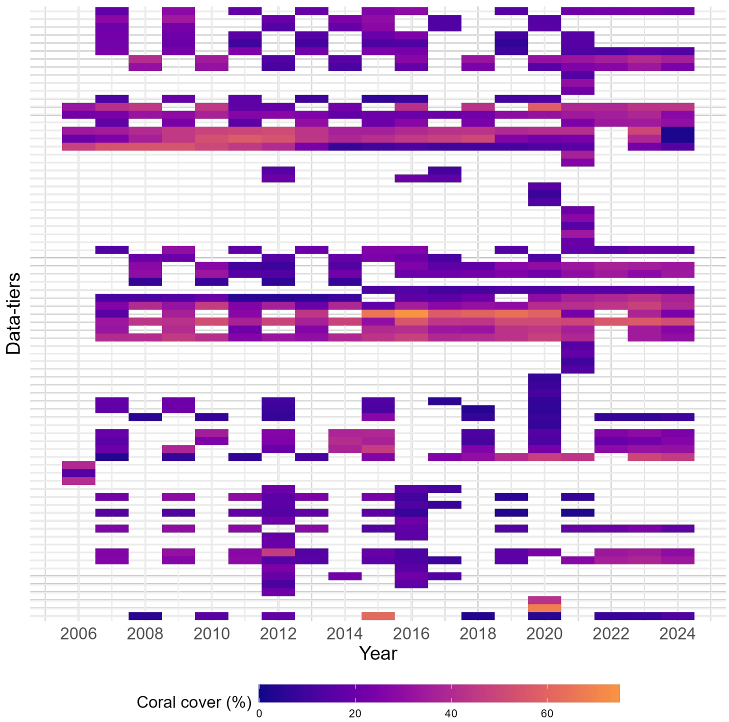

Figure 2: Temporal pattern of mean coral cover (%) by data-tiers in the Wet Tropics (2006–2024). White gaps represent missing data.

The Wet Tropics NRM region is subject to frequent disturbances, including multiple bleaching events and cyclones over the past 18 years, most notably the back-to-back mass bleaching events of 2016 and 2017 (Hughes et al., 2018; Madin et al., 2018; Vercelloni et al., 2020; Emslie et al., 2024a). The extracted disturbance values reveal multiple potential events, including eight years with detected exposure to cyclonic waves and five years with non-zero DHW values (Figure 3). Despite covering only a small portion of the region, the data-tiers capture disturbance intensity that reflects the broader regional signal. Notably, the 2016 heat stress event appeared more severe within the data-tiers compared to the regional mean, with high DHW values detected in 19 tiers (representing 1.8% of all-tiers), potentially indicating a stronger local signal compared to the rest of the region. Note that a non-zero disturbance intensity does not necessarily result in coral cover decline as specific, but generally poorly understood, thresholds need to be exceeded before leading to potential impacts (?Vercelloni et al., 2020; Puotinen et al., 2020; Castro-Sanguino et al., 2021). Nevertheless, in the modelling framework, disturbance values are treated as continuous variables.

Predicted trends in space and time

In our modelling framework, regional trends can be estimated at all-tiers (Figure 4a) or at data-tiers (Figure 4b). In the Wet Tropics, coral cover across all locations declined gradually from 25.2% in 2015 to 19.1% in 2020, before

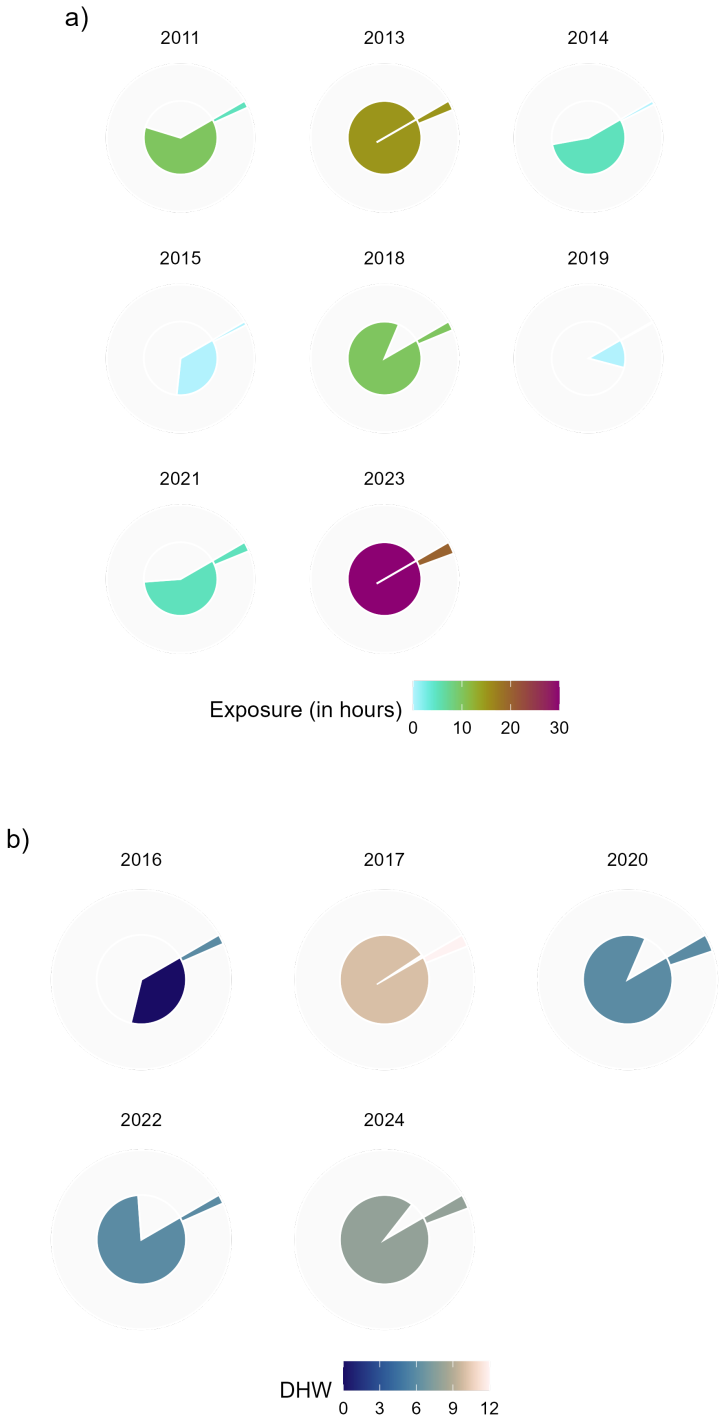

Figure 3: Proportion of regional areas affected by disturbances across two data levels: all-tier (inner ring) and data-tier (outer ring) for each year between 2006 and 2024 (in the case of data-tier, the proportion is calculated with respect to the number of all-tiers). Colours indicate: a) average exposure to cyclone waves, and b) average Degree Heating Weeks (DHW). Light grey in the inner ring denotes regional areas without disturbance detections in that year. Light grey in the outer ring indicates areas that were not surveyed during that year.

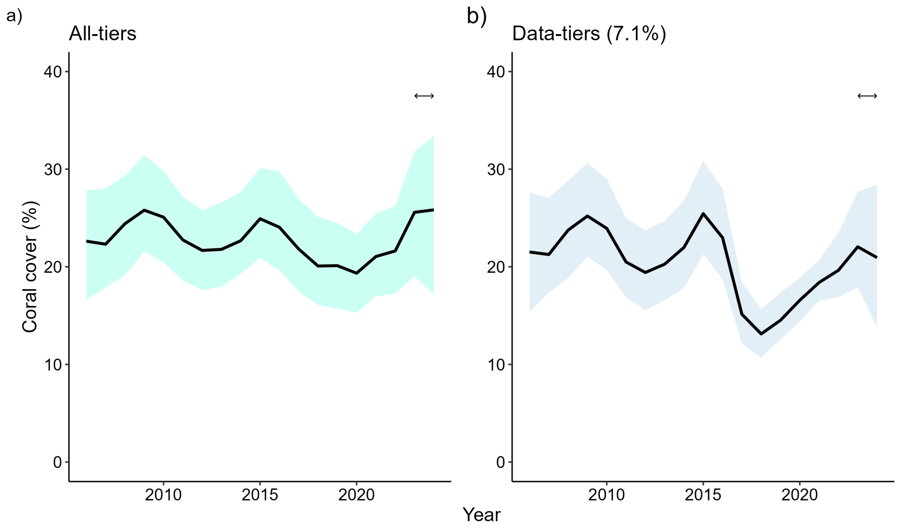

Figure 4: Regional coral cover trends predicted by the spatio-temporal model when considering a) all-tiers (prediction-tiers + data-tiers) and b) data-tiers only. The black lines show mean coral cover values and shaded areas the associated 95% prediction intervals. The percent value indicates the proportion of data-tiers across the Wet Tropics region. The flat arrows indicate an absence of significant changes in coral cover between the two latest surveyed years.

recovering to 25.3% in 2024. When considering only the data-tiers, the trend shows a steeper decline from 25.6% in 2015 to 13.0% in 2018, followed by a recovery to 22.0% in 2023 and a decrease to 20.7% in 2024. These sharper changes are less apparent in the all-tiers trend due to the higher uncertainty associated with predictions from the prediction-tiers (Appendix A, Figures 1 and 2). After aggregation, these higher uncertainties contribute to smoothing the overall regional trend when more tiers are included. However, for both spatial aggregation scales, coral cover is estimated to have remained largely unchanged between 2023 and 2024 as indicated by the flat arrows in Figure 4.

At a finer spatial scale, predicted coral cover ranges from 1% to 50% (Appendix A, Figure 3). Between 2006 and 2011, predicted coral cover is generally lower in the southern section of the Wet Tropics region. However, the coral cover increases in these locations between 2012 and 2016. The impact of the 2017 heat stress event is evident across the entire region, with consistently lower predicted coral cover from 2018 to 2022. Coral cover values show a region-wide recovery in 2023 and 2024, although some locations in the southern part continued to exhibit low predicted values. The spatio-temporal patterns of uncertainty reveal lower uncertainty at and near data-tier locations, with increasing uncertainty in areas farther from these sites, consistent throughout the years (Appendix A, Figure 4). Additionally, uncertainty generally increased across the region in 2024.

Attributing drivers of change

The attribution of changes in coral cover across 2006-2024 reveals significant negative effect sizes (95% prediction intervals do not overlap-zero) associated with cyclone exposure at one-year time lag and heat stress at one- and two-year time lags across the region (Figure 5). The model predicts substantial declines in coral cover driven by increasing disturbance intensity (Figure 6). The maximum relative decline associated with heat stress is estimated at lag 0, with a 49.1% reduction in coral cover during periods of 14 DHWs, the highest level observed in 2017. The magnitude of decline decreases with longer time lags, dropping to 42.9% at lag 1 and 24.5% at lag 2. We estimate a maximum relative decline of 97.6% in coral cover (from 21.0% to 2.4%) associated with cyclone exposure at lag 1, corresponding to 0–45 hours of cyclonic wave conditions, the maximum intensity recorded during Cyclone Jasper in 2023 (Figure 6). However, the widening prediction intervals at higher exposure values indicate substantial uncertainty in these estimates.

The predictions under low and high heat stress intensities show distinct spatial variability of coral cover (Figure 8). Under low heat stress (2 DHWs), more than half of the region is estimated to have coral cover above 25%, with only a few locations below 10% coral cover. Under high heat stress (14 DHWs), the coral cover declines across the entire region, with most locations below 15% and only a few tier locations sustaining cover around 25-30%.

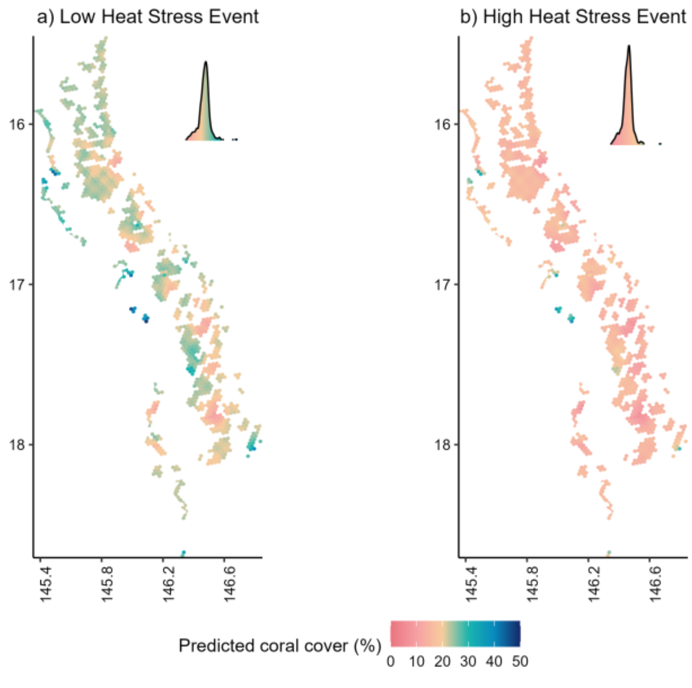

Figure 8: Predicted regional coral cover under low and high levels of cyclone exposure and heat stress with means of a) 2 DHWs and b) 14 DHWs. The inset plots show the regional distribution of predicted coral cover, with colors representing the corresponding predicted values.

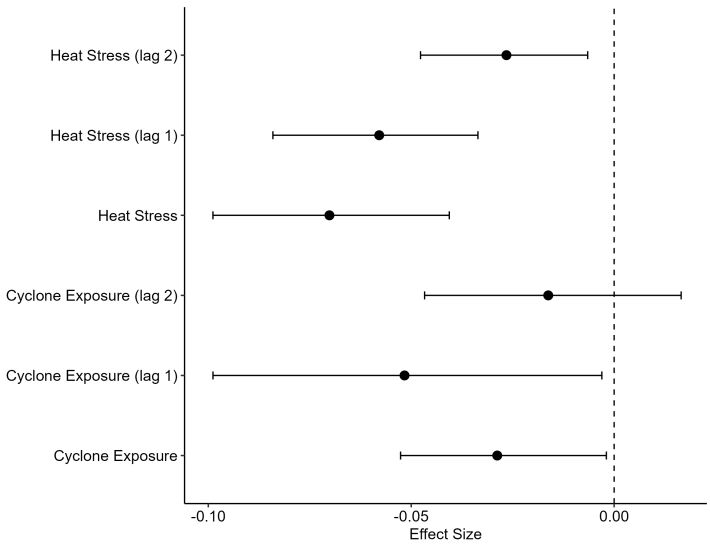

Figure 5: Overall attribution of disturbances.

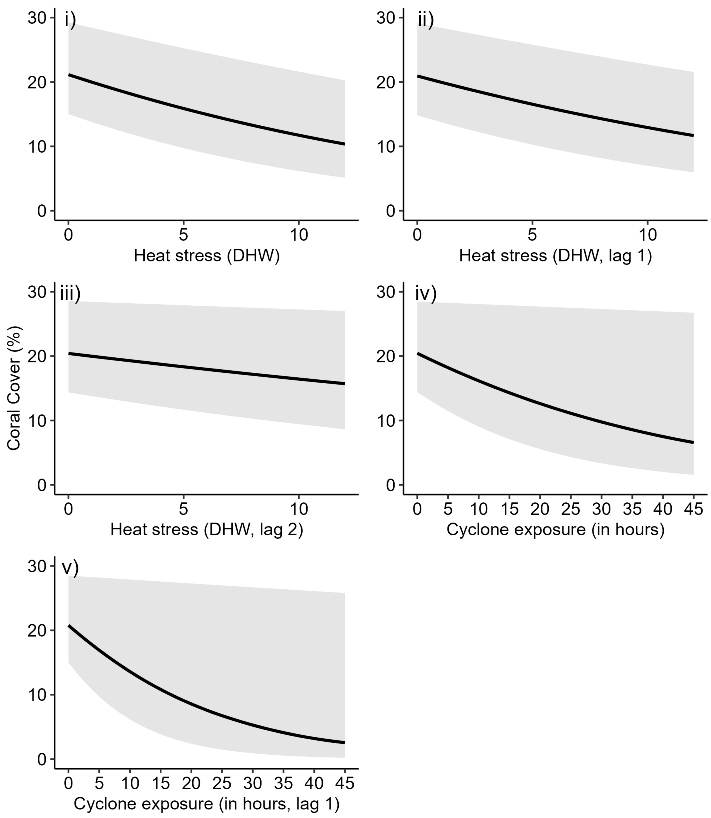

Figure 6: Conditional attribution of disturbances.

Figure 7: Attribution of disturbances. The top panel shows the estimated effect sizes of disturbance exposure (in the logit scale). The points represent the estimated effect and the intervals represent the corresponding 95% credible intervals. The bottom panels display the predicted coral cover (in the observed scale) across the range of disturbance values, from the minimum to the maximum values observed in the region. The lines correspond to the averaged predicted values and shaded areas their associated 95 % prediction intervals. Effects have been calculated at the mean values of all the other covariates. Note that only the four disturbances deemed to be significant by the model fit are displayed.

Model validation

Model performance shows a strong agreement between predicted and observed coral cover at the data-tier level, with an R^2 of 89% (Appendix A, Figure 8). The final model, whose results we show here, was chosen via a model comparison study, which showed that incorporating time-lagged disturbances and reef random effects are important for good model fit.

Results from the data analysis that tested the exclusion of data (leave-out-data) indicate that the model predictive performance declines when entire blocks of observations, such as specific reefs and sites, are removed (Appendix A, Figure 9). As anticipated, the number of temporal basis functions in the model affects the smoothness of coral trends at the tier level, which subsequently impacts the uncertainty in regional trends (Appendix A, Figure 10 and 11). The number of basis functions also influence the pattern of attribution of disturbance effects that is inferred when fitting the model (Appendix A, Figure 12).

Case-study 2: Simulation experiments

Our spatio-temporal model provides the opportunity to predict values in coral cover at locations without observations and for missing years. The FRK framework handles spatial and temporal gaps by combining spatio-temporal random effects estimated across the region for each year with disturbance values to generate predictive distributions at prediction-tiers. From these distributions, both mean prediction and associated uncertainties are derived. However, in the absence of observational data for validation, assessing the accuracy of these predictions remains difficult. Our simulation study allows us to explore the robustness of the predictive model under known conditions, specifically by evaluating its predictive performance when observations are sparse in the spatial dimension.

Generation of synthetic data

Simulation scenarios were created using the R package synthos (https://github.com/open-AIMS/synthos). synthos generates virtual atoll reefs from which synthetic spatio-temporal patterns of coral cover are produced using dependency structures mimicking realistic baselines, population dynamics, disturbance regimes and latent stochastic processes. The sampling design mirrors monitoring programs on the Great Barrier Reef, incorporating a nested structure of reefs (50 reefs), sites (fixed at 2 per reef), transects (5 per site), images (100 per transect), and points (50 per image). Point-based count data are simulated to emulate the GBR data produced from the ReefCloud image analysis framework (Wyatt et al., 2025). A predictive tier-grid of 0.1-degree resolution is created, onto which disturbance effects are projected. The FRK model is fit using the synthetic coral cover values at data-tiers, and the model predictive performance is evaluated using four predictive measures to assess the overall accuracy of coral cover predictions at prediction-tiers, where now true values are known (Table 1). Additional model diagnostics include evaluating model goodness-of-fit and the ability to recover true projected coral cover across all virtual reefs. Detailed descriptions of the synthetic data generation process, model diagnostics, and associated code are provided in Appendix B.

Three scenarios were tested, representing low, medium, and high numbers of monitored reefs, based on annual surveys conducted over a 15-year period. These scenarios were selected to represent the long-term coral reef monitoring efforts across the Pacific region. A fourth scenario represents a sparse temporal resolution, in which 50 reefs are monitored over 15 years with varying survey intensities. Each reef is randomly surveyed between 2 and 15 times, with no more than 5 years between any two consecutive surveys. This scenario mimics the aggregation of different data sources with permanent and opportunistic observations.

The scenarios are defined as follows:

- The high-resolution scenario includes 25 reefs monitored annually for 15 years.
- The medium-resolution scenario includes 15 reefs monitored annually for 15 years.
- The low-resolution scenario consists of five reefs monitored annually for 15 years.
- The sparse-temporal scenario is based on 50 reefs monitored over 15 years with heterogeneous temporal sampling intensities.

Table 1: Details of predictive measures used to evaluate the predictive performances of the models in the simulation experiments. The metrics yield scores between 0 and 1, where values closer to 0 indicate a better predictive performance.

Name	Details
Coverage error (CvgErr)	The absolute difference between the proportion of times the 95% prediction intervals include the true values and 0.95.
Root-mean-squared prediction error (RMSPE)	Indicates how far predictions deviate from true observations, without accounting for uncertainty.
95% interval score (IS)	Balances accuracy and precision by rewarding intervals that include the true value and penalizing those that are too narrow or too wide.
Continuous Ranked Probability Score (CRPS)	Assesses the overall quality of the predictive distribution, penalizing inaccuracies, imprecision, and overconfidence.

Predictive performance

Validation diagnostics suggest that the FRK model performs reliably in all tested scenarios in terms of predictive accuracy (Appendix B, Figure 9). The low-resolution data (5 reefs monitored annually over 15 years) results in reduced predictive performance based on the continuous ranked probability (CRPS) and root-mean-squared prediction error (RMSPE) and interval score (IS). This result reflects a higher model uncertainty associated with coral cover predictions at locations without observations, inflating the uncertainty associated with the predicted regional trend and disturbance effects (Appendix B). The high- and medium-resolution scenarios exhibit similar predictive performances, although the medium-resolution scenario demonstrates undercoverage, suggesting that the model is overconfident in its predictions. The temporally-sparse scenario (50 reefs sampled with varying temporal intensities) shows the best predictive performance for all metrics.

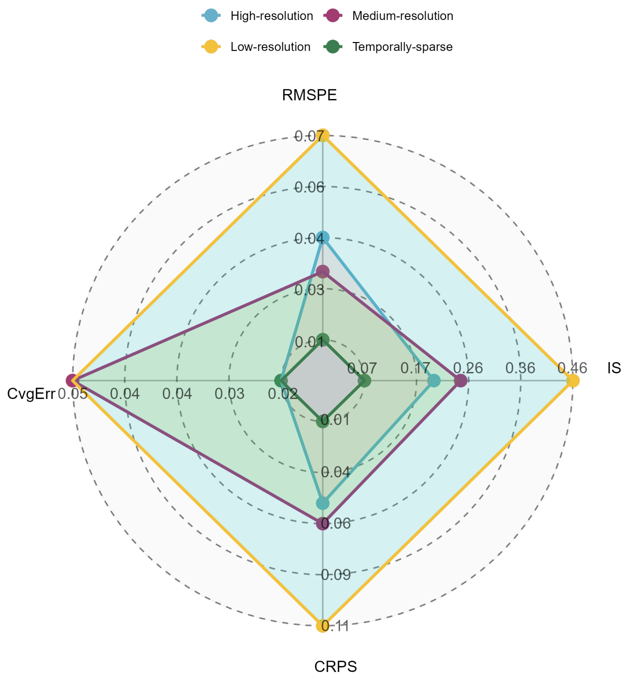

Figure 9: Predictive performances of the four simulation scenarios with different temporal and spatial data resolution. Each axis represents one of the evaluation metrics described in Table 1. Overall, better predictive performances of the models are indicated by smaller polygons.

Discussion

In this study, we introduced a new modelling framework to assess coral cover trends from local to global scales and attribute drivers of coral cover loss, and validated its performance. Through two case studies, we demonstrated that the approach enables generating new insights from long-term monitoring data to understand the variability in hard coral coverage across temporal and spatial dimensions with greater confidence. We showed that the predictive model performs best in regions with high data resolution across space and time. However, globally, locations with widespread and regular coral reef monitoring activities continue to be rare (Souter et al., 2021; Wicquart et al., 2025). This hampers the provision of reliable data to guide evidence-based management and conservation decisions in many regions (Fisher et al., 2011). The ReefCloud platform has been addressing this issue in two ways. First, the automation of image analysis allows users to generate ecological data in a more cost- and time-efficient manner (Australian Institute of Marine Science (AIMS), 2024). Second, the predictive model fills the spatial and temporal observational gaps inherent in coral reef monitoring programs and can guide users in selecting additional monitoring locations, either in space (e.g., new sites) or in time (e.g., repeated observations) to improve the spatial representation and reduce current geographic biases.

Insights gained from decades of data highlight the critical importance of long-term coral reef monitoring to detect trends and attribute key drivers of change with confidence (Fine et al., 2019; Obura et al., 2019; Donovan et al., 2021; Emslie et al., 2024b; Edmunds, 2024; Wicquart et al., 2025). To manage existing significant data gaps, predictive models can support the assessments of temporal trends in coral cover and attribution to associated pressures. However, in many studies on habitat change, the spatial structure is often overlooked in analyses of long-term data (Vercelloni et al., 2023; Johnson et al., 2024). In their most recent analyses, the Global Coral Reef Monitoring Network employed a machine learning approach to predict reef habitat conditions in the Pacific using latitude and longitude as spatial input (Wicquart et al., 2025). In the modelling framework reported here, we model space directly by incorporating spatio-temporal dependencies that vary at different spatial scales, which is then combined with information on disturbances affecting the chosen metric, coral cover. The use of spatial and temporal correlation structures into predictive modelling helps to detect significant trend changes more rapidly, as they borrow information across multiple locations and time points. Our framework predicts coral trends at multiple spatial scales and attributes the drivers of coral cover loss while accounting for uncertainty.

Our first step was to address the observational gaps in space and time within the long-term monitoring surveys. The use of correlated random effects and available information on key disturbances informs estimates of coral cover changes at un-monitored reef locations (prediction-tiers) and missing years using nearby observed values of coral cover at monitoring locations (data-tiers) and time points. Monitoring programs are typically designed to address specific local or regional management needs, often within the constraints of limited logistics and funding (Obura et al., 2019). Consequently, sampling designs are frequently unbalanced and irregular across space and time (Souter et al., 2021), which can bias regional trends if observed changes at monitoring locations are not representative of broader areas. Predicting coral cover trends continuously across space and time helps to overcome these limitations by generating regional estimates based on more complete and representative patterns of change. Unlocking this information from monitoring data provides reliable, evidence-based guidance for the management and conservation of coral reefs at scales ranging from local to global. Furthermore, the integration of the model into the ReefCloud platform adds value to existing monitoring programs by integrating all publicly available data to bridge gaps in space and time.

The second step aimed at handling uncertainty when scaling up predictions of coral cover. We used a bottom-up approach to propagate uncertainty across space. First, predictions at tier-scale are weighted by the percentage of reef area to account for variations in reef extent among the tiers. Then, we aggregated and summarized predictive distributions within a larger spatial scale to obtain the regional trend. The modelling framework is designed to generate predictions beyond regions by integrating outputs from different regional models. The framework design is inherently flexible, allowing users to incorporate customized spatial scales, to represent, for example, jurisdictional or ecological boundaries or particular management needs. For instance, in the northern Great Barrier Reef (GBR), management practices distinguish between inshore and offshore reefs (Emslie et al., 2024a). Using the model outputs, coral cover predictions were easily generated at these sub-regional scales, revealing a decreasing trend for the inshore reefs (see Appendix A, Figure 6). The modelling framework illustrates year-to-year changes in coral cover using arrows, helping users to confidently interpret the estimated trends.

Our third step was to quantify the effects of environmental drivers contributing to coral cover decline. Our predictive framework enables to gain new insights on how disturbances influence coral cover spatially. In the Wet Tropics region of the GBR, marine heatwaves and their associated time lags emerged as the primary drivers of coral cover decline. Model predictions suggest that approximately half of the regional coral cover would be lost under heat exposure of 14 DHWs, with broad impacts persisting for one to two years after the event. This pattern is reflected in the spatial predictions, where coral cover is estimated to fall below 15% across the entire region under high marine heatwave intensity, while coral cover would be more than 25% under a low heat stress scenario. These predictions also highlight the spatial variability in coral cover, with some locations remaining at low levels (15%) of coral cover under low heat stress, while a few tiers maintain high coral cover despite experiencing high heat stress. This pattern suggests the presence of localized processes that may not be fully captured at the 5 km^2 disturbance resolution. Our findings also likely reflect the large spatial footprint of heat stress events compared to cyclone exposure, as 4 out of 5 events affected the entire region. The modelling framework was developed to incorporate spatial layers that are continuously available across global regions. This limits the inclusion of additional variables that influence coral cover changes, such as local disturbances (Good and Bahr, 2021; Walker et al., 2024; Emslie et al., 2024b). Integrating additional disturbances that act at local scales, such as outbreaks of crown-of-thorns starfish, would enhance the model's capacity to attribute changes in coral cover accurately. However, such datasets are only available for some sites or local regions. In the absence of such data products, the inclusion of correlated random effects helps to account for unobserved variables.

Within ReefCloud, the sparse and fragmented distribution of monitoring locations limits the robustness of the predictive model. Validating coral cover predictions used to fill spatial and temporal gaps in monitoring data remains challenging due to the lack of independent datasets for direct comparison. In the Bayesian paradigm, all data are used to fit the model, which limits the possibility of reserving truly independent observations for validation (McElreath, 2018). The simulation scenarios overcome this challenge by generating predictions at reef locations where true values of coral cover are known. Satisfying model performances confirmed that the modelling approach can accurately retrieve true values and capture long-term coral cover trends at prediction-tier locations and years under variable sampling designs. However, the predictive capacity of the model declines in regions with sparse monitoring, especially in the spatial dimension. This is a result of the predictive model attributing higher uncertainty to areas far from observed data, particularly in very large ecoregions with unevenly distributed monitoring sites. Uncertainty will decrease with the availability of more data, especially when surveying new reefs and sites, but will likely remain high in the remote coral reef regions of the world without monitoring programs.

One way to address this challenge is to integrate different data sources. This approach was tested under the simulated 'Temporally-sparse' scenario, which yielded to the best model predictive performance. This result highlights the value of integrating data from multiple monitoring programs with varying temporal and spatial resolutions. Such integration enables the capture of temporal dynamics through repeated observations and spatial patterns through the inclusion of additional monitoring locations simultaneously. Deploying the modelling framework into the ReefCloud platform allows the automated incorporation of diverse data sources that have been made publicly available by their owners. In this study, we showed that the individual observations are aggregated within tiers, meaning that the raw data remain private. Making the model outputs accessible to all users supports evidence-based management actions from local to global scales. This may also convince more users to make additional datasets publicly available, which over time will increase the value and robustness of the modelling framework.

Finally, the estimated trend changes and model insights on the attribution to drivers of change can guide the selection of additional monitoring locations. For example, if a significant change is detected at the regional scale (indicated by a downward or upward arrow), it reflects a period of instability associated with either a decline or recovery in coral cover. In such cases, monitoring efforts should focus on resurveying the same locations to establish if subsequent observations agree with expected trajectories and to inform potential management interventions (Castro-Sanguino et al., 2021). The same approach can be applied at the tier-level scale, using trend change indicators (Appendix A, Figure 5) to identify more localized sites for resurveying when monitoring the entire ecoregion is not feasible. During periods of stability and/or lack of detectable changes from predicted coral trends (indicated by a flat arrow), monitoring efforts could also be shifted to additional sites. The selection of these new sites is guided by several factors, including their distance from existing monitoring locations, with greater distances helping to reduce model uncertainty. Users can also use disturbance values from previous years to select new monitoring sites, aiming to reduce uncertainty in the attribution of coral cover loss to disturbances. It is important to consider the spatio-temporal trade-offs involved, where the decision to establish additional sites or to prioritize repeated observations will likely need to be made on a case-by-case basis by the local reef scientists and managers.

Author contributions

JV, KM, BS and MGR conceived the idea; JV, AZM, MSD and KM contributed to the development of the predictive model and associated outputs; JV and ML developed the synthetic data framework; JV, KM and MGR created the data presentations; JV wrote the original draft and revised the final version for submission based on feedback from all authors.

Data availability

All code and data required to reproduce the results can be accessed at https://github.com/open-AIMS/RC_modelling. The ReefCloud public data used in case study 1 are available at (Australian Institute of Marine Science (AIMS), 2025).

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