Predicting coral cover trends from local to broad spatial scales

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Abstract

Modern biodiversity monitoring programs are designed to assess trends in abundance and distribution of keystone taxa and deliver scientific insights to inform decision-making and policy development. An important consideration when applying this information is the quantification of uncertainty, which determines the robustness of detecting changes across habitats and regions. In coral reefs, sparse and fragmented monitoring datasets hinder the assessment of reef habitat changes. We introduce a new spatio-temporal prediction framework for estimating trends in hard coral cover and associated uncertainty at a local scale (5 km^2 spatial units). The model accounts for spatial and temporal dependencies in coral cover through a latent process formulation, where correlation is structured explicitly in space and time, and includes environmental variables describing exposure to heat stress and tropical cyclones. We use a weighted spatial aggregation approach to predict trends at the regional scale, with the spatial extent of a region varying according to the geographic context. The same approach is applied to estimate trends at broader spatial scales by combining outputs from multiple models through the ReefCloud platform, ensuring that predictions reflect the spatial distribution of reef-building corals and that uncertainty is appropriately propagated across spatial scales. The model also quantifies effects of heat stress and tropical cyclones and characterizes their associations with coral cover change across gradients of disturbance intensity.

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We demonstrate the value of the framework using three use cases: the central Great Barrier Reef in Australia, American Samoa and simulation experiments. Together, these applications highlight the potential of our integrated approach as a widely applicable method for predicting coral cover trends at various spatial scales. We also discuss the substantial uncertainty associated with the framework due to the limitations of available datasets and suggest approaches to improve the robustness of trend detection for coral reefs and their attribution to environmental disturbances.

Introduction

At the heart of addressing the biodiversity crisis, global efforts focus on obtaining reliable trends in abundance and distribution across taxonomic groups and biodiversity metrics, while explicitly accounting for dependence structure in monitoring data (Dornelas et al., 2023; Johnson et al., 2024). 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 (Lindenmayer and Likens, 2010; Tekwa et al., 2023; Gonzalez et al., 2023; Johnson et al., 2024). A key challenge is the robust detection of increasing and decreasing trends in the presence of sparse monitoring data, sampling biases, and limitations in statistical approaches to account for uncertainty and multiple non-independent correlation structures, including those in space and time (Thomas, 1996; Yoccoz et al., 2001; Peterson et al., 2020; Hughes et al., 2021; Dornelas et al., 2023; Tekwa et al., 2023; Johnson et al., 2024; Boënnec et al., 2024). Additional monitoring data can alleviate some of the above challenges by improving the confidence in trend detection and enabling more effective data-driven management actions (Leung and Gonzalez, 2024), and forecasting (Dietze et al., 2018; Edmunds, 2024). However, the scale and speed 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 (Yoccoz et al., 2001; King and Halpern, 2025). Methodologies that can extract deeper insights from existing datasets, represent complex dependence structure, improve interpretability, and explicitly account for uncertainty 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 also 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; Johnson et al., 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).

Marine ecosystems present additional challenges for monitoring and assessing habitat conditions due to the limitations of traditional survey methods, which are often costly and time-consuming (Ditria et al., 2022; Borja et al., 2024). As a result, monitoring efforts are not necessarily concentrated in countries with the most unique marine biodiversity or the greatest environmental threats, but rather in those with higher per capita gross domestic product, where wealthier nations have a greater capacity to support long-term monitoring programs (Fisher et al., 2011; McClanahan and Rankin, 2016; Moussy et al., 2022). Across the world, a major constraint in tracking changes in the condition of coral reef ecosystems is the limited availability of long-term monitoring data (i.e., more than 15 years of sampling) due to irregular data collection, or sampling at time intervals not capturing the complex responses of Scleractinian hard corals to environmental pressures (Obura et al., 2019; Peterson et al., 2020; Mellin et al., 2020; Souter et al., 2021). For example, despite representing 26% of the global coral reef area and being highly susceptible to climate change impacts, including marine heat stress and tropical cyclones, only 50 locations in the Pacific region of the Global Coral Reef Monitoring Network (GCRMN) are regularly sampled (Souter et al., 2021; Wicquart et al., 2025). By comparison, in the Australian GCRMN region, 157 monitored locations are classified as long-term, of which 89.8% are situated along the Great Barrier Reef (GBR) (Souter et al., 2021). Many more reef locations are surveyed in these regions (Souter et al., 2021; Wicquart et al., 2025), but not in a consistent or permanent manner. This likely reflects the various purposes of monitoring programs (Lindenmayer and Likens, 2010; Obura et al., 2019), resulting in annual inferences that are often not based on repeated observations from the same reef locations and may be biased by substantial data gaps.

Automating assessments of reef habitat conditions facilitates the generation of larger and more consistent datasets over time (Obura et al., 2019; Gonzalez-Rivero et al., 2020; Wicquart et al., 2022; Ditria et al., 2022). Improved use and access to these data, together with new quantitative methods to capture patterns of variability in coral cover, is expected to accelerate our ability to assess changes in coral cover trends (as the key indicator of coral reef habitat condition) with greater robustness. ReefCloud is a digital platform designed to support decision making for the management and conservation of coral reefs using data-driven products (Australian Institute of Marine Science (AIMS), 2024). The pipeline uses machine learning algorithms to analyze underwater reef images of the seafloor (Gonzalez-Rivero et al., 2020; Wyatt et al., 2025) and tracks changes in reef habitat conditions with statistical modelling methods. In this paper, we introduce a new analytical framework that integrates a state-of-the-art spatio-temporal model and weighted spatial aggregation into the ReefCloud pipeline to predict coral cover trends at multiple spatial scales and quantify their associations with disturbances while ensuring that uncertainty is appropriately estimated throughout the modelling framework and across spatial scales. We demonstrate the framework's capability using case studies from the central subregion of the Great Barrier Reef in Australia, American Samoa and simulation experiments.

The Spatio-Temporal Prediction Framework

Benthic Monitoring Data

Coral cover was estimated from downward-looking underwater photoquadrats using a convolutional neural network and point-sampling methodology (Gonzalez-Rivero et al., 2020; Wyatt et al., 2025). The neural network classified a total of 50 points per image, and these classifications were used to estimate the coverage of benthic communities on the image scale. Underwater images were taken along a transect. We defined observed coral cover at the transect scale as the proportion of points classified as hard coral across all images collected along that transect.

Local Spatial Scale

The finest scale of prediction employed a surface tessellation of 5×5 km hexagonal units as they are known to improve the representation of complex spatial processes like neighbour distances and disturbance impacts (Birch et al., 2007). These gridded locations, hereafter referred to as tiers, were delineated using the Tropical Coral Reefs of the World global map (Burke et al., 2011). Tiers were constrained to shallow coral habitats (0-12m), areas where scleractinian hard corals and the majority of coral reef monitoring programs occur, ensuring model predictions align with the spatial distribution of reef-building corals. Reef area per tier was calculated by summing the proportion of reef area within each tier. By aggregating monitoring data into these uniform 5 km^2 tiers, we standardized spatial units for modelling purposes and ensured computational feasibility at large scales. However, this aggregation results in a loss of the finer-scale variability in coral cover and reduces the ability to explicitly represent uncertainty at these finer spatial resolutions.

Disturbances

The framework considered two types of disturbances, tropical cyclones and heat stress exposure. They were selected because of their global data availability and their well-documented direct and drastic impacts on coral cover across large areas (Harmelin-Vivien, 1994; Hoegh-Guldberg, 1999; Adjeroud et al., 2009; Cheal et al., 2017; Hughes et al., 2018; Puotinen et al., 2020; Eakin et al., 2026). The first metric, cyclone exposure, defined 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 was estimated using the duration and speed of modelled cyclonic winds. Potential destructive waves were 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 potential damaging wave conditions was treated as the disturbance value for any given year.

The second disturbance metric, Degree Heating Weeks (DHW), was used to quantify exposure to heat stress that are potentially linked to mass coral bleaching events. DHW values were obtained from the Coral Bleaching HotSpot product, which provides near-real-time estimates of accumulated thermal stress over a rolling 12-week period (Liu et al., 2018). For modelling purposes, the annual maximum DHW was used to represent the intensity of an heat stress event for a given year.

Cyclone exposure and DHW values were available at the tier-level. When the annual maximum occurred after the field observations in a given year, the observation in that year was assigned to the following year to ensure temporal consistency. Disturbance values were incorporated into the model across multiple time lags (up to 2 years) to account for their potential delayed influence on coral recovery.

Predictive Model

We developed a predictive model to: (1) predict changes in coral cover across space and time at local scale; (2) quantify uncertainty in a statistically sound manner; (3) estimate disturbance effects; and (4) minimize computing resources. We modelled coral cover data using a Fixed-Rank Kriging (FRK) approach, which jointly represents space and time (Cressie and Johannesson, 2008; Zammit-Mangion and Cressie, 2021; Sainsbury-Dale et al., 2024). FRK accounts for spatio-temporal dependencies using basis functions and correlated random effects. The spatial 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 and spatial domains (Cressie and Johannesson, 2008) and therefore circumvents computational challenges previously associated with spatio-temporal statistics (Wikle, 2015).

The spatio-temporal basis functions are constructed as tensor products of spatial basis functions at multiple spatial scales and temporal basis functions (Zammit-Mangion and Cressie, 2021). Their associated random weights induce spatio-temporal dependence through a covariance matrix governing the random effects, which in turn defines the dependence between locations. The specification of spatio-temporal basis functions is automatically generated in the FRK package (Zammit-Mangion and Cressie, 2021).

This modelling approach is ideal for capturing the spatio-temporal variability in coral cover data. It also naturally handles sampling inconsistencies in monitoring datasets and predicts coral cover at unobserved space-time locations, like unmonitored reef locations and missing years. The model was included within a regression framework to quantify effects of disturbances as fixed effects. Uncertainty associated with predicted coral cover was quantified through Monte Carlo sampling from predictive distributions at local scale. Model parameters were estimated as the posterior mode; these estimates were comparable to maximum likelihood estimates. The predictive model was 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).

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

$$Z_i \sim \text{Binomial}\big(N_i, Y(s_i,t_i)\big) \tag{1}$$
$$\text{logit}(Y(s_i,t_i)) = x(s_i,t_i)^\top \alpha + v(s_i,t_i) + \zeta(s_i,t_i) + R(s_i) \tag{2}$$

Here, $Y(s,t)$ is a non-linear function that represents the underlying spatio-temporal processes influencing the proportion of coral cover at tier i, and N_i is the total number of image points summed across all the images in tier i. The N_i parameter controls for sample size and reflects the sampling effort associated with transect length. $\mathrm{Y}(s_\mathrm{i},\mathrm{t_i})$ is related to the observed count Z_i via a logit transformation.

The model formulation includes between two to four sources of spatio-temporal variability. The first source of variability is attributed to spatially referenced heat stress and cyclone exposure disturbances at lag of 0 years, 1 and 2 years in the matrix $x(s_i,t_i)$, with corresponding predictive effects, α vector. The inclusion of a disturbance into the model formulation was based on their distributions at multiple spatial scales. Specifically, a disturbance was retained when its 75th percentile exceeded zero across the spatial domain of interest and when weak collinearity was detected among disturbance time lags at data locations. The second and third sources are a large-scale variation associated with spatio-temporal basis functions across the whole domain of prediction, $v(s_i,t_i)$, and a fine-scale variation at local scale, $\zeta(s_i,t_i)$, that are always included in the model. The fourth source of variability is associated with independent and identically distributed reef random effects, $\mathrm{R}(s_\mathrm{i})$. Coral reefs are identified within each tier using the open-access Tropical Coral Reefs of the World global map (Burke et al., 2011), with reef presence encoded as a categorical variable for each spatial unit. The latest is included if more than one reef is detected in the spatial domain.

Model Assessments

Model performance was assessed using visual and statistical diagnostics, including model fit, and residuals 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)). This approach enabled us to examine the influence of disturbance presence or absence and the inclusion of random effects on the model predictive performance. It also allowed us to explore the contribution of basis function sizes to model predictions and disturbance size effects.

Weighted Spatial Aggregation

In our spatio-temporal prediction framework, coral predictions were aggregated across spatial scales via a systematic integration of model outputs within the ReefCloud pipeline (Figure 1). The first step consisted of generating local predictions of coral cover for all years, t_i, and tiers (5 km^2 spatial units, s_i) within a given region, using the predictive model. Local predictions were then stored as posterior predictive distributions, $Y(s_i,t_i)$, within the ReefCloud pipeline.

For the second step, local predictions were aggregated to estimate trends at broader spatial scales within a hierarchical framework that explicitly propagated uncertainty across space. Before the aggregation, predictive distributions were weighted by the reef area to account for spatial differences in reef extent within each tier and ensure standardized, comparable spatial units. The weighted predictions were subsequently summed across each region or subregion and normalized by the total reef area of that region or subregion to estimate coral cover (Souter et al., 2021; Wicquart et al., 2025).

For predictions of coral cover trends at other spatial scales, local predictive distributions from multiple regional models were aggregated and weighted following the same spatial aggregation method described above. Significant year-to-year fold changes in coral cover were derived from predictive distributions estimated at multiple spatial scales and represented using arrows. An upward arrow indicates a 90% probability of increase, a downward arrow a 90% probability of decrease, and a horizontal arrow no detectable change.

Simulation Experiments

The performance of the model was initially assessed using simulation experiments (Logan and Vercelloni, 2025), designed to address two objectives. First, the simulation study allowed us to evaluate the robustness of the predictive model across the entire synthetic spatial domain, rather than at a limited number of randomly chosen locations. This framework enabled the assessment of prediction accuracy at the domain scale by recovering the true simulated temporal field that is not observable in real data. Second, the simulation scenarios evaluated model performance under varying spatial and temporal data resolutions. A common characteristic of coral reef monitoring programs (Gardner et al., 2003; Bruno and Selig, 2007; Obura et al., 2019; Souter et al., 2021; Wicquart et al., 2025) is also reflected in the ReefCloud database (Australian Institute of Marine Science (AIMS), 2024), which is dominated by short-term public datasets (i.e., reef locations surveyed for less than five years) and shows geographic biases in monitoring effort (Table 1, Appendix A). Detailed methods and results of the simulation experiments are presented in Appendix A.

Association with Disturbances

The association between disturbances and coral cover change was evaluated at the regional level by examining the α model parameters (effect sizes and corresponding 95% predictive intervals). Disturbance effects were inferred when the predictive intervals were entirely below zero. We also combined these model parameters with observed range of disturbance values to predict coral cover across increasing disturbance intensity and to characterize the shape and magnitude of the predicted coral cover responses. A similar spatial approach was used to predict disturbance-specific patterns in the spatial distribution of coral cover. This was done by fixing other disturbance variables at values close to zero while varying values of the disturbance of interest. Spatial patterns of predicted coral cover associated with each disturbance were evaluated across its observed range, from absence to maximum values, with changes expressed in absolute terms.

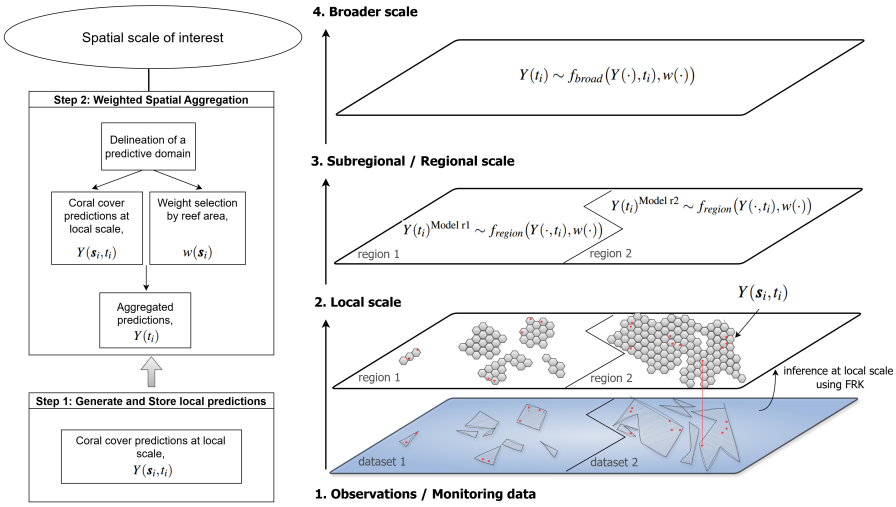

Figure 1: Schematic representation of the spatio-temporal prediction framework. Coral cover predictions at the local scale (5 km^2 spatial units) are estimated using the FRK model and stored in the ReefCloud pipeline as predictive distributions. At the scale of a region, predictions are generated through a weighted spatial aggregation approach. The framework is extended to broader spatial scale(s) by combining predictive distributions from multiple regional models.

Use Cases

The Central Great Barrier Reef

We focus first on the central subregion of the GBR, which extends from latitude 15.4° to 20.7° S and corresponds to a distinct Marine Ecoregion of the World (MEOW) unit (Spalding et al., 2007). The Central GBR covers a reef area of 5,300 km^2 and comprises three Natural Resource Management (NRM) regions, including the entirety of the Wet Tropics and Burdekin NRM regions, as well as approximately 60% of the Mackay Whitsunday NRM region (Figure 2). Image-based coral cover data were extracted from the ReefCloud database on 01 December 2025, comprising 358 coral reefs and 1,728 transects surveyed between 2006 and 2024 at depths of 2–10 meters. Reefs in this subregion benefit from extensive monitoring across multiple programs with varying temporal resolutions, with three of five monitoring programs having survey records spanning more than 15 years (Tables 1-3, Appendix B) for each NRM regions.

The Central GBR was subject to frequent disturbances (Done, 1982; Hughes, 1992; Osborne et al., 2011; De'Ath et al., 2012; Vercelloni et al., 2017; Mellin et al., 2019; Emslie et al., 2024b), including multiple heat stress events and cyclones across the three regions over the past 18 years (Figures 3, 5 ,7 in Appendix B). The Wet Tropics NRM region experienced substantially higher thermal stress during the 2017 bleaching event, with mean DHWs peaking at 12 recorded at data-tier locations, compared to a maximum of 8 DHWs in the other regions. The mean duration of exposure to cyclonic waves was nearly

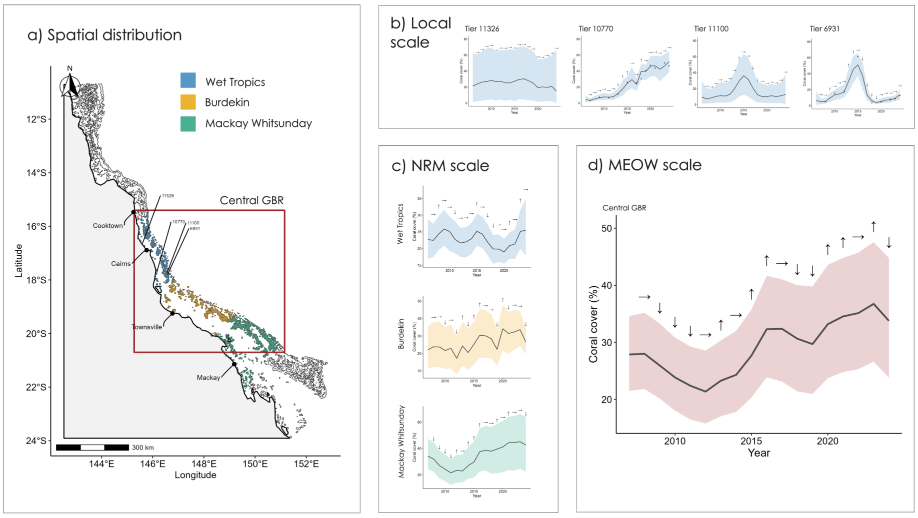

Figure 2: a) Location of the Central Great Barrier Reef (GBR) subregion and its three Natural Resource Management (NRM) regions. Each NRM region is divided into tiers (5km^2 spatial units) that represent the local scale at which the predictive model estimates coral cover. Four example local trends from the Wet Tropics region are presented. b) Three predictive models, one per NRM region, are fitted and associated predictive distributions of coral cover combined with the weighted spatial aggregation approach to generate predictions at the NRM and MEOW scales. Black lines show mean predicted coral cover, with shaded areas representing 95% prediction intervals. Dots indicate observed coral cover at the local (tier) scale, and arrows mark significant year-to-year changes in coral cover, with at least 90% probability. Note that the y-axes are on different scales for visualization purposes.

twice as long in the Mackay Whitsunday region compared to the other regions related to the 2017 Cyclone Debbie. In the Wet Tropics, disturbance values at data locations reflected the broader regional signal, while in the other regions records of heat stress were sightly higher and cyclone exposure lower.

Trends Across Spatial Scales

The predictive model was fitted at the scale of the NRM regions, rather than the central GBR MEOW region, due to its very large spatial extent, resulting in three individual models. Across the three NRM regions, the best predictive model formulations accounted for four sources of variability, including heat stress and cyclone exposure at lags of 0, 1, and 2 years. The models exhibited strong predictive performance, with close agreement between predicted and observed coral cover and R^2 values ranging from 0.79 to 0.89 (Figure 23, Appendix B). The weighted spatial aggregation method was used to estimate coral cover trends at the NRM region and MEOW scales.

At the local scale, predicted coral cover displayed varying spatial and temporal patterns within each region associated with different degree of uncertainty (Figure 2, Figures 8-13 in Appendix B). In all regions, uncertainty is generally lowest at and near tier locations containing data and increases with distance from these areas. The Wet Tropics NRM region exhibits lower uncertainty than the Burdekin NRM region, which shows high uncertainty in its southern extent across all years, whereas the Mackay Whitsunday region displays increasing uncertainty from 2017 onwards. The propagation of these differing levels of uncertainty is evident at the regional level, with the Wet Tropics showing narrower prediction intervals for coral cover trends (Figure 2).

At broader spatial scales, the predictive models capture some fluctuations in coral cover; however, the relatively large uncertainty associated with these estimates limited our ability to detect robust trend changes for most years. Nevertheless, the framework allows the detection of significant changes associated with decline and recovery in coral cover. At the regional scale, Wet Tropics coral cover fluctuated between 20% and 25%, with one significant regional decline occurring in 2017 and two increases in 2015 nd 2023 (Figure 2). In the Burdekin NRM region, coral cover ranged from 18% to 32%, showing the greatest temporal variability over the past 18 years, with more frequent fluctuations than in other regions. A significant recovery was estimated between 2015 and 2016, followed by a gradual decline that became significant in 2019, a short recovery in 2020, and a subsequent decline again in 2024. In the Mackay Whitsunday NRM region, coral cover exhibited a sustained decline from 2008 to 2010, dropping from 35% to 20%, followed by approximately three years of significant increase, reaching around 40% by 2021. At the MEOW scale, coral cover across the central GBR fluctuated between approximately 20% and 35%, with the framework detecting significant periods of recovery in 2007, 2015, 2016, and 2020 over the study period.

Association with Disturbances

Associations between changes in coral cover indicate negative predictive effect sizes associated with disturbances in each NRM region, as evidenced by 95% prediction intervals that do not overlap zero (Figure 3). Five of six disturbances were associated with coral cover decline in the Wet Tropics, with heat stress at lags 0 and 1 showing the largest mean effects, followed by cyclone exposure at lag 1. In the Mackay Whitsunday NRM region, four disturbances were associated with coral cover change, with the largest negative associations observed for cyclone exposure at lags 0 and 2. In the Burdekin NRM region, coral cover decline was associated with cyclone exposure at lag 1.

Increasing heat stress was associated with a linear decline in predicted coral cover (Figures 14, 17 and 20 in Appendix B). Across 0-12 DHW, heat stress was associated with declines in predicted coral cover ranging from 11% in the Mackay Whitsunday region (Figure 20 in Appendix B) to 18.3% in the Wet Tropics (Figure 14 in Appendix B). Increasing cyclone exposure was associated with a non-linear decline in coral cover, with a steep initial decrease occurring within the first 10–15 hours of exposure (Figures 14, 17 and 20 in Appendix B). The predicted coral cover reduction associated with cyclone exposure was consistently larger than that associated with heat stress, ranging from approximately 38% to 44% across all regions and time lags, with maximum exposure durations of 30–45 hours.

Spatial patterns of absolute changes associated with individual disturbances show smaller predicted declines in coral cover at the local scale, with some re-

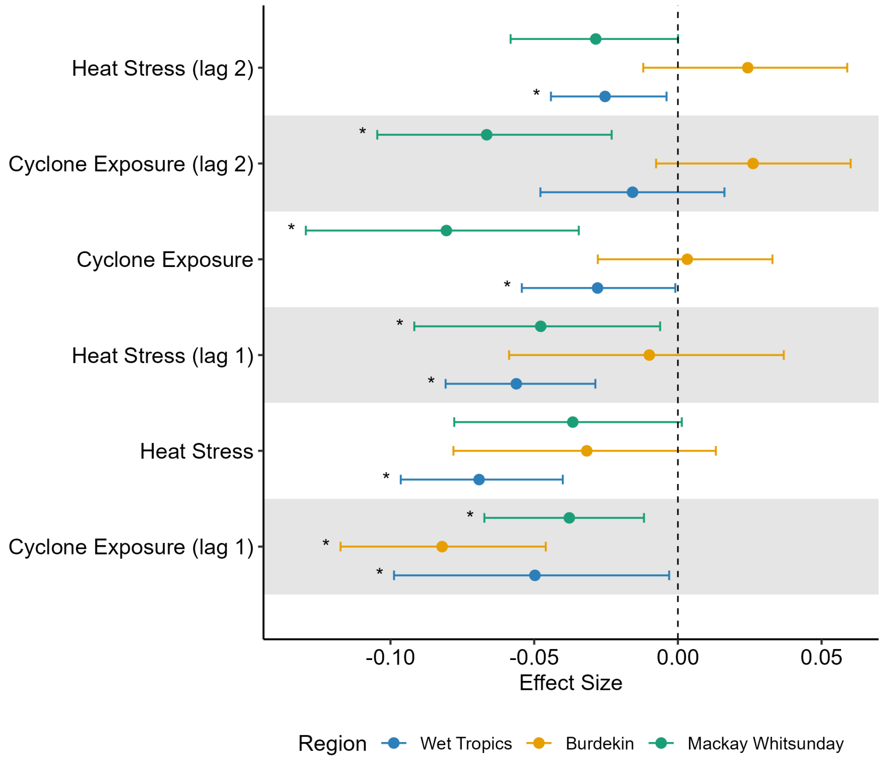

Figure 3: Predicted effect sizes of disturbances. The dots represent the predicted averaged effect and the intervals represent the corresponding 95% predictive intervals. Stars show significant effect sizes when values of predictive intervals are entirely negatives.

gional variations (Figures 15, 16, 18, 19, 21, 22 in Appendix B). This consistent pattern across regions and disturbance types may indicates that isolating individual disturbances (by holding others constant) yields smaller estimated local declines than models that allow disturbances to vary jointly (Figures 14, 17 and 20 in Appendix B).

American Samoa

The second use case focuses on American Samoa, located in Polynesia in the South Central Pacific Ocean. The country covers a reef area of 59.2 km^2 and is composed of a unique MEOW unit with three islands and two atolls (Figure 5). Image-based coral cover data were extracted from the ReefCloud database on 15 March 2026 including a total of 507 transects deployed across the four islands and one atoll and surveyed in 2015, 2018 and 2023, at depths of 3-10 meters (Table 1, Appendix C). These data come from a single monitoring program led by the National Oceanic and Atmospheric Administration (NOAA) as part of the U.S. Pacific Islands National Coral Reef Monitoring Program (National Oceanic and Atmospheric Administration (NOAA), 2025).

American Samoa was potentially exposed to five heat-stress events and two cyclones between 2015 and 2023 (Figure 4, Appendix C). These events were infrequently captured in the monitoring data. Only the 2015 heat-stress event was recorded, with a mean DHW of 8 (consistent with the regional signal), and only low mean duration exposure to cyclonic waves was detected in association with Cyclone Gita (2018).

Trends Across Spatial Scales

We fitted the predictive model to the American Samoa monitoring data using four sources of variability, including heat stress and cyclone exposure at lag 0 only, because observations at lags 1 and 2 years were unavailable. The predictive performance of the model was lower than for the Central Great Barrier Reef with a R^2 of 0.55 (Figure 14, Appendix C). The weighted spatial aggregation method was used to estimate coral cover trends at the island and MEOW scales.

At the local scale, predicted coral cover was approximately 20% across the five islands and atolls with varying temporal changes (Figure 4), with a few higher values observed in the southwest of Tutuila Island in most years (Figure 5), as well as across the entirety of Swains Island in 2015 (Figure 9, Appendix C). Uncertainty showed limited spatial and temporal variation (Figure 5), remaining relatively homogeneous across islands and years, with values ranging from 0 to 70% (Figures 5-9 in Appendix C).

At the island scale, coral cover exhibited broadly similar trends across the three islands, with a pronounced decline observed in Tutuila in 2020, whereas Ofu–Olosega and Taʻū showed smaller declines in 2018 and 2020 (Figure 4). On Swains Island, predicted coral cover declines significantly in 2016 and 2018, from approximately 40% to below 20%, followed by recovery in 2019. In contrast, no discernible trend is captured by the model for Rose Atoll. At the MEOW scale, predicted coral cover varied between 25% and 15%, with two distinct declines observed in 2018 and 2020, the latter being more pronounced. In both cases, these declines were followed by increases in the subsequent year (Figure 4).

Association with Disturbances

Despite a weak disturbance signal in the data (Figure 4, Appendix C), the model estimates a negative effect of cyclone exposure (Figure 10, Appendix C). Increasing cyclone exposure duration is associated with a linear decline in coral cover over durations of 0 to 15 hours, decreasing from approximately 50% to 35%, with relatively large uncertainty (Figure 11, Appendix C). Spatial patterns of absolute change associated with maximum cyclone exposure across American Samoa indicate declines ranging from 5% to 27%, with variation among islands and greatest changes in coral cover predicted in the southern part of Tutuila island (Figures 11-13 in Appendix C).

Discussion

In this study, we present a novel integrated approach to track coral cover trends across multiple spatial scales, ranging from a local scale of 5 km^2 to a broad sub-regional exceeding 5,000 km^2. Through use cases, we demonstrate that the predictive framework can generate new insights from monitoring data across

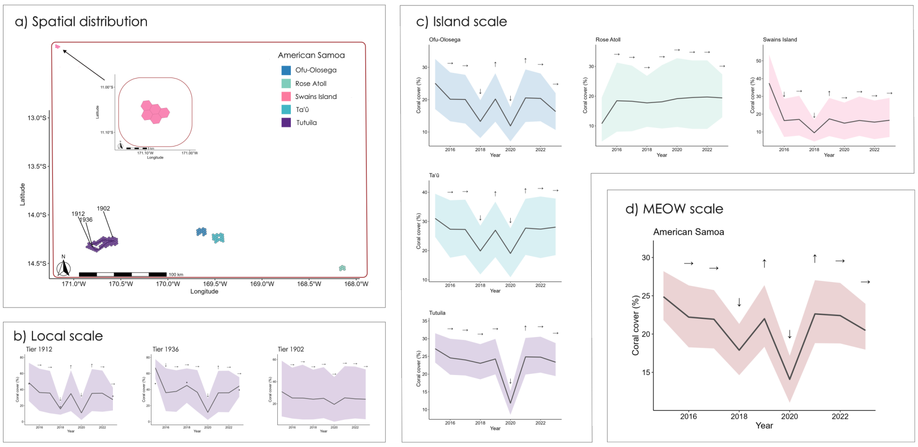

Figure 4: a) Location of the American Samoa islands including its islands and atolls. The region is divided into tiers (5km^2 spatial units) that represent the local scale at which the predictive model estimates coral cover. Four examples of local trends from Tutuila island are shown. b) Predictive distributions of coral cover are combined with a weighted spatial aggregation approach to generate predictions at the island and MEOW scales. Black lines show mean predicted coral cover, with shaded areas representing 95% prediction intervals. Dots indicate observed coral cover at the local (tier) scale, and arrows mark significant year-to-year changes in coral cover, with at least 90% probability. Note that the y-axes are on different scales for visualization purposes.

varying spatial and temporal data resolutions, by estimating coral cover trends at scales relevant to regional decision making, attributing changes to environmental disturbances and quantifying the influence of uncertainty on the robustness of trend detection.

The ReefCloud platform

Despite recent efforts and international calls to expand reef monitoring worldwide, locations with widespread and regular coral reef monitoring remain largely concentrated in a few regions (Souter et al., 2021). The ReefCloud platform has been developed to address this issue by enabling public access to three components: data coverage, analysis, and reporting. First, its machine learning algorithms for management and processing of underwater reef images allow users to generate ecological data in a cost- and time-efficient manner, thereby easing monitoring efforts and increasing data availability (Gonzalez-Rivero et al., 2020; Australian Institute of Marine Science (AIMS), 2024; Wyatt et al., 2025). Second, these data feed a statistical model that predicts annual hard coral cover and macroalgae at the site level. Third, data summaries and model outputs are presented on a public dashboard, allowing users to assess coral reef habitat condition and promote collaboration by enabling regional comparisons and sharing insights across institutions and sectors. 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. The framework

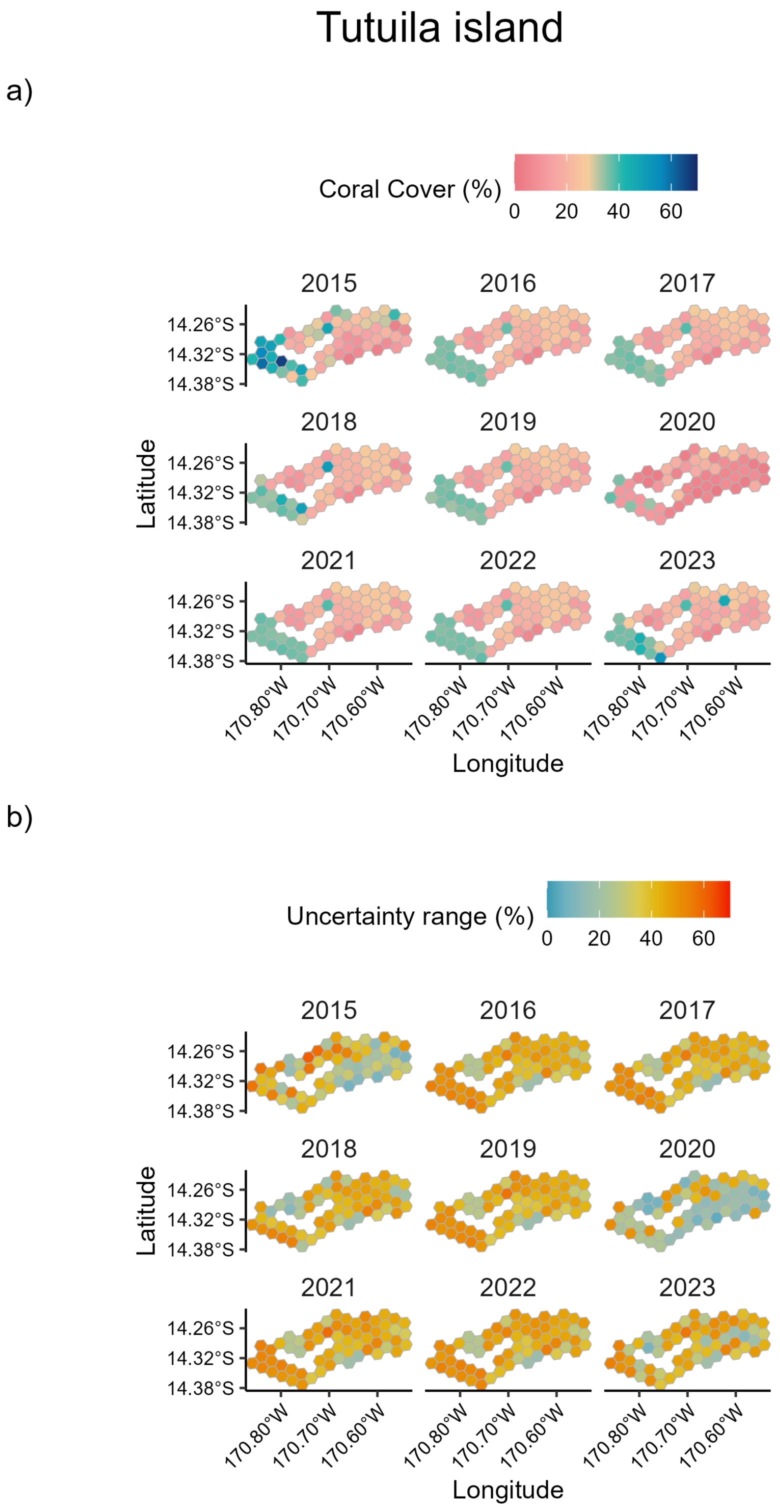

Figure 5: a) Predicted coral cover across Tutuila island with values correspond to the posterior means between 2015-2023 and b) associated uncertainty range for each year. Values correspond to the lower and upper bounds of the 95% posterior credible intervals of the estimated coral cover.

proposed here complements the second component by providing additional information on coral cover trends across multiple spatial scales, uncertainty and disturbance effects. Monitoring observations at the transect scale are aggregated within tiers, ensuring that the raw data remain confidential. Making the model outputs accessible to all users supports evidence-based management and may encourage more contributors to make additional datasets publicly available. Over time, these contributions will enhance the value and robustness of the ReefCloud components.

The Spatio-Temporal Prediction Framework

Insights gained from decades of data highlight the importance of long-term coral reef monitoring for detecting robust trends and attributing the key drivers of coral cover change (Fine et al., 2019; Obura et al., 2019; Donovan et al., 2021; Emslie et al., 2024b; Edmunds, 2024; Wicquart et al., 2025). However, studies of coral reef habitat condition rarely account for spatial dependence in long-term data analyses, but see (Edmunds and Bruno, 1996; Peterson et al., 2020; Roelfsema et al., 2021; Edmunds and Smith, 2022; Vercelloni et al., 2023; Srednick et al., 2023), which may lead to the underestimation of uncertainty in predicted trends (Johnson et al., 2024) and likely bias inference on disturbance effects.

In the framework presented here, spatio-temporal dependencies are represented as a latent process that is not directly observed (to rather than of explanatory variables) but inferred from the data. By incorporating spatial and temporal correlation structures, the model captures dependencies among observations, reflecting that nearby reef locations respond similarly and that this similarity evolves over time. These dependencies also enable us to predict coral cover values at unmonitored locations and supports a better quantification of uncertainty (Johnson et al., 2024). By tracking coral cover continuously across space and time (within the range of the observed data), quantifying uncertainty directly from the data and accounting for disturbances, more complete and representative patterns of change can be captured which can improve the robustness of trend change detection and reducing the risk of false positives (when a trend change is detected but with high uncertainty).

The integration of the model into the ReefCloud pipeline is tailored to the need of tracking coral changes across multiple spatial scales. By integrating predictive distributions at local scale into the pipeline, we demonstrate the scalability of the approach, enabling predictions at relevant scales, from broad regions such as the Central GBR in Australia to finer scales such as the American Samoa islands and atolls. The weighted aggregation approach ensures the standardization of coral cover predictions while explicitly accounting for the spatial heterogeneity of coral reefs which, in our case, is also key to propagate uncertainty across spatial scales in a statistically robust manner. A similar approach is already used by the Global Coral Reef Monitoring Network (GCRMN) in its synthesis of global and regional changes in coral cover (Souter et al., 2021; Wicquart et al., 2025). With the spatio-temporal prediction framework fully developed and tested, the next step is to automate the approach for application across many regions.

Limitations

The application of the framework to the three use cases highlights several limitations that should be considered for broader applications. The prevalence of short-term datasets in the ReefCloud database can reduce the model's predictive performance, potentially underestimating local-scale uncertainty and limiting the ability to draw robust inferences about the effects of disturbances (Figures 10-11 in Appendix C, Appendix A). In contrast, geographical biases, where long-term monitoring is concentrated in small areas within a vast region, contribute to increase local uncertainty at locations far from the observed data, even when disturbances are relatively well represented in the data like in the Central GBR (Figure 2, Figures 7-13 in Appendix B). We also show that local uncertainty can be substantial even at locations relatively close to existing data when observations are fragmented, as exemplified by the American Samoa use case (Figure 4). Despite high spatial sampling density within each island (Figure 2, Appendix C), the opportunistic sampling across years did not allow the model to capture the effects of disturbances, contributing to increased uncertainty. For example, the model attributed coral cover declines to cyclone exposure (Figure 10, Appendix C), predicting a large regional decline in 2020, when 75% of the region was exposed to cyclonic waves (Figure 4, Appendix C). However, because of the absence of coral cover observations in 2020, the model could not reliably capture the relationship between coral cover changes and cyclone exposure, suggesting that this decline may not reflect the reality. Additional criteria will need to be imposed before including disturbances in the model, not only regarding their regional distribution and potential collinearity, but also in relation to the temporal alignment of observations, particularly in regions with limited short-term monitoring programs.

The spatio-temporal predictive framework can only incorporate disturbances that are continuously available at the local scale, both to predict unmonitored locations and to enable automation across many regions. Consequently, the inclusion of additional local disturbances, such as crown-of-thorns starfish outbreaks, other coral predators, water quality changes, coral disease outbreaks, or localized human impacts, is challenging, even though they could improve predictions and strengthen attribution to coral cover changes (Connell et al., 1997; Bruno and Selig, 2007; Osborne et al., 2011; De'Ath et al., 2012; Kayal et al., 2012; Mellin et al., 2019; Peterson et al., 2020; Castro-Sanguino et al., 2021; Walker et al., 2024; Emslie et al., 2024b; McClanahan et al., 2024). This limitation restricts the conclusions that can be drawn from the framework, as it focuses only on disturbances that have a drastic impact on coral cover across large reef areas and cannot capture the cumulative effects of multiple disturbances.

Future perspectives

By estimating trends and disturbance effects, the model can guide users in selecting additional monitoring locations where logistically possible, either in space (e.g., new sites) or in time (e.g., repeated observations) and improve the spatial coverage of observations and their alignment with disturbance events. For example, if a significant change is detected at the regional scale (indicated by a downward or upward arrow, Figures 2 and 4), 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 (Castro-Sanguino et al., 2021). The same approach can be applied at the island scale, using trend change indicators (Figure 4) to identify monitoring locations for resurveying when monitoring across the entire MEOW is not feasible. During periods of stability and/or lack of detectable changes from predicted coral trends (indicated by horizontal arrow), monitoring efforts could also be shifted to additional sites. The selection of new monitoring sites is guided by multiple factors, including their distance from existing monitoring locations and the disturbance values recorded in previous years. It is important to consider the spatio-temporal trade-offs involved, particularly when repeated observations are essential for producing robust long-term trends (Hughes, 1992; Lindenmayer et al., 2022; Edmunds, 2024; Emslie et al., 2024a). 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, managers and stakeholders.

Finally, an important avenue for future development is the extension of the framework to additional benthic groups including macroalgae and soft corals which would provide a more comprehensive understanding of shallow reef dynamics. Beyond coral reefs, the framework could also be adapted for other marine ecosystems where spatio-temporal standardized monitoring data are available. These extensions would not only broaden the scope of the predictive framework but also enhance its utility for ecosystem-based management and conservation across local to broad spatial scales.

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, ML and KM developed the synthetic data framework and weighted aggregation method; 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

Appendices and associated code required to reproduce the results can be accessed at https://github.com/open-AIMS/RC_modelling. The data used in case study 1 and 2 are available at (Australian Institute of Marine Science (AIMS), 2025) and (National Oceanic and Atmospheric Administration (NOAA), 2025), respectively.

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