

Global opportunities for climate-resilient coral reef conservation to 2050

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Abstract

Climate change is accelerating the decline of coral reefs, yet some locations may retain conditions that support persistence under future warming. We compiled 45,064 coral field observations from 1960–2025 and 42 climate, biophysical, and human-pressure predictors to train machine-learning ensembles estimating coral cover and community composition in 2020 and 2050. We then used a multi-objective optimization framework to select, within each ecoregion, 30% of the reef area (consistent with the GBF 30x30 target) that jointly maximized current and future coral cover, community composition, spatial cohesion, and model certainty as indicators of climate resilience. Finally, we evaluated our results against three global coral reef habitat layers, including two products from the Allen Coral Atlas (visible reef extent and a coral habitat subset) and a UNEP-WCMC global distribution of coral reefs. The three layers identify between 36,466 to 167,352 km² of coral reef areas with relatively high projected persistence to survive climate change, spanning 79 to 81 national EEZs and 57 to 60 territories and jurisdictions. These findings show how empirical observations and multivariate machine learning can be combined to map candidate climate-resilient reefs at fine resolution, and reveal their uneven but widespread global distribution. While predictive skill was modest and varied among provinces, our results identify candidate locations with the highest probability of sustaining functioning coral reef futures rather than definitive priorities, and should be combined with local knowledge, national assessments and improved monitoring data to inform conservation policy, finance and management.

Introduction

Coral reef ecosystems are experiencing unprecedented stress from increasingly frequent and severe marine heatwaves, driving widespread bleaching and mortality (Hughes et al 2017; Li and Donner 2022). These events have caused major losses in living coral cover (Hoegh-Guldberg et al 2023), reorganization of reef communities (Hughes et al 2017), and declines in ecological functioning (Pratchett et al 2011). Recent global bleaching has exposed an estimated 68–84% of shallow tropical reefs to bleaching-level heat stress, highlighting rapidly shifting climate baselines (Spady et al 2026). Consequently, climate models suggest widespread losses of reefs under future warming scenarios (Frieler et al 2013; Cornwall et al

2021; Dixon et al. 2022; Zeng et al 2025); however, multivariate and finer spatial and temporal resolution are needed to evaluate how excess heat interacts with many potentially influential environmental factors that modulate coral persistence (McClanahan et al 2024a, McClanahan 2025). Machine learning forecasts indicate projections vary with the inclusion of variables, training data, model structures, and taxa (Klein et al 2024; McClanahan 2025).

Global heat stress and risk projections are not well supported by the observed local to global persistence of coral cover (González-Rivero et al. 2026). For example, global coral cover summaries report a ~30-year rise in coral cover in the western Indian Ocean and stability in the Coral Triangle and much of Southeast Asia. These empirical observations of persistent cover need to reinvigorate investigations into other environmental factors that influence reefs and the consequences for further conservation actions. Early work in coral reefs focused on where corals can avoid excess heat (e.g., “refugia”), bleaching, or experience hydrodynamic cooling from hurricanes, internal waves, and upwelling (Nakamura et al 2005; Schmidt et al 2016) or reduced solar irradiance from clouds or turbidity (Gonzalez-Espinosa and Donner 2021; Morais et al 2026; Sully and Van Woessik 2020). Recently, considerations of climate and ecological heterogeneity have expanded to include not only areas that avoid excess heat, but also areas where modifying variables and coral adaptation produce the conditions for resistance and recovery. Thus, creating three ecological climate change responses defined as avoidance, resistance, and recovery (ARR) environments (McClanahan et al 2024b).

Global efforts to map future reef environments have primarily focused on identifying areas that avoid acute and repeated thermal and cyclone stress (Frieler et al. 2013; Dixon et al. 2022). For example, the ‘50 Reefs’ assessment optimized the selection of large reef areas (500 km²) projected to experience lower thermal stress and storm damage while maintaining strong larval connectivity (Beyer et al 2018; Hoegh-Guldberg et al 2018). The recommendations from this analysis have guided more than US\$100 million in conservation investments (Bloomberg Philanthropies 2021). However, environmental datasets available in 2018 were relatively coarse (5 km or 0.05° resolution, ~31 km²), and the analysis did not integrate modifying variables such as oceanography or human pressures, factors known to strongly mediate local bleaching, coral mortality, and persistence (Loya et al 2001; Darling et al 2019; MacNeil et al 2019; McClanahan et al 2020; McClanahan 2023, 2025). In addition, Beyer et al (2018) did not incorporate empirical observations of coral cover or composition, nor use training and testing approaches to make predictive fits, limiting the ability to characterize the ecological contexts and responses that underpin the resilience of corals. These limitations highlight the need for updated, higher-resolution assessments that incorporate a broader suite of ecological and environmental drivers and predictive modelling approaches that utilize emerging data streams.

Mapping the next generation of global reef conservation priorities requires empirical measures of coral condition, including total coral cover and community composition. Total percent live coral cover is a composite metric aggregating many scleractinian coral taxa whose relative abundance influences the outcomes of heat and other climate change stresses. Nevertheless, coral cover is the most frequently measured variable to assess reef status and likely reflects cumulative impacts, resistance, and recovery potential that supports key ecological functions and services (Perry et al 2013; Beck et al 2022). Community composition captures functional

differences influencing adaptation, resistance, and recovery. Pooling taxa into competitive, stress-tolerant, and weedy life-history categories provides a potentially useful framework for interpreting resilience (Darling et al 2012; Darling et al 2013). Dominance by large branching and plating competitive corals can indicate avoidance environments; stress-tolerant assemblages of massive corals often signal resistance; and communities dominated by fast-growing weedy taxa typically support rapid recovery. These life-history strategies help identify the three ARR environments (McClanahan et al 2024b). While observations to coral genera are less commonly recorded than total coral cover, modelling coral life histories is investigated here as a potential proxy for identifying ARR environments.

Here, we aim to identify contemporary and future ARR environments using machine learning and multi-objective prioritization algorithms. The analysis links empirically based predictions of coral cover and community composition to spatial optimization for conservation prioritization. Our framework also leverages a comparison of three high-resolution reef habitat maps (UNEP-WCMC et al. 2021; Lyons et al 2024) and incorporates model uncertainty to identify locations for coral resilience on a 250 m grid, providing critical information to complement local knowledge and decision-making to ensure the persistence of reef ecological services to tropical stakeholders. Our goals are to: (1) model the current and future environmental conditions that influence coral cover and community composition; (2) identify and prioritize ARR environments using machine learning and a multi-objective optimization resilience framework; and (3) evaluate outcomes across global, regional, and national scales to inform conservation decision-making.

Methods

The workflow is summarized in Figure 1.

Empirical observations and predictor variables

We compiled a global dataset of 45,064 coral reef ecological surveys conducted between 1960 and 2025 (Fig. S1). Of these, 37,689 surveys recorded total coral cover and 7,375 recorded coral community composition as genus-level abundance. Surveys were drawn from long-term monitoring programs, academic and government studies, published datasets, and other publicly available sources (Table S1). We classified each community composition survey by its dominant coral life history strategy (Table S2; Darling et al 2012, 2019) to evaluate different persistence strategies under climate change (ARR; McClanahan et al 2024b). Observations were retained if they fell within a “coral reef extent” product defined as the location of shallow coral reef features that can generally be seen from satellites (Allen Coral Atlas 2022, <https://allencoralatlas.org/>; Lyons et al. 2024) or the UNEP-WCMC Global Distribution of Coral Reefs (UNEP-WCMC et al 2021). Genus-level surveys were not available from Brazil or West Africa and these geographies were therefore excluded from further analysis that required both coral cover and community composition observations.

Environmental and anthropogenic predictors included 42 variables representing ocean temperature, chemistry, geomorphology, connectivity, and human pressure (see

Supplementary Information; Table S3). Sea surface temperature (SST) metrics captured both central tendencies and variability, including chronic long-term climatologies and 6-year windows preceding each survey year to represent background conditions and recent disturbances (McClanahan et al 2019). Additional predictors described chemistry (e.g. calcite, nutrients, dissolved oxygen, pH), light availability (PAR, Kd, benthic light), and modifying variables (e.g., depth, slope, ruggedness, geomorphic zones). These data combined static layers (e.g. human gravity, sediment plumes, connectivity) and time-varying layers derived from a diversity of sources and spatial resolutions (Table S3). All environmental and anthropogenic predictors were spatially matched to surveys by extracting raster values at the latitude and longitude of each survey site; where time-varying layers were used, values were drawn from the annual or 6-year time window preceding the survey year. We removed observations when essential predictors were missing; depth was the most frequently absent predictor and could not be reliably imputed in shallow, complex coastal settings with coarse scale predictions.

Model development and training

All predictors were harmonized to a global 250 m x 250 m reef grid generated by combining two reef-extent products: the 5 m resolution Allen Coral Atlas visible extent layer (Lyons et al. 2024) and the UNEP-WCMC vector reef-extent dataset (UNEP-WCMC et al. 2021), retaining grid cells where either source indicated the presence of reef habitat. This maximized the inclusion of reef pixels for gridding predictors, which was then refined to more specific reef habitat maps during spatial prioritization (see *Spatial optimization*). This cumulative reef extent comprised 8,922,528 pixels, or 557,658 km² of potential coral reef extent. Resampling introduced minor boundary deviations, especially along sharp coastlines and environmental gradients, but ensured that all predictors were aligned at a common resolution. Coarse predictors were not downsampled, as interpolation would introduce spurious precision without adding information. While ARR predictions are reported on a 250 m grid, the effective resolution is set by the coarsest input layer, producing visible artefacts where coarse predictors are clipped to fine-resolution boundaries or where grids are misaligned (Fig. S2; Table S3). Predictors were screened for multicollinearity using variance inflation factors ($VIF < 7$), yielding non-collinear feature sets for model training.

We modelled total hard coral cover and the cover of competitive, weedy, and stress-tolerant life histories using XGBoost gradient tree boosting (Chen and Guestrin 2016). Coral province was included as a categorical predictor to capture broad biogeographic structure (Keith et al 2013). To reduce spatial and temporal autocorrelation, surveys were grouped into spatiotemporal bins of ~11 km and five years. Bins were randomly assigned to training (50%), validation (25%), or testing (25%) sets using a three-way holdout (Raschka 2018). This procedure was repeated independently for 100 model runs per response variable ($n = 4$ responses: total coral cover, competitive, stress-tolerant, and weedy corals). Models were trained with early stopping based on validation error, and hyperparameters were tuned within constrained ranges for tree depth, learning rate, subsampling, and regularization. In total, we trained 400 gradient-boosting models to quantify predictive robustness and variability.

Model performance assessment and prediction

We evaluated each model's predictive performance against a null model of mean coral cover by province using two error metrics: mean absolute error (MAE) and median absolute deviation (MAD). We defined skill as the proportional reduction in each error metric relative to the null model, and retained a model for prediction only if it improved on the null by at least 10% for both metrics. Because models were assessed separately for each province, the set of retained models could differ among provinces and we used paired permutation tests to assess whether model skill exceeded the 10% thresholds in each province. For each province, predictions from models above the accuracy thresholds were averaged to estimate coral cover and life-history cover in 2020, and coral cover in 2050. Finally, we calculated training and testing R^2 for each of the 100 models across all provinces combined, where training R^2 is calculated from prediction error on the training data, and testing R^2 is calculated from prediction error on the held-out test data.

Predictions to 2050 used CMIP6 SSP3-7.0 forcing, a moderate mid-century emissions scenario (Eyring et al 2016) that we selected as the primary scenario because: (i) it has emerged as a standard reference in recent coral reef projection studies (e.g. Kalmus et al 2022; DeCarlo et al 2025; Mellin et al 2025), and (ii) it sits within the plausible upper range of 21st-century emissions outcomes following the community's reassessment of SSP5-8.5 as implausibly high (Hausfather 2025; Van Vuuren et al 2026). For comparison and continuity with prior coral reef projection literature, we note that SSP2-4.5 and SSP3-7.0 converge to similar warming estimates by mid-century, and as a sensitivity analysis with a higher warming scenario we present results under SSP5-8.5 in the Supplementary Information.

Identifying drivers of coral cover and composition

Variable importance and effect direction were evaluated using Shapley Additive Explanations (SHAP; Lundberg et al 2019), which decompose model predictions into additive contributions from individual predictors while accounting for interactions and correlated features. For each model, we computed mean absolute SHAP values to summarize variable influence and examined SHAP–predictor correlations to determine effect direction. Conditional SHAP dependence plots were used to visualize nonlinear and threshold relationships while conditioning on the remaining predictors. Ensemble SHAP patterns were then used to characterise global drivers of total coral cover and community composition.

Spatial optimization of potential climate-resilient coral reefs

We tested the sensitivity of spatial prioritizations to the choice of reef habitat map within EEZ areas. We compared three alternative reef layers built from two global sources: the Allen Coral Atlas (ACA; Lyons et al 2024) and the UNEP-WCMC global map of tropical and subtropical warm-water coral reefs (UNEP-WCMC et al 2021). The layers were (i) the combined extent, merging ACA's total mapped reef extent with the UNEP-WCMC map (557,658 km²); (ii) the UNEP-WCMC map alone (189,434 km²); and (iii) pixels classified as coral/algae in ACA's benthic habitat map (121,471 km²).

For each habitat layer, we first aggregated 250 m predictions to 5 km² (2.24 km × 2.24 km) planning units and formulated spatial prioritization as a binary integer linear program under a fixed 30% area budget applied independently per marine ecoregion (Spalding et al 2007), consistent with Kunming–Montreal Global Biodiversity Framework Target 3 (CBD 2022). Drawing on portfolio theory (Markowitz 1952), the model jointly optimizes four complementary objectives (equations in Appendix S1; see also Supplementary Information): (i) a blended measure of present (2020) and projected future (2050) coral cover, weighted 0.7:0.3 to prioritize existing biological capital while addressing expected persistence; (ii) spatial cohesion, rewarding compact, connected reef networks via a *k*-nearest-neighbour metric with distance-decay weighting; (iii) representation across coral life-history strategies (competitive, stress-tolerant, weedy), with a square-root transformation to introduce diminishing returns and optional ecoregion-level rarity weighting; and (iv) risk minimization, penalizing reefs with high predictive uncertainty across 100 ensemble runs and projected coral cover declines between 2020 and 2050 (see Appendix 1). Optimizations were solved using the Gurobi Optimizer (Gurobi Optimization LLC 2026) with lexicographic multi-objective settings. Reef pixels (selected and unselected) were intersected with Exclusive Economic Zones and protected area polygons (UNEP-WCMC and IUCN 2026), and compared with the Beyer et al (2018) portfolio. To evaluate the robustness of spatial prioritisation outcomes, we conducted a structured sensitivity analysis across all regions across three dimensions: objective formulation, ecological uncertainty and solver-level variability (see Supplementary Methods; Figs. S9-S10).

Overall, our modelling framework extends the global climate-refugia or avoidance assessment of Beyer et al (2018) by explicitly incorporating empirical observations and relationships of coral cover and community composition predicted from a broader suite of environmental domains, and cross-validated model evaluation. Whereas the original 50 Reefs analysis focused primarily on excess heat, cyclone exposure, and larval connectivity, we integrate these drivers alongside a broader set of climate, oceanographic, and human pressure predictors with documented links to coral assemblages (e.g. McClanahan and Azali 2021; Table S3). By directly training machine learning models for total coral cover and life history abundance with these variables, we improve the ecological realism and spatial resolution of reef status predictions based on the direct modelling of present and future coral cover and composition.

Results and Discussion

Predictive modelling and performance

Machine-learning model performance for total coral cover and life histories showed marked differences among provinces (Fig. S3). Africa-India, Indonesian, Atlantic Caribbean, and Hawaii-Line Islands provinces had the highest proportion of total coral cover models meeting skill thresholds (Table S4). In 8 out of 13 provinces, ≥75% of coral cover models passed both mean absolute error (MAE) and median absolute deviation (MAD) skill thresholds (Table S5). Among life histories, stress-tolerant models most often exceeded both thresholds, followed by competitive and then weedy models (Table S4). Only one of 52 (1.9%) province-life history combinations – competitive corals in the Persian Gulf – failed to produce any model above the skill threshold; this combination was excluded from subsequent predictions and analyses.

Variation in model skill across provinces likely reflects limitations in training data availability and expanded access to monitoring data would improve future predictions.

Across all provinces and responses, predictive R^2 was modest and ranged from 0.08 to 0.28 (training R^2 0.59–0.85; Table S5). Low predictive R^2 is not surprising for site-level predictions of total coral and life history cover, which can be strongly influenced by local factors such as disturbance history and environmental influences that are not captured by broader-scale predictors. However, the higher explained variance (training R^2) means that the trained models are identifying relationships between the response variables and the selected predictor datasets. Although predictive R^2 was low when pooled across all 100 models, retained models consistently reduced prediction error (MAD, MAE) relative to a mean-only null by at least 10%, indicating that they capture truly predictive relationships that can generalise to new sites at least 55.5 km away from sites included during model training. Because our prioritization selects reef areas based on their relative rank within each ecoregion and incorporates model certainty as an objective, it depends less on precise prediction of absolute coral cover and community composition. Despite low absolute R^2 , prioritization outputs were highly stable to uncertainty perturbations, indicating that uncertainty did not materially alter refuge rankings.

Drivers of coral cover and composition

SHAP summaries and partial dependence plots (Fig. 2, Fig. S4) highlighted consistent predictors of coral cover, including temperature variability and extreme heat, distance from 500 m depth, light, cyclone maximum wind speed, and connectivity. Coral cover declined with increasing SST variability (SD, skewness), acute extreme heat (6-year DHW), maximum cyclone strength and light, and increased with extreme heat (SST 0.9 quantile), distance from 500 m depth, and connectivity. Non-linear responses were common but ecologically realistic (Fig. S4). These same predictors structured trait-specific responses across coral life histories (Fig. 2), though with weaker overall model fits: competitive corals declined with human gravity (a fishing pressure proxy; Cinner et al 2018), depth, and temperature; weedy corals showed opportunistic positive responses to human gravity, cyclones, light, sedimentation, and SST metrics (Darling et al 2012, 2013; Zinke et al 2018); and stress-tolerant corals declined under most environmental stressors but increased under extreme heat (SST 0.9 quantile), consistent with their replacement of more thermally sensitive taxa after repeated bleaching (Darling et al 2019; McClanahan et al 2020).

Spatial prioritization

We identified between 36,466 km² and 167,352 km² of coral reefs likely to be resilient to climate change using the three reef habitat layers (see Tables S6–S8). Each portfolio of climate-resilient reef areas was globally distributed (Fig. 3) and based on the selection of the top 30% of reef pixels within each ecoregion that optimized the four objectives (Fig. 4); z-score maps show how objective variability shaped outcomes (Fig. S5). Selected areas for each reef layer by national exclusive economic zones, marine territories and jurisdictions are reported in Tables S6–S8. Across all regions and robustness formulations, spatial prioritisation outcomes

295 were highly consistent. Across spatial optimisation runs that varied objective formulation,
296 uncertainty treatment and solver settings, planning-unit selection frequencies were strongly
297 bimodal: most planning units were either selected in every run (selection frequency = 1) or
298 never selected (selection frequency = 0), with few intermediate values (Figs S9–S10).

299
300 Despite variability in total amount of potential coral reef habitat (km²) across the three reef
301 habitat maps, the number of selected top countries and territories or maritime jurisdictions was
302 relatively consistent (Fig. 5), identifying potential climate-resilient coral reefs in 79 – 81 national
303 EEZs and 56 – 60 additional territories and jurisdictions (Tables S6–S8). However, the
304 countries and territories contributing the most selected reef area varied depending on the
305 habitat layer. The ACA x UNEP-WCMC combined reef habitat layer identified more than half of
306 the priority areas (103,160 km², or 61.6%) in five countries: the Bahamas, Cuba, Australia,
307 Indonesia, and the Philippines; Fig. 5; Table S6). However, the Allen Coral Atlas visible reef
308 extent layer is known to classify extensive areas of the Bahamas and Cuba as shallow coral
309 reef habitat despite these being predominantly soft-sediment habitats (seagrass and sand) with
310 low coral cover (Peng et al 2026, Lyons et al 2024). Focusing on hard substrate areas more
311 typical of coral reef habitats (e.g., warm-water global coral extent, UNEP-WCMC et al. 2021;
312 algae/coral class, Lyons et al. 2024), >50% of the priority areas are consistently identified in
313 Australia, Cuba, Indonesia, Papua New Guinea, the Philippines, and Solomon Islands (Fig. 5;
314 Tables S7–S8). The 250 m global prioritization surfaces for each reef extent are publicly
315 available as GeoTIFFs (<https://doi.org/10.5281/zenodo.18686274>).

316
317 Compared with the original prioritisation by Beyer et al. (2018), all three habitat layers
318 identified substantially more areas of climate-resilient reefs in Atlantic-Caribbean
319 ecoregions, including Belize, Panama, Honduras, the Dominican Republic, and Nicaragua.
320 This difference likely reflects our broader assessment framework, which evaluates the full
321 suite of ARR characteristics rather than focusing primarily on thermal-stress avoidance,
322 while maintaining the same ecoregion-balanced approach used by Beyer et al. (2018). The
323 results suggest that the Caribbean may harbour greater localised resilience potential than
324 previously recognised, despite remaining highly vulnerable because of low coral species
325 diversity, intense human pressures, repeated marine heatwaves, and recent functional
326 losses including local extinctions of *Acropora* (Manzello et al. 2025; see also Chollett et al.
327 2022). These areas emerge as priorities when resistance and recovery capacity are
328 considered alongside thermal-stress avoidance using a broader empirical predictor set
329 than the SST- and DHW-based metrics applied by Beyer et al. (2018). Additional priority
330 areas identified here but not highlighted by Beyer et al. (2018) include New Caledonia, the
331 Federated States of Micronesia, French Polynesia, and the Chagos Archipelago, as well as
332 several small island states and territories, such as Niue, Vanuatu, Comoros, American
333 Samoa, and Christmas Island, where selected reef areas comprise a large proportion of
334 national EEZs.

Implications for conservation of climate-resilient coral reefs

Our approach builds on Beyer et al (2018), the most comparable global assessment, by generating explicit predictions of coral cover and community composition validated against observed data, with province-level skill estimates that allow users to calibrate confidence by region (Table S5). Predicting not only where reefs may persist but what kinds of coral communities are likely to survive has direct implications for reef function and recovery potential. Where our identified ARR locations overlap spatially with Beyer et al.'s priority bioclimatic units (Tables S6-S8), convergence across independent methodologies strengthens confidence in those locations; where they diverge, differences likely reflect our incorporation of observed coral cover, community composition, and an expanded predictor set (for more details, see Supplementary Information).

Of the 167,352 km² of climate-resilient coral reef identified in the ACA–WCMC layer, 45,486 km² (27.2%) currently falls within protected and conserved areas (UNEP-WCMC and IUCN 2026), with comparable coverage in the WCMC (36.3%) and ACA Coral/Algae (32.6%) layers (Table S11). These rates are almost identical to protection of reefs outside the portfolio (28.0%, 37.8% and 30.3%, respectively), indicating that climate resilience does not yet shape where reefs are protected. This represents a clear near-term opportunity under Target 3 of the Kunming–Montreal Global Biodiversity Framework, which commits Parties to effectively conserve and manage 30% of coastal and marine areas by 2030 through ecologically representative and well-connected systems. Prioritizing climate-resilient reefs in new designations, rather than selecting sites on opportunity or feasibility alone, would align Target 3 implementation with Target 8's call to strengthen ecosystem resilience to climate change. Equally, reefs already within protected and conserved areas cannot be assumed secure: without adequate resourcing, enforcement and management capacity, designations risk becoming “paper parks” that deliver neither ecological nor social benefits (Gill et al. 2017; Stephenson et al. 2025). Realising the conservation value of climate-resilient reefs will therefore require both strategic expansion of protected and conserved areas, and sustained investment in the effectiveness of those already designated.

Translating global resilience assessments into conservation action requires spatial information at management-relevant scales. Our 250 m gridded predictions substantially improve on previous global assessments, including the ~500 km² bioclimatic units of Beyer et al. (2018), providing predictions of coral condition and community composition suitable for reef management, MPA network design, and national conservation planning. The three alternative habitat layers allow managers to validate predictions against local surveys, mapping products, and expert knowledge, and select the most appropriate layer for their region. These outputs are intended to support, not replace, locally and nationally led planning efforts, helping identify candidate sites for Target 3 expansion and prioritise investment within existing protected areas. The approach is already being applied in practice, including in Fiji's National Coral Reef Action Plan, the first such plan in the Pacific.

Limitations and future directions

Several limitations warrant consideration. Our machine-learning models describe statistical rather than mechanistic relationships and assume that historical environmental responses remain valid under future climates, potentially underestimating novel ecological states. Predictor layers also differ markedly in resolution, and monitoring data remain unevenly distributed across regions, contributing to lower model performance in data-poor areas (Fig. S1; Table S5). These limitations underscore the need for standardized monitoring, local model calibration, and greater incorporation of site-specific ecological processes and coral adaptation (McClanahan and Sola 2024). Predictions are also sensitive to modelling choices, as documented across coral reef machine-learning studies (McClanahan 2025). Finally, because the CMIP6 ensemble was not weighted by equilibrium climate sensitivity, inclusion of high-sensitivity models may render projected refugia estimates conservative. Future work should evaluate performance- and independence-based climate model weighting.

Second, provincial variation in model performance has direct implications for spatial prioritization. Where models did not pass accuracy and significance thresholds, no predictions were made rather than contributing uncertain values. For provinces where models passed thresholds but with weaker fits, the per-ecoregion portfolio structure, spatial cohesion objectives, and 100-run ensemble averaging buffer the prioritization against pointwise prediction error; however, ARR priorities in these provinces should be interpreted as more provisional than those in well-fit provinces (notably Africa-India, Indonesian, Atlantic Caribbean, and Hawaii-Line Islands). Improved field monitoring in data-sparse provinces remains a key path to reducing this uncertainty in future assessments.

Third, the prioritization does not incorporate governance feasibility, management capacity, or implementation costs, factors that ultimately determine whether climate-resilient reefs can be effectively conserved and managed. For example, many protected and conserved areas remain under-resourced (Gill et al 2017; Stephenson et al 2025), and assessing conditions of socioeconomic and political enabling conditions, compliance and enforcement, and long-term sustainable financing for conservation will be key to enduring ecological outcomes in these critical areas of climate resilience.

Several opportunities exist to strengthen future assessments. Improved consensus on global reef habitat mapping (e.g., Andréfouët et al. 2024), incorporation of higher-resolution environmental predictors, expanded monitoring of coral taxa and life-history groups, and greater use of hierarchical and transfer-learning approaches could all improve predictive performance. Because reef conditions, climate impacts, and available observations will continue to change, prioritizations should also be updated iteratively through time. Despite these limitations, the framework provides a scalable approach for identifying potential climate-resilient reefs at global extent. Its value is greatest when combined with local ecological knowledge, adaptive management, and national conservation priorities. Given the scale of investment now directed towards coral reef conservation, site selection should draw on multiple lines of evidence rather than any single model output. Accordingly, our predictions are intended to complement, not replace, local assessments, with SHAP values (Fig. 2) and z-score

distributions across prioritization objectives (Fig. S5) providing transparent insight into why particular reefs are identified as climate resilient and how those assessments can inform conservation planning.

Conclusions

This study shows that combining empirical coral reef observations with machine-learning predictions and multi-objective spatial optimization expands the identification of candidate reef conservation priorities at a global scale. By integrating present and projected persistence of coral cover and community composition, we provide a high-resolution assessment to help identify candidate reefs with the potential to endure severe mid-century warming. Despite widespread and increasing thermal stress, we find large and spatially distinct areas with ecological and environmental conditions that potentially support coral reef persistence. These candidate areas are concentrated in a subset of countries but widely occur in most reef regions, highlighting opportunities to strategically align conservation and management actions to reefs offering potential for sustaining long-term ecological and societal returns. These results argue against framing coral reef futures around a binary global tipping point. Climate-driven coral decline is ongoing, but spatially heterogeneous, and coral reef futures require engagements at local to global scales.

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Data Availability. All code used in modelling and spatial prioritization is available at https://github.com/Kylezx1/zawada_et_al_2026_global_coral_climate_refugia. Additional results summaries are available at: https://github.com/esdarling/50reefs_plus. Publicly available datasets used in modelling are available on request to the authors.

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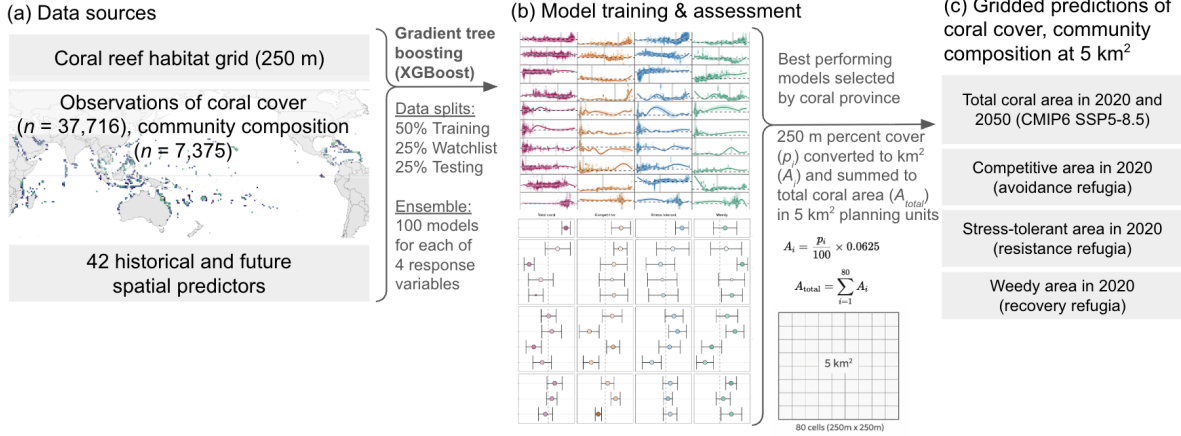
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Machine-learning predictions



Spatial prioritization of climate refugia

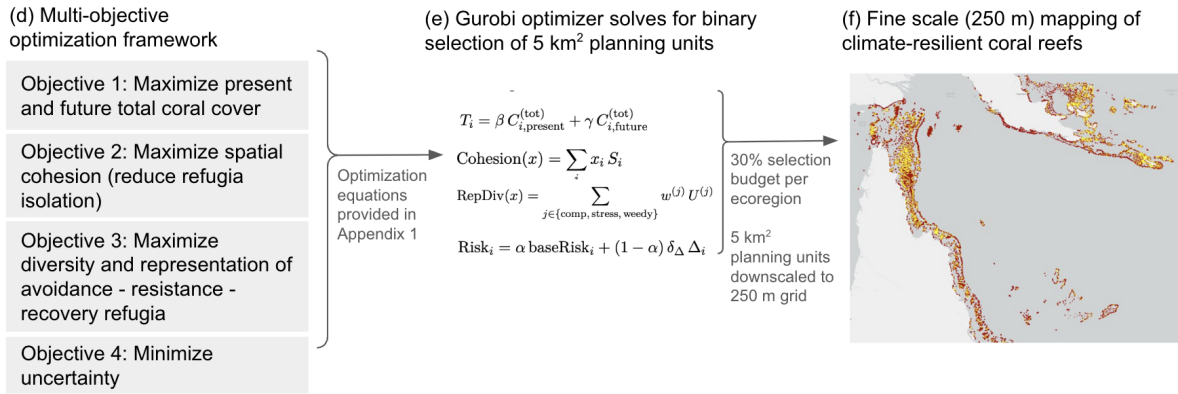


Figure 1. Overview of the analytical workflow used to model global coral cover and coral community composition and to prioritize climate-resilient reef refugia. (a) Coral cover and community observations were linked to a 250 m global coral reef habitat grid and 42 historical and future environmental predictors. (b) We trained ensembles of XGBoost gradient-boosted tree models for each response variable, evaluated model performance by coral province, and predicted percent cover of four coral responses at 250 m resolution. (c) Spatial predictions were converted to coral area (km^2) of total coral cover and three life-history types (competitive, stress-tolerant, and weedy) on a 5 km^2 grid of planning units. (d) A multi-objective optimization framework was used to identify portfolios of climate refugia that maximize present and future coral area, spatial cohesion, and life-history representation while minimizing uncertainty. (e) Optimization was solved as a binary integer program in Gurobi under a 30 percent per-ecoregion budget, variables defined in Appendix S1. (f) Selected 5 km^2 planning units (yellow) were downscaled to 250 m to map fine-scale distributions of climate-resilient coral reefs, and compared to unselected planning units (red). Models (a–b) were fitted and predicted once on the combined reef grid; steps (c–e) were repeated for each of three reef habitat layers: (i) the combined Allen Coral Atlas and UNEP-WCMC extent, (ii) the UNEP-WCMC map alone, and (iii) Allen Coral Atlas coral/algae benthic habitat (see Supplementary Information).

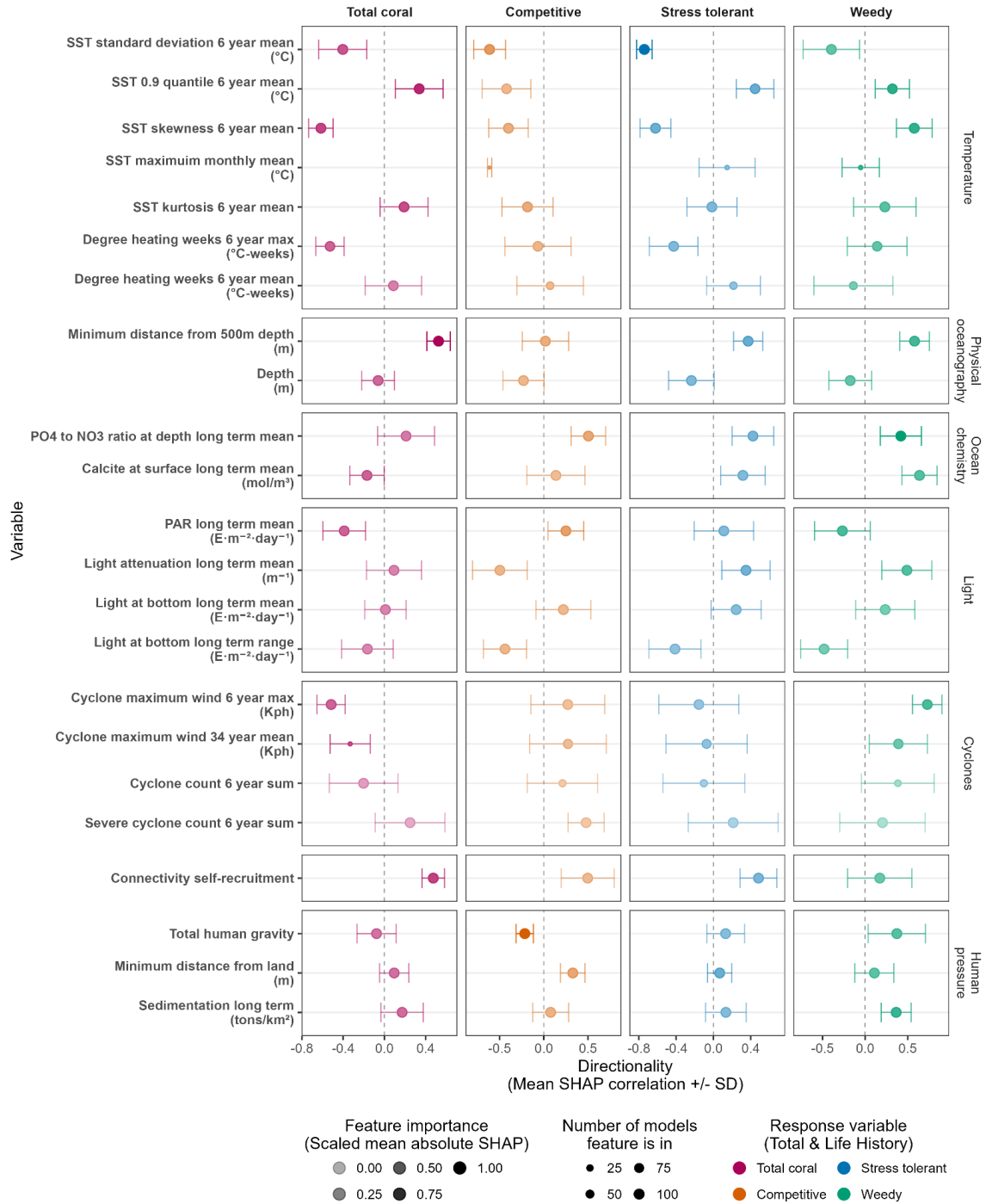


Figure 2. Direction and relative importance of environmental drivers of cover differ among total coral cover and life-history groups. Results are based on 100-model machine-learning ensembles for each response. Correlations represent Pearson coefficients between each predictor and its SHAP contribution to predicted cover. Points show mean correlations across models, with point size indicating the frequency with which each variable was retained after variance-inflation screening. Colour saturation corresponds to feature importance (mean absolute SHAP value). Error bars denote standard deviations, and vertical dashed lines indicate zero correlation. Corresponding response curves and partial dependence plots are provided in Figure S3.

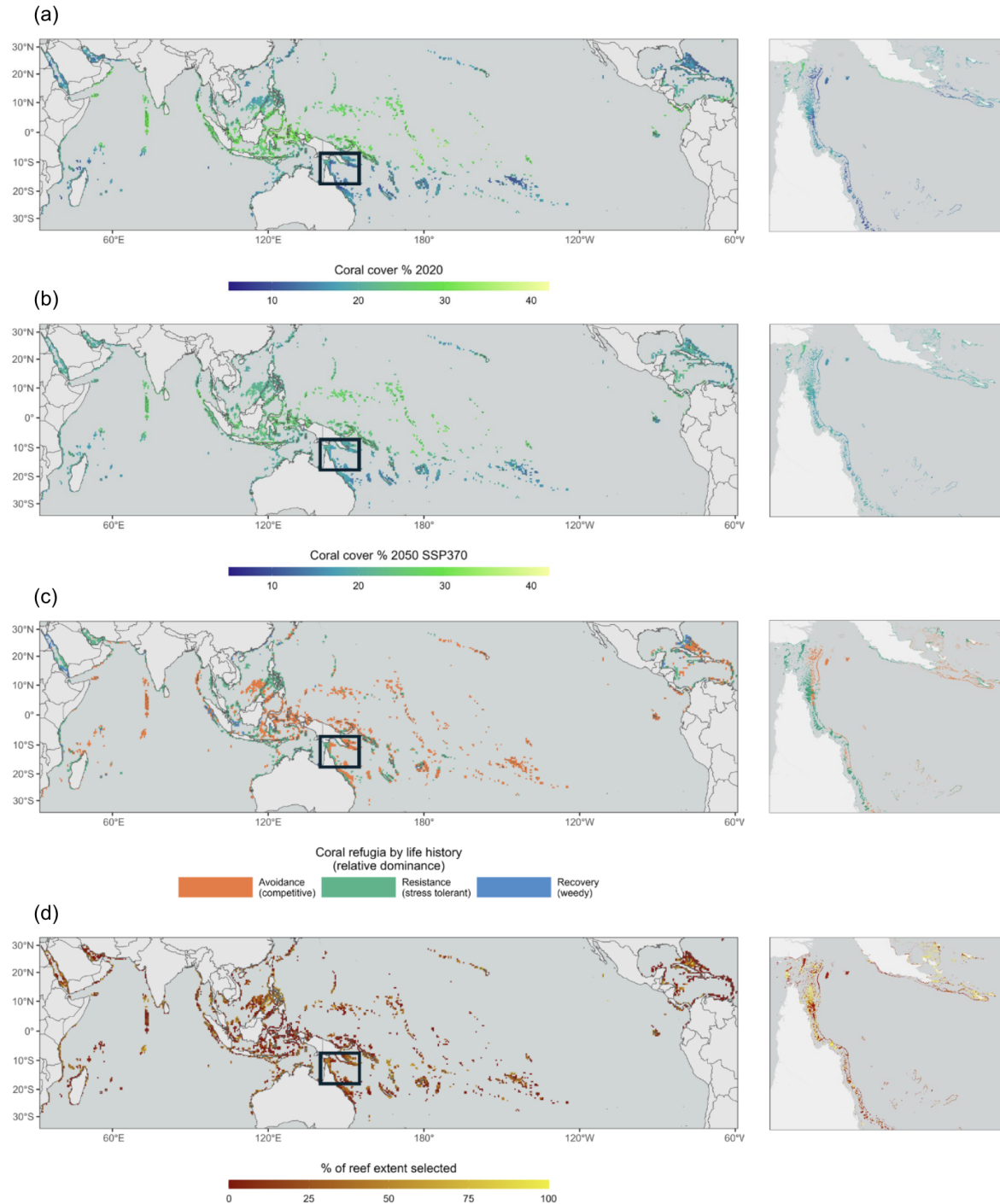


Figure 3. Machine learning and spatial optimization identify contemporary coral conservation priorities from predicted coral cover and life-history composition. (a) Predicted 2020 coral cover from 100-model ensembles. (b) Predicted 2050 cover under CMIP6 SSP3-7.0 (see Figure S6 for SSP5-8.5 predictions). (c) Avoidance, resistance, and recovery refugia based on dominant life-history groups. (d) Global prioritization of climate-resilient reefs using a 30% per-ecoregion portfolio that favours high cover, diverse life histories, spatial cohesion, and low ecological risk. Left panels show global patterns at 50 km resolution for visualization of global patterns; right panels illustrate high-resolution examples in the northern Great Barrier Reef and southern Papua New Guinea.

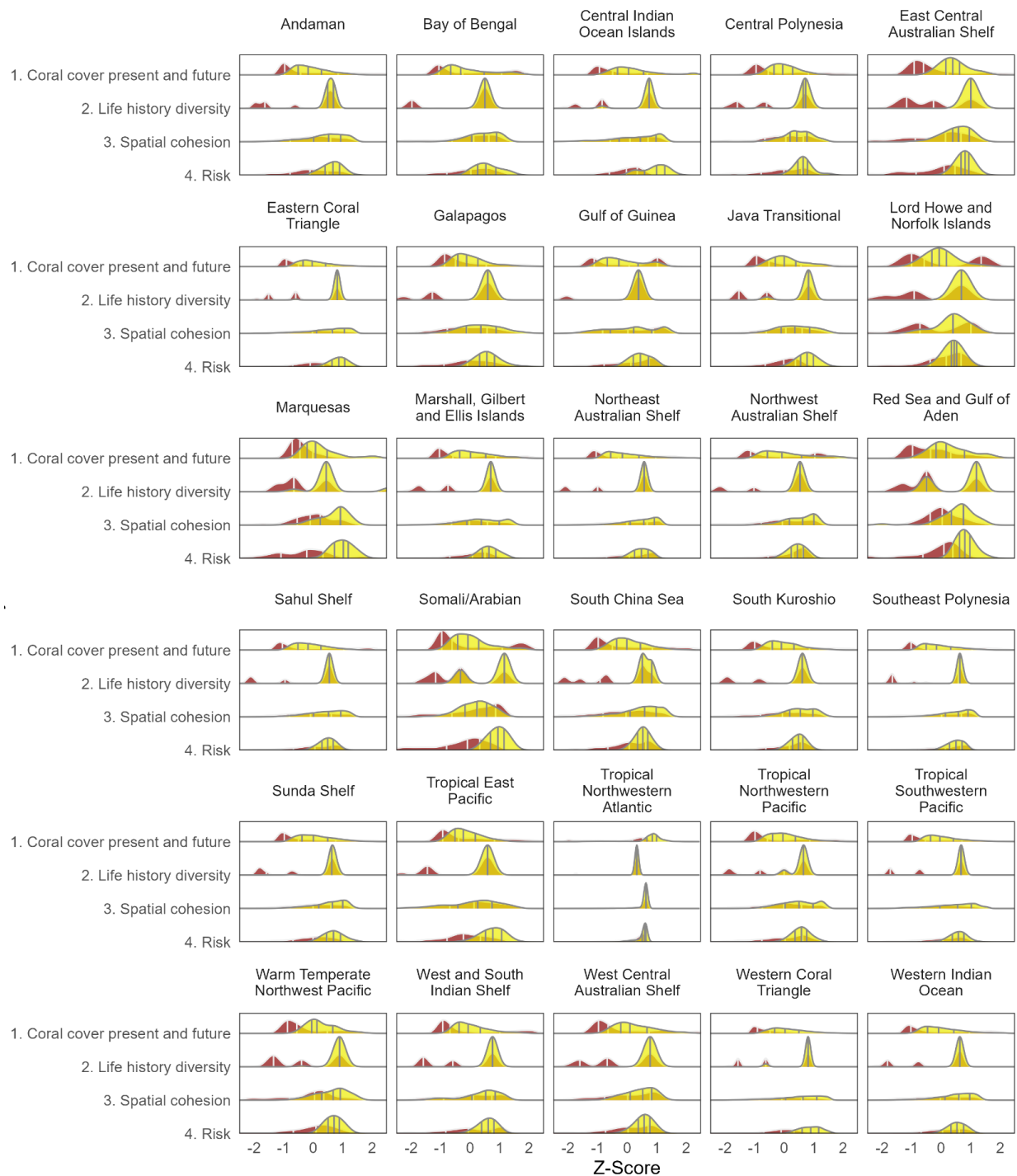


Figure 4. Density plots showing the relative influence of each objective function on prioritization outcomes across marine ecoregions. Distributions represent normalized Z-scores for all planning units within each ecoregion. Grey curves indicate units not selected in the optimization, and red curves indicate units selected in the final 30% portfolios. Overlapping densities illustrate how objective contributions differed between selected and unselected areas and how these patterns varied among ecoregions.

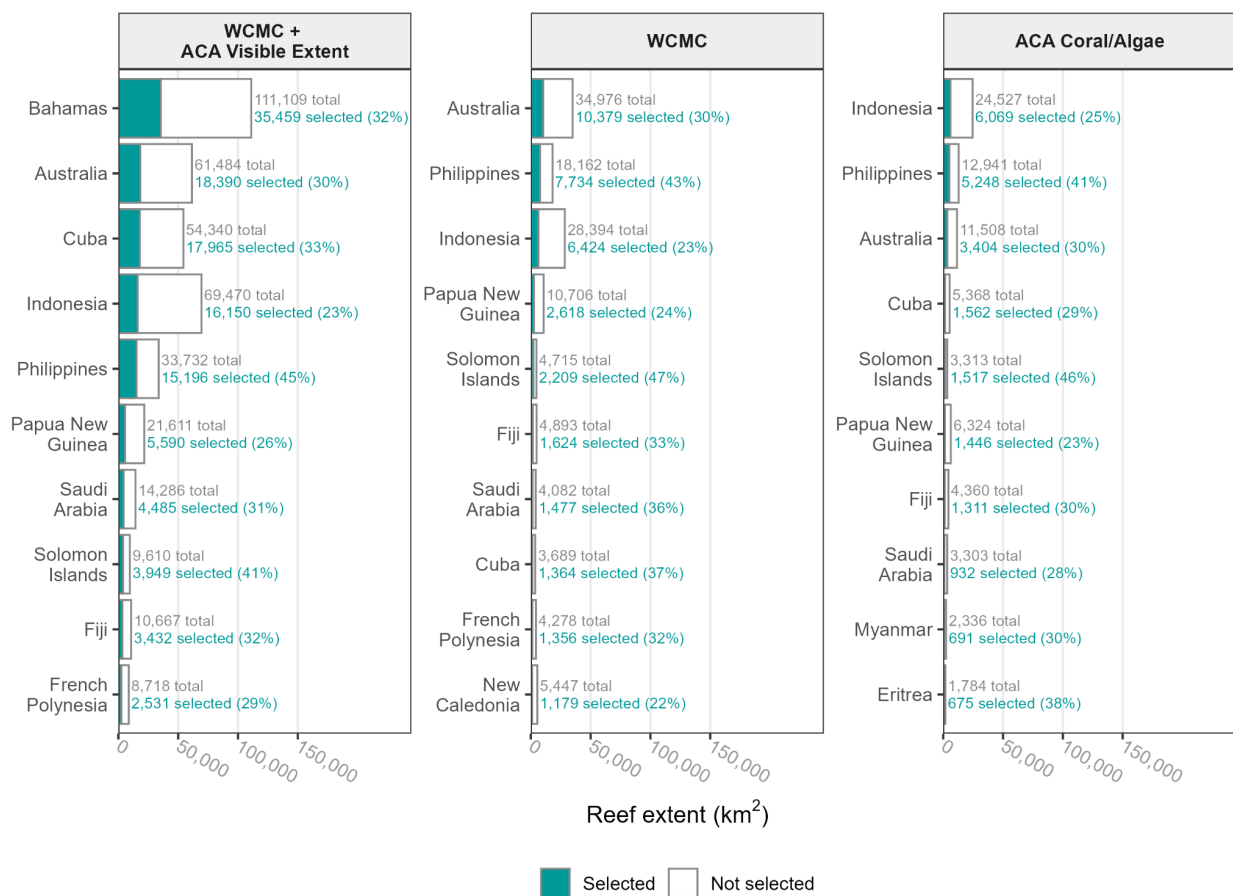


Figure 5. Top 10 selected climate prioritization areas for coral reefs are unevenly distributed across coral reef countries and territories and are dependent on underlying reef extent layers. Exclusive Economic Zones (EEZs) define national, territorial, and jurisdictional units, grouped by coral province. Bars show coral reef habitat that was selected (blue) or not selected (white), with grey labels indicating total reef extent (km²). Blue labels show the area of climate resilient reefs and percent of total reef extent. Top 10 countries by selected reef area shown; full results are provided in Tables S6-S8.