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Planning for resilience: Incorporating scenario and model uncertainty and trade-offs when prioritizing management of climate refugia

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Abstract

Climate change has become the greatest threat to the world's ecosystems. Locating and managing areas that contribute to the survival of key species under climate change is critical for the persistence of ecosystems in the future. Here, we identify 'Climate Priority' sites as coral reefs exposed to relatively low levels of climate stress that will be more likely to persist in the future. We present the first analysis of uncertainty in climate change scenarios and models, along with multiple objectives, in a marine spatial planning exercise and offer a comprehensive approach to incorporating uncertainty and trade-offs in any ecosystem. We first described each site using environmental characteristics that are associated with a higher chance of persistence (larval connectivity, hurricane influence, and acute and chronic temperature conditions in the past and the future). Future temperature increases were assessed using downscaled data under four different climate scenarios (SSP1 2.6, SSP2 4.5, SSP3 7.0 and SSP5 8.5) and 57 model runs. We then prioritized sites for intervention (conservation, improved management or restoration) using robust decision-making approaches that select sites that will have a benign climate under most climate scenarios and models. The modelling work is novel because it solves two important issues. (1) It considers trade-offs between multiple planning objectives explicitly through Pareto analyses and (2) It makes use of all the uncertainty around future climate change. Priority intervention sites identified by the model were verified and refined through local stakeholder engagement including assessments of local threats, ecological conditions and government priorities. The workflow is presented for the Insular Caribbean and Florida, and at the national level for Cuba, Jamaica, Dominican Republic and Haiti. Our approach allows managers to consider uncertainty and multiple objectives for climate-smart spatial management in coral reefs or any ecosystem across the globe.

KEYWORDS
Caribbean, climate change, coral reefs, robustness, spatial planning, spatial prioritization

1 | INTRODUCTION

Climate change has become the greatest threat to the world's ecosystems (Hoegh-Guldberg & Bruno, 2010; Rosenzweig et al., 2008). Although the current climate is unlikely to be maintained anywhere, some areas will still be milder than the surrounding areas and might allow the persistence of populations and species. Locating and protecting (including improving management) or restoring areas that contribute to the survival of key species under climate change is critical for the persistence of ecosystems in the future (Reside et al., 2018). To date, there has been a general reluctance to include climate change in spatial management plans and prioritization processes on the ground because of the uncertainty in future climate predictions (Frazão Santos et al., 2020). However, effective management must acknowledge climate change impacts to keep plans viable, relevant, and sustainable in the long term as global climate conditions continue to change (Frazão Santos et al., 2020).

Spatial prioritization is the process of ranking locations in which to take conservation action, such as protection or restoration (Reside et al., 2018). Spatial prioritization approaches that consider climate change require integrating models of future climate scenarios and accounting for associated uncertainties. Here, we are dealing with deep uncertainty: we can enumerate multiple alternatives (i.e. emission scenarios), but ranking scenarios by plausibility is unreasonable given the many unknowns (technology, politics, socio-economics, epidemics, etc.) that will dictate future emissions (Zandvoort et al., 2017). What was considered 'business as usual' a decade ago now seems unlikely (Hausfather & Peters, 2020); nonetheless, spatial prioritization should integrate climate change projections and provide solutions even with uncertainty. There are two main levels of uncertainty associated with climate projections. First, there is uncertainty about future greenhouse gas emissions and atmospheric concentrations (i.e. *scenario* uncertainty). Second, within each scenario, there is uncertainty over how to mathematically represent physical processes (i.e. *model* uncertainty). The temporal and spatial magnitude, distribution and variability of physical variables (e.g. sea surface temperature) are affected by both scenarios and models. Therefore, the need to include uncertainty in spatial prioritization has long been acknowledged, but very few studies have tackled the issue quantitatively (see reviews by Frazão Santos et al., 2020; Reside et al., 2018).

Climate change uncertainty has been included in spatial planning either through dealing with multiple scenarios (Ando & Mallory, 2012; e.g. Graham et al., 2009; Schuetz et al., 2015) or multiple models within a scenario (e.g. Beyer et al., 2018; Reside et al., 2018), but so far, no study has harnessed uncertainty in both, climate scenarios and models when planning for climate change. Initially, climate uncertainty was addressed using scenario planning, where several scenarios are presented to stakeholders for discussion (Peterson et al., 2003). There have been, however, many developments in analytical approaches to support decision making under deep uncertainty that provide answers across scenarios (Dittrich et al., 2016). Current approaches either define flexible, adjustable strategies over time (real option analysis, e.g. Buurman & Babovic, 2016), or, if a definite plan is needed, find the least vulnerable strategy across scenarios (robust decision making, e.g. Radke et al., 2017), or diversify options to reduce overall risk (portfolio analysis, e.g. Beyer et al., 2018).

Many decision problems in conservation involve several conflicting objectives. These are generally converted to single-objective problems, using an index that collapses all the information into a univariate decision (e.g. Burke et al., 2011; Halpern et al., 2015) and methods able to deal with univariate information only (e.g. Marxan or Zonation: Ball et al., 2009; Lehtomäki & Moilanen, 2013). This could be appropriate if there are obvious win-win options when some sites are good for all objectives, but this approach is unlikely in many real-world cases. In contrast to the single-objective approaches, multi-objective optimization aims to solve decision problems without such reduction (Williams & Kendall, 2017). Very few studies of spatial prioritization under climate change have considered trade-offs in the design (see review by Reside et al., 2018). Here, we use the term trade-off in a general sense, consistent with economic theory and multi-objective decision making, and use it to characterize the balancing of factors all of which are not attainable at the same time (Leader-Williams et al., 2011). Therefore, our definition does not imply any biological connotation nor considers biological thresholds. Methodologies to include trade-offs in spatial prioritization include building trade-off curves and finding Pareto frontiers, to identify the best possible combination of objectives within a framework of multivariate optimization (Kennedy et al., 2008; White et al., 2012). Very few examples in the marine realm have used trade-off analyses for more than two objectives, and to our knowledge, no study has considered both, trade-offs and uncertain climate change impacts, when prioritizing sites for conservation action.

Here, we present the first analysis of uncertainty in climate change and models, along with multiple objectives, in a marine spatial planning exercise and offer a comprehensive approach to incorporating uncertainty and trade-offs in conservation planning. We prioritize sites for conservation by identifying Climate Priority sites, this is, sites that have a higher probability of persistence in the face of climate change impacts. We focus on coral reef ecosystems, one of the ecosystems under the heaviest pressure from climate change (Kleypas et al., 2021), and particularly in future temperature impacts which have a large influence on reef structure and function (Hughes et al., 2003). We identify top priority reef sites by incorporating uncertainty in climate change scenarios and models as well as trade-offs between multiple planning objectives. We show our approach for the Insular Caribbean (The Bahamas, the Greater Antilles, and the Lesser Antilles) and Florida. Additional analyses were performed at the national level in Cuba, the Dominican Republic, Haiti, and Jamaica, where The Nature Conservancy is working with local partners to plan and carry out intervention actions. The combination of these national-level analyses with local knowledge facilitated the selection of a single priority site within each country to be targeted for conservation and/or restoration actions.

2 | MATERIALS AND METHODS

As resources and capacity for coral reef management are frequently limited (Gill et al., 2017), investments often must be made for targeted locations where conservation success is more likely to occur. Here, we frame the spatial prioritization process around the question often faced by marine managers: 'If you needed to prioritize management actions in only one coral reef in a particular region due to future predicted climate change conditions, which one would you choose?' Similar to previous work (Morelli et al., 2020 and references therein), we chose to prioritize management activities on reefs that (1) have the lowest climate exposure and, therefore, the highest potential to survive climate change; (2) have high larval connectivity to potentially seed other coral reef areas. To that end, we described each reef site (0.01 degree cells, approximately 1 km^2, with more than 5 ha of reef area), herein called 'sites', using relevant information (larval connectivity, hurricane influence and acute and chronic past and future temperature conditions) under different climate change scenarios. The scenarios considered cover a spectrum of possible futures: sustainability (SSP1 2.6), middle of the road (SSP2 4.5), regional rivalry (SSP3 7.0) and fossil-fuelled development (SSP5 8.5). To identify priority reefs, we used an approach that considers the complex interactions between environmental drivers and identifies 'Climate Priority' sites, that will more likely persist under different possible future climate scenarios (Figure 1).

The insular Caribbean and Florida harbour an extensive network of Marine Protected Areas (MPAs). Whilst unprotected reefs would benefit from protection and/or management activities, reefs belonging to the current system of MPAs would also benefit from improved management, restoration activities, or threat abatement. To identify protection and management gaps in potential Climate Priority sites, we identified reefs for intervention both inside and outside the current MPA system.

Below, we describe the methodological approach in detail. First, we describe the input data used in the model, then we provide an overview of the methodology used to identify Climate Priority sites. We present our approach for the Insular Caribbean and Florida, as well as at the national level in Cuba, Dominican Republic, Haiti and Jamaica, countries where The Nature Conservancy is working with local stakeholders and partners to plan conservation and/or restoration actions on reefs likely to survive climate change.

2.1 | Input data

We collated a set of key variables that describe the ability of a coral reef site to function as a Climate Priority area, based on our definition above: the recent and future thermal conditions, recent hurricane regime and coral larval connectivity (Table 1).

2.1.1 | Reef locations

Shallow coral reef habitats (<30 m depth) were mapped by The Nature Conservancy (Schill et al., 2021) and were produced at 4m resolution from a mosaic of Planetscope Dove Classic satellite scenes acquired between 2017 and 2019. An object-based classification using a ruleset that operated on surface reflectance, depth and geomorphic zone information was used to extract the classes, followed by manual corrections. The coral reef habitats classes used in this analysis included coral/algae, back reef, fore reef, reef crest and spur and groove. The ability to distinguish the difference between

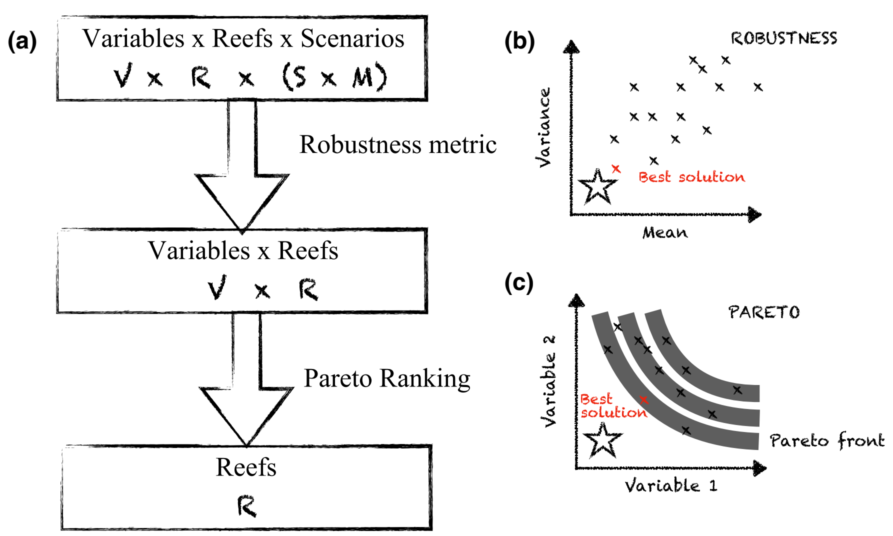

FIGURE 1 Overview of prioritization approach. (a) The input dataset includes V variables, R reefs and SxM climate change scenarios and models. A robust future thermal stress variable was calculated to provide a matrix of V variables per R reefs. Then, Pareto optimization was used to rank each reef. (b) Using a robustness metric, an ideal site (location shown by the star symbol) has a low mean and variance. In other words, consistently low thermal stress under all scenarios. (c) According to the Pareto ranking, an ideal site (star location) has low stress for all variables. Sites closest to the optimal solution are preferred (red x)

TABLE 1 Summary of data sources

Data	Variable	Spatial resolution (m)	Temporal coverage	Dataset/Reference
Reef locations	Reef habitat	4 × 4	2017–2019	Schill et al. (2021)
Historical thermal conditions	Trend in temperature (°C decade^{-1}), sum Degree Heating Weeks > 4 over the entire period (° weeks)	~1000 × 1000	1985–2020	Dixon et al. (2022)
Future thermal conditions	Trend in temperature (°C decade^{-1}), sum Degree Heating Weeks > 8 over the entire period (° weeks)	~1000 × 1000	2020–2100	Dixon et al. (2022)
Hurricane impacts	Inverse return period	NA	1980–2020	The International Best Track Archive for Climate Stewardship (IBTrACS) dataset, v4 (Knapp et al., 2018)
Larval connectivity	Generic broadcast spawning coral. In-strength and out-strength	8000 × 8000	2008–2011	Schill et al. (2015)

healthy and dead coral reefs is beyond the spectral capacity of the satellite imagery used to define the habitats and is particularly problematic for the coral/algae category, which tends to overestimate the amount of living reef. The overall accuracy of reef areas was, however, high, reaching 72% (Schill et al., 2021). To identify the unit of analysis, a 0.01 × 0.01 degree (about 1 km) grid was overlapped to the entire region of study and the total reef area was calculated for each cell. These cells represented each individual reef site and any cell containing less than 5 hectares of reef area were excluded from the analyses, given they were too small to justify conservation actions (Supplementary S1). This grid was the unit of study of all subsequent analyses and included 33,735 cells.

Reefs were attributed to their EEZ using the dataset by the Flanders Marine Institute (2020) with a few exceptions. Reefs off Navassa Island, in dispute with the US, were assigned to Haiti. The entire Formigas bank (just west of Navassa) was assigned to Jamaica.

2.1.2 | Marine Protected Area locations

Locations of Marine Protected Areas (MPAs) were based on The Nature Conservancy Caribbean's protected areas database (March 2021 version). This database is more current and accurate than widely available databases such as the World Database on Protected Areas. We included both declared and proposed MPAs in the analyses.

2.1.3 | Historical thermal conditions

Corals are affected by both chronic, long-term warming and by acute, punctuated heat events (Chollett et al., 2012; Muñiz-Castillo et al., 2019). Both types of stress are likely to influence coral reef ecosystems in different ways, i.e. whilst chronic warming reduces coral calcification and growth, acute warming causes bleaching and mortality (Bozec & Mumby, 2015; Lindsey et al., 2013). The exposure to this threat varies spatially both at global and regional scales (Heron et al., 2016; Muñiz-Castillo et al., 2019).

Historical daily Sea Surface Temperature (SST) data at 0.01 degree spatial resolution for 1985–2019 were produced from two different observational SST datasets: the European Space Agency Climate Change Initiative SST Analysis at 5 km (1985–2006, Good et al., 2019; Merchant et al., 2019), and the Multi-scale Ultra-high Resolution SST Analysis at 1 km spatial resolution (2006–2019, Chin et al., 2017). Details of the merging procedure can be found in Dixon et al. (2022).

For each site, we calculated a metric of chronic thermal stress (trend in temperature) and a metric of acute thermal stress (sum of Degree Heating Weeks, DHW, above 4°C weeks for the entire period). Degree Heating Weeks is a metric of accumulated thermal stress over a 12-week window. Thermal anomalies are calculated as any temperature that exceeds the summer maxima by 1°C (Liu et al., 2003). Although many metrics have been used to describe acute thermal stress in corals, DHWs above 4 have been related numerous times to broad-scale coral bleaching and was used for this study (e.g. Eakin et al., 2010). DHW above 8° weeks, associated with coral mortality, was not used to describe the historical acute thermal conditions because these events were extremely rare within the four target countries (occurring in less than 1% of the reefs).

2.1.4 | Future thermal conditions

Future projections in temperature indicate increases in chronic and acute temperature disturbances to corals (Dixon et al., 2022). Taking these increases into account is essential for developing robust management plans that are useful in the long term (Beyer et al., 2018; Dixon et al., 2021).

SST data were obtained for four different emission scenarios, or Shared Socioeconomic Pathways (SSP): SSP1 2.6 (sustainability, 14 models), SSP2 4.5 (middle of the road, 15 models), SSP3 7.0 (regional rivalry, 13 models), SSP5 8.5 (fossil-fuelled development, 15 models) that cover a wide spectrum of possible futures. SSP data for 2020–2100, originally at about 25–100 km spatial resolution, were downscaled to 0.01 degrees. We converted climate SSP data to 0.01 degree (~1 × 1 km) resolution using bilinear interpolation (Brito-Morales et al., 2020; van Hooidonk et al., 2015) and used statistical downscaling by asynchronous linear regression (Stoner et al., 2013). Although these analyses were first implemented in Dixon et al. (2022), data were produced specifically for this research to provide full coverage to the reef habitat data. Acute and chronic thermal stress metrics were calculated for each model and scenario. For each site, to mirror metrics used with the historical data, we calculated a metric of chronic thermal stress (trend in temperature) and a metric of acute thermal stress (sum DHW > 8 for the entire period).

2.1.5 | Hurricanes

Hurricanes are the main disturbance producing mechanical damage to reefs. They can physically damage reefs and shape their community structure and ecological condition (Gardner et al., 2005). Although climate change might change the frequency or intensity of hurricanes, future effects are uncertain and have not been modelled at a spatial scale relevant for management. Therefore, we only used the historical hurricane regime.

To describe the hurricane regime in the region we used the International Best Track Archive for Climate Stewardship (IBTrACS v4) dataset (Knapp et al., 2018). IBTrACS provides location and intensity for global tropical storms. The dataset provides information on hurricane location as points or lines. Point locations of hurricane centres every six hours are transformed into lines (tracks) using a spline interpolation (Knapp et al., 2018). This study includes all hurricanes (when maximum sustained winds were equal or larger than 64 knots) during the period 1980–2020. Although the hurricane record starts in 1842, we chose 1980 as a start date because that coincided with the routine use of microwave imager satellites improving the quality of the data. Hurricanes were identified within a radius of 100 km. This area of influence echoes the grid size commonly used in storm climatological studies (Elsner et al., 2012) and encompasses potential damage from storms to reef communities observed in situ (Gardner et al., 2005; Puotinen, 2004; Wolff et al., 2016). From this dataset, we calculated the inverse of the return period so low hurricane exposure would be related to lower numbers. For example, the return period of a hurricane might be 100 years, and the inverse being 1% in any given year. Return periods capture the essence of uncertainty in extreme meteorological phenomena such as hurricanes, floods, or earthquakes.

2.1.6 | Larval connectivity

We incorporated two aspects of connectivity in this work: incoming and outgoing larvae. For a coral reef to persist in the face of climate change impacts, it requires larval input (either from within the reef or from neighbour reefs). Given that many reefs are expected to be badly impacted by climate change, it is also important to prioritize sites that are valuable sources of larvae, which can provide reseeding and recovery benefits to other areas. Climate change, modified currents, and increased temperatures are expected to change connectivity patterns (Figueiredo et al., 2022; Munday et al., 2009). Future changes in connectivity are dependent on multiple processes such as increased mortality, decreased reproductive output and faster larval development (Munday et al., 2009) which makes the modelling of future connectivity patterns challenging. Although attempted in some regions such as the Great Barrier Reef (see Figueiredo et al., 2022), this kind of information is not available for the Caribbean and was not included here.

We used a coral reef larval dispersal model developed by Schill et al. (2015) that is based on dispersal simulations of a generic broadcast spawning coral that highlight the most important reef-building species in the region. The simulation for the larval transport model was summarized for August and September 2008–2011. The amount of larvae released in each simulation was proportional to the reef area within each release unit. To describe the ability of a reef to receive larvae, we used in-strength, the sum of all ingoing connections, including the diagonal (local retention, Ospina-Alvarez et al., 2020). To describe the ability of a reef to supply larvae, we used out-strength, the sum of all outgoing connections excluding the diagonal, an appropriate metric to identify good source areas that allow emigration and foster post-disturbance recovery (Magris et al., 2016, 2018; Ospina-Alvarez et al., 2020). Each site was associated with the connectivity value closest to its location. The scale of the connectivity data was reversed (new value = maximum − old value) so lower values corresponded to stronger connections.

2.1.7 | Anthropogenic threats

The ability of a reef to survive climate change impacts is influenced by local anthropogenic stressors impacting the site: if a reef is under too much stress it might be unable to withstand climate change. We considered including local anthropogenic-based threats such as fishing and land-based stressors as additional factors that might tip the balance towards the survival of coral reefs in a climate change context. However, after close examination of the available data, we decided against it. For example, there was no coherent, unbiased spatial dataset on fishing intensity available for the entire area of study, and after consulting with local partners, we could not reach a consensus on an appropriate dataset on land-based threats that accurately reflected local threats to reef ecosystems. We decided to include this information using local knowledge or national-scale data within the stakeholder consultation phase of the project when selecting the final intervention site.

2.2 | Identifying Climate Priority sites

To identify sites that have the greatest chance to survive climate change and potentially seed other areas, we first used a robustness metric to quantify the ability of a site to have low thermal stress across all climate change scenarios and models. Sites were then ranked using Pareto ranking to identify Climate Priority sites that perform well across all possible future climate scenarios and variables. We explain both approaches in detail below.

2.2.1 | Robust future climate predictions

Robust results can be selected using several measures (McPhail et al., 2018). In this study, we measure the robustness of each future thermal stress variable across each of the 57 different climate scenarios and models using the mean/variance metric (Hamarat et al., 2014; See Supplementary S2 for a comparison of alternative metrics). This metric, inspired by the signal-to-noise ratio in control theory, is based on the intuition that a robust solution will have a low average and very limited dispersion around it (Figure 1b). Here, a robust Climate Priority site will have consistently low thermal stress under different climate scenarios (Equation 1):

$$\text{mean/variance} = \left(\mu_{\mathrm{i}} + 1\right) / \left(\sigma_{\mathrm{i}} + 1\right), \quad (1)$$

where μ is the mean over the set of i scenarios and σ is the standard deviation. Sites with lower values will be more desirable to meet our objective. In Equation (1) we add one to handle situations when the parameters are close to 0. This metric has proved to be intuitive, simple, and appropriate for many situations (e.g. Kwakkel et al., 2016). This metric was conceived to consider a set of equally likely climate scenarios. Climate change data, however, is structured and includes multiple models (in our case 13–15), each within a climate scenario. Climate variables can vary considerably amongst models, but ecological studies rarely incorporate information on model and scenario uncertainty simultaneously (Harris et al., 2014). To account for the structure of the data, we calculated a novel variation of the mean-variance metric using a random effect model by including the climate scenario as a random component. The model was fitted using the *lme4* library in R (Bates et al., 2014). The inclusion of this random effect was always significant but provided small quantitative differences to the general approach of averaging models within each scenario (Supplementary S2). Using the random effect implementation of the mean-variance metric, we summarized information from different scenarios and models into only two values per site: future chronic and acute thermal stress.

2.2.2 | Climate Priority sites

The next step in the process of identifying Climate Priority sites was to perform a trade-off analysis and rank each reef using all the available information: historical thermal conditions, (robust) future thermal conditions, hurricanes and larval connectivity. We ranked each site using Pareto rankings, a multivariate method that ranks sites through optimization, by taking multiple objectives into account without reducing them into a single value (Kennedy et al., 2008). This approach allowed us to not only identify priority sites for guiding management efforts in the region but also to look explicitly at the trade-offs between these variables.

In an ideal world, optimal sites for protection or restoration will have low thermal stress and hurricane impacts as well as high connectivity. In reality, however, these sites might not be widely available because variables have trade-offs. For example, sites with fewer hurricanes may also have the lowest connectivity. To rank sites according to their value for management, many researchers tend to combine all the variables into a univariate index and choose the site that has the best value (e.g. Burke et al., 2011; Halpern et al., 2015). Whilst this approach is simple it requires that all variables are measured with the same 'currency', and, therefore, involves assigning weights to each variable to integrate them into a single variable of the same units. These weights are uncertain and are generally not well known and based on expert opinion. Additionally, a drawback to this approach is that because objectives often conflict, good sites may be missed or sites may be chosen that are very deficient for one variable just because the site scored well for other variables (Kennedy et al., 2008).

An alternative solution is to use multi-objective ranking and consider all the variables and their trade-offs explicitly. Pareto ranking is such a method and considers the trade-off between each pair of variables, identifying the Pareto frontier' (e.g. a set of feasible values that provide good solutions in terms of all variables), and then ranks sites by their proximity to the Pareto frontier (Kennedy et al., 2008, Figure 1c). In general, there are no single solutions to a multi-objective problem, and the best solutions are found through optimization (Kennedy et al., 2008).

All data were normalized using min-max normalization before the analyses, where variables are rescaled in a range of 0–1 following the minimum and maximum values of each variable (Han et al., 2011). To produce the rankings, we used the 'non-dominated ranking' procedure from the R package *emoa* (Mersmann, 2012). The procedure determines all non-dominated solutions and assigns them to the first (best) class. A solution is defined as non-dominated if there exists no other feasible solution that will give an improvement in one objective without a subsequent degradation in at least one other objective. These solutions are then iteratively removed from the population and all non-dominated solutions are again determined. The next best class is then assigned until the population is empty.

Ranking procedures considering Pareto sorting include a two-step process. First, non-dominated sorting is performed. This ranking depends only on the Pareto order. Afterwards, sites that share the same rank are ranked according to a distance criterion (Bartz-Beielstein et al., 2014; Emmerich & Deutz, 2018). Breaking the ties between sites within a non-dominated front has been done using multiple methods, including minimizing the distance to a reference point (e.g. Euclidean distances: Fonseca & Fleming, 1998), or maximizing diversity (e.g. crowding distances: Emmerich & Deutz, 2018). Selecting a particular ranking method is a management decision, which is based on the planning objectives and the relative preferences of the managers and decision scientists. In this study, within a class, we gave the best rank to the solution closest to the goal or reference point using Euclidean distances (Fonseca & Fleming, 1998), which is a method consistent with the definition of climate refugia and our desire to find Climate Priority sites less affected by stressors. By calculating Euclidean distances to normalized data we are giving equal importance to each variable. In this way, it is possible to obtain a best-compromise solution, that is closest to the ideal point, where all objectives are at their optimal values. Pareto dominance ranking is computationally intensive and, therefore, largely avoided in spatial prioritization exercises.

3 | RESULTS

3.1 | Robust future climate predictions

Robust metrics were calculated for both future chronic and acute thermal stress (Figure 2), which are spatially represented differently across the study area. Chronic thermal stress has larger dispersion patterns at larger averages: models and climate scenarios have more disagreement at higher chronic thermal stress (Figure 2a). Most sites in the Caribbean are under harmful conditions for this metric (Figure 2b). Robust future chronic thermal stress is higher in the Northern Caribbean (Figure 2c). Within the region of interest, stress is lower in the north shore of Cuba and southeast shores of Haiti, the Dominican Republic and Jamaica (Figure 2c).

Acute thermal stress has larger dispersion patterns at lower averages: models and climate scenarios have more disagreement at lower values of acute thermal stress (Figure 2d). Most sites in the Caribbean are under relative benign conditions for this metric (Figure 2e). Robust future acute thermal stress is larger in the Southern Caribbean (Figure 2f). Within the region of interest, stress

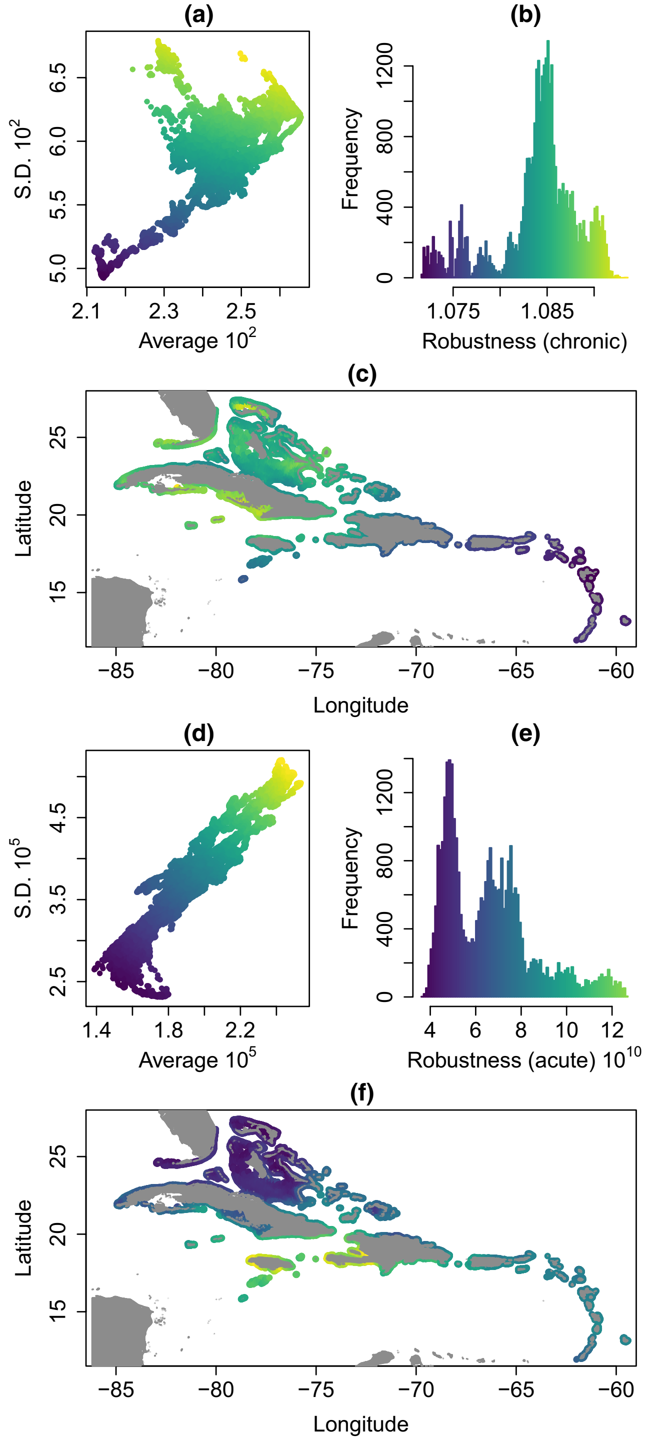

FIGURE 2 Robustness metric for chronic and acute thermal stress. (a) Mean versus standard deviation of chronic thermal stress under different climate scenarios and models. (b) Histogram of robustness metric for chronic thermal stress. (c) Map of chronic stress robustness metric. (d) Mean versus standard deviation of acute thermal stress under different climate scenarios and models. (e) Histogram of robustness metric for acute thermal stress. (f) Map of acute stress robustness metric. The change in colour from purple to yellow depicts the magnitude of the robustness metric in all panels

is lower in the north shore of Cuba, Haiti and the Dominican Republic, as well as the east of Jamaica and its offshore reefs (Figure 2f).

3.2 | Climate Priority sites

The Insular Caribbean and Florida have a wide distribution of climates (Figure 3). Different variables have distinct distributions, with acute thermal stress and hurricanes showing positive skewness (low median values with long tails) and the rest of the variables having negative skewness, with most sites having high environmental stress (Figure 3).

When looking at a scatterplot with two objectives or variables that need to be minimized, we would like to see linear relationships, when two variables increase and the site with the minimum value for one objective also has the minimum value for the other objective. However, this is not the case for any of the objectives included in this study (Figure 3). Most environmental variables show trade-offs, and it is not possible to find sites with low stress for all variables. It is particularly challenging finding sites with low values for future chronic temperatures that are also suitable for the other variables (Figure 3).

Another way to look at the context of the best three sites within MPAs and non-MPAs across the Insular Caribbean Region and Florida is presented in Figure 4, where sites are plotted on top of a box plot for each input variable. The best Climate Priority sites have particularly low values of historic thermal stress, hurricane frequency and connectivity, about average values of historical chronic thermal stress and future acute thermal stress, but relatively high values of future chronic thermal stress.

The distribution of best-ranked sites is heterogenous along the Caribbean, with the top 5% ranked sites located in Cuba, Bahamas, the Dominican Republic, United States (Florida), Guadeloupe, and Haiti. The top 615 sites are, however, all located within Cuba (Figure 5).

The distribution of the input variables and the shape and nature of trade-offs patterns vary across space. Therefore, a national-scale ranking was conducted for Cuba, the Dominican Republic, Haiti, and Jamaica—countries where The Nature Conservancy is currently planning coral conservation and/or restoration activities (Supplementary S3). For some countries, such as the Dominican Republic, changing the spatial scale of the analysis resulted in a minimal difference in the ranking (Figure 6b). For other countries, such as Jamaica, large differences resulted (Figure 6d), indicating each analysis needs to be tailored to the region of study to accommodate the spatial variation of the input variables and trade-offs that are characteristic of the specific region (Supplementary S3).

The information from the national-scale ranking was used by The Nature Conservancy, alongside extensive stakeholder consultations, to select sites for coral reef conservation and/or restoration in the four countries for which this was conducted (Cuba, the Dominican Republic, Haiti, and Jamaica). A web mapping tool that allows for interaction with or download of the climate priority ranking results can be found at https://CoralRefugia.tnc.org.

4 | DISCUSSION

The uncertainty associated with climate change makes prioritizing sites for conservation a challenge for planners and natural resource managers. Our model considers multiple possible futures to provide decision support on which places to prioritize in the future. These sites represent climate priorities, where coral reefs are more likely to withstand climate change impacts and the uncertain time ahead. We identified Climate Priority areas that are less likely to be adversely affected by climate change. The lack of true refugia in the insular Caribbean, sites with low projected chronic thermal exposure and also low stress for other variables considered in this study, indicate we need urgent greenhouse gas emission reductions to allow the survival of reefs in this region of the globe. These results are also supported by other work, which argues reefs will lack thermal refugia globally at 2.0°C of global warming (Dixon et al., 2022).

The information produced during this project was used by The Nature Conservancy to select an intervention site to strengthen coral reef management activities in Cuba, the Dominican Republic, Haiti and Jamaica. Besides this real-world application, the datasets have been made public through a web mapping tool that puts these data into the hand of researchers and decision makers. The input datasets on thermal conditions, hurricane regime, and connectivity will be useful to aid research and spatial management activities in the region. The output dataset on Climate Priority ranking can be used to guide regional spatial planning actions that address climate change and to help with the development of climate-smart marine protected area networks by addressing gaps at national and regional levels.

When prioritizing sites for conservation in a climate change context, there are a variety of strategies that can be used. Prioritization exercises, such as the one we present, may highlight areas that are expected to remain climatically stable into the future, assuming species will be more likely to persist in climate refugia areas, where the climate is less extreme (Fredston-Hermann et al., 2018; Tingley et al., 2014). However, when choosing multiple sites for conservation, some researchers have suggested the protection of diverse environmental regimes, to safeguard cooler refuges, heat resistant populations, and the steppingstones between them (McManus et al., 2021; Mumby et al., 2011; Walsworth et al., 2019). Facing the need for prioritizing management activities in only one site, we chose climate refugia. It is clear that the rapid pace of climate change has overwhelmed the capacity for adaptation in many species (Logan et al., 2021; Thomas et al., 2004), and that by protecting climate refugia sites now, we hope to buy time for species to adapt to new environmental conditions (Morelli et al., 2020).

Whilst the identified Climate Priority sites may be less affected by climatic threats, broadly speaking, refugia sites are not only defined by climatic exposure, but also by how species respond to it (their sensitivity) and their ability to adapt (adaptive capacity). Sensitivity and adaptive capacity are trait-specific characteristics related to the life history, ecophysiology, phenotypic plasticity, genetic diversity, evolutionary rates, dispersal and colonization ability

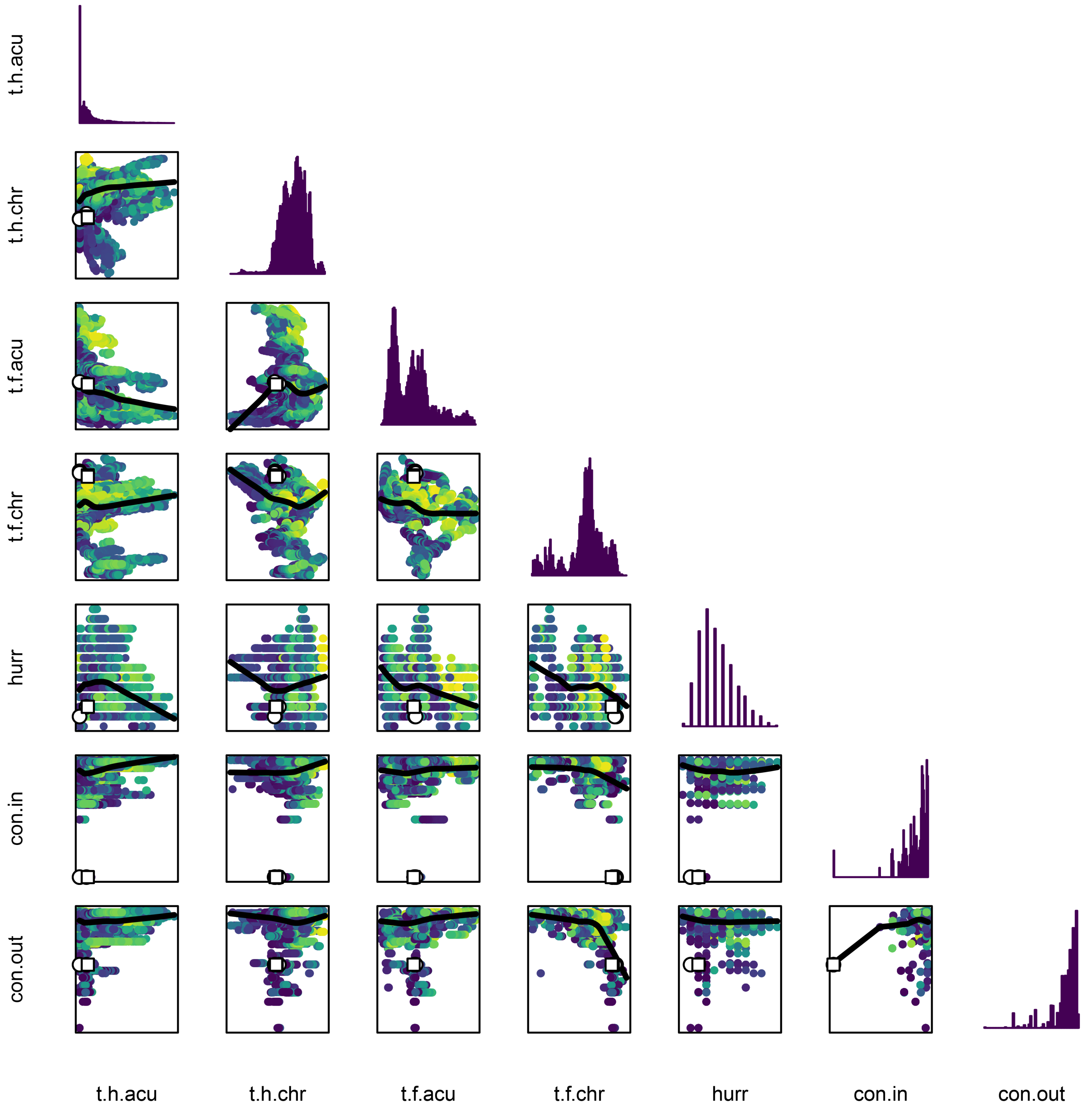

FIGURE 3 Trade-offs between input variables: acute historical thermal stress (t.h.acu), chronic historical thermal stress (t.h.chr), acute future thermal stress (t.f.acu), chronic future thermal stress (t.f.chr), hurricane impact (hurr), in-strength connectivity (con.in), and out-strength connectivity (con.out). Diagonal contains histograms for each variable. The lower diagonal has pairwise scatterplots (lower values are always desired). Each variable ranges between 0 and 1. Each circle represents a site. Sites have been coloured according to their Pareto ranking, with purple showing the lowest values and yellow the highest values. Blackline shows a lowess smoother. The three best ranking MPA sites (circles) and non-MPA sites (squares) are highlighted

and microhabitat preferences of the particular species at a coral reef site (Dawson et al., 2011). Mapping these variables is not possible in large regions and therefore most efforts identifying refugia at regional scales focus on climatic exposure (Dawson et al., 2011).

Trade-off analysis is a critical tool for effectively integrating multiple objectives into spatial plans, but so far this method has not been widely used in the marine realm. Lester et al. (2013) first discussed how the Pareto frontier could be used to evaluate trade-offs amongst ecosystem services and since then, a growing number of researchers are demonstrating the utility of Pareto analyses to identify the best possible marine spatial plans considering two objectives (Fox et al., 2019; Oyafuso et al., 2020; Rassweiler et al., 2014, but see Lester et al., 2018; White et al., 2012). However, including multiple objectives in spatial planning comes with its challenges. A common issue for multi-objective

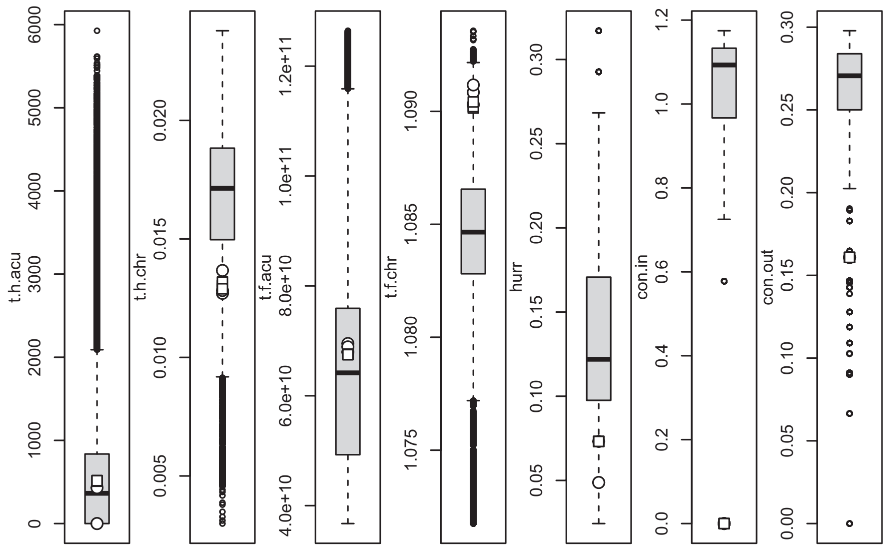

FIGURE 4 Boxplots showing input variables for the region of study. In boxplots, the line indicates the median, boxes the interquartile range (IQR, 25th and 75th percentile) and whiskers the highest and lowest value excluding outliers (1.5*IQR). Dots show potential outliers. The three best ranking MPA sites (circles) and non-MPA sites (squares) are highlighted. Variable names are the same as in Figure 3

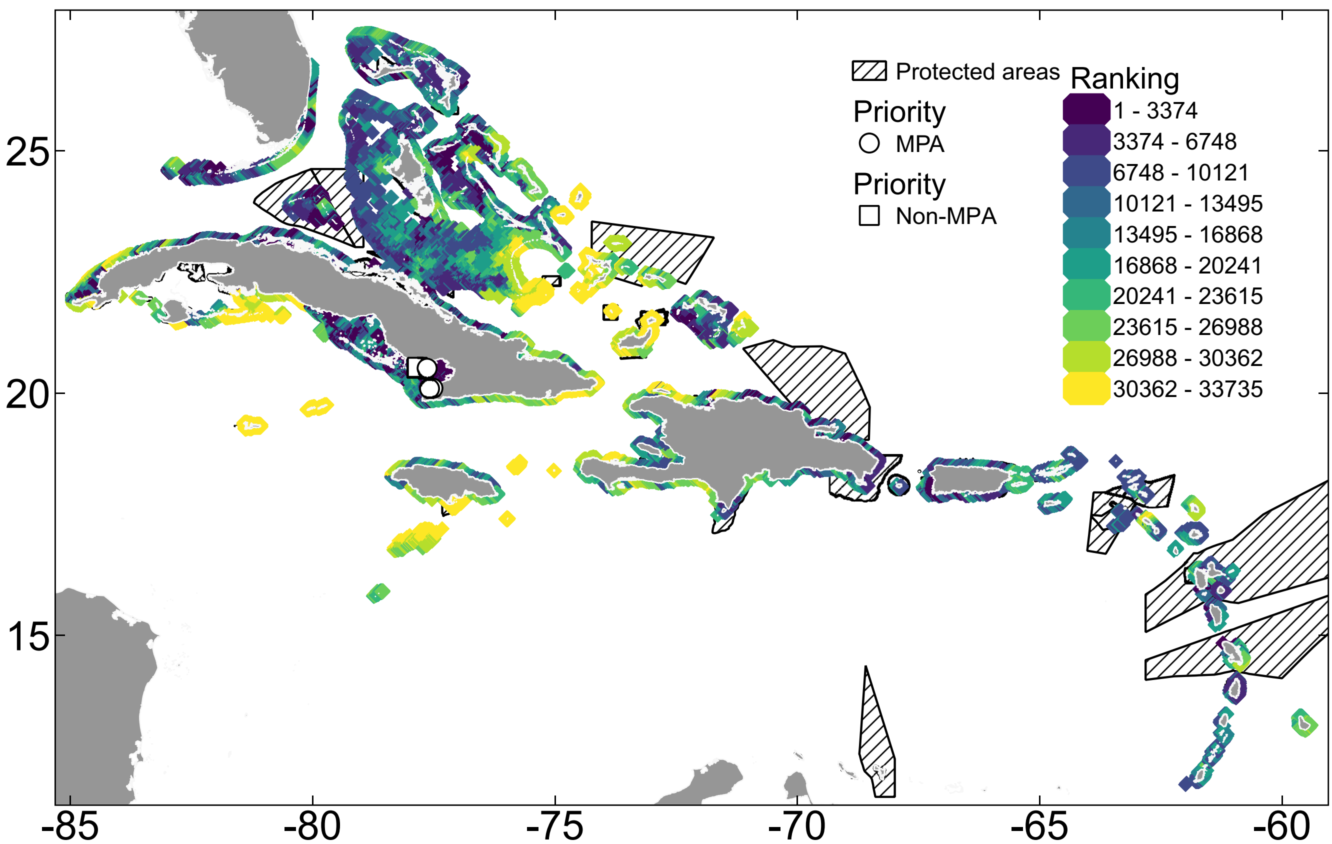

FIGURE 5 Map showing the Climate Priority rankings and best solutions across the region. Rankings are categorized according to quantiles. In purple sites with the best ranking and milder environments, in yellow sites with worst ranking under harsher environments. The three best ranking sites within MPAs are shown in circles and the three best sites outside MPAs are in squares. All top-ranking Climate Priority sites for the region overlap along the southeast coast of Cuba

spatial prioritization is that it is difficult to obtain a win-win solution where a site meets all objectives. In our model, we observed trade-offs that were unavoidable when considering chronic temperature, and it was not possible to find sites with low chronic thermal exposure and also low stress for other variables. Planners and resource managers need to address trade-offs, and one path forward includes involving stakeholders and the use of local information to refine results that focus protection on sites based on the best ecological state and enabling conditions for management. For example, interventions should be conducted at sites where local capacity can carry out work, current protection or management actions are effective, and there is sufficient local political will and/or community buy-in and support.

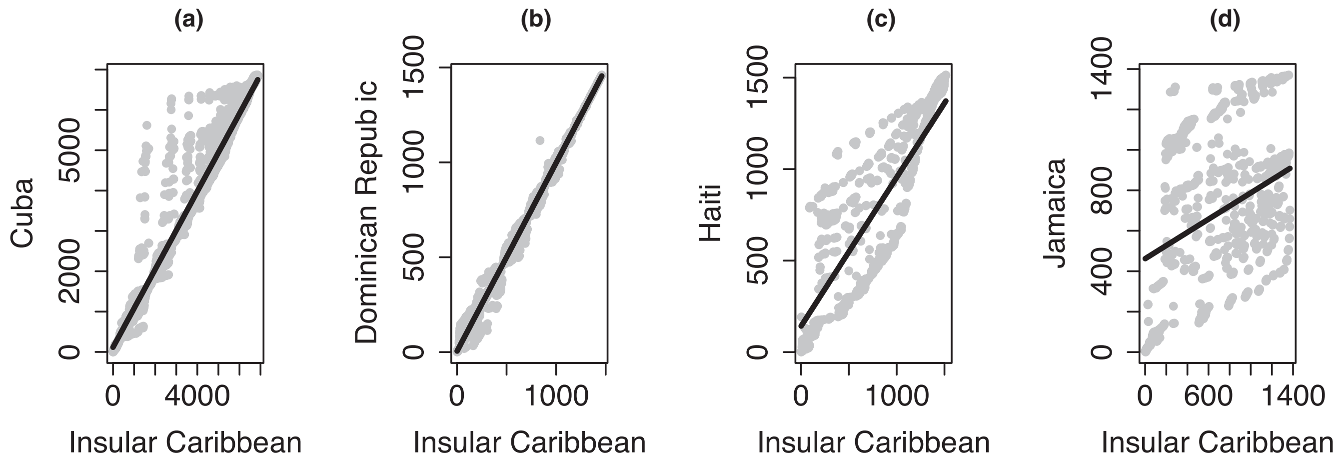

FIGURE 6 Regional ranking for the insular Caribbean vs. country ranking. (a) Cuba; (b) Dominican Republic; (c) Haiti; (d) Jamaica

For marine spatial plans and successive management and conservation efforts to be relevant in the long term, they must integrate the effects and future impacts of climate change. Very few countries have considered climate adaptation explicitly in their marine spatial plans. For example, three out of 27 countries in the European Union have marine spatial plans that consider climate change as an explicit objective (Frazão Santos et al., 2020). Modelling work generally focuses on only one climate scenario, and if dealing with multiple scenarios, scenario analysis is used (Frazão Santos et al., 2020). Very few examples in the marine realm have dealt with the uncertainty associated with climate change predictions, an exception being Beyer et al. (2018) who considered uncertainty in multiple models within one climate scenario, the most optimistic climate scenario at the time (RCP 2.6). To our knowledge, we present the first analysis of uncertainty in climate change and models, along with multiple objectives, in a marine spatial planning exercise.

Incorporating climate change uncertainty is key for successful spatial planning. Here, we focused on uncertainty about climatic change due to variability in climate scenarios and models. We recognize there are other sources of uncertainty associated with climate change that were not addressed by this work. These other types of uncertainty revolve around two main themes: incertitude or imperfect knowledge of the system and uncertainty in ecosystem response to climatic changes (Reside et al., 2018). There is uncertainty associated with the datasets used as input in spatial planning, from the habitat maps used to define target areas (Tulloch et al., 2013), to the downscaling method used to produce detailed spatial information on climate impacts (Fowler et al., 2007; Fowler & Wilby, 2007). There is also another layer of uncertainty related to the response of species to climate change (Mair et al., 2014; Moritz & Agudo, 2013), which is exacerbated by the lack of knowledge about the interactive effects of multiple stressors, and the different vulnerability of diverse habitat types to similar threats (Foley et al., 2010).

We offer a comprehensive approach to incorporating uncertainty and trade-offs into spatial plans in a climate change context. The explicit trade-off analysis shows the complexity of considering multiple stressors in marine spatial planning and identifies efficient solutions for improving management outcomes. Including stakeholders in the marine spatial planning process is a critical component for success in achieving zoning outcomes (Reed, 2008). Stakeholders can provide valuable insight to refine the plan, such as information that is not available spatially and cannot be included during the modelling stage, thereby enhancing the quality of conservation decisions (Reed, 2008). The results of this work were combined with stakeholder input to select priority intervention sites in four countries in the Caribbean. We suggest such an approach will increase the likelihood of social acceptance and adoption of the final plan and subsequently, a higher potential for successful conservation actions and management implementation (Gilliland & Laffoley, 2008; Pomeroy & Douvere, 2008).

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CONFLICT OF INTEREST

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in Dryad at https://doi.org/10.5061/dryad.sf7m0cg83.

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