A climate-smart spatial planning framework

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Method Article

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A climate-smart spatial planning framework

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Abstract

1. Climate change is already having profound effects on biodiversity, but climate change adaptation has yet to be fully incorporated into area-based management tools used to conserve biodiversity, such as protected areas. One main obstacle to its inclusion is the lack of consensus regarding how impacts of climate change can be included in spatial conservation plans.
2. We propose a climate-smart framework that prioritizes the protection of climate refugia—areas of low climate exposure and high biodiversity retention—identified using climate metrics. We explore four aspects of climate-smart spatial planning in the proposed framework: i) climate model ensembles; ii) multiple emission scenarios; iii) climate metrics; and iv) approaches to identifying climate refugia. We illustrate this framework in the Western Pacific Ocean, but it is equally applicable to terrestrial systems.
3. All aspects of climate-smart spatial planning considered affected the configuration of spatial plans. The choice of climate metrics and approaches to identifying refugia result in large differences in climate-smart spatial plans, whereas the choice of climate models and emission scenarios have smaller effects. As configuration of spatial plans depended on climate metrics used, a spatial plan based on a single measure of climate change (e.g., warming) will not necessarily be robust against other measures of climate change (e.g., ocean acidification). We recommend including climate metrics most relevant for the biodiversity considered. To include the uncertainty associated with different climate futures, we recommend using multiple climate models (i.e., an ensemble) and emission scenarios. Finally, we show that the approaches we used to identify climate refugia come with trade-offs between the degree to which they are climate-smart and their efficiency

in meeting conservation targets. Hence, the choice of approach will depend on the relative value stakeholders place on climate change adaptation.

4. By using this framework, protected areas can be designed with improved longevity and thus safeguard biodiversity against current and future climate change. We hope that the proposed climate-smart framework helps transition conservation planning towards climate-smart approaches.

Keywords

climate resilience; environmental decision making; Marxan; MPAs; prioritizr; spatial prioritization; systematic conservation planning

INTRODUCTION

Climate change is a major threat to biodiversity (IPCC, 2021). Although protected areas have long been used to safeguard biodiversity (Bates et al., 2019), climate change reduces their effectiveness by exposing biodiversity to a suite of environmental changes, including warming, changes in rainfall, increasing ocean acidification, and deoxygenation (Bruno et al., 2018). Warming can also cause species to move beyond boundaries of protected areas (Loarie et al., 2009; Heikkinen et al., 2020). Thus, protected area design needs to explicitly account for climate exposure and species retention (Harris et al., 2019; Doxa et al., 2022). However, there is currently little consensus on these practical strategies (Tittensor et al., 2019; Wilson et al., 2020).

Many different approaches have been proposed for such "climate-smart spatial planning", which refers to the design of protected area systems robust to climate change (Tittensor et al., 2019). The most common approach is to fit species distribution models, use them to predict distribution shifts under climate change, and incorporate these into the design process (e.g., Pacifici et al., 2015; Araújo et al., 2011). Although this approach can account for species-specific responses to u models for hundreds of species; and it may not be feasible to fit such models where data are scarce (Bellard et al., 2012; Pacifici et al., 2015). To avoid these limitations, studies have employed other approaches such as protecting keystone species (e.g., Patrizzi & Dobrovolski, 2018; Wilson et al., 2020), conserving heterogeneous environments to hedge against uncertainty in climate change predictions (e.g., Walsworth et al., 2019), and preserving redundant areas to minimize risk (e.g., Magris et al., 2014). Although these approaches protect important species and critical habitats and are simpler than using species distribution models, protection against current threats does not equate to protection against impacts of climate change (Bates et al., 2019; Bruno et al., 2018).

Climate metrics offer a simple and tractable method for incorporating climate change into the design of protected area systems (Brito-Morales et al., 2018; Nadeau et al., 2015; Stralberg et al., 2020). They are calculated based on projected changes in environmental conditions, such as temperature (e.g., García Molinos et al., 2016), rainfall (e.g., Wu et al., 2011), and dissolved oxygen concentration (e.g., Bopp et al., 2013; Bruno et al., 2018). Such metrics can be used to identify areas where climate is projected to remain relatively stable or where climate change might pose less of a threat to biodiversity. These areas are considered climate refugia (Morelli et al., 2017; Pacifici et al., 2015) and can be incorporated in spatial prioritization— the structured process of identifying protected areas for conservation (Harris et al., 2019). By designing protected area systems that safeguard climate refugia, conservation efforts can help ensure protection of biodiversity in future (Brito-Morales et al., 2022; Doxa et al., 2022; Jones et al., 2016).

Here, we provide a framework for designing climate-smart spatial prioritizations based on climate metrics. We begin by describing the framework, detailing four key climate-smart aspects that could influence spatial plans: viz. climate models; emission scenarios; climate metrics; and approaches to identifying climate refugia. We then apply the framework to the Western Pacific Ocean by describing the methods we use and comparing the resulting climate-smart spatial plans. Finally, we provide recommendations for practitioners to apply our framework to terrestrial, freshwater, estuarine, and marine systems.

THE CLIMATE-SMART FRAMEWORK

Our framework comprises three steps (**Figure 1**): 1) selecting climate data, which involves deciding on the climate models, emission scenarios, and climate variables; 2) calculating climate metrics from model outputs; and 3) choosing an approach for identifying refugia based on climate metrics. Climate refugia could then be incorporated into a spatial prioritization using a range of decision-support tools (Moilanen et al., 2009), including *Marxan* (Ball et al., 2009), *Zonation* (Moilanen et al., 2009), and the R package *prioritizr* (Hanson et al., 2021). Although each decision-support tool uses different algorithms, they share several characteristics, including: 1) a planning domain; 2) a cost layer; 3) conservation features with representation targets; and 4) an objective function (Moilanen et al., 2009). We next discuss the three steps in our framework.

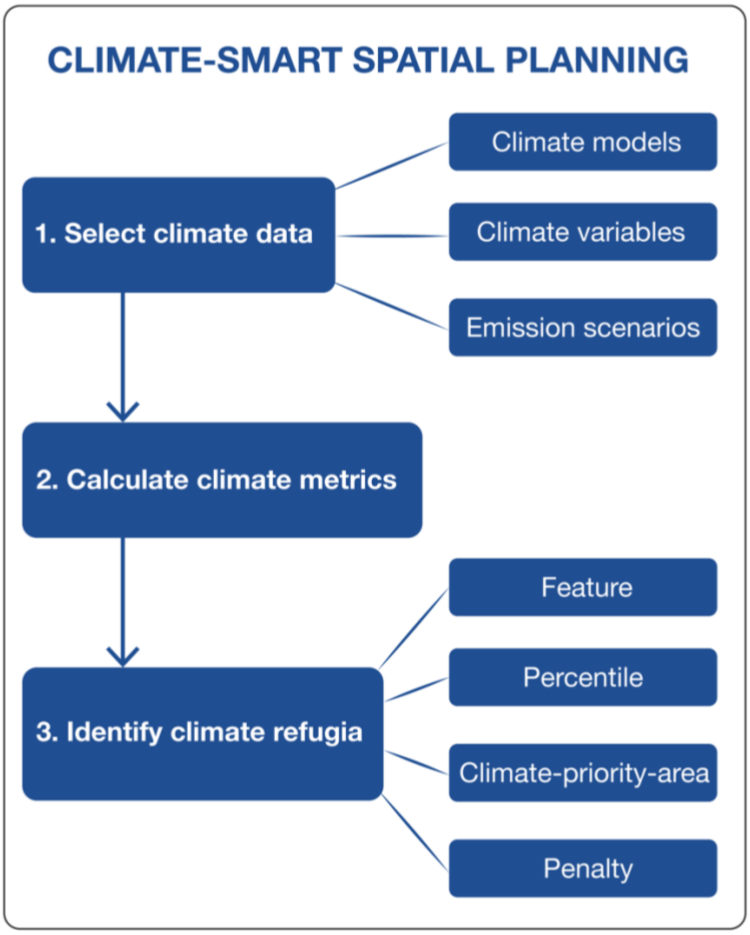


Figure 1. Climate-smart spatial planning framework. Model outputs are extracted based on the selected climate data (Section 2.1) and are used to calculate climate metrics (Section 2.2) to identify climate refugia (Section 2.3). These climate refugia can then be incorporated in a spatial prioritization, generating climate-smart spatial plans.

2.1 Select climate data

Climate-smart spatial prioritization first requires selecting climate variables based on outputs from climate models under different emission scenarios.

2.1.1 Climate models

There are dozens of global climate models available (CMIP6; https://esgf.llnl.gov), each with somewhat different underlying physical, chemical and biological processes. This variation will produce different future projections for environmental variables under any particular emission scenario (Raäisaänen, 2007; Gu et al., 2015). Therefore, using a single model in climate-smart reserve design will not adequately encompass uncertainties in future conditions (Makino et al., 2014). A common solution is to use multiple models to create a model ensemble (Tegegne et al., 2020; Porfirio et al., 2014), in one of two ways: 1) a multi-model-ensemble using outputs of individual models; and 2) an ensemble mean (or median) that represents all models with a single layer. Temperature is the most used variable to describe impacts of climate change because it is the primary climate driver in many ecosystems (Poloczanska et al., 2013) and there is higher confidence in its projection than for other climate variables (Raäisaänen, 2007). Rainfall (Wu et al., 2011), dissolved oxygen (Bopp et al., 2013), net primary production (Wu et al., 2011), and ocean pH (Kroeker et al., 2013) are other variables used to describe impacts of climate change on biodiversity.

2.1.2 Emission scenarios

Climate models project different climate futures when forced under different emission scenarios (Makino et al., 2014). These range from scenarios assuming low emissions of greenhouse gases such as SSP1-2.6 (an optimistic future that successfully limits warming to 2°C compared to pre-industrial temperatures) to high-emission scenarios such as SSP5-8.5 (a pessimistic future where the world continues to require more fossil fuels) (O'Neill et al., 2017). As our climate future is uncertain, it is best practice to include multiple emission scenarios (Harris et al., 2014).

2.2 Calculate climate metrics based on climate model outputs

Variables from climate models can then be used to calculate climate metrics. These metrics can provide a measure of acute exposure, chronic exposure, relative exposure, and biodiversity retention.

2.2.1 Metrics of chronic exposure

Projected rates of change in temperature, precipitation, ocean acidification, and oxygen can all be considered metrics of chronic exposure, reflecting the degree of exposure to gradual climate change (Wilson et al., 2020; IPCC, 2021). Although temperature-derived metrics are the most used, other metrics such as the change in precipitation could be pertinent in tropical forests (Cornelissen, 2011) and rate of ocean acidification in coastal ecosystems with corals (McLeod et al., 2013). Moreover, the rate of ocean deoxygenation may be a more suitable exposure metric when characterizing shallow benthic areas or hypoxic areas (Breitburg et al., 2018). There are other options beyond these simple exposure metrics.

2.2.2 Metrics of acute exposure

Acute-exposure metrics provide insight into discrete anomalous events, such as wildfires, cyclones, and heatwaves (e.g., Magris et al., 2015; Foresta et al., 2016). Heatwaves are prolonged anomalously warm events (Hobday et al., 2016), increasing in severity with climate change (Oliver et al., 2019). On land, heatwaves and drought decrease photosynthetic activity and induce plant stress (Wang et al., 2019). In the ocean, marine heatwaves (MHWs) cause coral bleaching, species migrations, and mass mortalities (Eakin et al., 2019). There are many metrics describing heatwave frequency, intensity, effect, and duration (Wohlfahrt et al., 2018; Hobday et al., 2016).

2.2.3 Metrics of relative exposure

Relative exposure metrics scale the change in the climate variable relative to its variation. For example, the relative climate exposure index scales the change in a climate variable such as temperature to its seasonal range (Brito-Morales et al., 2022) and the climate hazard metric scales it to its standard deviation (Levin et al., 2020). Relative exposure metrics are more sophisticated than simple exposure metrics because they consider that species inhabiting more variable environments might be less susceptible to gradual environmental change.

2.2.4 Metrics of retention

The most common metric used to infer the retention of biodiversity is climate velocity (Loarie et al., 2009). This metric serves as a proxy for shifts in species distributions (VanDerWal et al., 2013) because it relates to the speed and direction that a species at a given point in space would need to move to remain in the same habitat conditions as the climate changes (Burrows et al., 2011; Loarie et al., 2009). Areas of slow climate velocity are expected to have high biodiversity retention (Brito-Morales et al., 2018; Burrows et al., 2011; Loarie et al., 2009).

2.3 Identify climate refugia

There are several ways of identifying climate refugia by creating climate layers and including them in a spatial prioritization. We describe four different approaches below, with the first three yielding binary climate layers across the planning region (0 = not climate refugia; 1 = climate refugia) while the "penalty" approach preserves the continuous nature of the metrics.

2.3.1 The feature approach

The simplest approach is to consider climate refugia based only on climate variables, ignoring biodiversity (Arafeh-Dalmau et al., 2021). Areas of low exposure and/or high retention can be determined by setting a threshold for identifying the range of climate metric values used to classify areas as climate refugia (**Supplementary Figure S1A**). For example, climate refugia could be defined based on a threshold of the lowest 30^{th} percentile of the rate of warming. This contributes a single additional layer to the spatial prioritization for each climate metric.

2.3.2 The percentile approach

The percentile approach identifies climate refugia for each biodiversity feature (Brito-Morales et al. 2022). The distribution of each biodiversity feature is intersected with the climate metric layer and—using a threshold—is then restricted to its climate refugia (**Supplementary Figure S1B**). Note that this approach replaces the original biodiversity features by restricting each to their climate-smart areas.

2.3.3 The climate-priority-area approach

This approach identifies the most stable climate refugia for each biodiversity feature and gives it higher prioritization by setting a higher target than the remainder of the distribution range of a species (**Supplementary Figure S1C**). The climate-priority-area approach is thus a variant of the percentile approach that focuses on high-value climate refugia and enables key areas outside of climate refugia to be included in the solution. This approach also results in the conservation of a greater diversity of future climate conditions.

2.3.4 The penalty approach

The penalty approach seeks to minimize climate exposure and/or maximize biodiversity retention while minimizing the cost of the solution. This approach treats the climate layers as linear penalties in the spatial prioritization (see Supplementary) to discourage the selection of less climate-smart areas.

CASE STUDY: Application to the Western Pacific

We use the case study to: (i) illustrate the utility of the proposed climate-smart framework for spatial prioritization; (ii) assess the relative effect on spatial plans of varying the climate models, emission scenarios, climate metrics, and approaches to identifying climate refugia; and (iii) develop key recommendations. Although this is a marine application, methods we develop are equally valid for other systems.

3.1 Spatial prioritization

The planning domain was the epipelagic layer of the Western Pacific, with 35,389 planning units of 0.25ºx0.25º resolution using the Robinson projection (**Supplementary Figure S2A**). We used current distribution maps from AquaMaps (Kaschner et al., 2019) with uniform targets of 30%, resulting in 8,711 biodiversity features in the region. We used *prioritizr* (Hanson et al., 2021) as our decision-support tool, but the framework we developed can be applied in other tools. All analyses were undertaken in the R statistical computing environment (version 4.1.1; see Supplementary).

3.2 Climate data

Historical daily temperature data (1982-2015) were downloaded from the NOAA ¼° Daily Optimum Interpolation Sea Surface Temperature (OISST; https://www.ncei.noaa.gov/products/optimum-interpolation-sst). Projections (2015-2100) from the climate models forced by several emission scenarios were downloaded at daily or monthly resolution (depending on the climate metric) from the Coupled Model Intercomparison Project Phase 6 (CMIP6; https://esgf-node.llnl.gov/). We re-gridded all data to 0.25°x0.25° using area-weighted bilinear interpolation (Brito-Morales et al., 2022) in the Climate Data Operators (CDO) software (Schulzweida, 2021).

3.2.1 Emission scenarios

To test how using climate projections forced under different emission scenarios influenced the resulting spatial plans, we created plans using three emission scenarios (Shared Socioeconomic Pathways or SSPs; SSP1-2.6, SSP2-4.5, and SSP5-8.5) and compared their solutions (O'Neill et al., 2017).

3.2.2 Climate models

As different climate models suggest different environmental futures, the aim here was to highlight methods of including multiple climate models in spatial prioritization. We used five climate models: 1) CanESM5; 2) CMCC-ESM2; 3) GFDL-ESM4; 4) IPSL-CM6A-LR; and 5) NorESM2-MM. We created spatial plans using both a model ensemble comprising outputs from individual models (**Supplementary Figure S3**) and an ensemble mean (**Supplementary Figure S2C-Q**).

3.3 Climate metrics

To investigate the effect of using different climate metrics on spatial plans, we developed separate plans based on five climate metrics: 1) rate of climate warming; 2) rate of ocean acidification; 3) rate of ocean deoxygenation; 4) climate velocity (based on temperature); and 5) sum of annual cumulative MHW intensity. On land, appropriate terrestrial metrics could be temperature- and precipitation-derived metrics (Araújo et al., 2011; Heikkinen et al., 2020).

Rates of climate warming, ocean acidification, and ocean deoxygenation are chronic-exposure metrics. For each, we defined and prioritized protection of areas characterized by low exposure to climate impacts (i.e., climate refugia as areas of low rates of warming, acidification, and deoxygenation). These metrics were calculated as the slope of the linear regression of projected mean annual values from each climate model output (Δ magnitude yr^{-1}, 2015-2100).

Despite climate warming, climate velocity, and the sum of annual cumulative MHW intensity all being calculated from temperature, they are fundamentally different metrics. Areas of slow climate velocity are areas of high biodiversity retention and were prioritized for protection (Arafeh-Dalmau et al., 2021; Stralberg et al., 2020). These climate refugia are more likely to retain their current environmental conditions, and consequently, their biodiversity (Brito-Morales et al., 2022). Climate velocity (km yr^{-1}) was calculated as the ratio of the temporal gradient (°C yr^{-1}, 2015-2100) to the spatial gradient (°C km^{-1}, 2015-2100) of temperature using the VoCC R package (see Supplementary). However, velocity can be calculated based on other variables such as rainfall (Brito-Morales et al., 2018; Heikkinen et al., 2020).

We used the sum of cumulative MHW intensity to measure long-term exposure to acute warming events (Hobday et al., 2016). As the frequency and magnitude of temperature anomalies vary non-linearly through time depending on emission scenario (Oliver et al., 2019), impacts are better represented by the sum of intensities than by the rate of change. We calculated this metric using the heatwaveR package following MHW equations (Hobday et al. 2016) and expressed it as total degree days, representing the sum of the annual temperature anomalies.

3.4 Climate refugia

Our aim was to demonstrate the use of each of the four approaches to climate refugia and investigate whether these yielded different climate-smart spatial plans. Percentile thresholds were chosen to allow for comparable 30% biodiversity protection targets for each approach. For the feature and percentile approaches, we defined climate refugia as areas within the lower 35th percentile to represent: 1) slow climate warming; 2) low MHW intensity; and 3) slow climate velocity, and the upper 65th percentile of the low rates of change in: 1) ocean acidification (i.e., smallest decreases in ocean pH); and 2) ocean deoxygenation (i.e., smallest decreases in ocean oxygen concentrations). Climate refugia were assigned targets of 85.71% (i.e., 30% ÷ 35th percentile of the original distribution). More demanding thresholds (lower 5th and upper 95th percentiles, respectively) were used in the climate-priority-area approach and these areas were assigned 100% targets (i.e., 5% ÷ 5th percentile of the original distribution). Areas outside climate-priority areas (i.e., the rest of the distribution range) for each feature were assigned an effective target of 26.31% (i.e., 25% ÷ 95th percentile of the original distribution). Summing the protection over these two categories of area results in an effective target of 30% for each feature.

3.5 Comparing spatial prioritizations

To illustrate differences among the climate-smart solutions, we used a simplified configuration for comparison (unless otherwise specified), viz. the ensemble-mean for warming forced under SSP 5-8.5 using the percentile approach. We used the Cohen's Kappa Coefficient (McHugh, 2012) to quantify the degrees of agreement between designs. We assessed climate-smart performance by comparing the resulting rates of climate exposure of the climate-smart solutions. We also reported how well these approaches met the target of 30% protection for each of the biodiversity features.

To identify how different options affected the resulting climate-smart spatial plans, we also completed prioritizations for every possible combination of the climate-smart aspects (three scenarios, five models and the ensemble-mean, five metrics, and four approaches). We compared all 360 plans by extracting the solutions (selected/not selected data across all planning units), creating a Jaccard similarity matrix, and visualizing the matrix using a non-metric multidimensional scaling (nMDS) ordination.

RESULTS

Spatial plans for the Western Pacific Ocean varied substantially depending on the chosen climate models, emission scenarios, climate variables, climate metrics, and approach used to identify climate refugia.

4.1 Climate models: multi-model-ensemble versus an ensemble-mean

Spatial plans designed using individual climate models differed from each other and from the spatial plan designed using the ensemble mean (**Figure 2, Supplementary Figure S4**). Less than a third of the planning domain was common to all individual solutions (**Figure 2B**) and protecting these common areas alone would lead to unmet targets in 18.5% of the biodiversity features (**Figure 2D**). The degree of agreement between spatial plans using different climate models were similar (**Figure 2C**). Although the ensemble mean did not cover the full range of climate projections for all models, it captures most of the important features of the individual model outputs (**Figure 2E**).

4.2 Emission scenarios: single versus multiple

Spatial plans created using the three emission scenarios had similar spatial configurations but had a slight increase in area required to meet targets as emissions increase (**Figure 3**). About 35% of the planning domain was common to solutions (**Figure 3D**) and protecting only these areas would meet the targets for 97.7% of the biodiversity features (**Figure 3F**). There was general agreement between the different plans (**Figure 3E**). As expected, the climate warming in planning units selected for conservation fall in the slowest tail of warming in the planning domain and were slowest in SSP1-2.6 and fastest in SSP 5-8.5 (**Figure 3G**).

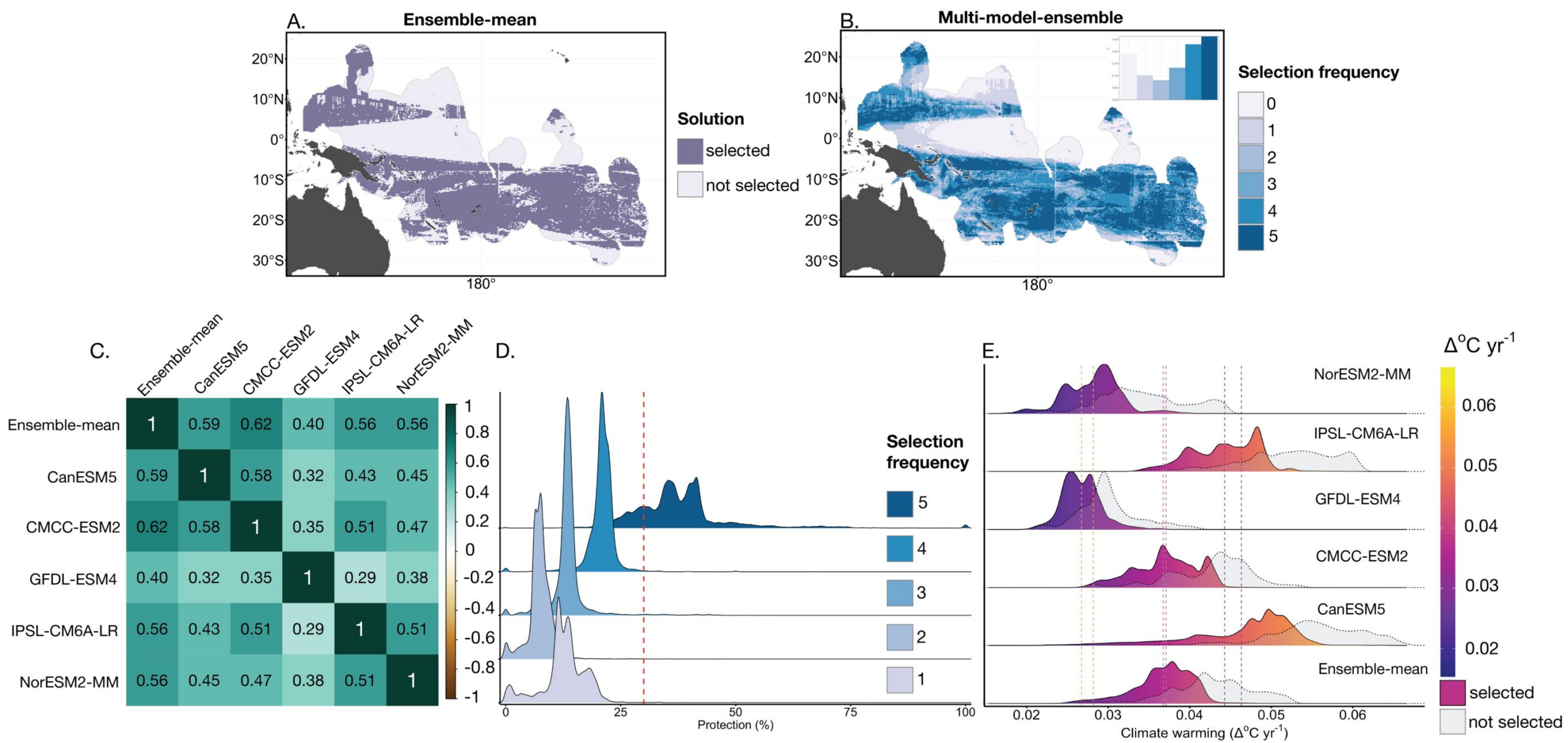


Figure 2. Using the climate model ensemble mean or the multi-model-ensemble. A. Spatial plan created using the ensemble mean. **B.** Selection frequency plot using the multi-model-ensemble with an inset histogram showing selection proportion across models. **C.** Cohen's Kappa coefficient matrix, showing correspondence between solutions. **D.** Kernel density estimates of the % protection of the biodiversity features across selection frequencies (dashed line represents the 30% protection target). **E.** Kernel density estimates of the degree of climate warming in the solutions. Colored polygons represent the warming in selected planning units; gray polygons represent warming of areas not selected for protection. Dashed lines represent the mean warming for each model across selected planning units.

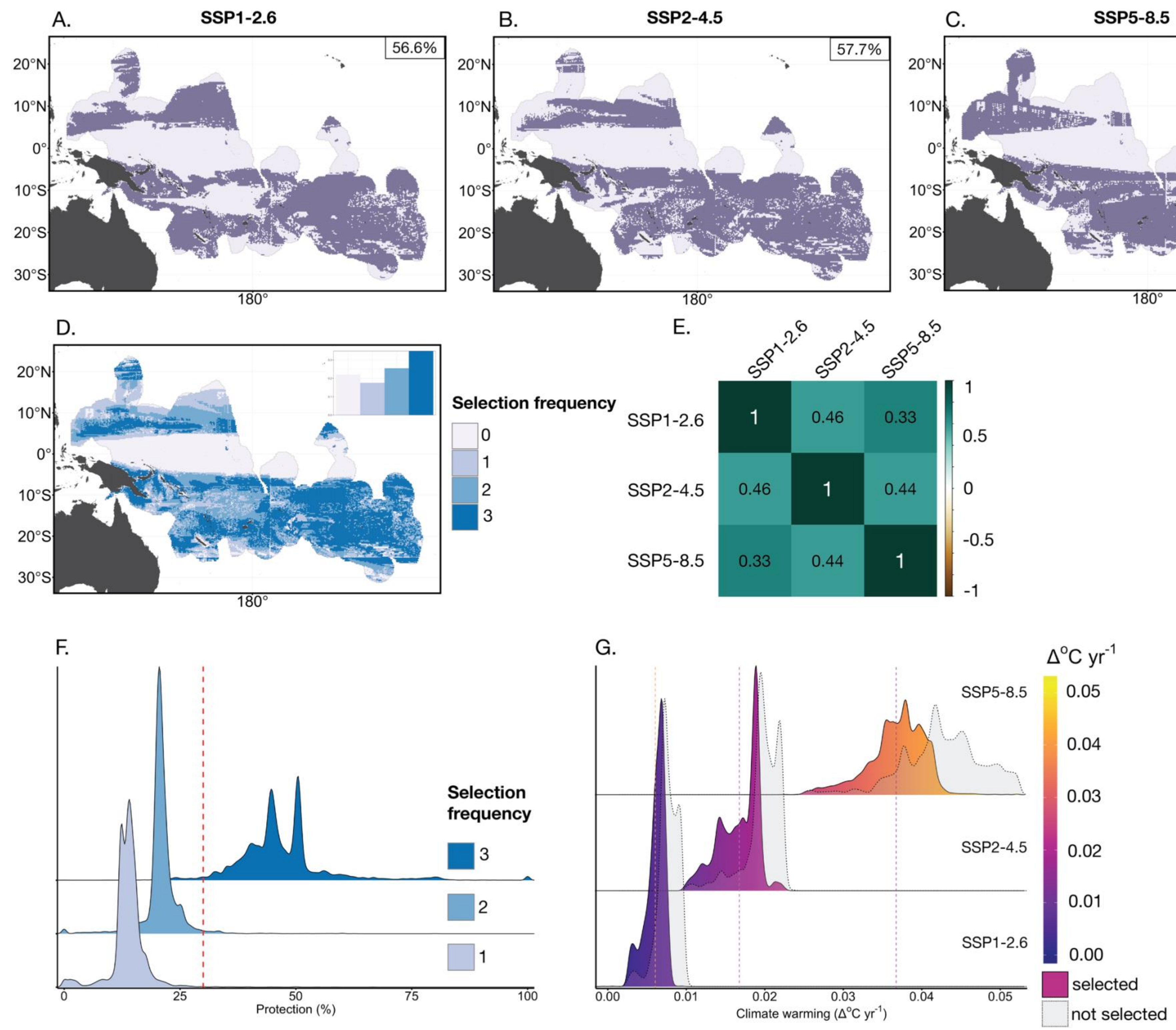


Figure 3. Incorporating different emission scenarios. Spatial plans (with % area selected in top right) designed using climate warming forced under: **A.** SSP1-2.6; **B.** SSP2-4.5; and **C.** SSP5-8.5. **D.** Selection frequency plot showing areas selected across scenarios with an inset histogram showing selection proportion. **E.** Cohen's Kappa coefficient matrix, showing correspondence between solutions. **F.** Kernel density estimates of the % protection of the biodiversity features across selection frequencies (dashed line represents the 30% protection target). **G.** Kernel density estimates of the degree of climate warming in the solutions. Colored polygons represent the warming in selected planning units; gray polygons represent warming of areas not selected for protection. Dashed lines represent the mean warming for each scenario across selected planning units.

4.3 Utility of different climate metrics

Configurations of the spatial plans created using different metrics contrasted strongly (**Figure 4**), although solutions based on warming and deoxygenation were relatively similar (**Figure 4G**). Unlike solutions created with different scenarios and models, selected areas common for all metrics constituted only 10.4% of the planning domain (**Figure 4F**), suggesting the spatial plans are quite different. Protecting these areas would result in unmet targets in 28.5% of the biodiversity features (**Figure 4H**).

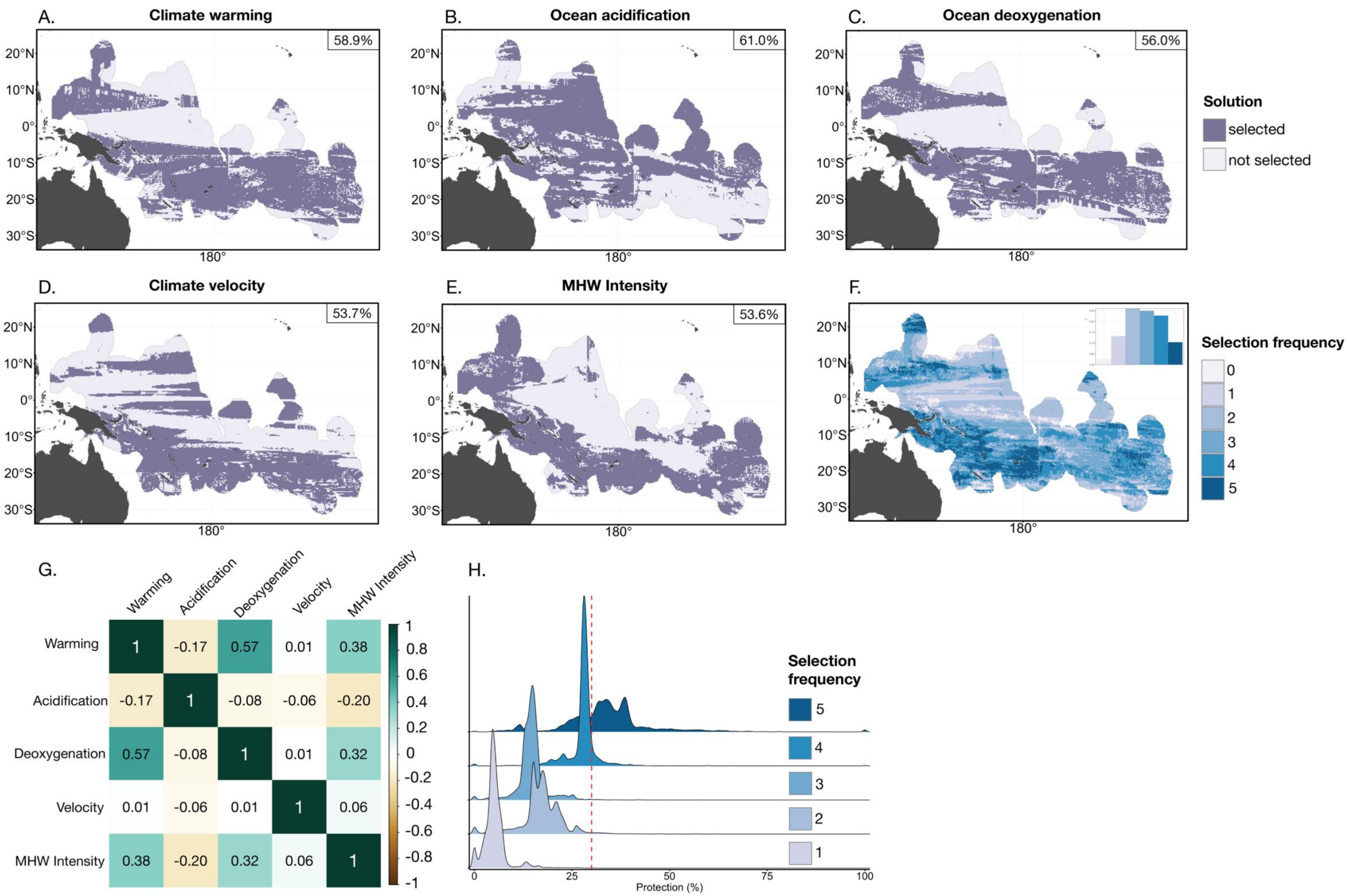
4.4 Identify climate refugia: trade-offs among approaches

Climate-smart spatial planning was sensitive to the ways in which climate refugia were identified (**Figure 5**). Despite using the same climate metric, only 14.6% of the planning domain was common across all approaches (**Figure 5E**). Protecting only these common areas resulted in unmet targets for 98.3% of the biodiversity features (**Figure 5G**). Percentile and climate-priority-area approaches were relatively similar (**Figure 5F**) and were less efficient in meeting biodiversity targets than the penalty and feature approaches (**Figure 5H**).

Approaches that resulted in a greater area selected were more efficient at selecting slower rates of warming (**Figure 5I**). This was also consistent with spatial plans using other climate metrics (**Figure 6**). The percentile approach repeatedly selected more climate-smart areas (**Figure 6A-D**) but seemed to be the most inefficient at reaching biodiversity targets and thus required more area conserved (**Figure 6E-H**). The climate-priority-area and feature approaches were intermediate in terms of their area requirements and climate-smart performance. Meanwhile, the penalty approach was the least climate-smart of the four approaches but selected the smallest area for protection.

4.5 Overall importance of different climate-smart aspects

The nMDS ordinations of the 360 different spatial plans showed that the chosen metric and climate-refugia approach influenced the resulting climate-smart solutions more than the climate model or emission scenario (**Figure 7**). This was evident with metrics (**Figure 7C**) and approaches to identifying climate refugia (**Figure 7D**) having more distinct standard deviation ellipses and their points were clumped across different regions of the 2-D space. By contrast, the climate models (**Figure 7A**) and emission scenarios (**Figure 7B**) had more overlapping ellipses and their points were randomly distributed across the 2-D space. Solutions using the ensemble mean reasonably represented the solutions based on individual models (**Figure 7A**). Configurations of solutions across scenarios showed overlapping ellipses, suggesting they were similar (**Figure 7B**). Of the five explored climate metrics, three were different—climate velocity, ocean acidification, and MHW intensity—whereas warming and ocean deoxygenation were similar (**Figure 7C**). Among approaches to identifying climate refugia, solutions from the percentile approach were the most tightly clustered. Solutions using the feature, climate-priority-area, and penalty approaches were increasingly dissimilar from each other and from other approaches (**Figure 7D**). Within each approach, the chosen metric considerably influenced the resulting spatial plan, showing that approaches were sensitive to the metrics (**Supplementary Figure S5**).



	Warming	Acidification	Deoxygenation	Velocity	MHW Intensity
Warming	1	-0.17	0.57	0.01	0.38
Acidification	-0.17	1	-0.08	-0.06	-0.20
Deoxygenation	0.57	-0.08	1	0.01	0.32
Velocity	0.01	-0.06	0.01	1	0.06
MHW Intensity	0.38	-0.20	0.32	0.06	1

Figure 4. Using different climate metrics. Spatial plans (with % area selected in top right) designed with the percentile approach using: **A.** Climate warming (Δ°C yr^{-1}); **B.** Ocean acidification (ΔpH yr^{-1}); **C.** Ocean deoxygenation (Δ[O_2] yr^{-1}); **D.** Climate velocity (km yr^{-1}); and **E.** Marine heatwave (MHW) intensity (total degree days). **F.** Selection frequency plot showing areas selected across different metrics with an inset histogram showing selection proportion. **G.** Cohen's Kappa Coefficient Matrix, showing correspondence between solutions. **H.** Kernel density estimates of the % protection of the biodiversity features across approaches (dashed line represents the 30% protection target).

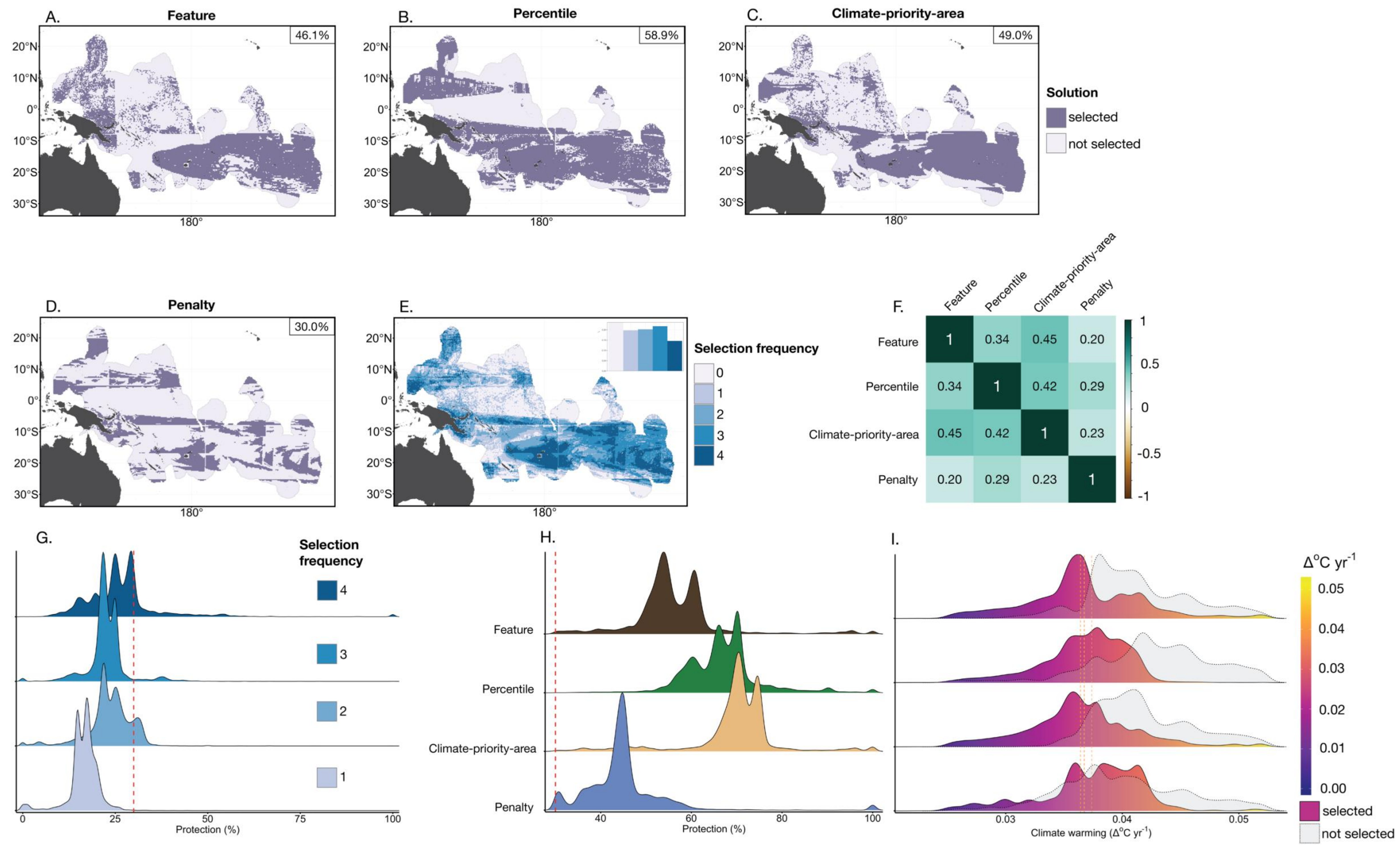


Figure 5. Exploring approaches of identifying and protecting climate refugia. Spatial plans (with % area selected in top right) designed using the following approaches: **A.** Percentile; **B.** Climate-priority-area; **C.** Penalty; and **D.** Feature. **E.** Selection frequency plot showing areas selected across approaches with an inset histogram showing selection proportion. **F.** Cohen's Kappa Coefficient Matrix, showing correspondence between solutions. **G.** Kernel density estimates of the % protection of the biodiversity features across selection frequencies (dashed line represents the 30% protection target). **H.** Kernel density estimates of the % protection of the biodiversity features across approaches (dashed line represents the 30% protection target). **I.** Kernel density estimates of the degree of climate warming in the solutions. Colored polygons represent the warming in selected planning units; gray polygons represent warming of areas not selected for protection. Dashed lines represent the mean warming for each approach across selected planning units.

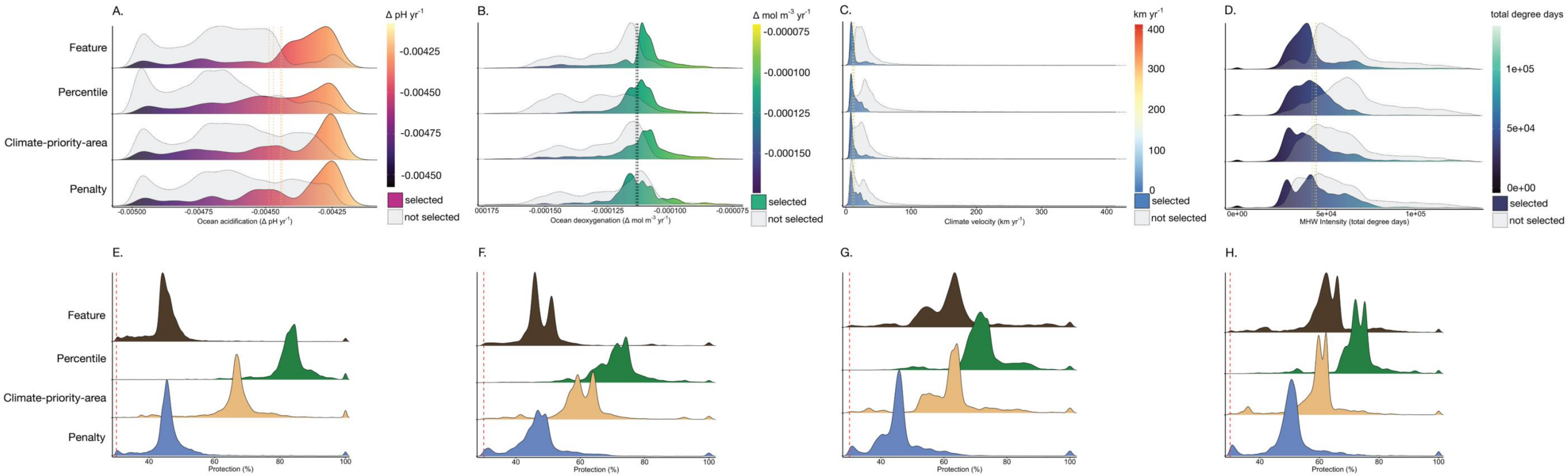


Figure 6. Performance of different approaches across metrics. A, E. Ocean acidification (ΔpH yr^{-1}), **B, F.** Ocean deoxygenation ($\Delta[O_2]$ yr^{-1}), **C, G.** Climate velocity (km yr^{-1}), and **D, H.** MHW intensity (total degree days). **A-D.** Colored polygons represent values of different climate metrics. Grayed polygons represent values for areas not selected for protection. Dashed lines represent the mean values across selected planning units. **E-H.** Kernel density estimates of the % protection of the biodiversity features (dashed line represents the 30% protection target).

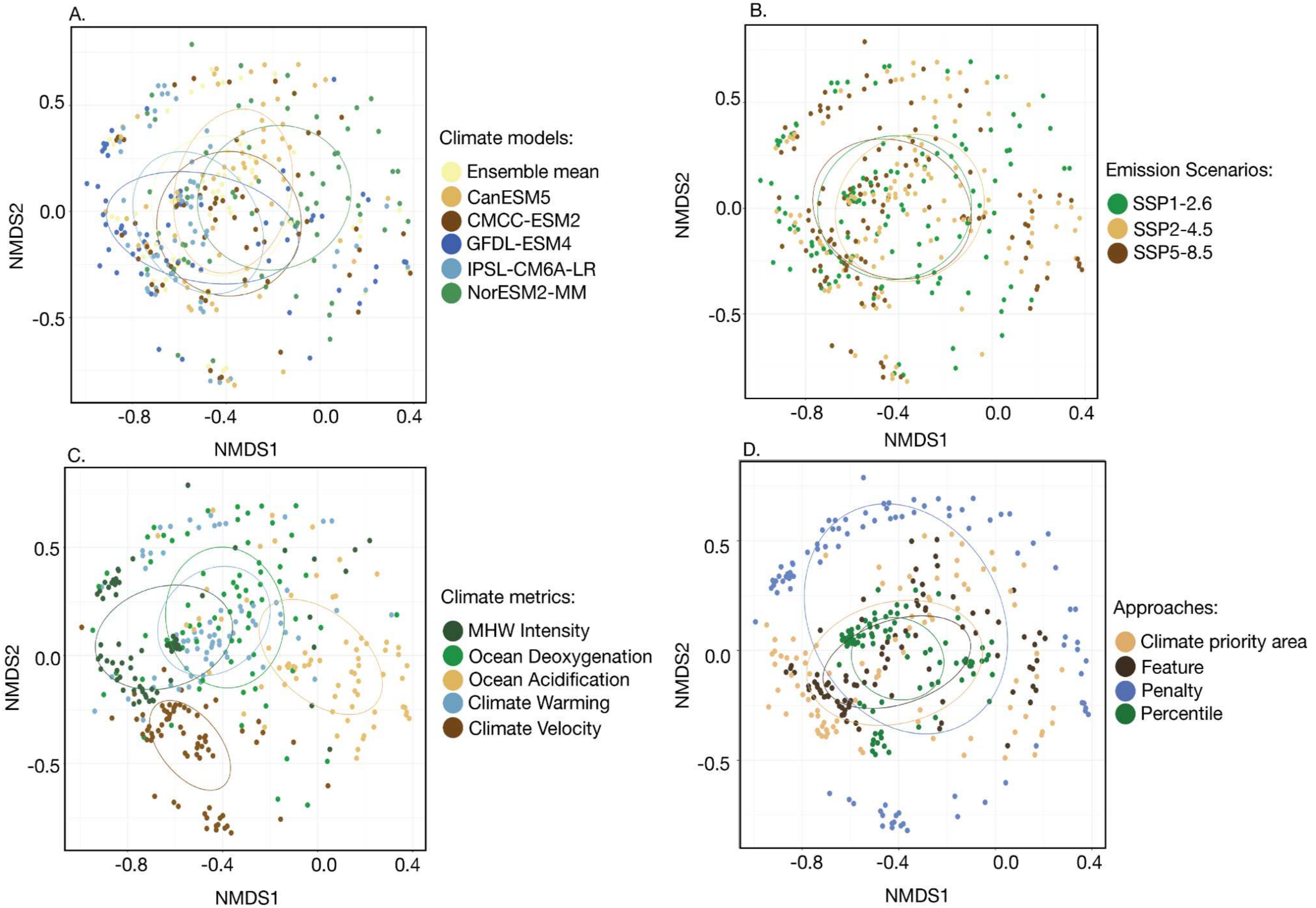


Figure 7. nMDS plots comparing 360 spatial plans across all combinations of options considered. Solutions by **A.** Scenario, **B.** Individual climate models. **C.** Climate metrics, and **D.** Approaches for identifying refugia. Stress = 0.23, number of iterations = 1000. Ellipses represent the standard deviation of the solutions.

DISCUSSION

We developed a climate-smart framework for designing protected areas, focusing on climate refugia and accounting for uncertainty associated with climate models and emission scenarios. By applying this framework to our case study, we found that among all aspects of designing climate-smart protected area systems, the choice of climate metrics and approaches for identifying climate refugia had the largest impact on the configuration of spatial plans. Accounting for uncertainty in climate models and scenarios had a smaller impact and can be captured with relative ease using our framework. The proposed framework could help practitioners incorporate climate-smart methods into spatial planning.

5.1 Capturing model and emission uncertainty

Our results show that using different model outputs and emission scenarios influenced spatial plans in a modest way. Some conservation studies use outputs from a single model (e.g., Magris et al., 2015; Patrizzi and Dobrovolski, 2018) and a single scenario (e.g., Stralberg et al., 2020), but these designs underestimate the uncertainty inherent in planning for climate change. Thus, unless there are compelling reasons—i.e., a particular climate model is known to perform particularly well in the region and there is more certainty about our climate future—we suggest using a model ensemble (e.g., Tegegne et al., 2020; Nadeau et al., 2015; Martins et al., 2021) and incorporating multiple emission scenarios (e.g., Araújo et al., 2011; Brito-Morales et al., 2022).

Using the ensemble mean is easier (e.g., Stralberg et al., 2020; Oliver et al., 2019) than using multiple models directly (Gu et al., 2015; Porfirio et al., 2014), although an ensemble median might be more appropriate to account for models with a higher climate sensitivity (Hausfather et al., 2022).

5.2 Selecting climate metrics

We found that different climate metrics result in markedly different spatial plans. Consideration of climate change in spatial planning has typically focused on temperature (Wilson et al., 2020; Magris et al., 2015; Nadeau et al., 2015). However, we show that protecting areas of high temperature exposure does not always result in protecting climate refugia defined by other variables (Bruno et al., 2018). In fact, even different climate metrics derived from the same variable (e.g., temperature yielding climate velocity or MHW metrics) produce contrasting results. We found that climate warming solutions were most similar to those for ocean deoxygenation, presumably because of the temperature dependence of gas solubility (Pörtner and Knust, 2007; Deutsch et al., 2015). Warming also exacerbates negative effects of ocean deoxygenation by increasing metabolic demands (Pörtner and Knust, 2007), suggesting synergistic impacts.

Given the potential for different outcomes arising from the choice of climate metric used, incorporating multiple metrics in climate-smart spatial planning may be useful (Harvey et al., 2013; VanDerWal et al., 2013). This could protect a system of climate-smart areas that will be more resilient to different aspects of climate change (Magris et al., 2015), but this is likely to come at the cost of requiring larger protected area systems. Thus, climate metrics used to define climate refugia should be carefully considered based on their strengths, weaknesses, and utility (**Table 1**).

Table 1. Overview of the options explored under each climate-smart aspect.

Climate-smart aspects		Strengths and weaknesses	Utility
Scenario	**Single emission scenario**	• Simple and more straightforward • Offers one solution but ignores uncertainty	• Focuses conservation efforts on one climate scenario
	Multiple emission scenarios	• More analyses • Produces a suite of solutions to a conservation problem • More complex	• Touted as "best practice" (Jones et al., 2016) • Captures variability among different scenarios (Makino et al., 2014; Brito-Morales et al., 2022) • Covers uncertainty associated with emission scenarios (O'Neill et al., 2017)
Ensemble	**Multi-model ensemble**	• Shows variability across climate models • More complex	• Areas selected frequently across climate models are more confidently climate refugia • Covers more uncertainty associated with climate models (Tegegne et al., 2020) • Increases complexity as number of climate models grows
	Ensemble mean (or median)	• Simpler and more straightforward • Offers one solution • More easily used in more elaborate analyses	• Used in indicative spatial planning (Brito-Morales et al., 2022; Stralberg et al., 2020) • Provides a sufficient representation of the climate

		● Loses information from individual climate models	models in the ensemble
	Climate warming	● Most similar with plans using declining oxygen concentration ● Intermediate in terms of total area selected for protection	● Chronic-exposure metric ● Temperature is the most common climate variable used in climate-smart planning (Burrows et al., 2011; Wilson et al., 2020)
Metric	**Ocean acidification**	● Most dissimilar with other climate metrics ● Under climate priority area and percentile approaches, spatial plans created had highest total area selected for protection	● Chronic-exposure metric ● Generally, negatively impacts ecosystems, however, its impact can also be positive or neutral for some species (Kroeker et al., 2013; Harvey et al., 2013) ● Can be influenced by anthropogenic activities other than climate change (Harvey et al., 2013)
	Ocean deoxygenation	● Most similar with plans using climate warming ● Intermediate in terms of total area selected for protection	● Chronic-exposure metric ● Directly correlated with temperature (Pörtner and Knust, 2007; Deutsch et al., 2015) ● Some organisms may be insensitive to small decines, but all suffer physiological stress once oxygen levels decline past a hypoxic threshold (Bopp et al., 2013)
	Climate velocity	● Calculation involves both temporal and spatial gradients of temperature	● Retention metric ● Can be calculated for variables other than temperature

		● More computationally complex than using the rate of climate warming	(Brito-Morales et al., 2018) ● Could inform how long a reserve remains effective in protecting biodiversity within its boundaries (Loarie et al., 2009)
	Sum of the annual cumulative MHW intensity	● Requires daily data, so more data intensive ● Measures discrete warming events ● More computationally complex than using the rate of climate warming	● Acute-exposure metric of discrete warming events (Magris et al., 2015; Hobday et la., 2016) ● Useful for protecting species susceptible to discrete warming events (Hobday et al., 2016; Magris et al., 2015)
Approach	**Feature**	● Simple approach ● Protects refugia that do not necessarily have any biodiversity value (Arafeh-Dalmau et al., 2021) ● Intermediate climate-smart approach ● Uses a binary climate layer, leading to some loss of data	● Not species specific ● Useful when climate refugia are considered as conservation features or areas to be protected ● Target percentages depend on threshold set for defining climate refugia
	Penalty	● Simple approach but penalty scaling is arbitrary ● Retains original distribution of features ● Least climate-smart approach but most efficient ● Climate layer retains continuous nature of the	● Alters objective function by minimizing the cost of the spatial planning solution and penalties (Hanson et al., 2021) ● Penalty scaling should be calculated through a series of

	climate metric	calibrations
Percentile	• More complex approach (Brito-Morales et al., 2022) • Protects climate refugia only when they have biodiversity value • Discards the rest of the distribution if they do not lie within the climate refugia • Most climate-smart approach but least efficient • Uses a binary climate layer, leading to some loss of data	• Species-specific climate refugia • Target percentages depend on threshold set for defining climate refugia
Climate priority area	• More complex approach • Modified percentile approach • Protects climate refugia only when they have biodiversity value • Protects parts of the distribution found outside areas of refugia • Uses a binary climate layer, leading to some loss of data	• Species-specific climate refugia • Core climate refugia assigned a more demanding threshold, allowing most climate-smart areas of each feature to be always protected (e.g., ≤5th percentile is 100% protected) • Target percentages depend on the threshold set for defining climate refugia • Provides protection for non-climate-smart areas

5.3 Prioritizing protection of climate refugia

Each of the four ways of identifying climate refugia and prioritizing their protection has its advantages and disadvantages (**Table 1**), resulting from the trade-off between climate-smart performance and efficiency of meeting biodiversity targets. Thus, the better the climate-smart performance of the approach (i.e., likely increased climate resilience), the less efficient the spatial plan will be in meeting targets and thus the larger protected area needed. Since each of the approaches requires carefully selecting thresholds or scaling penalty values to parameterize the trade-offs, we recommend consulting with stakeholders and conducting calibration analysis to identify spatial prioritizations that strike the right balance. To help understand trade-offs between each of the four approaches, we synthesize our findings below.

<u>The percentile approach</u> was the most climate-smart because it selected areas of lower exposure and higher implied biodiversity retention, but it was extremely costly in terms of the area selected for protection. This is because it considers only the climate-smart areas of the biodiversity features for protection, which limits possible areas for selection and decreases the efficiency of the approach.

<u>The climate-priority-area approach</u> represents a modified version of the percentile approach and addresses its limitations. It prioritizes the most climate-smart areas while still providing a degree of protection to non-climate-smart areas. The approach has an intermediate trade-off between climate-smart performance and efficiency in meeting targets. This approach is more computationally demanding though.

The feature approach is the simplest but lacks ecological relevance because the climate metric is not tied directly to the conservation features. This approach protects the climate-smart areas of the entire planning domain regardless of whether the area has any biodiversity value or not (Arafeh-Dalmau et al., 2021).

The penalty approach was the least climate-smart because it did not limit features to just core climate refugia. This approach maintains the continuous nature of the climate metrics, allowing the selection of areas of intermediate climate exposure. Although it results in the least climate-smart spatial plans, it is the most efficient in minimizing the cost (i.e., area) of the solution. A challenge in implementing this approach is deciding on an appropriate scaling to parameterize trade-offs between cost and safeguarding climate refugia.

5.5 Caveats

Our analysis has several caveats that should be noted. First, to explore the different climate-smart aspects of spatial planning, we simplified the spatial plans, but any real application would likely include: 1) a cost layer representing the opportunity costs of closing an area for protection (we used area); 2) targets reflecting the threat status or size of the distribution of a species; and 3) greater emphasis on the selection of biodiversity features. Second, we created spatial plans using individual climate climate metrics, but refugia could be identified based on a combination of climate variables or metrics (e.g., Rojas et al., 2022) and included in a single prioritization (Kujala et al., 2013). Last, we use a large area and relatively coarse spatial resolution in our analysis, which might not be applicable to conservation planning conducted at finer spatial scales, especially on land (Bellard et al., 2012; Wilson et al., 2020). Nevertheless, because impacts of climate change on ecosystems are more evident at larger spatial scales (Edgar et al. 2014), regional or global spatial planning could determine climate-resilient priority areas that then inform spatial planning at more local scales. Thus, rather than ignoring climate change at finer scales, successful planning could be achieved by complementing local, bottom-up spatial planning with regional, climate-smart spatial planning that identifies key areas for protection (Gaymer et al., 2014).

Key Recommendations for climate-smart spatial planning

1. **Most thought needs to be focused on choosing appropriate metrics and approaches** because they most influence the solution.
2. **Incorporate model outputs from an ensemble of models** to encompass model uncertainty. For most cases, it may be sufficient to **use the ensemble-mean (or median) to represent the ensemble**.
3. **Use a range of emission scenarios** to incorporate the uncertainty in environmental futures.
4. **Select climate metrics** depending on the habitats, species, and region in the analysis, as they will produce markedly different plans.
5. **Carefully choose the approach for identifying climate refugia based on how important climate change is in the prioritization**, as different approaches produce strikingly different solutions. Generally, the more climate smart the approach, the larger the area needed for protection. We **recommend the climate-priority-area approach represents a good tradeoff** because it protects the core climate-resilient refugia and affords some protection for the rest of the species' distributions while not requiring huge areas.

Although our framework prioritizes protection of climate refugia, recommendations of using a range of emission scenarios, model ensembles, and appropriate metrics could be applied to other climate-smart spatial planning methods. Further, instead of prioritizing protection of low-exposure and high-retention climate refugia, our framework could be generalized in many ways to: protect areas of high chronic but low acute thermal stress (Magris et al., 2015); ensure a range of areas, from low to high climate exposure, are protected (Tittensor et al., 2019); and design dynamic closures and stepping-stone protected areas (Tittensor et al., 2019; Burrows et al., 2014).

The complexity of conservation planning is increased by adding the uncertainty of climate change into spatial prioritization. This is one reason why there has been little consensus on methods for climate-smart spatial planning, and why protection against climate change has not yet been fully incorporated in conservation planning (O'Regan et al., 2021). Our proposed framework helps to close this gap. We suggest that using climate metrics that identify low-exposure, high-retention climate refugia is an informative and simpler approach than building many species distribution models for biodiversity features to inform a climate-smart spatial plan. We hope that this framework will be a valuable addition to the conservation practitioner's toolkit in a range of ecosystems.

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Conflict of interest statement

The authors declare no conflict of interest.

Author contributions

KCVB, DCD, JDE, IBM, DSS, JOH, and AJR conceived the ideas and designed methodology. KCVB, JDE, DSS, IBM, AD, and SN analyzed the data. KCVB and AJR led the writing of the manuscript. All authors contributed critically and significantly to the manuscript drafts, and all gave their approval for publication.

Data Availability

The data used for the case study are available at Zenodo under the identifier: http://www.doi.org/10.5281/zenodo.6669867. The global AquaMaps data are freely available at https://www.aquamaps.org/. The global future model projections are available at https://esgf-node.llnl.gov/ and the historical projections are available at https://www.ncei.noaa.gov/products/optimum-interpolation-sst.

Code Availability

All scripts are published at Zenondo under the identifier: http://www.doi.org/10.5281/zenodo.6669867. To ensure that the code runs smoothly, use the updated versions of R and all Comprehensive R Archive Network (CRAN) packages declared in the repository. We used R version 4.0.3. To aid in interpretation, we have created a Shiny App that can be accessed along with the other code. This Shiny App briefly explains the climate-smart spatial planning framework and allows the user to compare solutions created from different options of the climate-smart aspects explored in this paper.

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Supporting Information

3.1.1 Planning domain

We defined the Western Pacific planning domain to be the epipelagic layer (0-200 m) of the exclusive economic zones (EEZs) of the countries in the Pacific Islands and areas beyond national jurisdiction (ABNJ) in between (covering 23,707,091 km^2). We chose the Western Pacific Ocean because it is a complex region, oceanographically (Williams et al., 2015), has rich biodiversity (Selig et al., 2014), and is at high risk from climate change (Burrows et al., 2011). We divided the region into 35,389 hexagonal planning units with a 0.25º x 0.25º resolution (**Supplementary Figure S3A**). All layers had the same spatial resolution and used the Robinson projection.

3.1.2 Biodiversity features

In the spatial plans, we included a suite of biodiversity features based on distribution maps from AquaMaps (Kaschner et al., 2019). AquaMaps is a large global dataset containing distributions of 33,518 species at 0.5° x 0.5° resolution. It predicts the probability of occurrence (0-1) of a species using an environmental niche model based on depth, temperature, primary productivity, salinity, and oxygen concentration. We interpolated and resampled the layers to 0.25° x 0.25°, restricted them to our planning domain, and set the maximum depth at 200 m. We used a cutoff threshold for probability of occurrence of 0.5, as is common in related studies (Brito-Morales et al., 2022; Sala et al., 2021). This yielded 8,711 species distribution layers (i.e., biodiversity features) (**Supplementary Figure S3B**). Since our focus is on describing the methods involved in climate-smart protected-area design rather than developing a spatial plan with a particular conservation purpose, we assigned uniform targets of 30% for biodiversity and climate-smart features.

Case study

Spatial prioritization

In this analysis, we used the R package *prioritizr* (Hanson et al., 2021) to solve the spatial planning problem. Inputs needed for spatial prioritization include: 1) the objective function, 2) a cost layer, 3) a planning domain, and 4) conservation features with their representation targets (Serra et al., 2020). For a detailed description of spatial prioritization, see Moilanen et al. (2009). The solver used was Gurobi Optimizer. The workflow for spatial prioritization and climate analyses were done using R. 4.1.1 (R Core Team, 2022) and Climate Data Operators Software (Schulzweida, 2019).

Prioritizations were generated using the minimum set formulation (minimum-set objective function) to create plans that conserve important biodiversity features and climate refugia while minimizing the cost (Rodrigues et al., 2000; Beyer et al., 2016). The spatial problem (without considering the boundary length of the selected planning units—an inverse measure of connectivity, where higher boundary lengths represent more fragmented solutions) is expressed as:

$$Minimize \sum_{i=1}^{I} x_i c_i \ \ subject\ to \sum_{i=1}^{I} x_i r_{ij} \geq T_j \forall j \in J$$

where the first term represents the opportunity cost lost by selecting an area for protection. x_i represents the decision variable. The decision variable is binary, representing whether the planning unit i in the set of planning units I is selected ($x_i = 1$) or not ($x_i = 0$). c_i represents the cost for planning unit i. The second term represents the set of conservation constraints, where r_{ij} represents the presence or absence of feature j (in the set of features J). This, multiplied with the decision variable, should be greater than or equal to the targets T_j (Hanson et al., 2021). Because we were not trying to generate actual conservation plans, we reduced complexity of the spatial planning problem by omitting consideration of boundary length penalties, or the part of the objective function which reduces fragmentation and allows for greater connectivity within spatial plans.

The exact solution to each problem was obtained by setting the optimality gap, representing the acceptable deviance from the optimal objective, at 0% (Beyer et al., 2016). The solution was binary, wherein each planning unit was either selected or not in the resulting spatial design. To understand the consequences of different decisions in the proposed framework on spatial prioritizations, we chose to use a uniform cost layer to focus on comparing the climate-smart aspects of the spatial planning problems. Therefore, the solutions minimized the number of planning units selected in the designs.

Representation targets for biodiversity features

Since our focus is on describing the methods involved in climate-smart protected-area design rather than developing a spatial plan with a particular conservation purpose, we assigned fixed targets of 30% for biodiversity and climate-smart features (CBD, 2020).

Climate velocity

Climate velocity was calculated using the equation following the VoCC R package (García Molinos et al., 2019):

$$Climate\ velocity\ (km\ yr^{-1}) = \frac{\Delta\ temperature\ over\ time\ (°C\ yr^{-1})}{\Delta\ temperature\ over\ space\ (°C\ km^{-1})}$$

The temporal gradient is the slope of the linear regression of projected mean annual temperatures. The spatial gradient was calculated from the vector sum of the latitudinal and longitudinal pairwise differences of the mean temperature at each focal cell using a 3x3 neighborhood window (Arafeh-Dalmau et al., 2021; Brito-Morales et al., 2018, 2022; Burrows et al., 2011).

Sum of cumulative marine heatwave (MHW) intensity

Marine heatwaves are periods lasting five days or longer over which the temperature remains warmer than a threshold that would be considered extreme for some historical baseline. Here, we used the 30-year period 1982 to 2011 (inclusive) as the historical baseline, and the 90th percentile of SSTs for each day of the Julian calendar as the respective threshold (by day). To develop the daily time series of SST required for this analysis, we spliced OISST data (see https://www.ncei.noaa.gov/products/optimum-interpolation-sst) for the period 1982 to 2014 onto CMIP6 daily projections for SST. To ensure a harmonious transition from interpolated observations to remapped projections, for each model in the ensemble, we: (i) converted the CMIP6 daily projections into anomalies relative to the first year of projection (2015); (ii) computed the daily anomalies (per grid square) of the CMIP6 data in 2015 relative to the 2015 CMIP6 mean; (iii) added the 2015 mean (by grid square) OISST to these anomalies; then (iv) added the adjusted 2015 data to the computed CMIP6 anomalies. This ensured that the global mean SST for 2015 matched the observed (OISST) mean, providing a harmonious basis for forward projection of SST. Using these data, we estimated the annual cumulative MHW intensity (°C days, or degree days) for each grid square using the heatwaveR package (Schlegel and Smit, 2018), which followed MHW equations described in Hobday et al. (2016) For our final metric, we took the sum of the annual cumulative intensities from 2015 to 2100.

Penalty approach

The penalty approach treats the climate metric as a linear penalty, where solutions that have higher (or lower, depending on the climate metric) penalty values are penalized.

$$Penalty = \sum_{i=1}^{I} P \cdot D_i \cdot X_i$$

where P is the penalty scaling, D_i is the penalty data per planning unit i in the planning domain I, and X_i is the decision variable per planning unit i. Each metric across the different climate scenarios was scaled to 30% of the total cost (penalty scaling, P).

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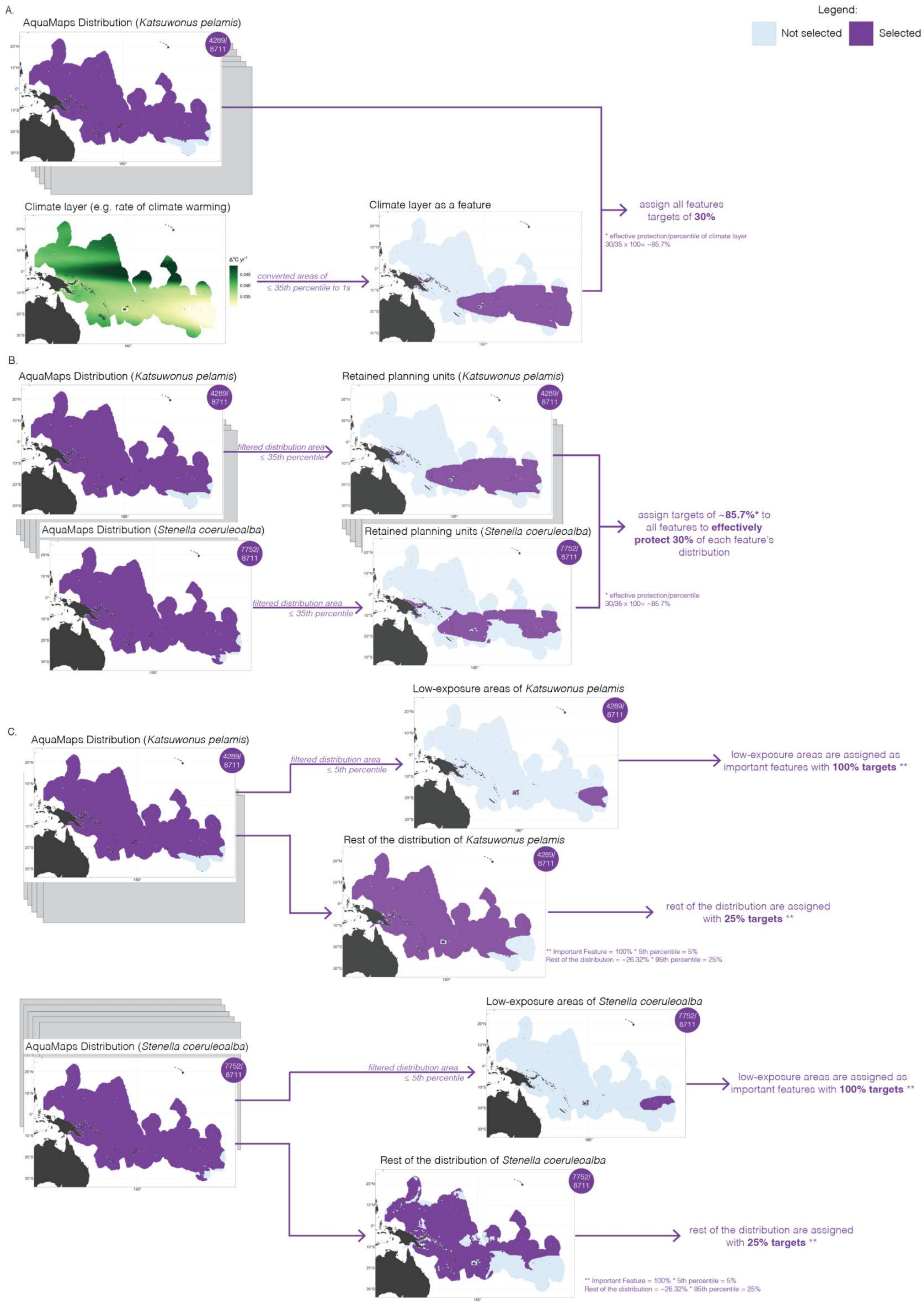
Supplementary Figures



Supplementary Figure S1. Workflows of the different approaches. A. "Feature" approach. **B.** "Percentile" approach. **C.** "Climate priority area" approach.

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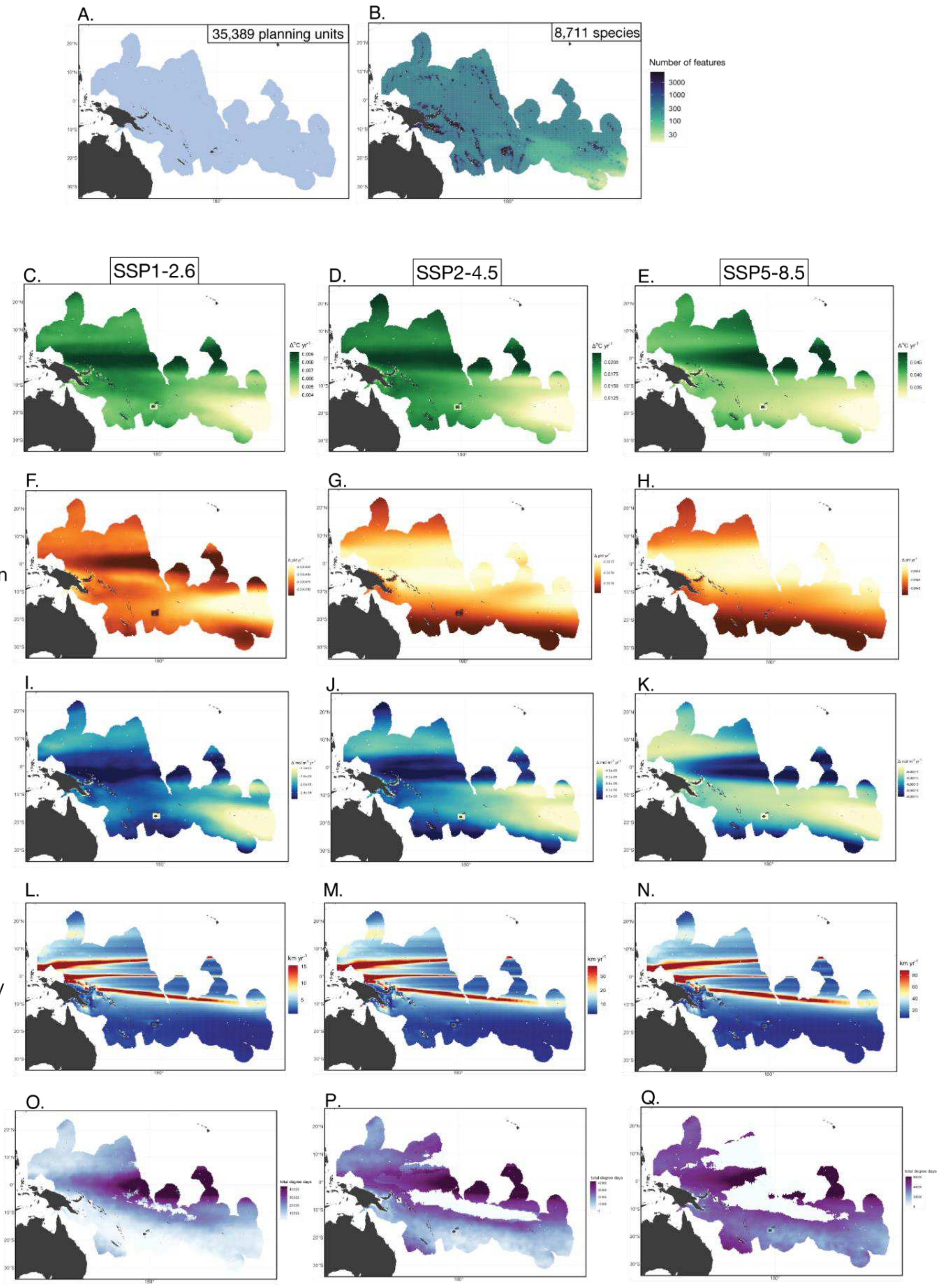

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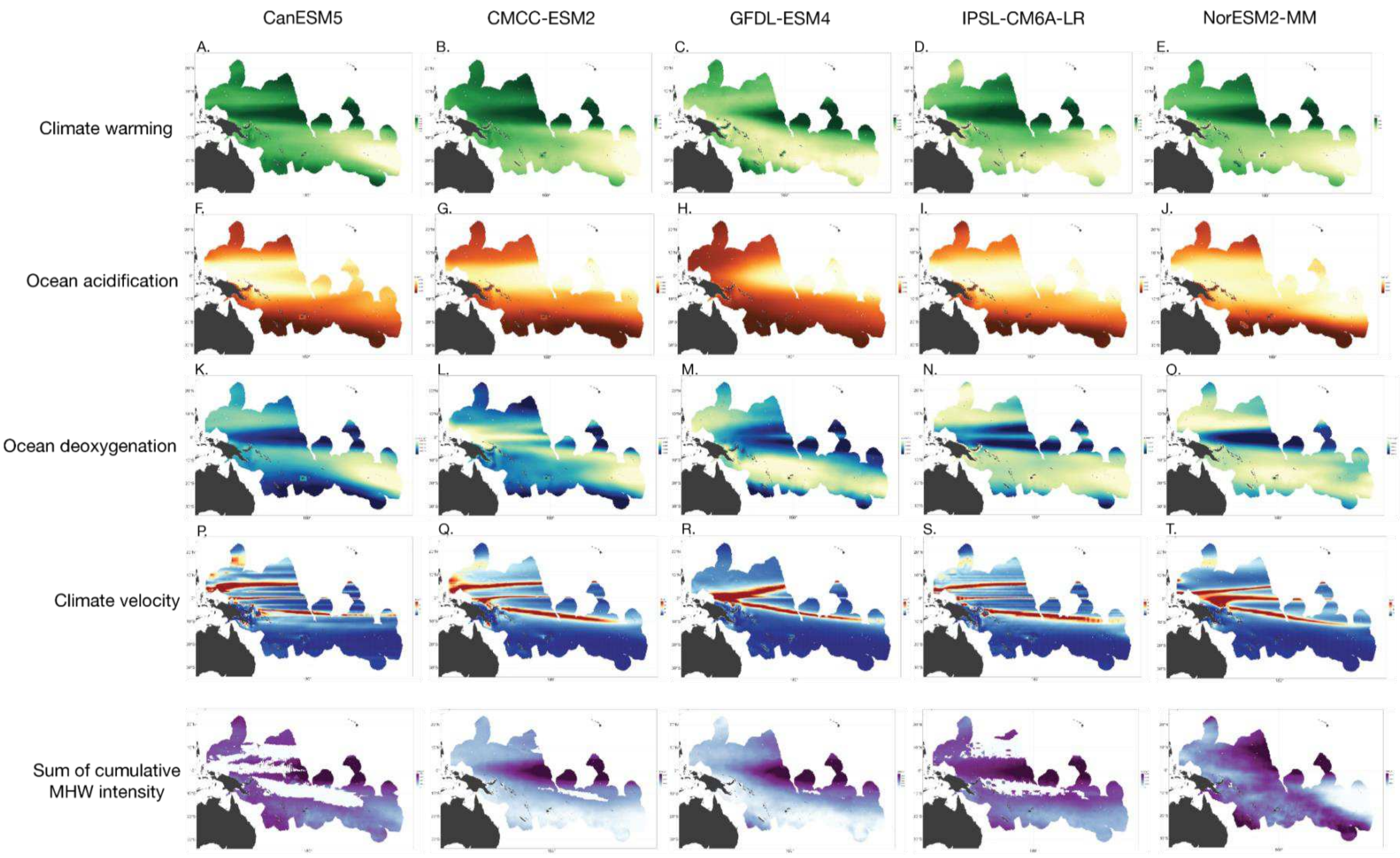
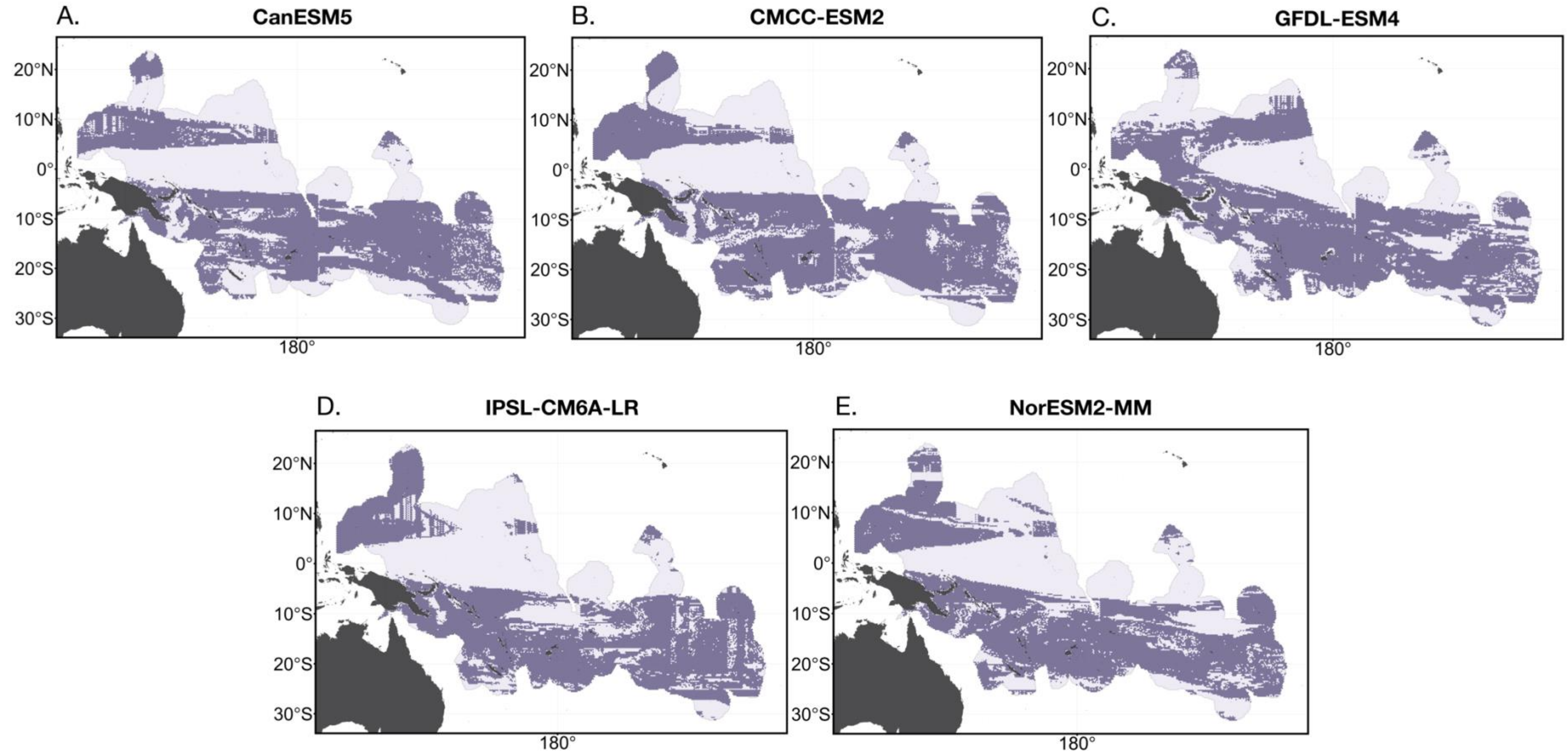
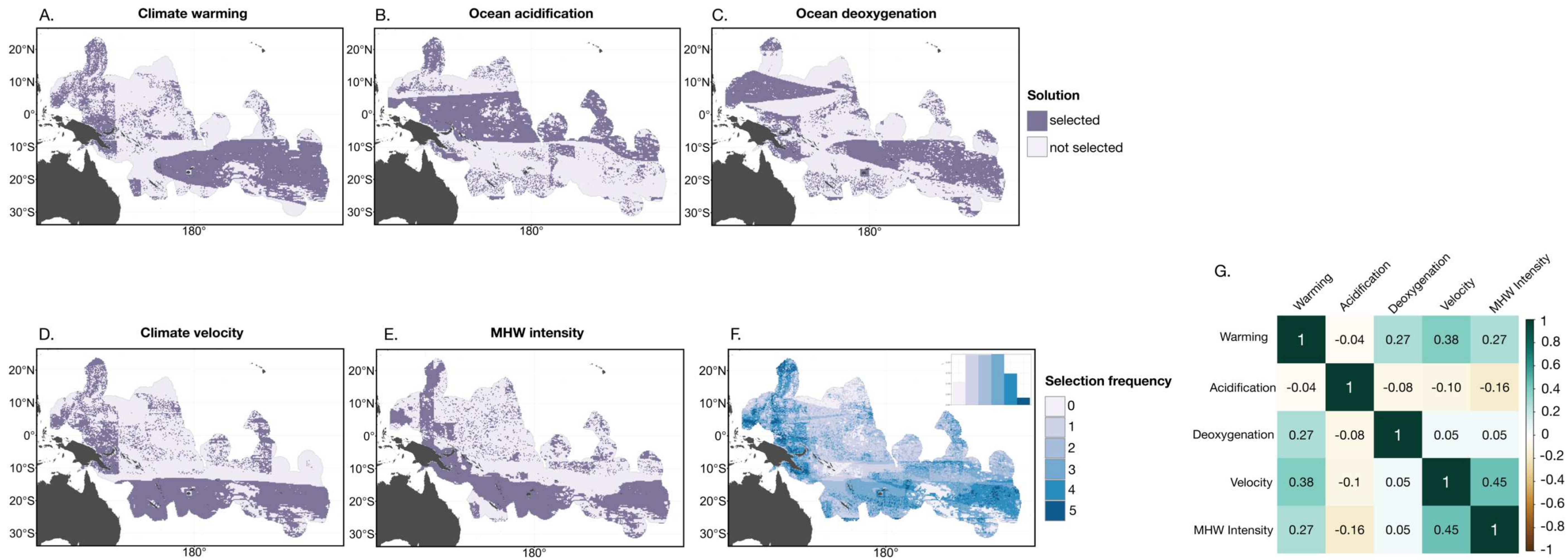
1024 **Supplementary Figure S2. Layers used to create climate-smart spatial plans. A.** planning domain. **B.** Summary of AquaMaps features. Columns of the climate layers
1025 represent the three climate scenarios wherein the models were forced under: 1) SSP1-2.6; 2) SSP2-4.5; and 3) SSP5-8.5. **C-E.** Climate warming (Δ°C yr^{-1}). **F-H.** Ocean
1026 acidification (ΔpH yr^{-1}). **I-K.** Ocean deoxygenation (Δ[O_2] yr^{-1}). **L-N.** Climate velocities (km yr^{-1}). **O-Q.** Sum of cumulative marine heatwave (MHW) intensity (total
1027 degree days).



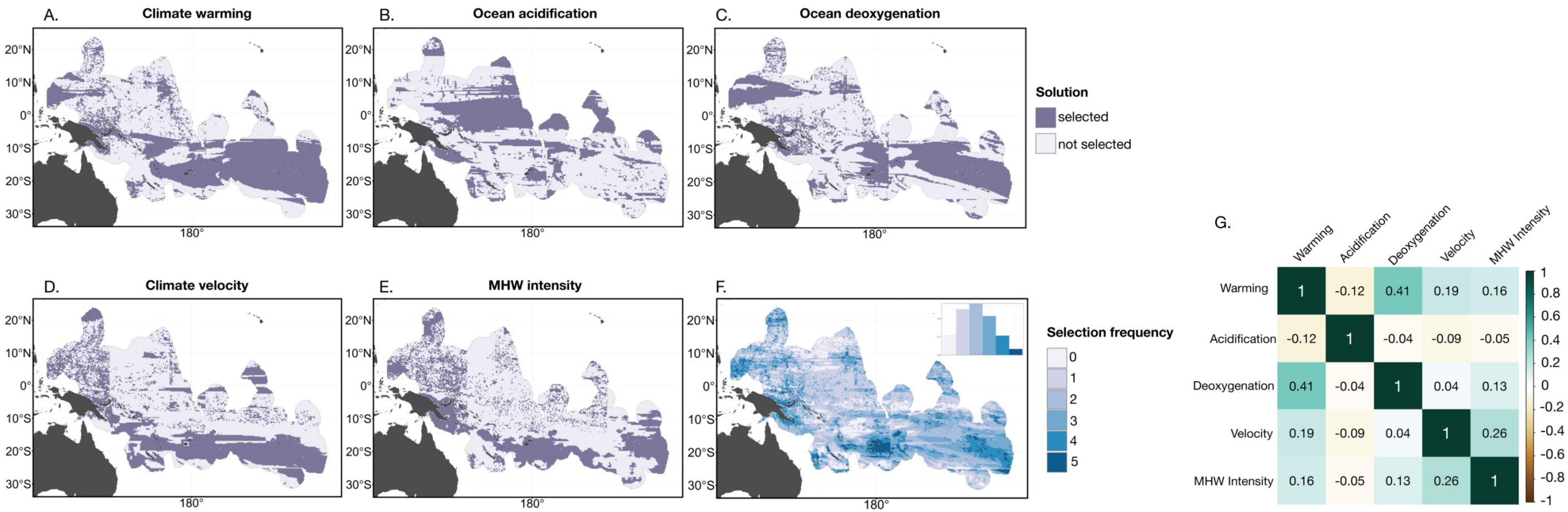
Supplementary Figure S3. Climate layers of each model in the ensemble. Columns represent the five climate models: 1) CanESM5; 2) CMCC-ESM2; 3) GFDL-ESM4; 4) IPSL-CM6A-LR; and 5) NorESM2-MM. **A-E.** Climate warming (Δ°C yr^{-1}). **F-J.** Ocean acidification (ΔpH yr^{-1}). **K-O.** Ocean deoxygenation (Δ[O_2] yr^{-1}). **P-T.** Climate velocities (km yr^{-1}). **U-Y.** Sum of cumulative marine heatwave (MHW) intensity (total degree days).



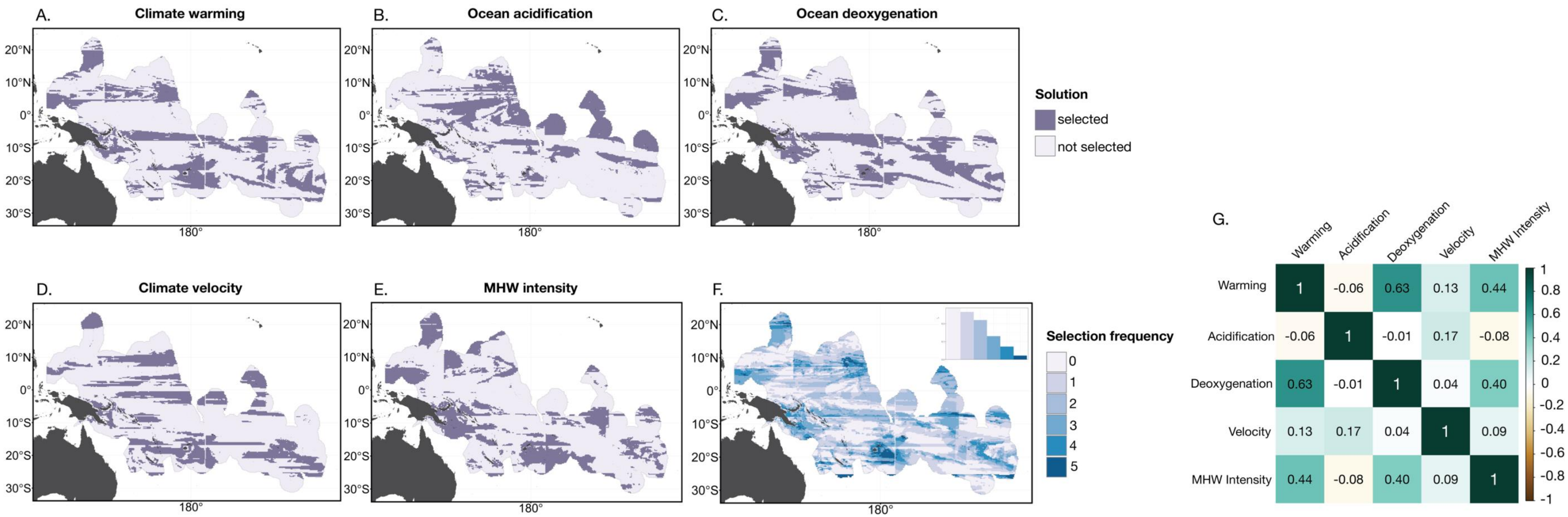
Supplementary Figure S4. Individual solutions for each model. Solutions created using climate warming as the climate metric using model outputs from the ensemble: **A.** CanESM5; **B.** CMCC-ESM2; **C.** GFDL-ESM4; **D.** IPSL-CM6A-LR; and **E.** NorESM2-MM.



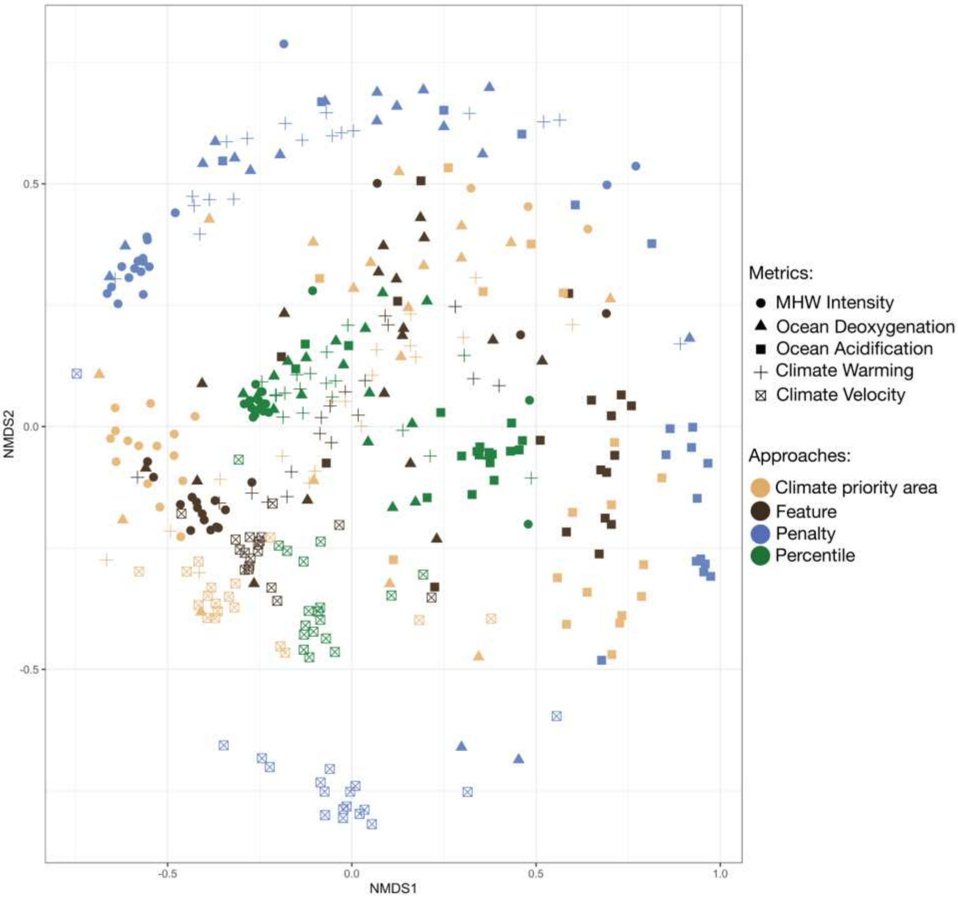
Supplementary Figure S5. Using different climate metrics. Spatial plans (with % area selected in top right) designed with the feature approach using: **A.** Climate warming (Δ°C yr^{-1}); **B.** Ocean acidification (ΔpH yr^{-1}); **C.** Ocean deoxygenation (Δ[O$_2$] yr^{-1}); **D.** Climate velocity (km yr^{-1}); and **E.** Marine heatwave (MHW) intensity (total degree days). **F.** Selection frequency plot showing areas selected across different metrics with an inset histogram showing selection proportion. **G.** Cohen's Kappa Coefficient Matrix, showing correspondence between solutions.



Supplementary Figure S6. Using different climate metrics. Spatial plans (with % area selected in top right) designed with the climate-priority-area approach using: **A.** Climate warming (Δ°C yr^{-1}); **B.** Ocean acidification (ΔpH yr^{-1}); **C.** Ocean deoxygenation ($\Delta[O_2]$ yr^{-1}); **D.** Climate velocity (km yr^{-1}); and **E.** Marine heatwave (MHW) intensity (total degree days). **F.** Selection frequency plot showing areas selected across different metrics with an inset histogram showing selection proportion. **G.** Cohen's Kappa Coefficient Matrix, showing correspondence between solutions.



Supplementary Figure S7. Using different climate metrics. Spatial plans (with % area selected in top right) designed with the penalty approach using: **A.** Climate warming (Δ°C yr^{-1}); **B.** Ocean acidification (ΔpH yr^{-1}); **C.** Ocean deoxygenation (Δ[O_2] yr^{-1}); **D.** Climate velocity (km yr^{-1}); and **E.** Marine heatwave (MHW) intensity (total degree days). **F.** Selection frequency plot showing areas selected across different metrics with an inset histogram showing selection proportion. **G.** Cohen's Kappa Coefficient Matrix, showing correspondence between solutions.



Supplementary Figure S8. nMDS plot showing the comparison of 360 spatial plans across metrics and approaches. Stress = 0.23, number of iterations = 1000.