Creating conservation-sensitive, climate-smart fisheries closures for the ABNJ of the Pacific Ocean

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Introduction

We wish to create **conservation-sensitive**, **climate-smart** fisheries closures for the ABNJ of the Pacific Ocean using *prioritizr*.

Prioritizr (Hanson et al., 2018) is a spatial prioritization software (R package) that uses integer linear programming (ILP) allowing it to create exact solutions to large spatial planning problems faster than its heuristic counterparts (e.g. Marxan).

This project has the following objectives:

1. How can we design **conservation-sensitive fisheries closures** that can conserve critical fisheries spawning habitats as well as protect vulnerable, threatened, and endangered bycatch species?
2. How can we best design **climate-smart fisheries closures** that can remain effective in the future?
3. What are the **net benefits or costs** to fisheries of establishing conservation-sensitive, climate-smart closures?

This file provides an overview of the project as well as the main results. This was made to streamline the numerous results that have been produced throughout the duration of the project. The scripts are found in tinbuenafe/PacificProj, where the scripts are explained in greater detail.

This spatial planning project uses the **minimum set objective function** wherein *prioritizr* aims to minimize the total cost of the resulting spatial plans, while still meeting the targets.

Assembling the data layers

Before running *prioritizr*, we first had to assemble the following data layers:

1. Study Area
2. Fisheries conservation features
3. Climate-smart features
4. Cost layer

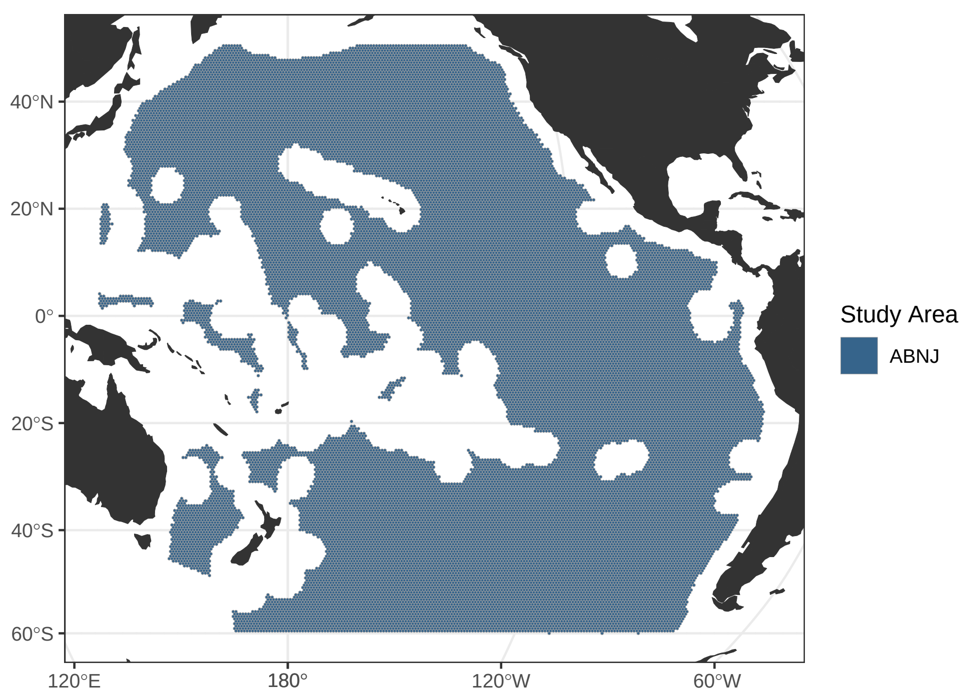
Study Area

The study area has the following characteristics:

- Pacific ABNJ
- Limited boundaries to areal jurisdiction of RFMOs responsible for managing large pelagic fisheries (IATTC and WCPFC)
- Robinson projection

We ran the following code using polygons from `rnaturalearth` package and the EEZ `.shp` files from Marine Regions (Flanders Marine Institute, 2019) to create a Pacific-centered map of the global ABNJs.

We created equal-area hexagonal planning units, or PUs, (0.5° x 0.5° at the equator) of the study area. This represented the grain size of the spatial plan. There 31,917 PUs in the entire planning region.



Fisheries conservation features

The following were used in this study:

1. Distribution of selected bycatch species
2. Distribution of larval spawning grounds of selected commercially targeted species

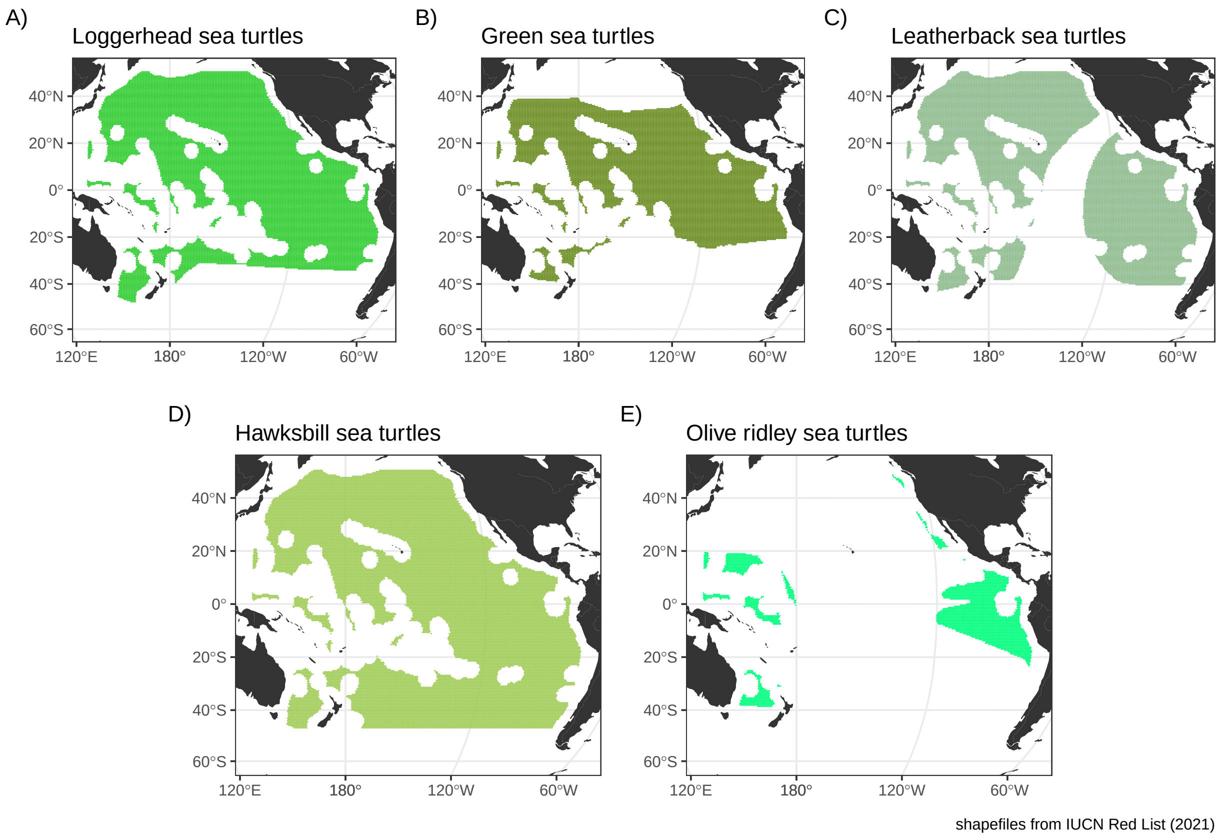
Bycatch distribution

First, we compiled a list of bycatch reported in the Pacific ABNJ. Then, we used the **IUCN** distribution maps for these species. These polygons are from the IUCN Red List, showing the known ranges of the species (IUCN Red List, 2021).

We limited the bycatch included in this study to **sea turtles**, but this workflow can be easily replicated and expanded to include more species.

The following were the sea turtles reported as bycatch and intersected with the study area:

- Loggerhead turtle (*Caretta caretta*)
- Green turtle (*Chelonia mydas*)
- Leatherback turtle (*Dermochelys coriacea*)
- Hawksbill turtle (*Eretmochelys imbricata*)
- Olive ridley turtle (*Lepidochelys olivacea*)

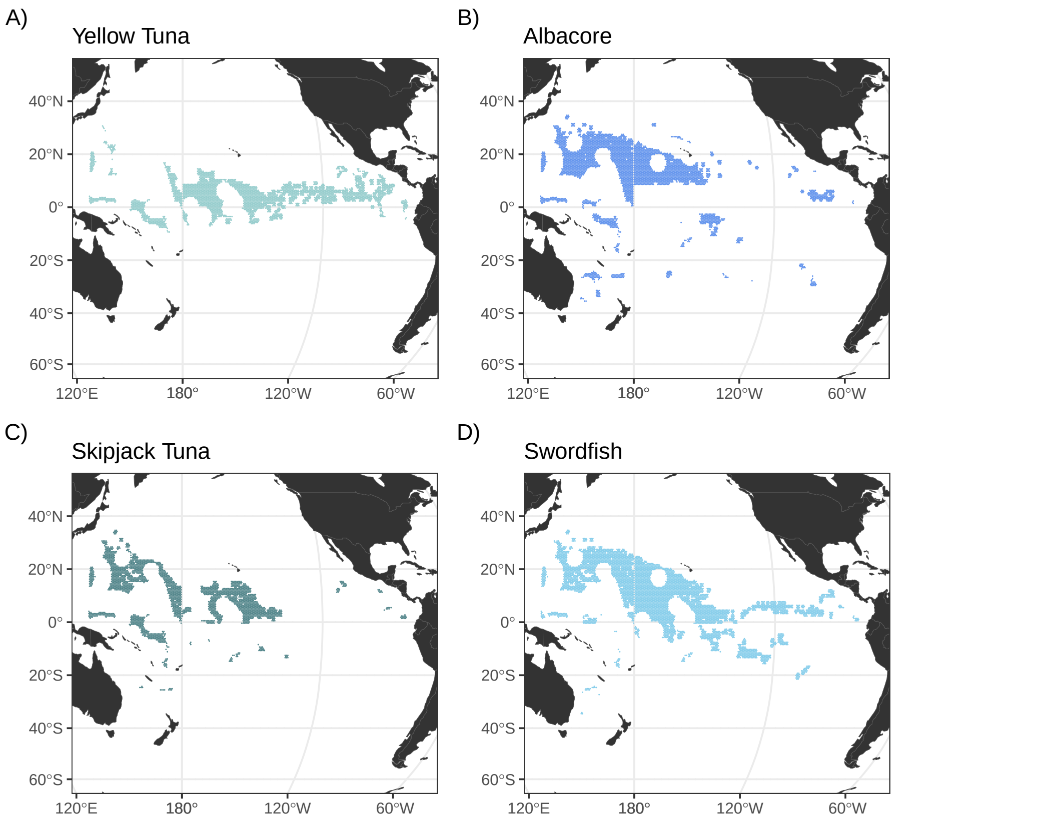


Spawning grounds of commercially targeted species

Just like the bycatch layer, we compiled a list of commercially targeted large pelagic species managed in the Pacific from different sources. From this list, we have 4 species with available data on their global larval spawning grounds:

- Yellowfin Tuna (*Thunnus albacares*)
- Albacore (*Thunnus alalunga*)
- Skipjack Tuna (*Katsuwonus pelamis*)
- Swordfish (*Xiphias gladius*)

The models for these species are from a report by Mercer (2019) where he created Generalized Additive Models (GAMs) to predict spawning grounds using (Nishikawa et al., 1985). He used mean seasonal abundance from a historical dataset of plankton tows of fish larvae (dated back to the 1950s), and oceanographic and environmental conditions from global databases.



Climate-smart features

To create climate-smart closures, we prioritized protection of areas with:

1. low levels of **exposure** to climate warming, and
2. high levels of potential **retention** of biodiversity.

We determined these areas using the following metrics:

1. **Relative Climate Exposure (RCE) index**

   $RCE(yr^{-1}) = \frac{Slope \quad (^{\circ}Cyr^{-1} \quad 2050-2100)}{Seasonal \quad Range \quad (^{\circ}C \quad 2015-2020)}$

- numerator is the slope of the linear regression of projected mean annual temperatures
- denominator is the current mean seasonal temperature range

Areas with low RCE index values are areas that will be exposed to low levels of warming relative to their current seasonal fluctuations of temperature. Areas of **low RCE index values** are prioritized for selection.

2. **Climate velocity**

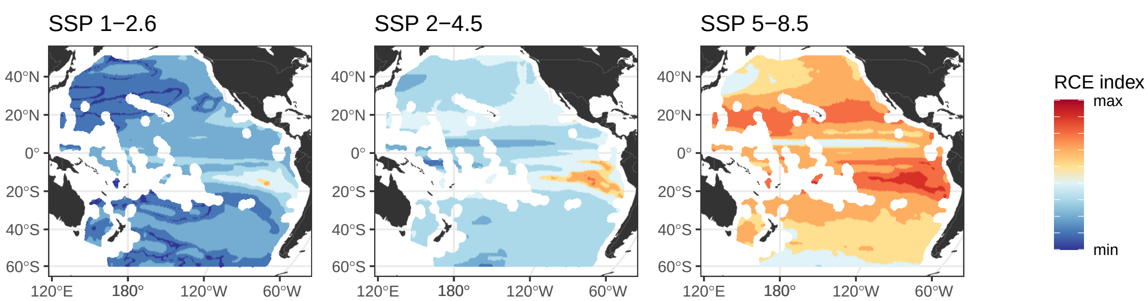
   $Climate \quad velocity \quad (kmyr^{-1}) = \frac{Slope \quad (^{\circ}Cyr^{-1} \quad 2050-2100)}{Spatial \quad gradient \quad (^{\circ}Ckm^{-1} \quad 2050-2100)}$

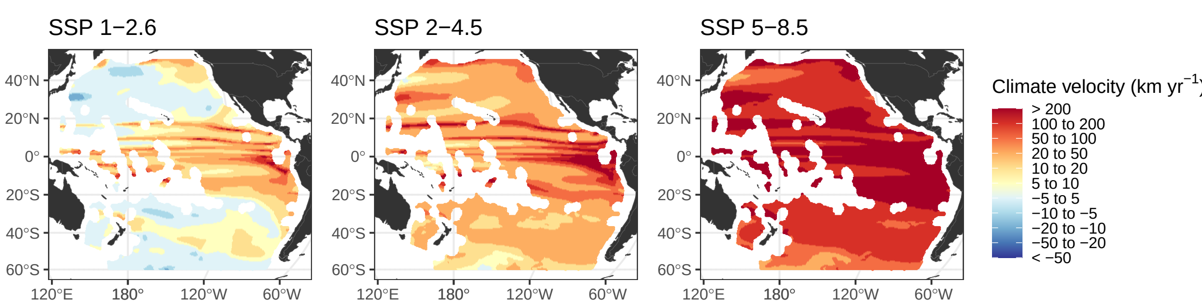
- numerator is the slope of the linear regression of projected mean annual temperatures
- denominator is calculated from the vector sum of the latitudinal and longitudinal pairwise differences of the mean temperature at each focal cell using a *3 x 3 neighborhood window*

Areas of slow climate velocity are areas that are more likely to retain their current environmental conditions and consequentially, their biodiversity. Areas of **slow climate velocity** are prioritized for selection.

The temperatures used to calculate the aforementioned metrics were derived from 12 Global Circulation Models (GCMs) from the Couple Model Intercomparison Project Phase 6 (CMIP6; https://esgf-node.llnl.gov). The GCMs are under these three climate scenarios:

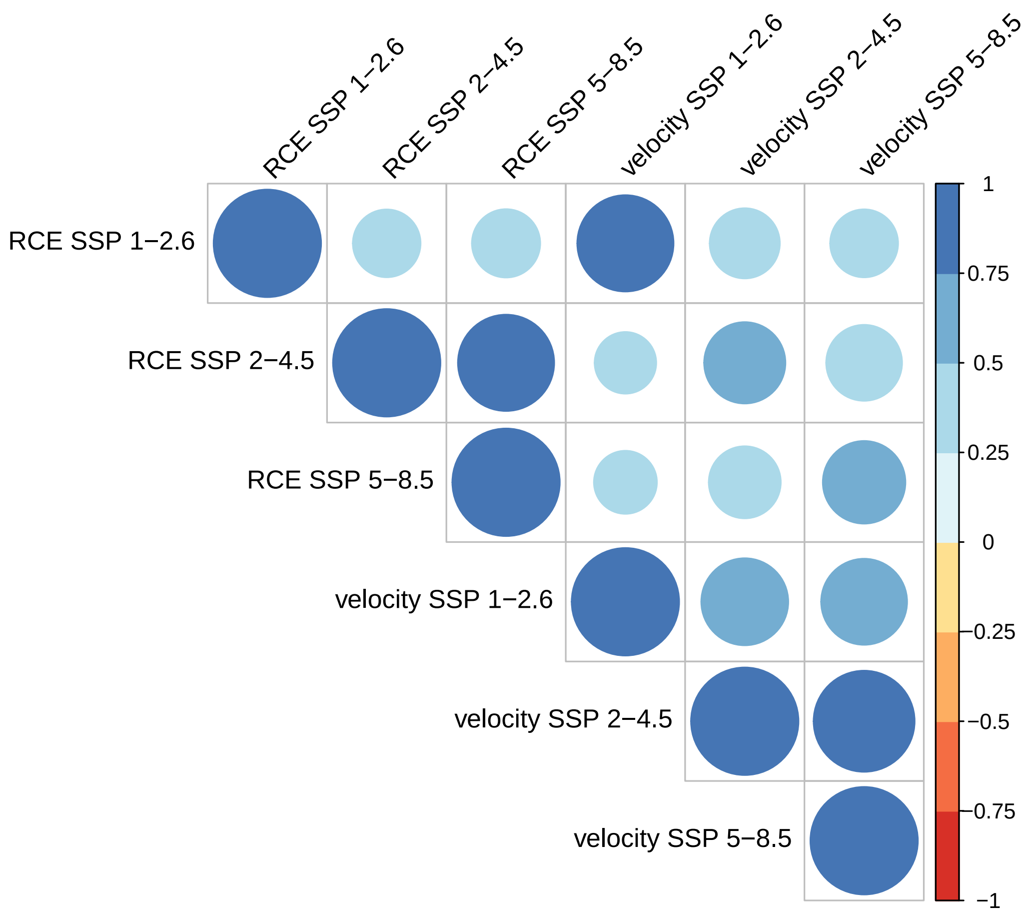
1. SSP1-2.6: optimistic scenario
2. SSP2-4.5: intermediate scenario
3. SSP5-8.5: pessimistic scenario





We also tested for the correlation of the climate metrics across different climate scenarios. We used **Spearman Correlation** since the distribution of these metrics are right-skewed, and their Shapiro-Wilk tests are $p < 0.05$.

RCE and velocity calculated for the same scenario are positively correlated (> 0.5), which could suggest that we can do with just using one of the two metrics. Correlations of climate metrics between scenarios are also positively correlated (> 0.3), with velocity showing higher correlation between metrics than RCE is. For both climate velocity and RCE, SSP 2-4.5 and SSP5-8.5 are also more positively correlated.



Cost layer

The cost layer represents the **opportunity cost** to fishing of establishing the proposed fisheries closures.

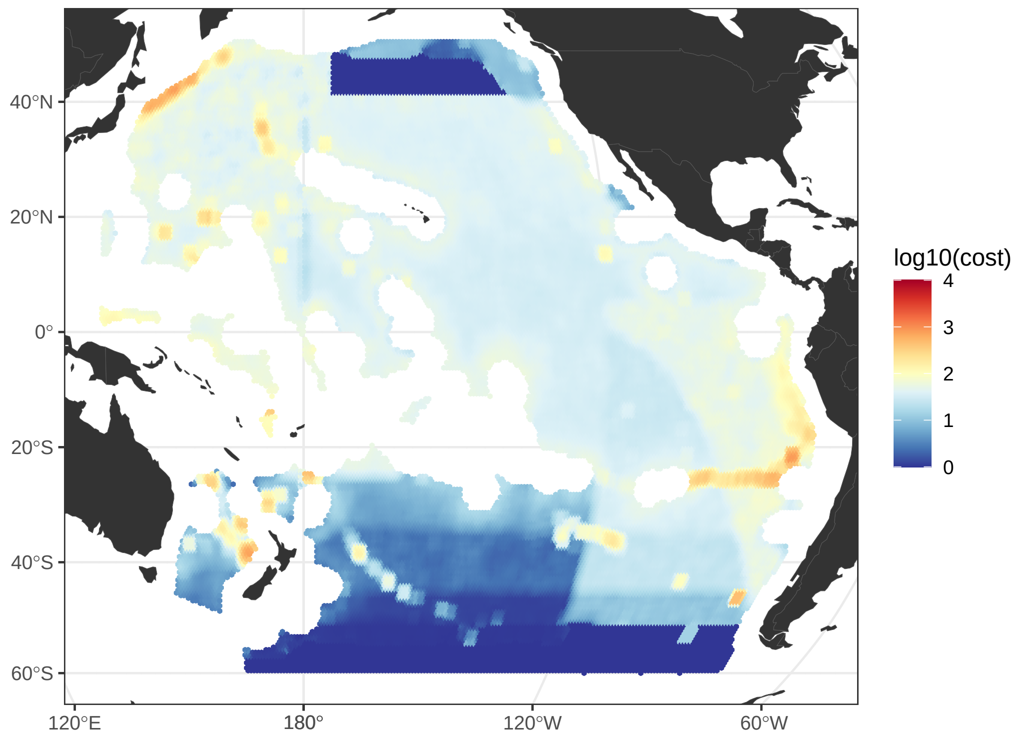
The cost layer for each planning unit was represented in US Dollars, and was calculated by multiplying the:

- estimated total catch of **medium - large pelagics** in *kg* (from Watson, 2017),and
- the ex-vessel price of the same species in the aforementioned functional groups in $US\$\ kg^{-1}$ (from Tai et al., 2017).

In addition, we smoothened the cost layer using `focal()` to reduce the splotchiness of the data.

```
## [1] "minimum: 0.00668002245947719 maximum: 813.370788574219"
```

We used *log-transformed* cost for the figure below:



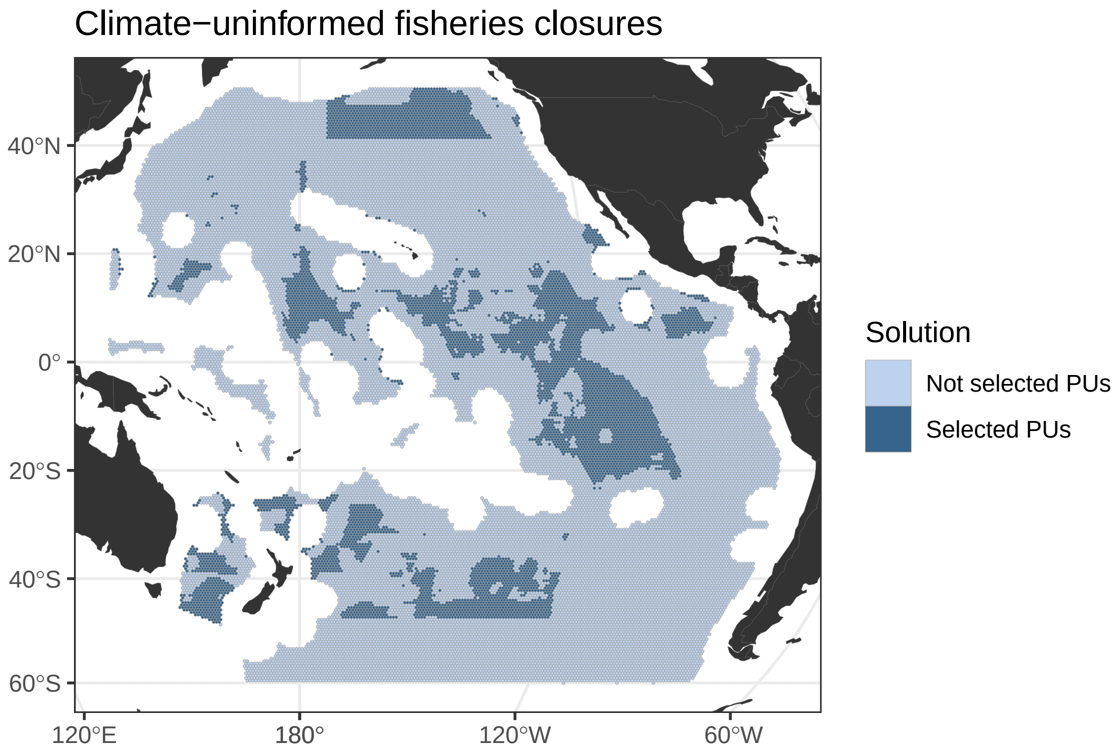
Used 2006 − 2015 catch data from Watson (2017) and ex−vessel prices from Tai et al. (2017)

Creating conservation-sensitive fisheries closures

Here, we answer the *first objective* by creating fisheries closures using only the *fisheries conseration features* in creating (and solving) the *prioritizr* problem. Because we are not including climate-smart features, we call the resulting spatial plans **climate-uninformed fisheries closures**.

We decided decided to use the same fixed target for both the bycatch and the spawning grounds. All the bycatch included in this spatial prioritization project are threatened species (IUCN Red List, 2021), and we also argue that the spawning grounds of the commercially targeted species can be considered 'important areas' for fisheries. We ran *prioritizr* across different targets (5 - 25%, with increments of 2.5%), but only those with a target of **22.5%** are reported. The results and summaries of all of the resulting closures are reported in the *Supplementary*.

The summary (e.g. total cost, % protected area) of this climate-uninformed closure will be reported below to compare it with the climate-smart closures.



Different methods of creating climate-smart closures

Essentially, we included the two climate metrics in spatial prioritization to create climate-smart closures. These closures are termed 'climate-smart' because we incorporated the effects of climate change in the creation of these closures. Again, we want to protect areas of low RCE (low exposure to warming) and low climate velocity (high retention of biodiversity). We used three climate scenarios; hence, there are a total of three spatial plans for each method (one for each scenario).

Here, we explored three different methods of creating climate-smart closures by:

1. using climate-smart features as **conservation features**

- RCE and climate velocity were included in the spatial problem as feature layers with their own targets (just like the fisheries conservation features) by conserving x% of the lower 25th percentile for both climate metrics (e.g. 90% of the 25th percentile = 22.5%).

2. intersecting climate-smart features with the fisheries conservation features and **retaining only planning units that are within the 25th percentile** of the climate metrics

- We further restricted the planning region by retaining planning units (with species information from the fisheries conservation features) that intersected with the 25th percentile of RCE and climate velocity.

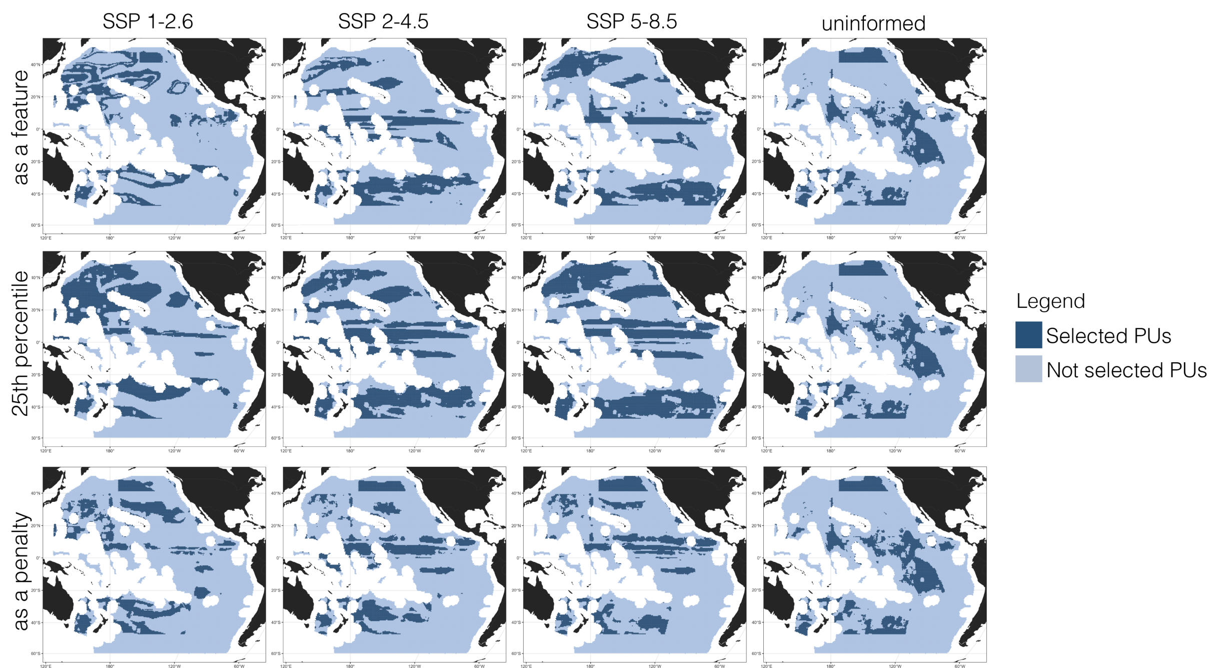
Note: the reason why 22.5% was chosen to be presented was because if we chose the maximum that was tested (25%), we would be constricting *prioritizr* to choose all of the planning units in equal or less than the 25th percentile of the climate metrics.

3. using climate-smart features as **linear penalties**

- RCE and climate velocity were treated as *penalties* which modified the objective function used in spatial prioritization. Penalties were given to planning units that had higher RCE and climate velocity values. Hence, this constricted *prioritizr* to select planning units with lower values for the two climate metrics, while still minimizing the costs and meeting the set targets.

The weights of the RCE and climate velocity were both 30% of the cost, to give more weight on the cost than on the climate metrics when choosing planning units. This weight can be changed to increase or decrease the weight of the penalties relative to the cost, but we decided to use **30%** since there weren't any significant changes in resulting total cost and % protected area when using weights of 20, 30, 40 and 50% of the cost (see Supplement).

First, here are the resulting climate-smart closures using the three methods outlined above. All of which had targets set at 22.5%.



Their summaries are shown below:

- A-D show the total cost, % protected area, median climate velocity and median RCE for each climate scenario across the different methods
- E-G show the representation of each conservation feature across the different methods
- H-J show the kappa correlation matrices of each closure (climate-smart and climate-uninformed) across the different methods

Just some notable points:

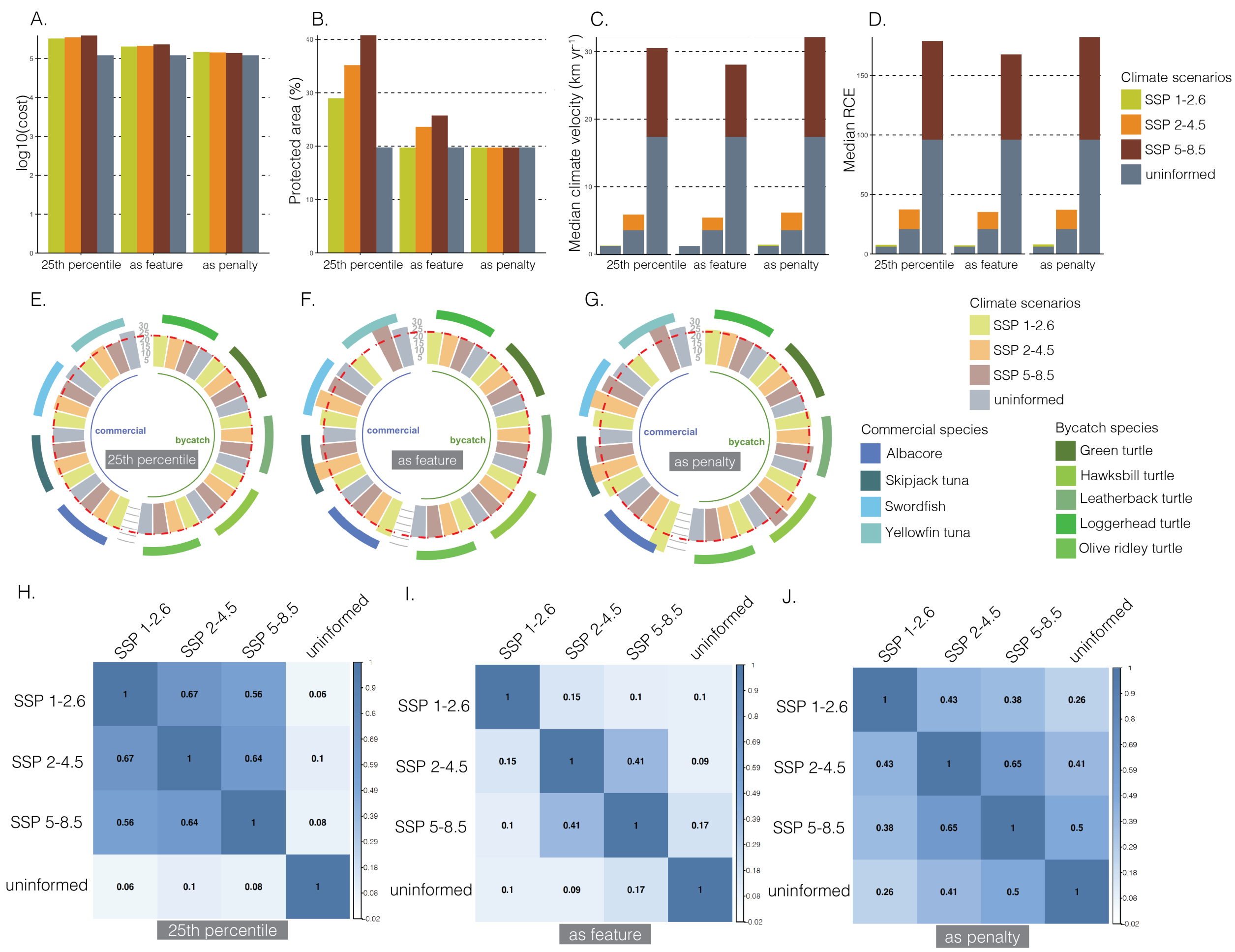
- as the percent of the protected area increases, the total cost of the closure also increases
  - with that being said, climate-smart closures protect more area, but are more costly compared to climate-uninformed closures
  - the least variation between climate-smart closures is in the third method (as penalties). This (I think) is because of the similarity in the scaling of the climate metrics (using 30% scaling for both RCE and velocity across *all scenarios*), and also because the metrics are positively correlated across the scenarios

- the method with the most % protected area (and the most costly) is the second method (25th percentile)

- as for the median velocity and RCE, there is not a lot of difference between methods; however, we can definitely see that climate-smart closures have lower median RCE and lower median climate velocity
  - we can say that these methods have successfully made climate-smart closures by allowing less exposure to warming and, possibly, more retention of biodiversity compared to climate-uninformed closures

- *prioritizr* will meet the targets set for each feature, and this is seen in figures E-F (showing the % representation of each conservation features— bycatch and commercially targeted species)
  - even though the second method offered the most % protected area, the first (as features) and the third methods (as penalties) had greater representation for some of the features (e.g. seen in some of the commercial species wherein target is exceeded by a significant amount)

- the closures made using the third method (as penalties) also seem to have more coherent spatial plans (again, can be attributed to the scaling of the penalties) and, interestingly, has the greatest coherence with the climate-uninformed closure



Every method presented here has its advantages and disadvantages. The main idea of presenting the results of these three methods is to show that there are multiple ways to create climate-smart closures with *prioritizr*. It is up to the objectives and the targets of the stakeholders involved in a spatial planning project to determine which method would be the best. I think the same can be said about the selected features as well.

Nonetheless I present some of the advantages and disadvantages I see for each method.

1. using climate-smart features as **conservation features**

- This can be more appropriate if we want to set actual targets (e.g. 30% protection) to areas of low RCE and low climate velocity regardless of whether they actually have biodiversity in it or not
- I think this is more appropriate for studies that can include benthic organisms
- Using this method would be easier to explain to different stakeholders

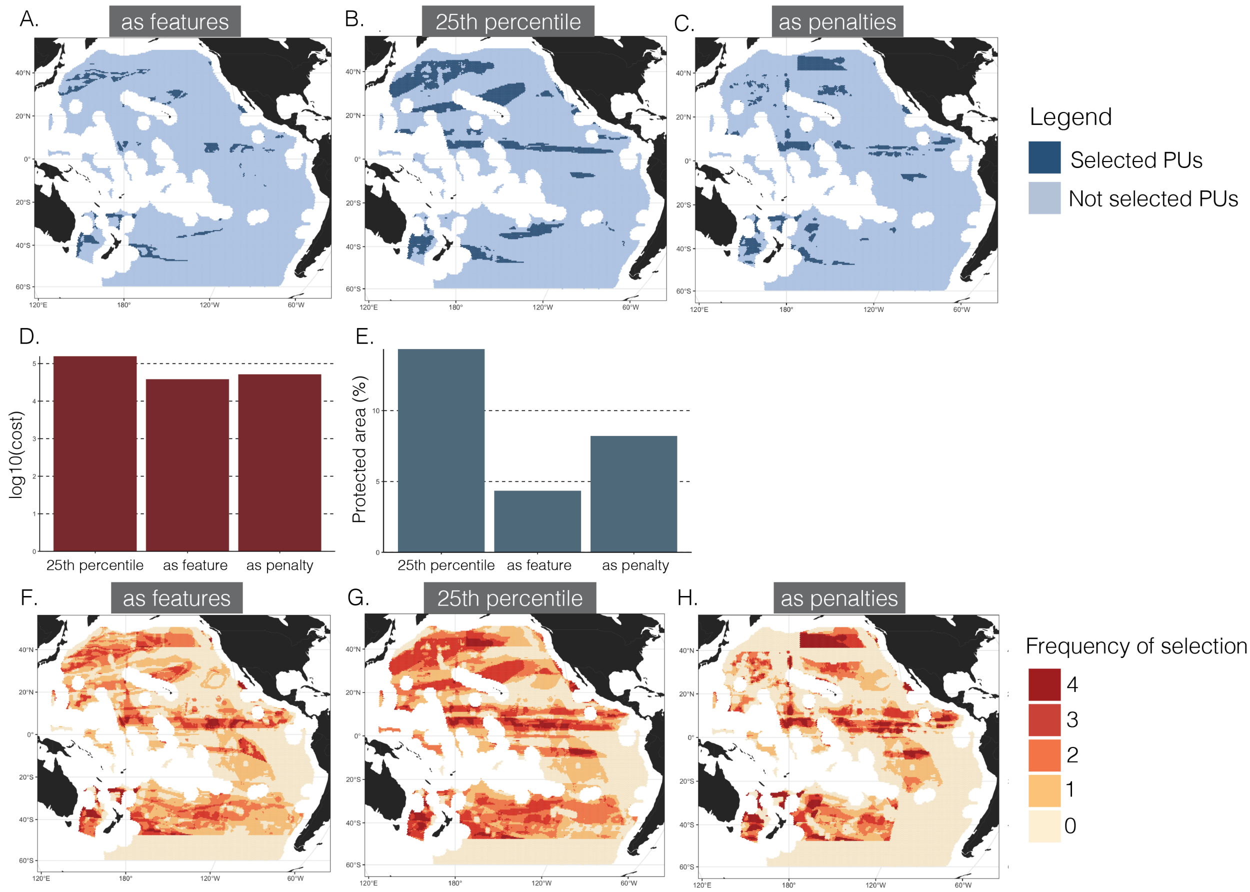
2. intersecting climate-smart features with the fisheries conservation features and **retaining only planning units that are within the 25th percentile** of the climate metrics

- This is an updated version of the first method, wherein the climate metrics are not actually feature layers, but instead provide thresholds for each of the conservation features.
- Here we wish to conserve biodiversity that intersect with equal to or less than 25th percentile of the climate metrics
- So, we only conserve low RCE and low climate velocity areas that have biodiversity values (of course, this is also dependent on the conservation features we're using)
- Using this method would be harder to explain to different stakeholders

3. using climate-smart features as **linear penalties**

- RCE and climate velocity are not involved in the feature layers; instead, they are used as penalties
- Doing this tells *prioritizr* to penalize selection of areas with higher RCE and higher velocity
- With this, constraints are further exerted on the minimum set objective function (aside from the cost)
- This method, however, does not allow RCE and velocity to be termed as 'features' we wish to have targets of. The only 'target' they have is to be low enough to keep the cost (and the panlty) of the resulting closures low.

Below are the results of the no-regret closures, which only show planning units that were selected across all the climate scenarios for each of the methods. In addition, their total costs and % protected area are shown. We also created maps showing the frequency of selection of the planning units, which can ultimately help managers and other stakeholders determine the more important planning units to protect.


A.
as features
B.
25th percentile
C.
as penalties
Legend
Selected PUs
Not selected PUs
D.
log10(cost)
25th percentile
as feature
as penalty
E.
Protected area (%)
25th percentile
as feature
as penalty
F.
as features
G.
25th percentile
H.
as penalties
Frequency of selection
4
3
2
1
0