Toward sustainable and resilient fisheries management for the Humboldt squid deep-water fishery

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Introduction

Background and Motivation

The Humboldt squid (Dosidicus gigas) is one of the most important deep-water fisheries (DWF) globally, playing a crucial role in both the economy and food security. These extraordinarily large squid are particularly sensitive to environmental changes, including fluctuations in sea surface temperature (SST), driven by the El Niño-Southern Oscillation (“ENSO”), that climate change increasingly intensifies. SST plays a pivotal role in determining where squid populations thrive, influencing their migration patterns and spawning grounds (@yu2018ocean). As these temperatures shift, so do the squid, leading to changes in fishing grounds and market demand (Powell, Levine, and Ordonez-Gauger (2022)). Understanding these dynamics is essential for sustainable fisheries management in an era of rapid climate change.

The urgency of this issue is highlighted by recent trends. From 2017 to 2020, the global squid fleet’s fishing effort increased by 68%, with most activity concentrated beyond a nation’s Exclusive Economic Zone (EEZ) particularly from international vessels (Seto et al. (2023)). This has led to significant geopolitical and environmental concerns, particularly around South America where the Humboldt squid is abundant (Montecalvo et al. (2023)). Although some regional fisheries management organizations, such as the South Pacific Regional Fisheries Management Organization (SPRFMO), have attempted to introduce regulations to moderate squid fishing, most squid stocks on the high seas remain largely unregulated. This lack of regulation, coupled with the sensitivity of squid populations to environmental changes, underscores the need for comprehensive research and effective management strategies.

To address these challenges and seize opportunities for sustainable management, it is crucial to understand how sea surface temperature (SST) changes will affect the Humboldt squid. While some research has begun to explore the impact of sea surface temperature (SST) on the Humboldt squid, few studies have connected these findings to policy implications (Yu and Chen (2018)). We propose to investigate the sensitivity of this fishery to climate change, with a particular focus on the implications for policy interventions. Our goal is to provide policymakers with the necessary data and insights to make informed, sustainable management decisions. Specifically, we will address the following research questions:

- How do fluctuations in sea surface temperature influence the distribution and abundance of Humboldt squid?
- What are the subsequent shifts in fishing demand and potential conflicts among fisheries?

- What specific challenges and opportunities for management enhancement exist n light of changing SST?
- What policy recommendations and fisheries management strategies can be developed to manage Humboldt squid fisheries sustainably in the context of climate change?
- How the relevant RFMO and DWF fleets or adjacent countries can collectively contribute to the sustainable management of jumbo flying squid in the context of climate change?

Approach

The project will be conducted in three phases:

Phase One: Literature review

We will begin with a review of scientific literature and existing studies on biological and ecological characteristics of Humboldt squid, including their life cycles, breeding patterns, and feeding behaviors. We will also compile information on how changes in SST have historically affected squid populations and identify key indicators of climate resilience. In addition, we will review socioeconomic studies that highlight the economic importance of Humboldt squid fisheries, their role in local economies, and the impact of environmental changes on these aspects.

Phase Two: Structural model development

In the second phase, we will develop a data-driven fishery model to simulate future SST scenarios and predict Humboldt squid responses. This model will integrate historical and current data from Global Fishing Watch and SPRFMO, as well as bioeconomic parameters in the existing study of this fishery. We will use this model to analyze the migration patterns of these squid in response to changing SST to predict shifts in fishing demand and the potential for conflict among fisheries.

Phase Three: Policy review and recommendations

Finally, we will assess various fisheries management strategies specific to individual country and regions, such as voluntary seasonal closures and enforced fishing moratoriums, to identify their effectiveness in addressing the challenges posed by climate change and overfishing. This will help us develop evidence-based policy recommendations aimed at ensuring the future profitability, resiliency, and sustainability of the Humboldt squid fishery.

Deliverables

- **Kickoff meeting**: Initial meeting with EDF to align on project priorities.
- **Literature review**: In-depth review of existing knowledge on Humboldt squid ecology, distribution, and response to SST fluctuations.
- **Model development**: A model predicting Humboldt squid responses to various climate change scenarios, integrating empirical data on fishing effort and catch.
- **Draft white paper**: A report on the impact of climate change on Humboldt squid fisheries, including policy recommendations supporting the sustainable management of the sector.

1 Methods

1.1 Data sources

1.1.1 Sea surface temperature (SST)

Sea surface temperature (SST) data come from NOAA's Optimum Interpolation Sea Surface Temperature (OISST) version 2.1 (Huang et al. (2021)), which were downloaded from their Coast Watch ERDDAP server. The raw data are provided globally at 0.25x0.25 degree daily resolution. Keeping the full 0.25x0.25 degree spatial resolution, we temporally aggregate the daily data to monthly resolution by calculating the mean, standard deviation, minimum, and maximum from across the days in each month.

1.1.2 Sea surface temperature (SST) forecasts under climate change

We use SST forecasts under climate change from the IPCC WGI Interactive Atlas(Iturbide et al. (2021)). The Atlas provides a platform for accessing ensemble forecasts from CMIP6 (Coupled Model Intercomparison Project Phase 6), which represent the latest global climate forecasts available and served as the basis of the 6th IPCC Assessment Report.

We pull 1x1 degree monthly mean SST data for three time horizons:

1. Near Term (2021-2040)
2. Medium Term (2041-2060)
3. Long Term (2081-2100)

And for each time horizon, we pull data from four climate change scenarios (more information on the scenarios can be found here:

1. SSP1-2.6
2. SSP2-4.5
3. SSP3-7.0
4. SSP5-8.5

This gives us a total of 12 different forecasts to analyze. The dataset can be loaded in targets using `targets::tar_load(sst_cc_forecast_data)`, and it has the following columns:

- **lon_bin**: 1x1 degree longitude bin (degrees) (numeric)

- **lat_bin**: 1x1 degree latitude bin (degrees) (numeric)

- **sst_deg_c_mean**: Mean sea surface temperature from across the ensemble of CMIP6 models (degrees C) (numeric)
- **time_period**: Future time horizon forecast time period (character)
- **scenario**: Climate change scenario (character)
- **month_number**: Month number (numeric)

1.1.3 Oceanic Niño Index (ONI)

According to NOAA:

- "The Oceanic Niño Index (ONI) is NOAA's primary index for tracking the ocean part of ENSO, the El Niño-Southern Oscillation climate pattern."
- "The ONI is the rolling 3-month average temperature anomaly—difference from average—in the surface waters of the east-central tropical Pacific, near the International Dateline."
- "Index values of +0.5 or higher indicate El Niño. Values of -0.5 or lower indicate La Niña."

We downloaded these data from `https://psl.noaa.gov/data/correlation/oni.data` on September 27, 2024.

1.1.4 AIS-based Fishing effort

We use satellite-based individual vessel monitoring AIS data processed by Global Fishing Watch (Kroodsma et al. (2018)). We use the V3 pipeline table `pipe_ais_v3_published.messages`. Variables of interest within this table include the following (descriptions are taken directly from the schema for `pipe_ais_v3_published.messages`):

- `ssvid`: source specific vessel id; MMSI for AIS
- `hours`: time since the previous position in the segment
- `timestamp`: timestamp for position
- `lon`: longitude
- `lat`: latitude
- `night_loitering`: 1 if the seg_id of every message of a squid_jigger that is at night and not moving, 0 if not.

In order to minimize noisy data, we only include AIS messages that have a `clean_segs` boolean (i.e., all messages must have `good_seg` boolean and must not have an `overlapping_and_short` boolean). We filter to just those messages where `night_loitering = 1`. For squid jigging vessels, GFW uses the heuristic of night loitering to identify when they are fishing. Therefore, any `hours` where `night_loitering = 1` can be classified as `fishing_hours`

We take the raw high-resolution AIS data and aggregate `fishing_hours` spatially (by 0.25x0.25 degree pixels, which are roughly 27.75km x 27.75km at the equator), temporally by month, and by flag. We currently process data from 2016-01-01 through 2024-08-31.

1.1.5 Vessel info

Vessel characteristics data processed are by Global Fishing Watch (Park et al. (2023)). We use the V3 pipeline table `pipe_ais_v3_published.vi_ssvid_v20240601`. Variables of interest within this table include the following (descriptions are taken directly from the schema for `pipe_ais_v3_published.vi_ssvid_v20240301`):

- `ssvid`: source specific vessel id; MMSI for AIS
- `best.flag`: best flag state (ISO3) for the vessel
- `best.best_vessel_class`: best vessel class for the vessel (using official registry information where available, or the GFW vessel characteristics algorithm where not available)
- `best.best_engine_power_kw`: best engine power (kilowatts) for the vessel (using official registry information where available, or the GFW characteristics algorithm where not available)
- `activity.active_hours`: hours the vessel was broadcasting AIS and moving more than 0.1 knots
- `activity.offsetting`: true if this vessel has been seen with an offset postition at some point between 2012 and 2019
- `activity.overlap_hours_multinames`: the total numbers of hours of overlap between two segments where, over the time period of the two segments that overlap (including the non-overlapping time of the segments), the vessel broadcast two or more normalized name, where each normalized name was bradcast at least 10 or more times. That is a bit complicated, but the goal is to identify overlapping segments where there were likely more than one identity. (this should be 0; if it is > 0, it can be used as a filter to remove potentially erroneous/noisy vessels)

We filter to just those vessels where `best.best_vessel_class = squid_jigger`. Additionally, to reduce noise, we filter out vessels that broadcast exceedingly infrequently (i.e., `activitiy.active_hours < 24`) or are noisy/spoofing/offsetting vessels (i.e., `NOT activity.offsetting OR activity.overlap_hours_multinames > 0.`) They are simply not reliable and will not provide good effort estimates. This leaves us with 1,561 squid vessels for our analysis.

1.1.6 EEZ information

For each 0.25x0.25 degree pixel, we determine a number of EEZ features. To do so, we leverage the EEZ shapefiles and boundaries from Marine Regions v12(Institute (2023)). We first determine whether the centroid of the pixel is on the high seas or within an EEZ (`high_seas`). For pixels that are within an EEZ (`eez_id`), we determine its Marine Regions EEZ ID and its ISO3 sovereign country code (`pixel_sovereign1_iso3`); for pixels that are on the high seas, the EEZ id takes a value of `high_seas` and the country code also takes a value of `high_seas`. We next determine the distance in meters from the centroid of the pixel to the nearest 200nm EEZ/high seas boundary line (`distance_to_nearest_eez_m`); so for pixels on the high seas, this number represents the distance to the nearest EEZ; for pixels inside EEZs, this represents the shortest distance to the high sea. For high seas pixels, we finally determine the country EEZ ID (`nearest_eez_id`) and ISO3 sovereign country code (`nearest_pixel_sovereign1_iso3`) of this nearest EEZ; for pixels that are within an EEZ, this both take the values of the EEZ the pixel is within. Note that for our analysis, we exclude the Anarctica EEZ and treat it as the high seas; we also exclude any joint claim or disputed EEZs.

1.1.7 Joined dataset: SST and AIS-based effort

One version of the final dataset we use for our analysis is a combination of the gridded AIS-based fishing effort data and gridded SST data. We inner join the AIS-based effort and SST datasets by 0.25x0.25 degree pixel and month. We finally left join the Oceanic Niño Index (ONI) monthly data (by month) and the EEZ information (by pixel). Since the AIS-based effort dataset is disaggregated by flag, each row in the joined dataset represents flag-level effort in a given pixel and month, with the corresponding SST for that pixel and month.

Note that the joined dataset includes pixel-month-flags when have SST data but with no AIS-based fishing effort (i.e., the data are *not* conditional on there being some fishing effort for any given pixel-month-flag). These rows get a value of `0` for `fishing_hours` and `fishing_kw_hours`.

The joined dataset can be loaded in R using the command `targets::tar_load(joined_dataset_ais)`. The dataset has the following colums:

- **month**: Month (first day of month) (date)
- **flag** : Fishing vessel flag (character)
- **lon_bin**: 0.25 degree longitude bin (degrees) (numeric)
- **lat_bin**: 0.25 degree latitude bin (degrees) (numeric)
- **flag**: Fishing flag (character)

- **sst_deg_c_mean**: Mean sea surface temperature, aggregated from the raw daily 0.25x0.25 degree data (degrees C) (numeric)
- **sst_deg_c_sd**: Standard deviation of sea surface temperature, aggregated from the raw daily 0.25x0.25 degree data (degrees C) (numeric)
- **sst_deg_c_min**: Minimum sea surface temperature, aggregated from the raw daily 0.25x0.25 degree data (degrees C) (numeric)
- **sst_deg_c_max**: Maxiumum sea surface temperature, aggregated from the raw daily 0.25x0.25 degree data (degrees C) (numeric)
- **fishing_hours**: Total fishing effort across vessels (hours) (numeric)

- **fishing_kw_hours**: Total fishing effort across vessels (kW-hours) (numeric)

- **oceanic_nino_index**: Oceanic Niño Index (ONI) (numeric)
- **eez_id**: Marine regions EEZ ID of the pixel; for high seas pixels, this takes a value of `high_seas` (string)
- **distance_to_nearest_eez_m**: This is the distance to the nearest 200nm EEZ/high seas boundary (for pixels on the high seas, this number represents the distance to the nearest EEZ; for pixels inside EEZs, this represents the shortest distance to the high seas) (meters) (numeric)
- **nearest_eez_id**: For high seas pixels, this is the Marine regions EEZ ID of the nearest EEZ pixel; for pixels within an EEZ, this is the Marine regions EEZ ID of the pixel (string)
- **eez_iso3**: For pixels within an EEZ, this is the ISO3 sovereign country code for the pixel; for high seas pixels, this takes a value of `high_seas` (string)
- **nearest_eez_iso3**: For high seas pixels, this is the ISO3 sovereign country code for the nearest EEZ pixel; for pixels within an EEZ, this the pixel's ISO3 sovereign country code (string)
- **high_seas**: This is a logical indicating whether the pixel is within the high seas or not (logical)

Here we summarize these data (Table 1.1):

1.2 Geographic analysis scope

Our proposed geographic scope encompasses a bounding box with a longitude range from -130 degrees to -70 degrees and a latitude range from -40 degrees to 10 degrees (Figure 1.1; Figure 1.2). This longitude range encompasses band of equatorial fishing effort to the west and the EEZs off the western coast of South America. The latitude range covers the maximum latitude of the South Pacific Regional Fisheries Management Organisation (SPRFMO) and extends beyond the southern latitude where the north-south band of fishing effort is currently concentrated. The bounding box extends beyond where fishing effort is currently concentrated,

Table 1.1: Summary statistics for joined dataset that includes gridded SST and AIS-based fishing effort

(a) Data summary

Name	joined_dataset_ais
Number of rows	41267304
Number of columns	17
Column type frequency:	
character	5
logical	1
numeric	10
POSIXct	1
Group variables	None

Variable type: character

skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
flag	4585256	0.89	3	3	0	8	0
eez_id	0	1.00	4	9	0	14	0
nearest_eez_id	0	1.00	2	5	0	24	0
eez_iso3	0	1.00	3	9	0	11	0
nearest_eez_iso3	0	1.00	3	3	0	12	0

Variable type: logical

skim_variable	n_missing	complete_rate	mean	count
high_seas	0	1	0.79	TRU: 32753448, FAL: 8513856

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
lon_bin	0	1	-102.56	16.08	-130.00	-116.50	-102.75	-89.00	-70.25	
lat_bin	0	1	-15.81	14.44	-40.00	-28.25	-16.50	-3.25	10.00	
sst_deg_c_mean	0	1	22.85	4.19	10.30	19.96	23.54	26.27	31.11	
sst_deg_c_sd	0	1	0.39	0.25	0.02	0.21	0.32	0.49	3.37	
sst_deg_c_min	0	1	22.17	4.23	8.96	19.23	22.83	25.62	30.60	
sst_deg_c_max	0	1	23.52	4.16	10.57	20.69	24.23	26.91	32.31	
fishing_hours	0	1	0.07	5.68	0.00	0.00	0.00	0.00	3430.50	
fishing_kw_hours	0	1	74.70	6175.53	0.00	0.00	0.00	0.00	3745373.67	
oceanic_nino_index	0	1	-0.01	0.85	-1.27	-0.73	-0.11	0.49	2.48	
nearest_eez_distance_m	0	1	592454.62	442780.49	1194.19	215031.75	497222.36	911947.29	1769305.06	

Variable type: POSIXct

skim_variable	n_missing	complete_rate	min	max	median	n_unique
month	0	1	2016-01-01	2024-08-01	2020-04-16	104

which means that in our predictions under future climate change scenarios, we could capture shifts of fishing effort beyond it current range.

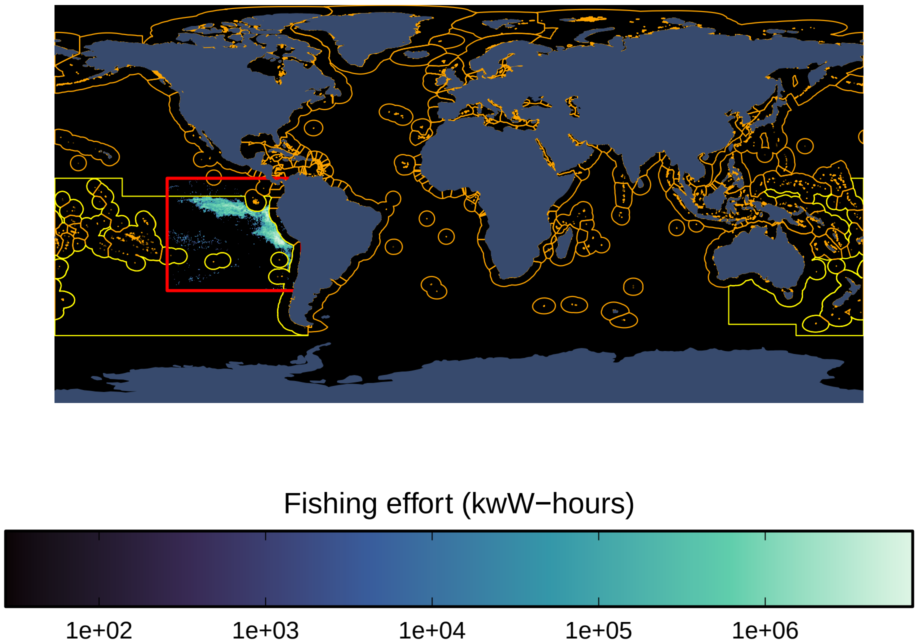


Figure 1.1: Map of squid jigger fishing effort from 2016 through August 2024, aggregating effort across effort, flags, and time for each pixel. EEZ boundaries from Marine Regions V12 are shown in orange; the SPRFRMO boundary is shown in yellow; the currently proposed analysis scope bounding box is shown as a red outline.

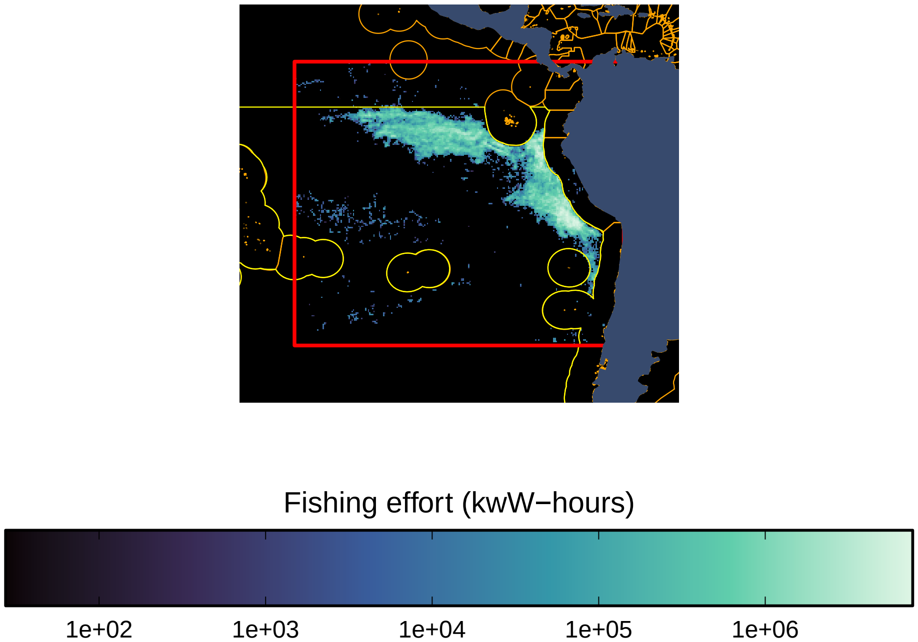


Figure 1.2: Zoomed in map of squid jigger fishing effort from 2016 through August 2024 to the proposed analysis scope, aggregating effort across effort, flags, and time for each pixel. EEZ boundaries from Marine Regions V12 are shown in orange; the SPRFRMO boundary is shown in yellow; the currently proposed analysis scope bounding box is shown as a red outline.

2 Exploratory data analysis

Note that all maps are zoomed into the area surrounded by the proposed geographic analysis scope.

2.1 Sea surface temperature (SST)

We can look at a map of SST, simply looking at the average monthly SST from across the entire January 2016 through August 2024 time series (Figure 2.1).

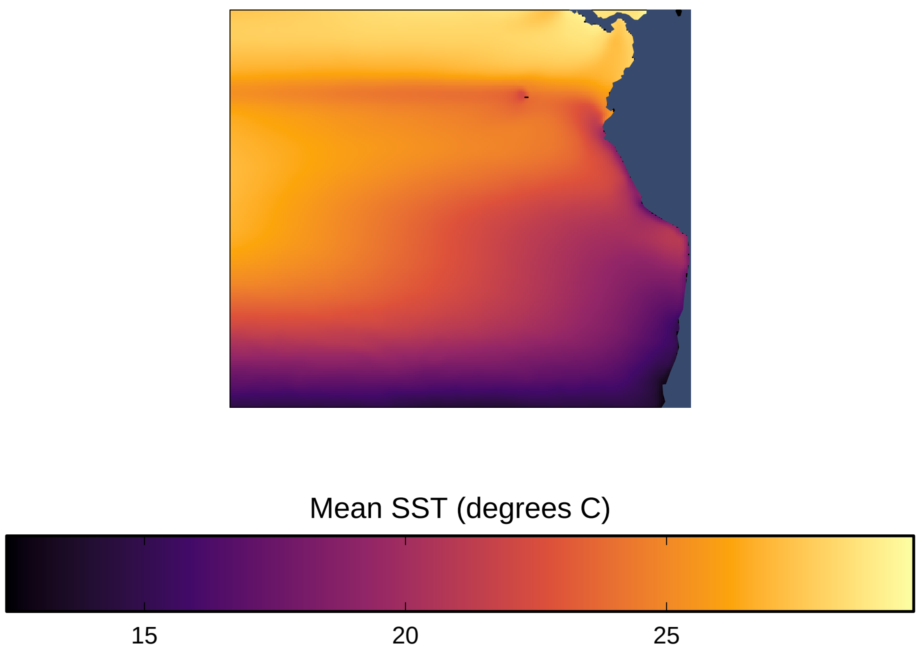


Figure 2.1: Map of mean sea surface temperature (SST) from across January 2016 through August 2024, using 0.5x0.5 degree pixels.

Aggregating across the mean sea surface temperatures of each pixel, we can calculate the mean sea surface temperature over time within our study scope (Figure 2.2). This allows us to see both seasonal trends and larger trends over time.

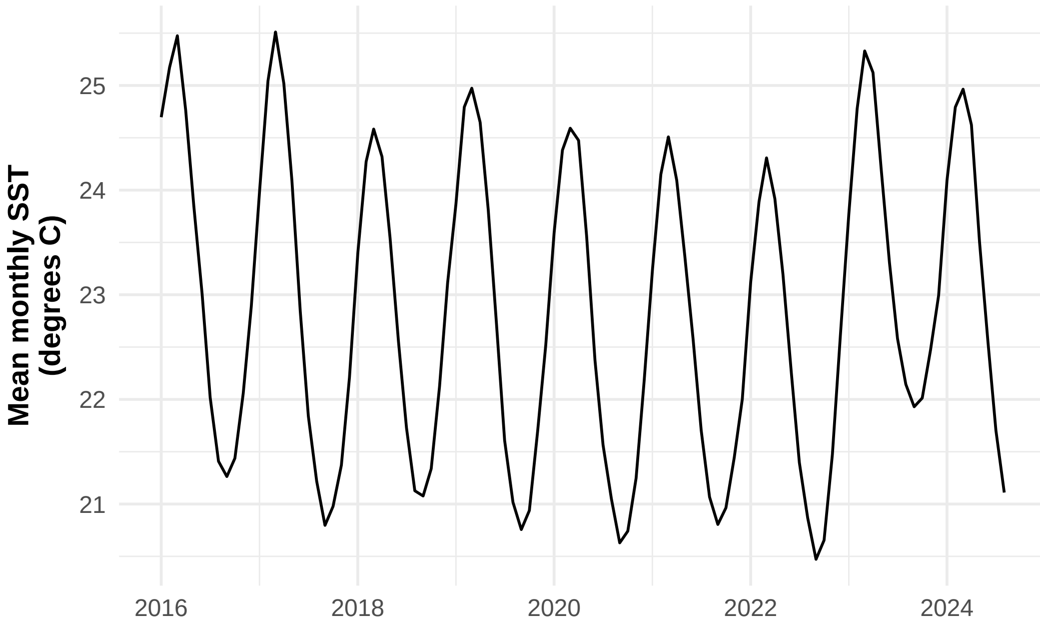


Figure 2.2: Time series of monthly mean sea surface temperature (SST) within our study scope.

2.2 Sea surface temperature (SST) forecasts under climate change

Here we look at a map of mean sea surface temperature (SST) under the four different climate change scenarios, and the three different forecast horizons, and focusing on the area of our analysis scope (Figure 2.3).

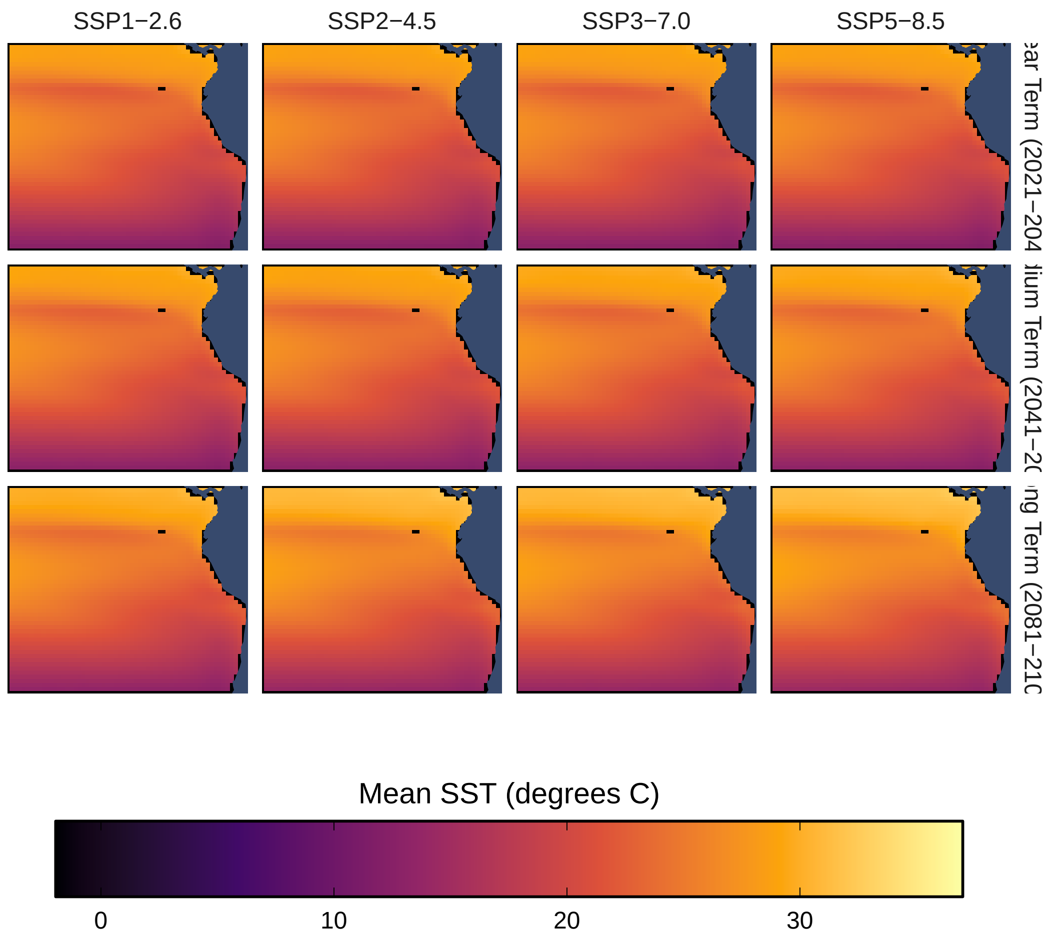


Figure 2.3: Map of mean August sea surface temperature (SST) under four different climate change scenarios, and three different forecast horizons. Data are for 1x1 degree pixels.

Here we look at time series of climate change forecasts for monthly average SST for each forecast time horizon and scenario, and focusing on our spatial analysis scope (Figure 2.4). As expected, projected SST is higher for time horizon further into the future, and for more extreme climate change scenarios.

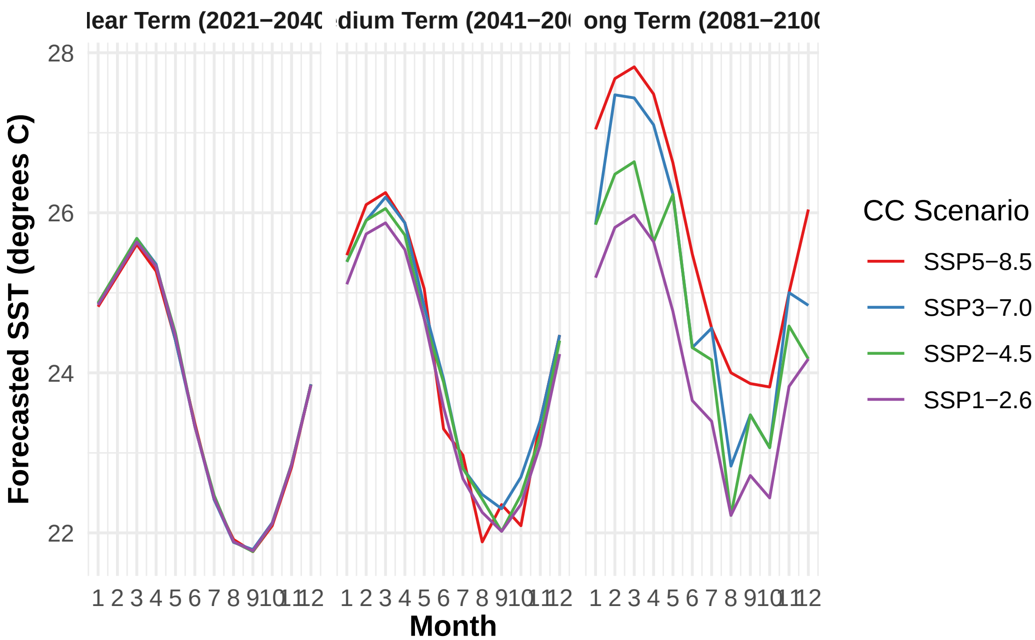


Figure 2.4: Climate change forecasts for monthly average SST for each forecast time horizon and scenario, within our spatial analysis scope

2.3 Oceanic Niño Index (ONI)

Here we look at the time series of ONI data, focused on the time period for which we have AIS-based effort data (Figure 2.5):

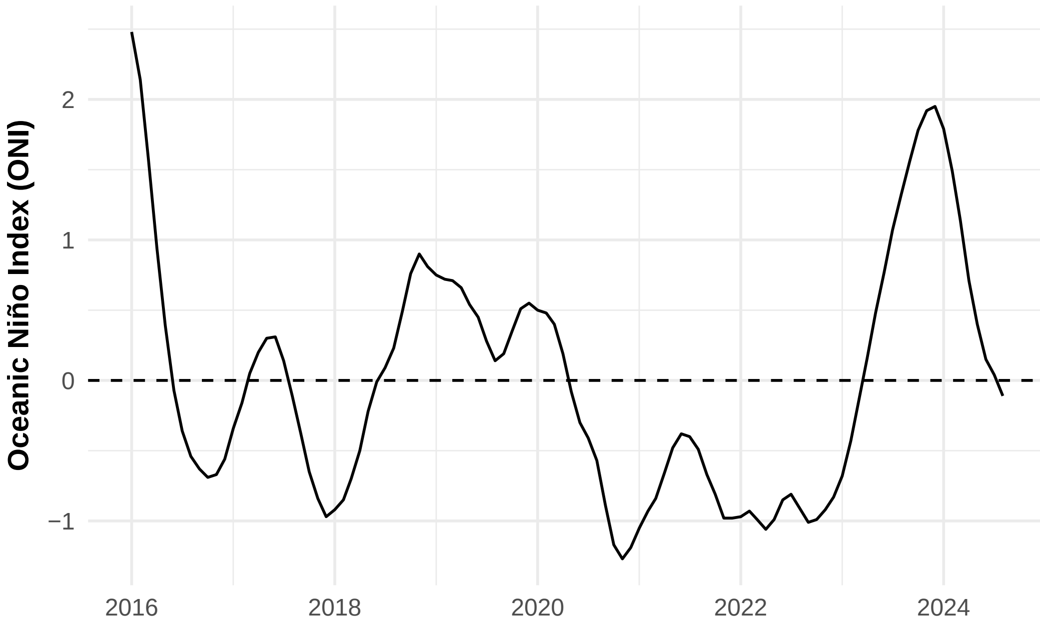


Figure 2.5: Time series of monthly Oceanic Niño Index (ONI).

2.4 AIS-based Fishing effort

Here we look at total fishing effort from 2016 through August 2024 within the analysis scope, by flag (Figure 2.6). China dominates the fishing effort with over 97% of all effort, with Taiwan a distant second at barely 1%.

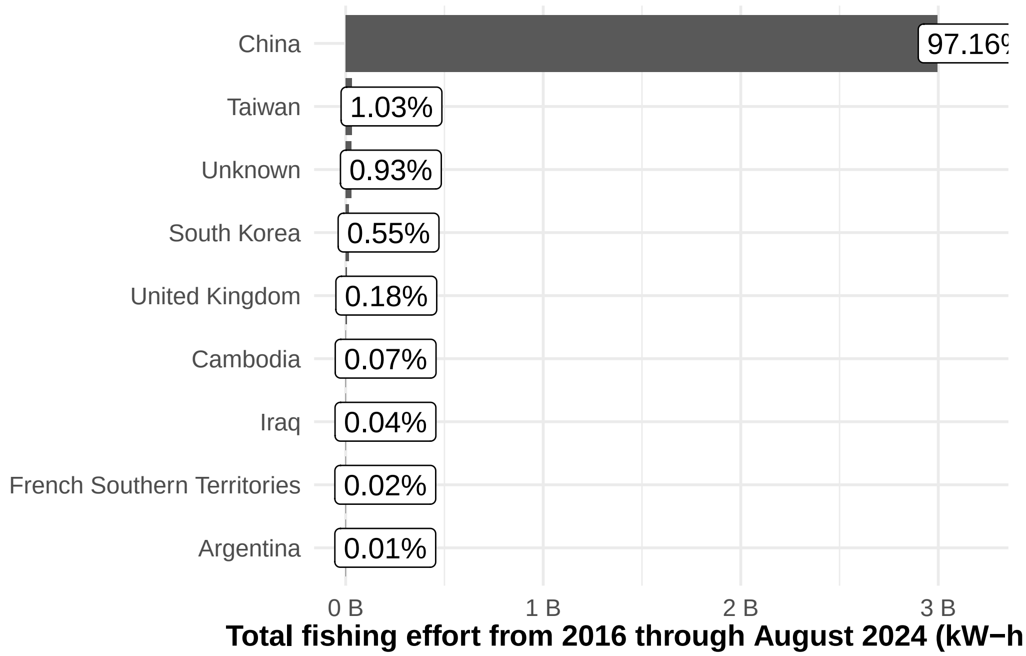


Figure 2.6: Total fishing effort, by flag, from 2016 through August 2024 within the analysis scope. The label shows the percentage of total fishing effort that each flag contributes.

Next we look at a time series of total monthly AIS-based fishing effort by fishing flag over time within the analysis scope (Figure 2.7). The top top 5 flags are shown.

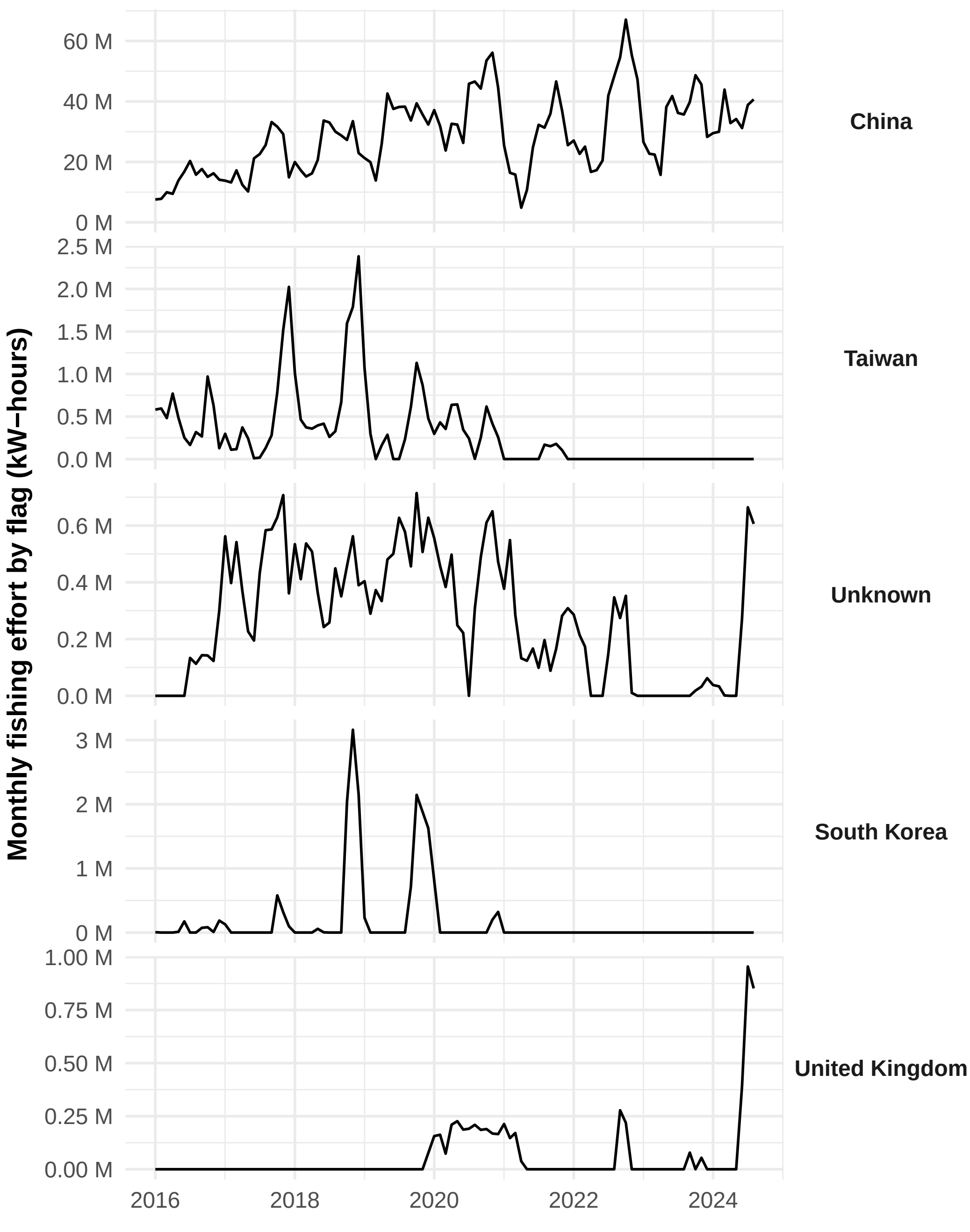


Figure 2.7: Monthly fishing effort by flag from 2016 through August 2024 within the analysis scope. The top 5 flags are shown individually.

Next we can look at the temporal trend of total fishing effort alongside the temporal trend of

SST (Figure 2.8).

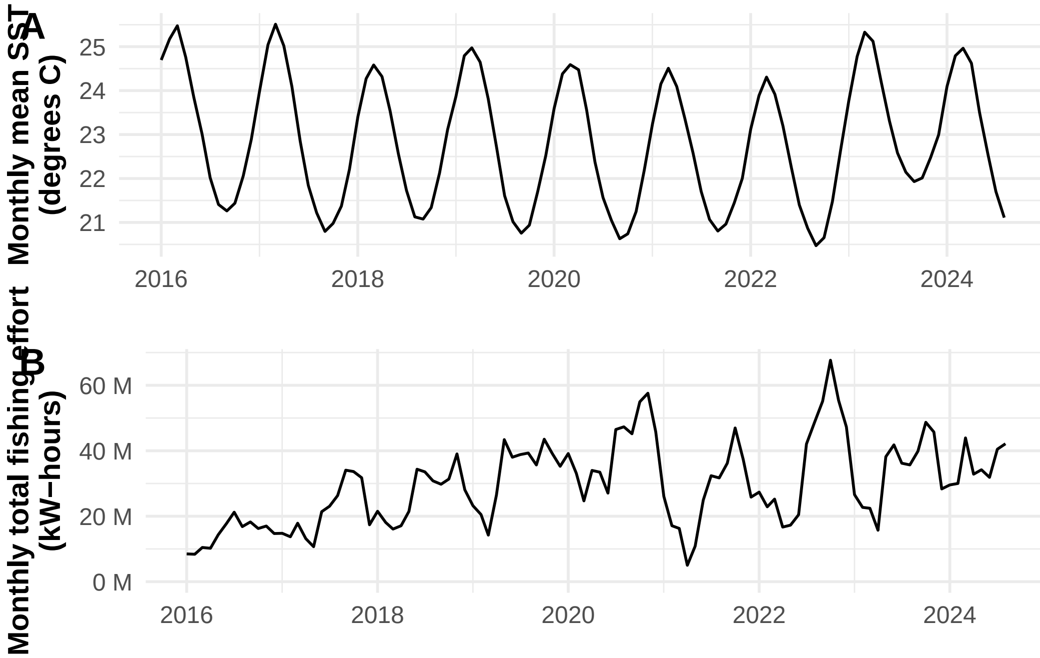


Figure 2.8: Monthly trends of of a) mean sea surface temperature (SST); and b) total squid jigger fishing effort. Both time series include data from across the entire January 2016 through August 2024 time period, and from only within our spatial analysis scope.

We can also aggregate the effort data by calculating the total effort for each month in each year, allowing us to look at the historic seasonal variation of total effort. We can do so for two regions: the "equatorial" region (latitude -10 to 10) and the "sub-equatorial" region (latitude -40 to -10) (Figure 2.11, Figure 2.12).

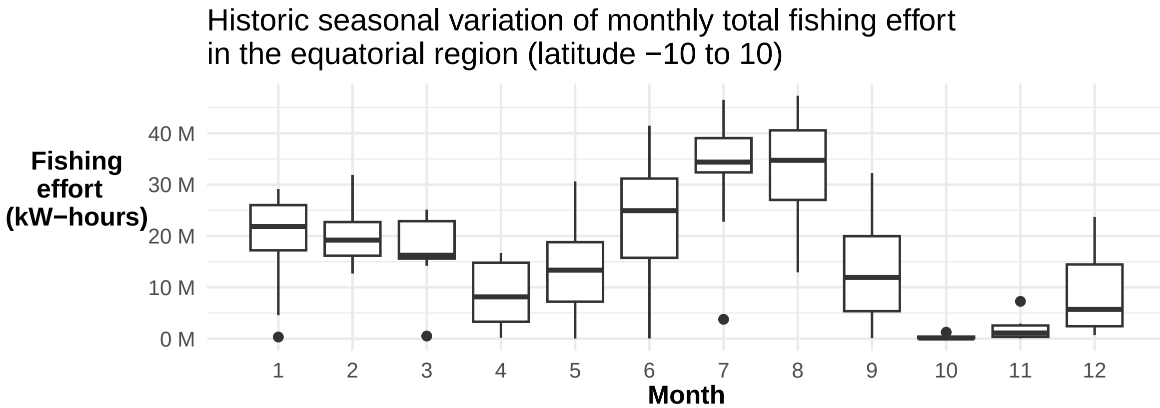


Figure 2.9: Historic seasonal variation of monthly total fishing effort for the equatorial region. The distribution for each month shows the spread of total fishing effort from each year in our historic dataset (January 2016 through August 2024) and within our spatial analysis scope.

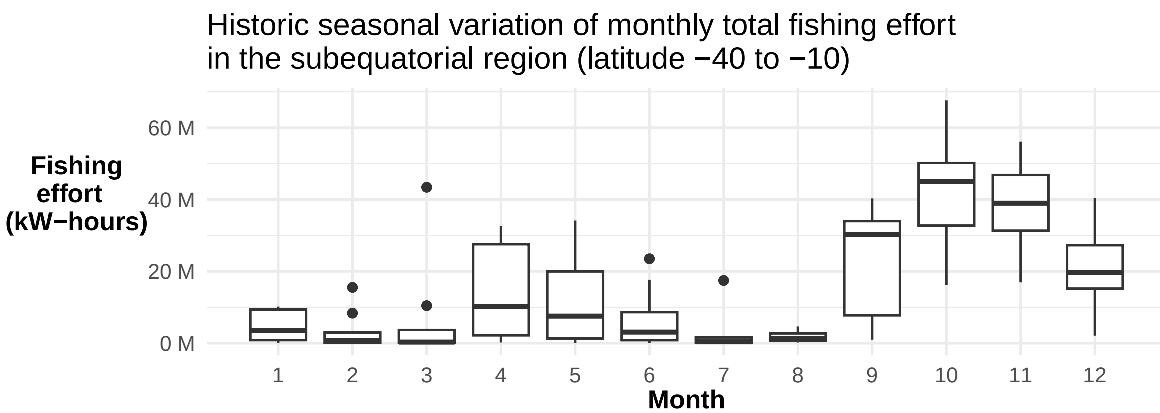


Figure 2.10: Historic seasonal variation of monthly total fishing effort for the sub-equatorial region. The distribution for each month shows the spread of total fishing effort from each year in our historic dataset (January 2016 through August 2024) and within our spatial analysis scope.

We can also aggregate the SST data by calculating the mean SST for each month in each year, allowing us to look at the historic seasonal variation of monthly mean sea surface temperature. We can do so for two regions: the "equatorial" region (latitude -10 to 10) and the "sub-equatorial" region (latitude -40 to -10) (Figure 2.11, Figure 2.12).

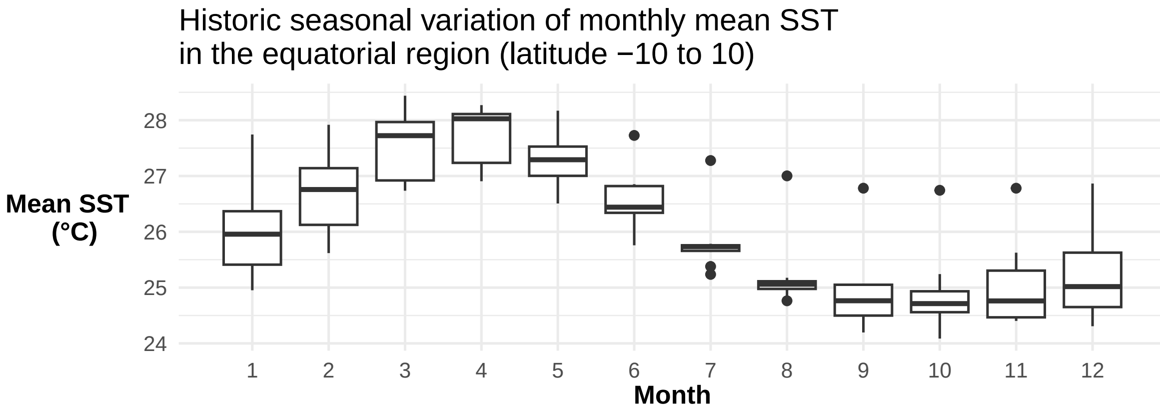


Figure 2.11: Historic seasonal variation of monthly mean sea surface temperature (SST) for the equatorial region. The distribution for each month shows the spread of mean SST from each year in our historic dataset (January 2016 through August 2024) and within our spatial analysis scope.

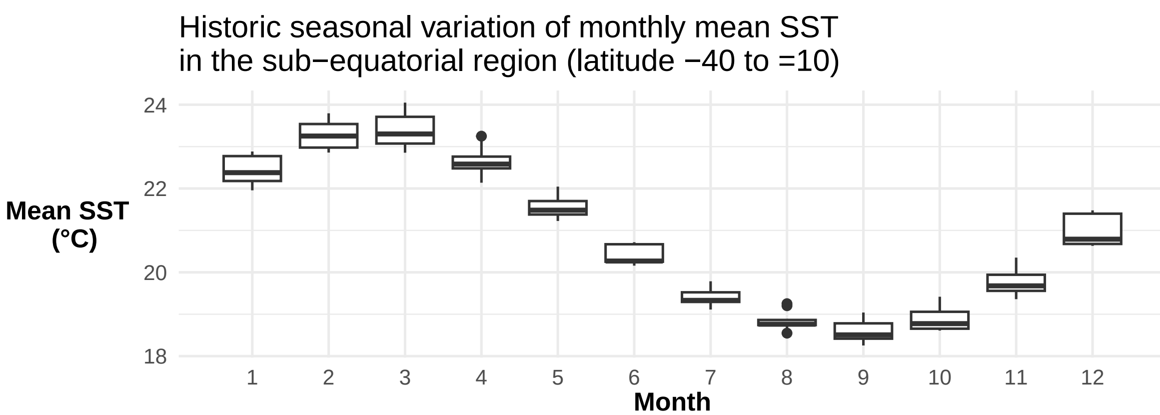


Figure 2.12: Historic seasonal variation of monthly mean sea surface temperature (SST) for the sub-equatorial region. The distribution for each month shows the spread of mean SST from each year in our historic dataset (January 2016 through August 2024) and within our spatial analysis scope.

Next we can look at at a map of AIS-based squid fishing effort (Figure 2.13), aggregating effort across effort and flags and time for each pixel across the entire processed time series. EEZ boundaries from Marine Regions v12 are shown in orange (Institute (2023)).

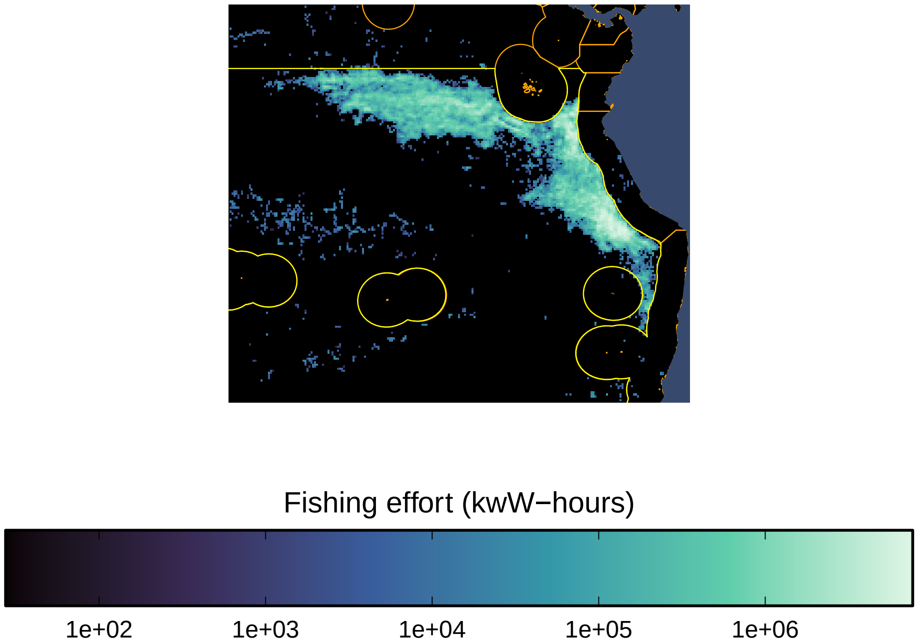


Figure 2.13: Map of squid jigger fishing effort from 2016 through August 2024, aggregating effort across effort, flags, and time for each pixel. EEZ boundaries from Marine Regions V12 are shown in orange; the SPRFMO boundary is shown in yellow.

We can also look at this map of total fishing effort alongside a map of mean SST (Figure 2.14).

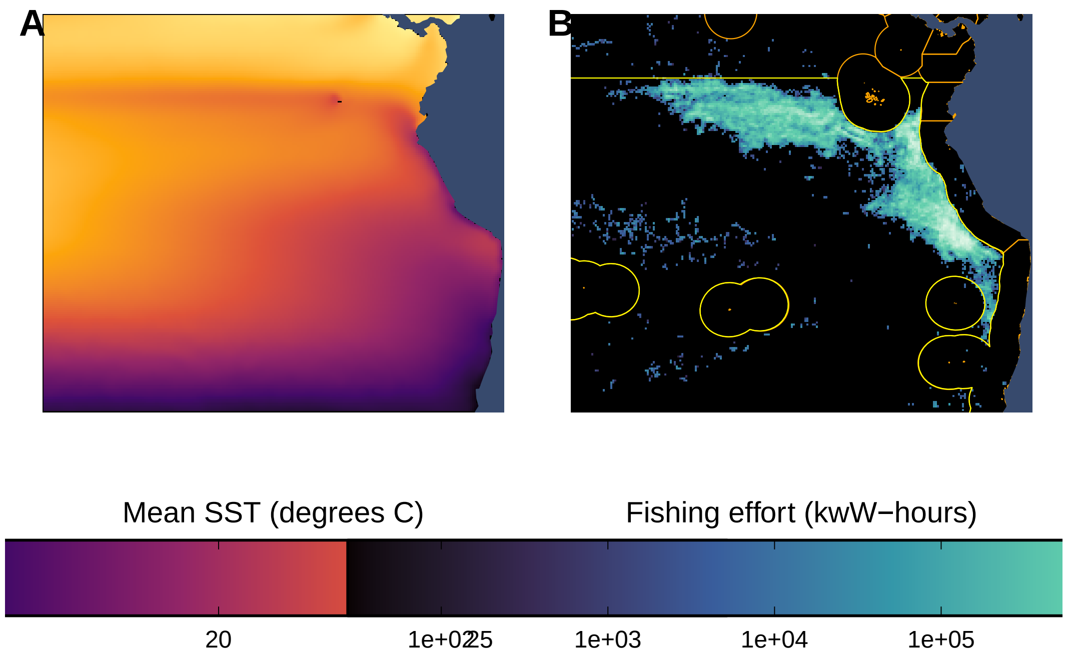
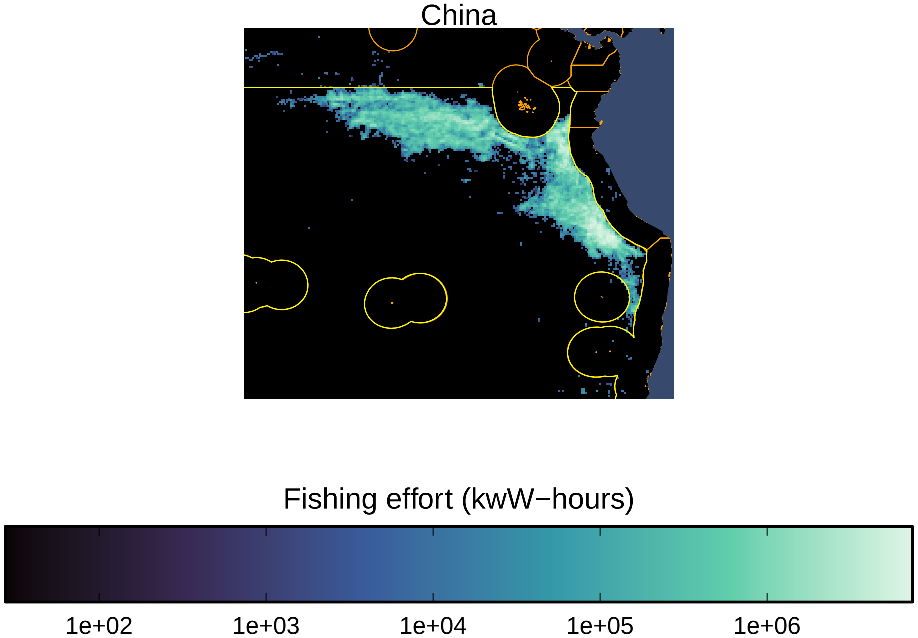


Figure 2.14: Maps of a) mean sea surface temperature (SST); and b) total squid jigger fishing effort (EEZ boundaries from Marine Regions V12 are shown in orange; the SPRFMO boundary is shown in yellow). Both maps include data from across the entire January 2016 through August 2024 time period, using 0.5x0.5 degree pixels.

We can also look at these effort maps, broken apart by flag, and still aggregating squid jigger fishing effort from 2016 through August 2024, aggregating effort across time for each pixel. The top 5 flags are shown.

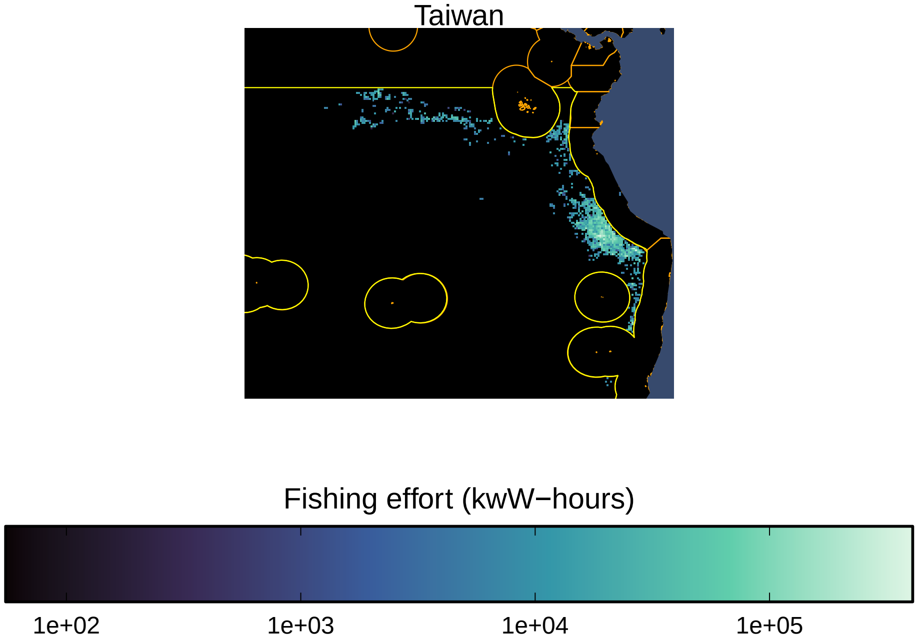
```
[[1]]
```

China

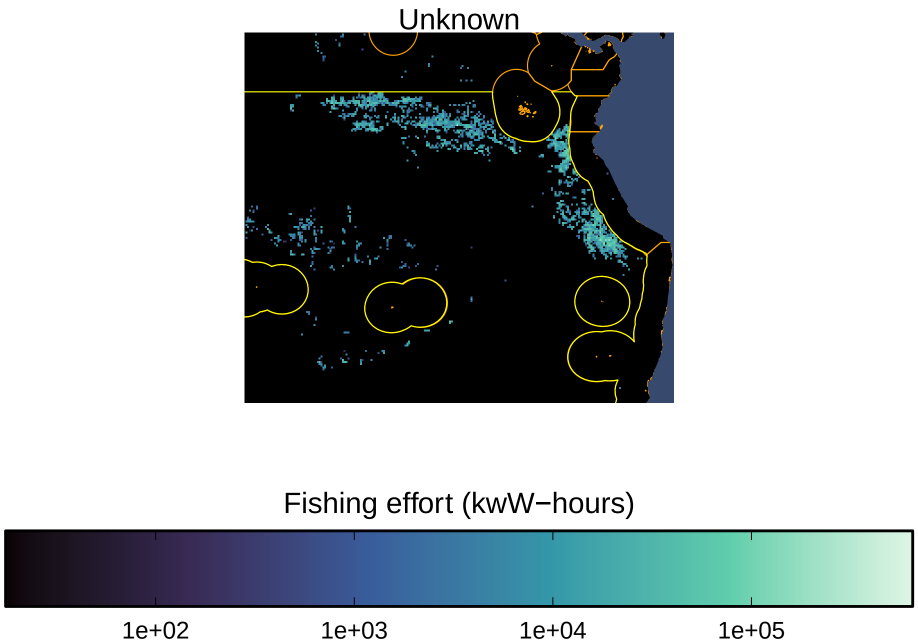


[[2]]

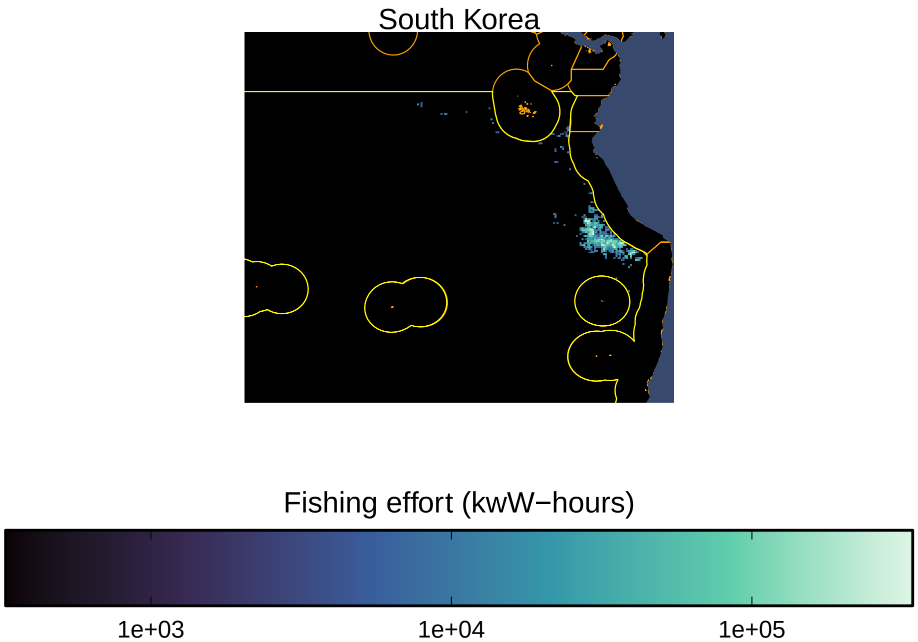
Taiwan



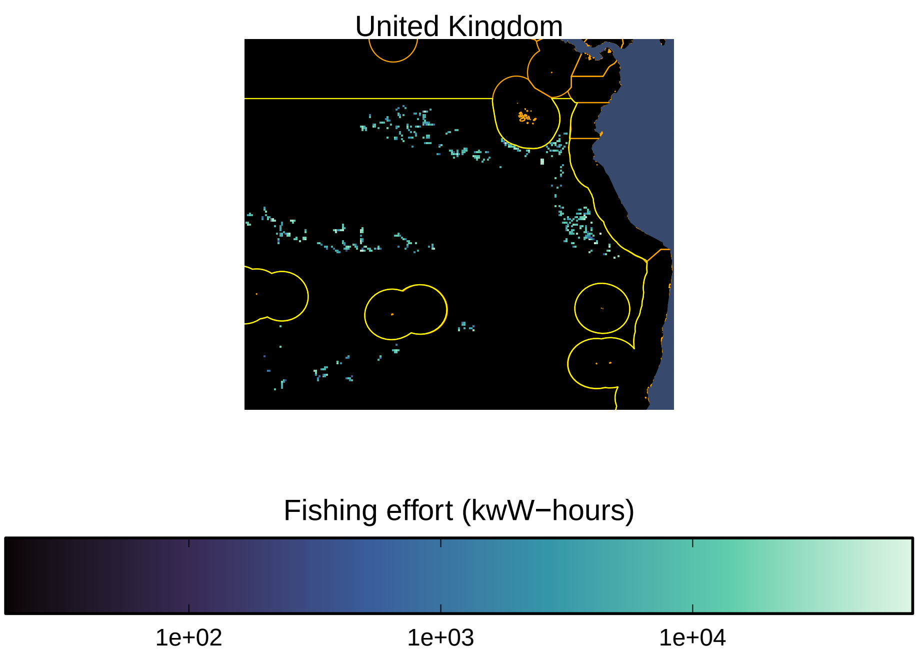
[[3]]



[[4]]


South Korea
Fishing effort (kwW−hours)
1e+03
1e+04
1e+05

[[5]]


United Kingdom
Fishing effort (kwW−hours)
1e+02
1e+03
1e+04

3 Distance to nearest EEZ

Here we look at a map showing the distance to the nearest 200nm EEZ/high seas boundary for each 0.25x0.25 degree pixel. For pixels on the high seas, this number represents the distance to the nearest EEZ; for pixels inside EEZs, this represents the shortest distance to the high seas.

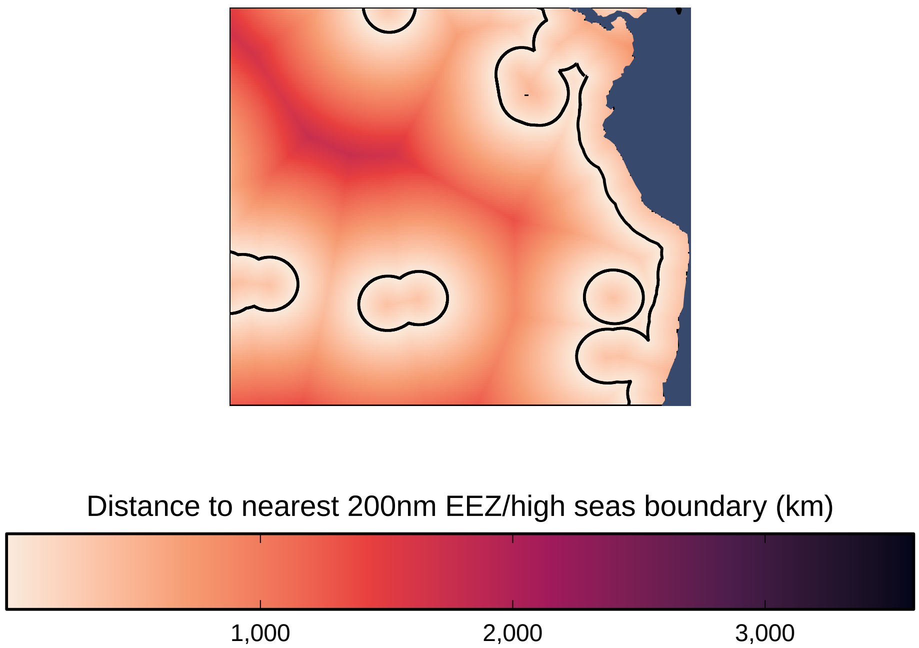


Figure 3.1: Map showing the distance to the nearest 200nm EEZ/high seas boundary for each 0.25x0.25 degree pixel. 200nm EEZ boundaries from Marine Regions V12 are shown in black.

4 Results

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