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. We spatiotemporally aggregate the data to 0.25x0.25 degree monthly resolution by calculating the mean from across days and 0.25x0.25 degree pixels.

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 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:

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.

We pull data for three dif

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 Night light detections using VIIRS (Visible Infrared Imaging Radiometer Suite)

As an alternative to AIS-based fishing effort, we can use the NASA VIIRS (Visible Infrared Imaging Radiometer Suite) data product to detect night light emissions from vessels. When the appropriate radiance threshold is applied, these can generally be assumed to represent light-luring squid vessels. Since use only the single most accurate VIIRS detection measurements each day, these can also be thought of as representing a fishing effort metric of vessel-days.

We use the VIIRS data as an alternative fishing effort metric to AIS-based fishing effort since AIS is not used on all vessels, and since it can also be disabled on the vessels that do use it.

We leverage the VIIRS boat detection (VBD) dataset developed by Elvidge et al. (2015). This dataset is available through GFW as the BigQuery table `pipe_viirs_production_v20180723.raw_vbd_global.` Variables of interest within this table include the following (descriptions are taken directly from the schema for `pipe_viirs_production_v20180723.raw_vbd_global`):

- `id_Key`: Unique VBD ID.
- `Date_Mscan`: VBD pixel date-time at mid-point of DNB scan reported in Universal Time
- `Lat_DNB`: VBD pixel latitude from VIIRS DNB geolocation file
- `Lon_DNB`: VBD pixel longitude from VIIRS DNB geolocation file
- `Rad_DNB`: Radiance of VBD pixel in VIIRS DNB band

- `QF_Detect`: Integer quality flag for VBD pixel, yielding information about quality and type of detection
- `SATZ_GDNBO`: Satellite zenith angle relative to the VBD pixel measured from the local vertical (from VIIRS GDNBO file)
- `File_DNB`: VIIRS DNB HDF5 file

We then apply similar processing as Seto et al. (2023), which includes the following steps:

- Reduce false detections near South America caused by the the South Atlantic Anomaly (an abundance of high-energy particles in the atmosphere).
- Use a same radiance threshold of 10 nW cm−2 sr−1 used by Seto et al. (2023) (and established by Park et al. (2020)) in order to filter detections to those likely engaged in in pelagic light-luring activity.
- To eliminate double-counting when there may be multiple satellite overpasses on a single night, only count detections from the overpass with the smallest satellite zenith angle (smaller zenith angles are more accurate)

We then finally aggregate the total detections for each 0.25x0.25 degree pixel and month.

1.1.7 Joined datasets

1.1.7.1 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. 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 does not contain flag-pixel-months with zero AIS-based fishing effort (i.e., the data are conditional on there being some effort for any given flag-pixel-month). If desired, once we have a spatial scope with which to restrict the analysis, we could construct a dataset for that bounding box that includes zero fishing effort flag-pixel-month rows.

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)

- **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)
- **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)

Here we summarize these data (Table 1.1):

1.1.7.2 SST and VIIRS detections

The other version of the final dataset we use for our analysis is a combination of the gridded VIIRS detections data and gridded SST data, and the gridded VIIRS detections. We inner join the VIIRS detections and SST datasets by 0.25x0.25 degree pixel and month. Note that the VIIRS detection dataset only covers January 2017 through December 2021, so that is also the time range of this joined dataset. We finally left join the Oceanic Niño Index (ONI) monthly data. Since the VIIRS dataset is not disaggregated by flag, each row in this joined dataset represents total detections in a given pixel and month, with the corresponding SST for that pixel and month.

Note that the joined dataset does not contain pixel-months with zero VIIRS detections (i.e., the data are conditional on there being some detections for any given pixel-month). If desired, once we have a spatial scope with which to restrict the analysis, we could construct a dataset for that bounding box that includes zero VIIRS detection pixel-month rows.

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

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	110347
Number of columns	8
Column type frequency:	
character	1
numeric	6
POSIXct	1
Group variables	None

Variable type: character

skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
flag	9307	0.92	3	3	0	45	0

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
lon_bin	0	1.00	9.64	108.94	-180.00	-83.25	-58.00	124.75	179.75	
lat_bin	0	1.00	2.91	30.46	-54.25	-16.75	-1.00	31.50	80.75	
fishing_hours	0	1.00	64.48	206.23	0.00	6.38	15.14	47.32	15298.78	
fishing_kw_hours	0	1.00	78828.48	294274.25	2.41	6818.36	17709.45	55348.18	22738775.12	
sst_deg_c_mean	0	1.00	20.03	6.74	-1.64	14.27	20.44	26.03	34.25	
oceanic_nino_index	1489	0.99	-0.01	0.86	-1.27	-0.81	-0.08	0.50	2.48	

Variable type: POSIXct

skim_variable	n_missing	complete_rate	min	max	median	n_unique
month	0	1	2016-01-01	2024-08-01	2021-02-01	104

- **month**: Month (first day of month) (date)

- **lon_bin**: 0.25 degree longitude bin (degrees) (numeric)

- **lat_bin**: 0.25 degree latitude bin (degrees) (numeric)
- **sst_deg_c_mean**: Mean sea surface temperature, aggregated from the raw daily 0.25x0.25 degree data (degrees C) (numeric)
- **viirs_detections**: Night light detections from the VIIRS dataset (numeric)

- **oceanic_nino_index**: Oceanic Niño Index (ONI) (numeric)

Here we summarize these data (tbl-summary-stats-joined-dataset-VIIRS):

Table 1.5: Summary statistics for joined dataset that includes gridded SST and VIIRS detections

(a) Data summary

Name	joined_dataset_viirs
Number of rows	724963
Number of columns	6
Column type frequency:	
numeric	5
POSIXct	1
Group variables	None

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
lon_bin	0	1	55.75	88.93	-180.00	-0.25	104.25	119.75	179.75	
lat_bin	0	1	15.83	28.02	-78.50	1.25	16.50	35.75	89.75	
viirs_detections	0	1	13.76	39.38	1.00	1.00	2.00	9.00	1821.00	
sst_deg_c_mean	0	1	21.87	9.12	-1.80	16.83	25.93	28.93	35.16	
oceanic_nino_index	0	1	-0.14	0.61	-1.27	-0.67	-0.11	0.40	0.90	

Variable type: POSIXct

skim_variable	n_missing	complete_rate	min	max	median	n_unique
month	0	1	2017-01-01	2021-12-01	2019-05-01	60

2 Exploratory data analysis

2.1 Sea surface temperature (SST)

We can look at a map of SST, using August 2024 as an example (Figure 2.1).

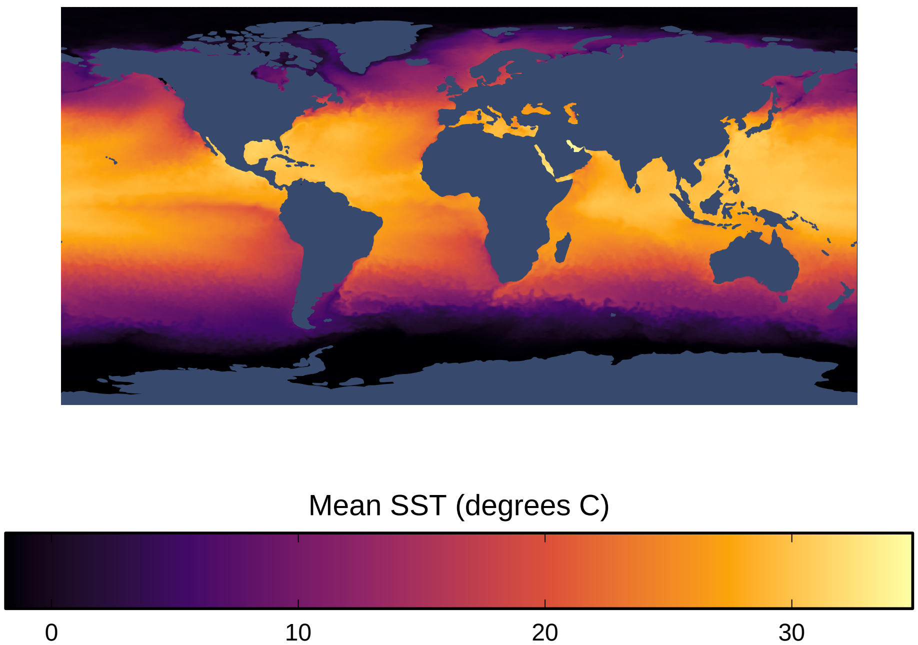


Figure 2.1: Map of mean sea surface temperature (SST) in August 2024, using 0.5x0.5 degree pixels.

Aggregating across the mean sea surface temperatures of each pixel, we can calculate the mean global sea surface temperature over time (Figure 2.2). This allows us to see both seasonal trends, and what appears to be a generally increasing trend over time.

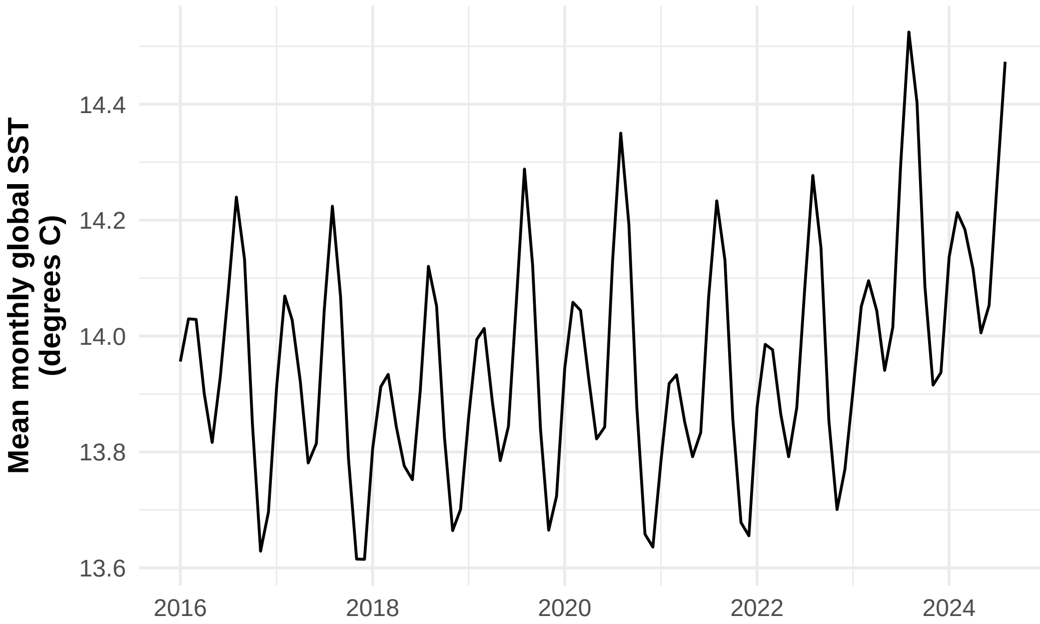


Figure 2.2: Time series of global monthly mean sea surface temperature (SST).

2.2 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 2.3):

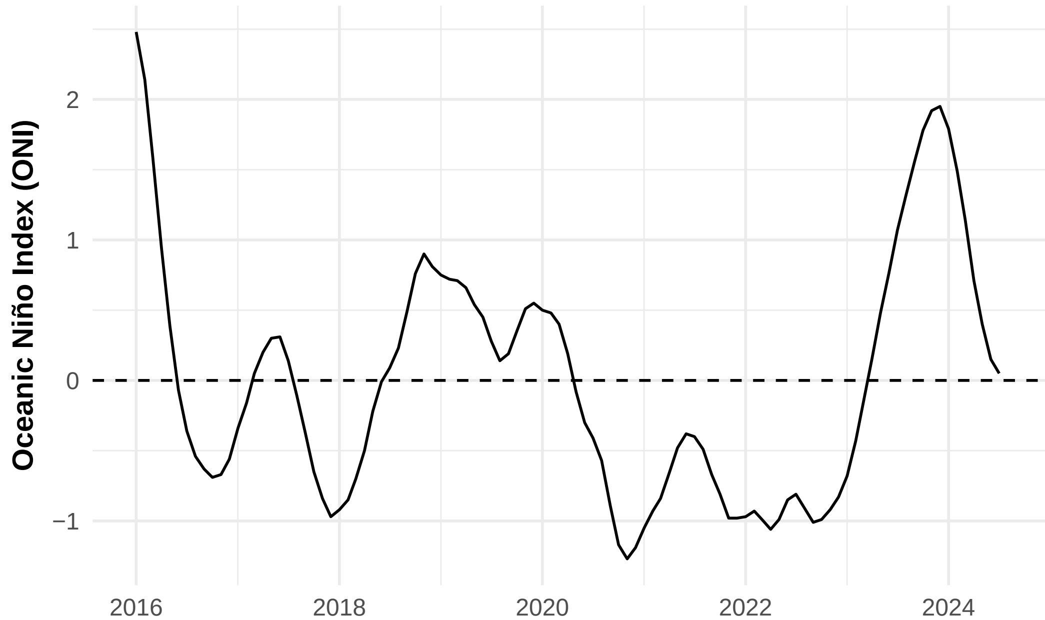


Figure 2.3: Time series of monthly Oceanic Niño Index (ONI).

2.3 Fleet characteristics

Our analysis includes 1,561 squid vessels spread across 52 flags. For each flag, we look at the total engine power (kW) across the fleet and total number of unique vessels and (Figure 2.4). China dominates the fleet, with Taiwan a fairly distant second.

Figure 2.4: Squid jigger vessel summary by flag, showing the total engine power (kW) and total number of unique vessels.

Next we look at total global fishing effort from 2016 through August 2024, by flag (Figure 2.5).

The top 10 flags are shown individually, with all other flags aggregated into "Other". Again, China dominates the fishing effort, with Taiwan a fairly distant second.

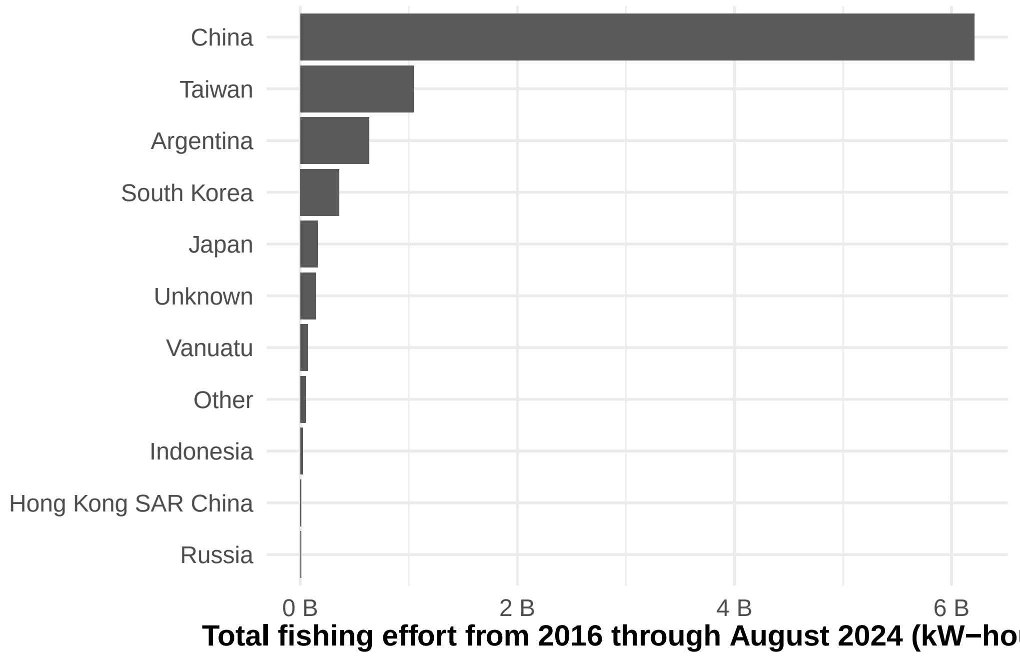


Figure 2.5: Total fishing effort, by flag, from 2016 through August 2024. The top 10 flags are shown, with all other flags aggregated into "Other".

2.4 AIS-based fishing effort

Next we look at a time series of total monthly global AIS-based fishing effort by fishing flag over time (Figure 2.6). The top top 10 flags are shown individually, with all other flags aggregated into "Other".

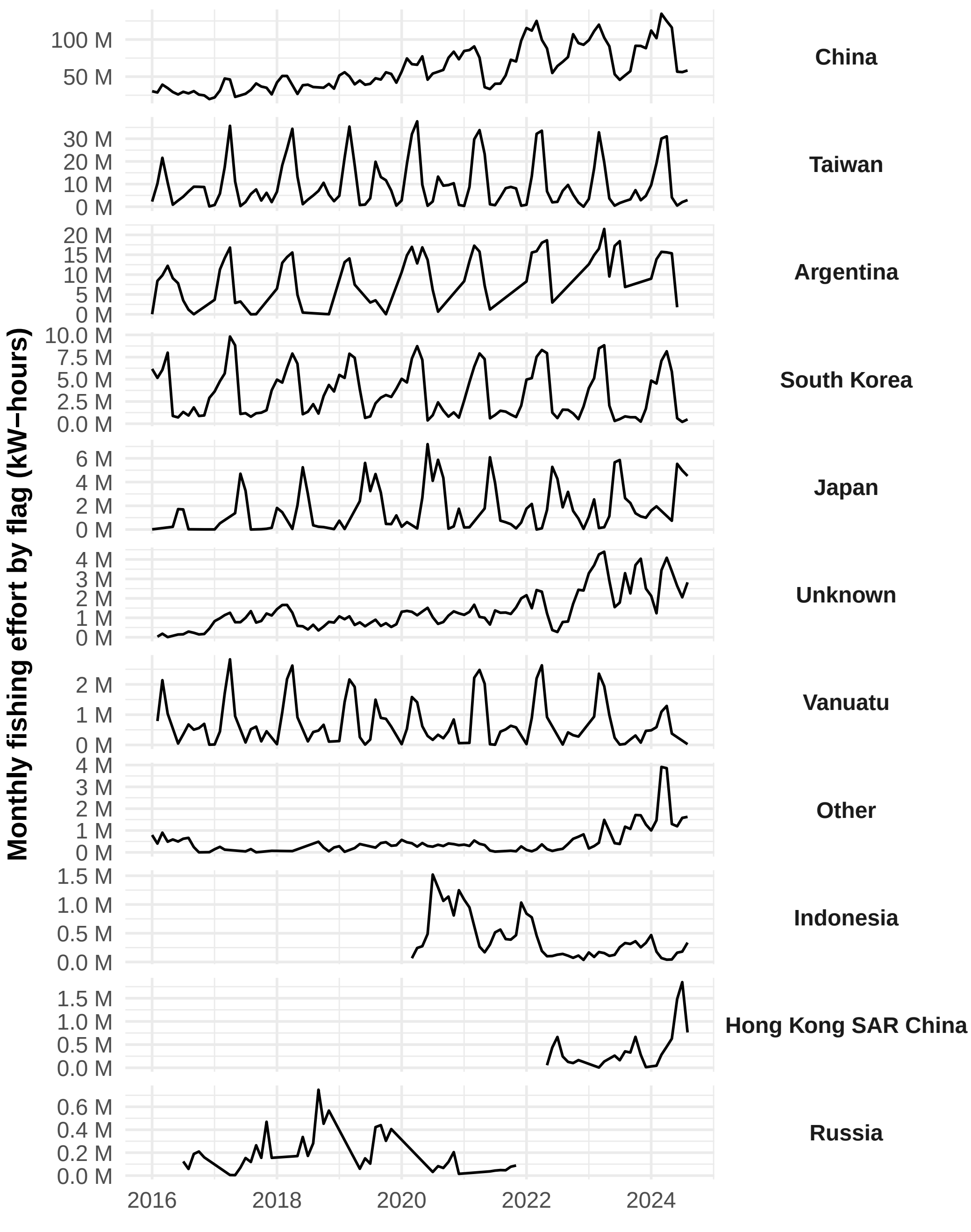


Figure 2.6: Monthly fishing effort by flag from 2016 through August 2024. The top 10 flags are shown individually, with all other flags aggregated into "Other".

Next we can look at at a map of AIS-based squid fishing effort (Figure 2.7), 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)).

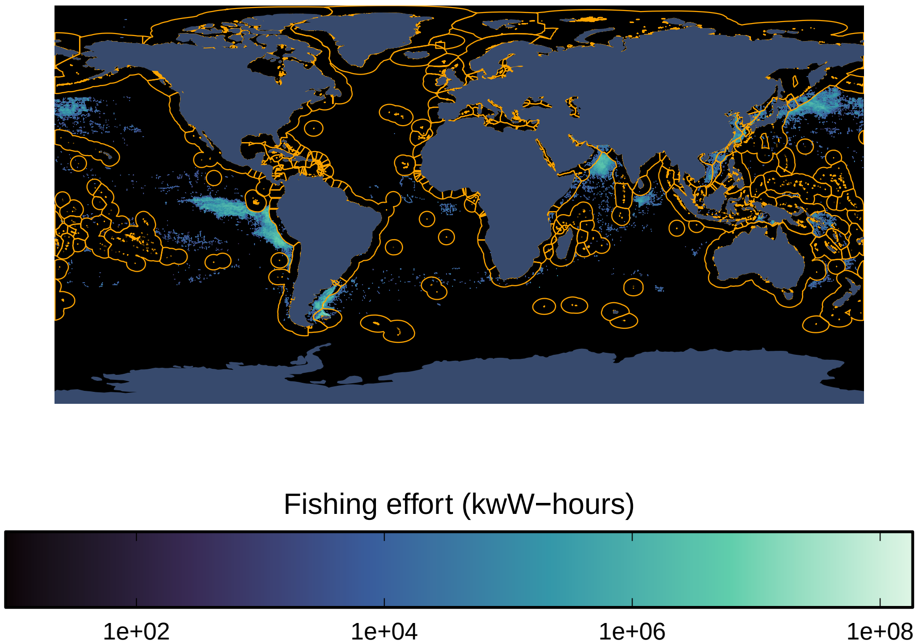
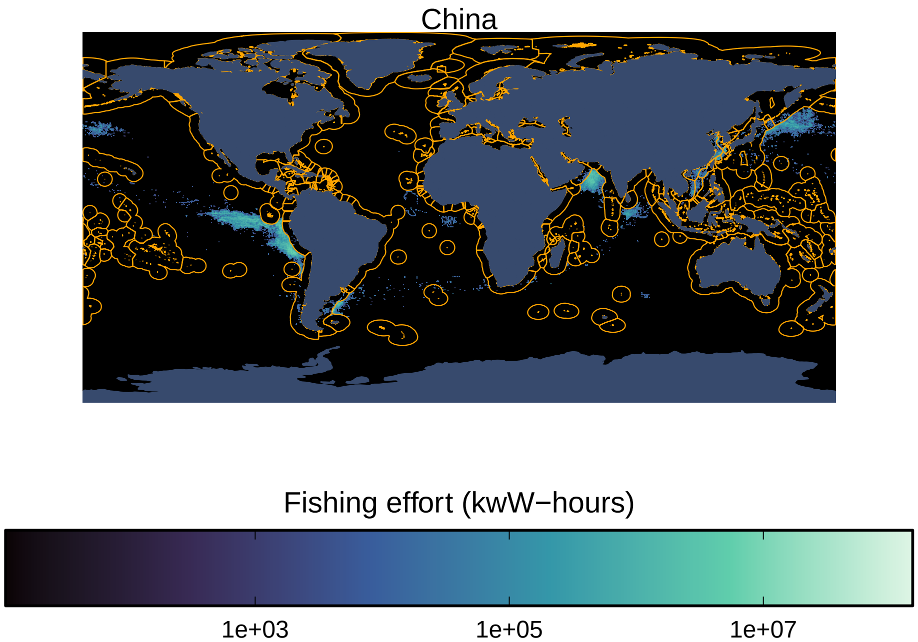


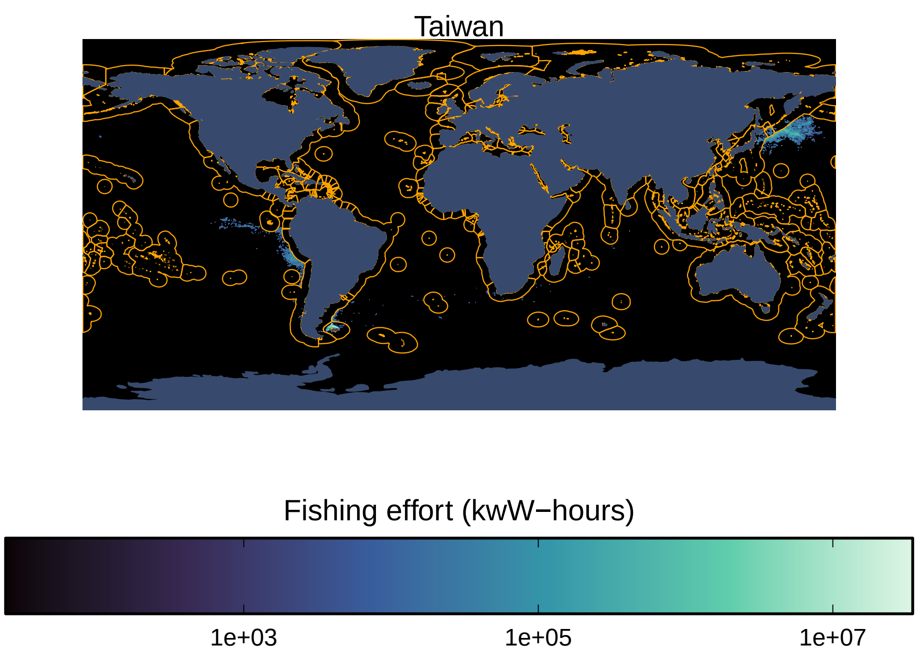
Figure 2.7: Map of squid jigger fishing effort from 2016 through August 2024, aggregating effort across effort, flags, and time for each pixel. EEZ boundaries from Marine Regions V12 are shown in orange.

We can also look at these 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 10 flags are shown individually, with all other flags aggregated into "Other".

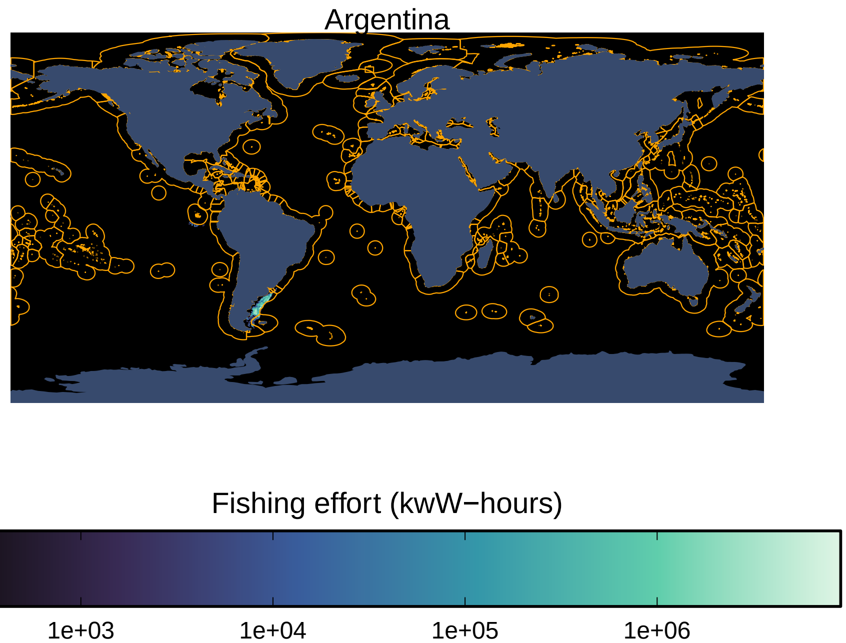
```
[[1]]
```


China
Fishing effort (kwW−hours)
1e+03
1e+05
1e+07

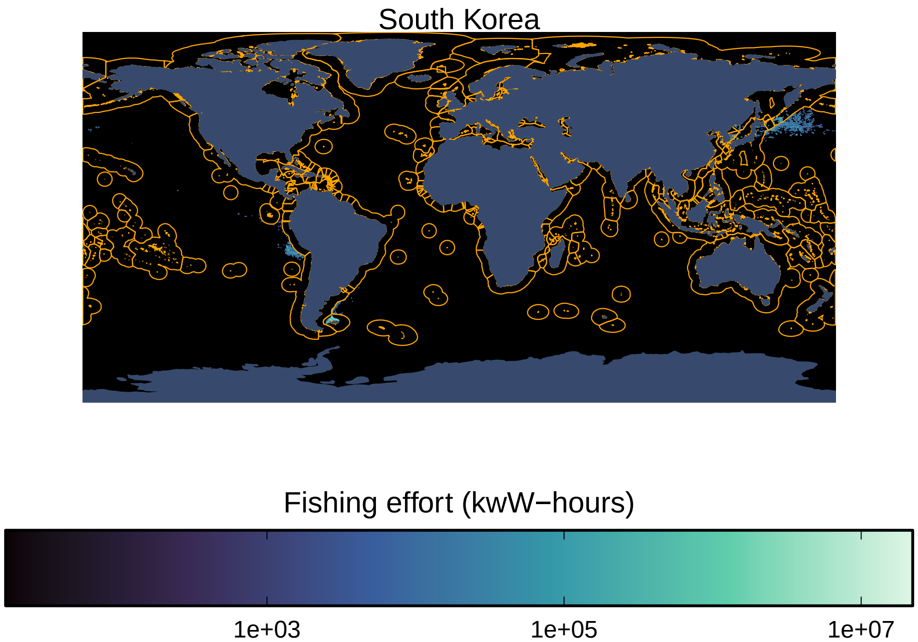
[[2]]


Taiwan
Fishing effort (kwW−hours)
1e+03
1e+05
1e+07

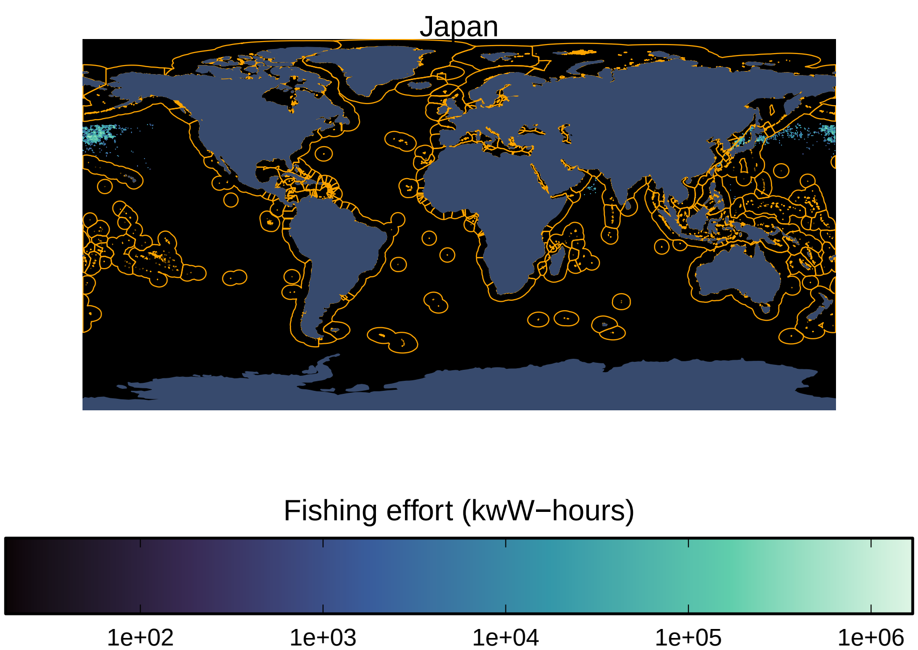
[[3]]



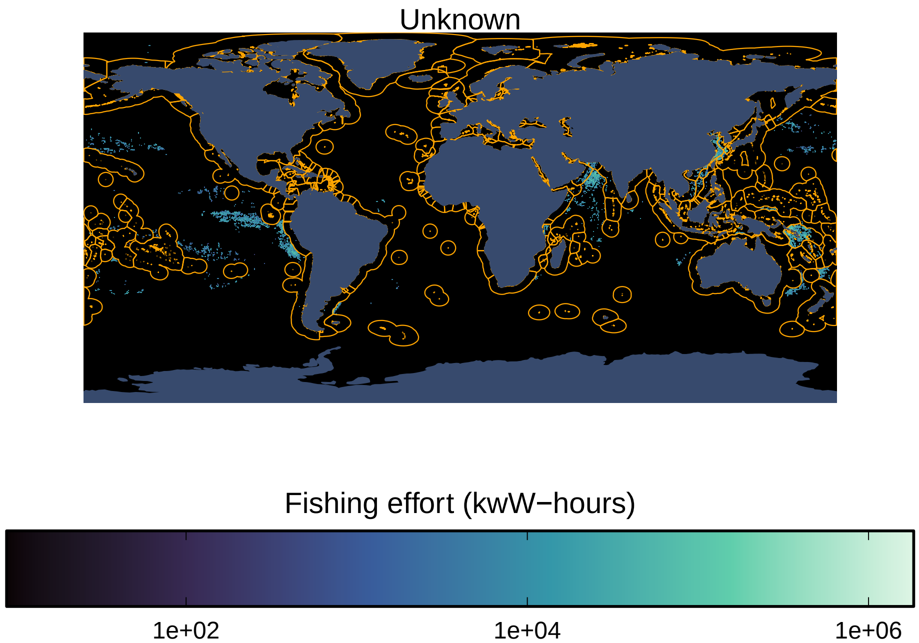
[[4]]


South Korea
Fishing effort (kwW−hours)
1e+03
1e+05
1e+07

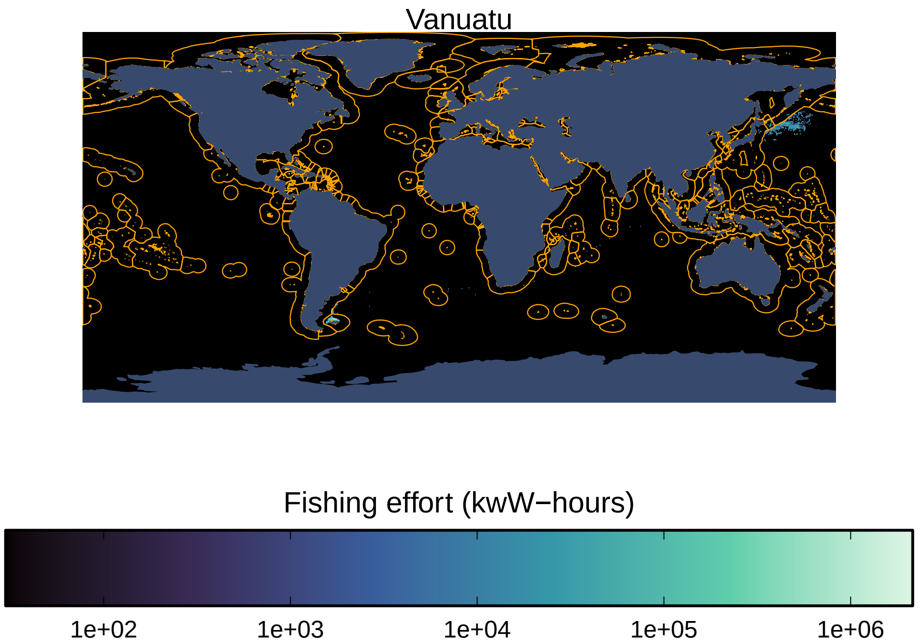
[[5]]


Japan
Fishing effort (kwW−hours)
1e+02
1e+03
1e+04
1e+05
1e+06

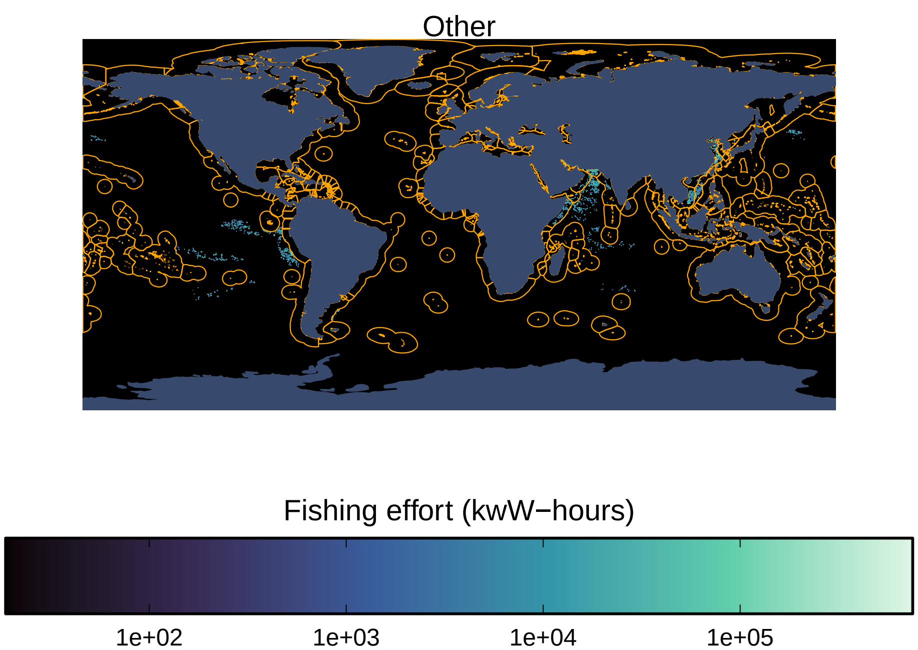
[[6]]



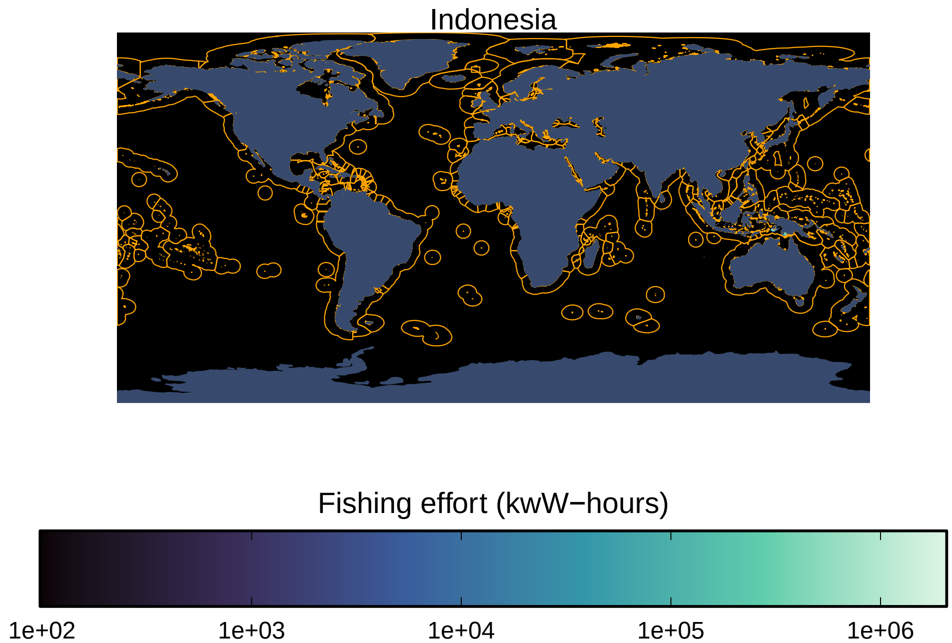
[[7]]


Vanuatu
Fishing effort (kwW−hours)
1e+02
1e+03
1e+04
1e+05
1e+06

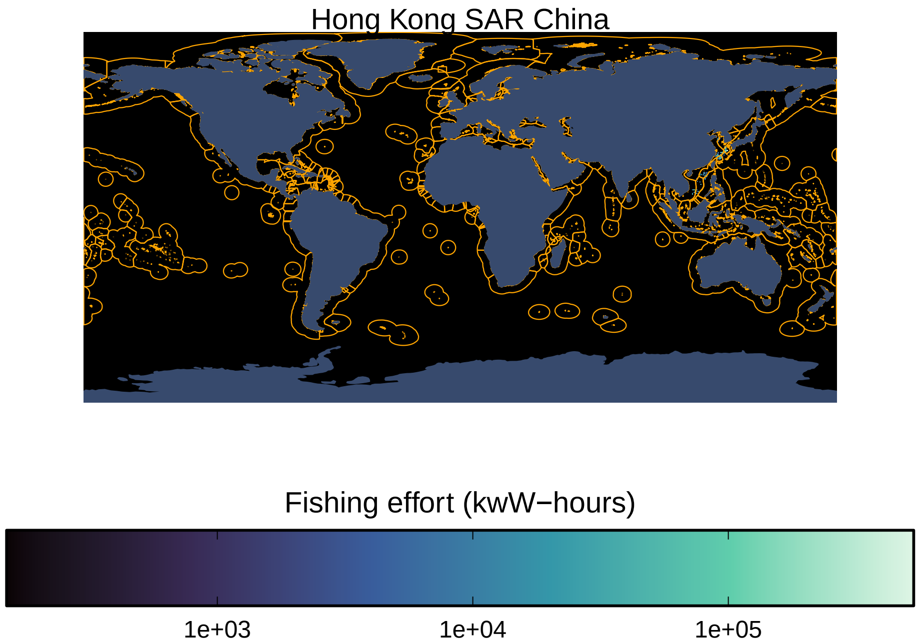
[[8]]


Other
Fishing effort (kwW−hours)
1e+02
1e+03
1e+04
1e+05

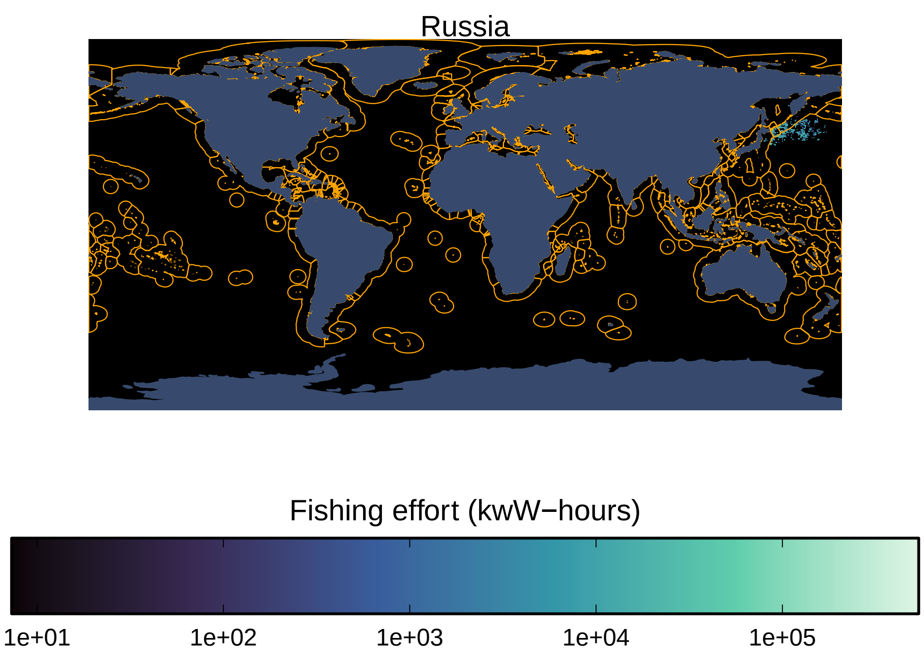
[[9]]


Indonesia
Fishing effort (kwW−hours)
1e+02
1e+03
1e+04
1e+05
1e+06

[[10]]


Hong Kong SAR China
Fishing effort (kwW−hours)
1e+03
1e+04
1e+05

[[11]]


Russia
Fishing effort (kwW−hours)
1e+01
1e+02
1e+03
1e+04
1e+05

2.5 VIIRS detections

First we look at a time series of monthly VIIRS detections globally (Figure 2.8). These can generally be thought of as representing light-luring squid vessels. Again we can see a clear seasonal pattern.

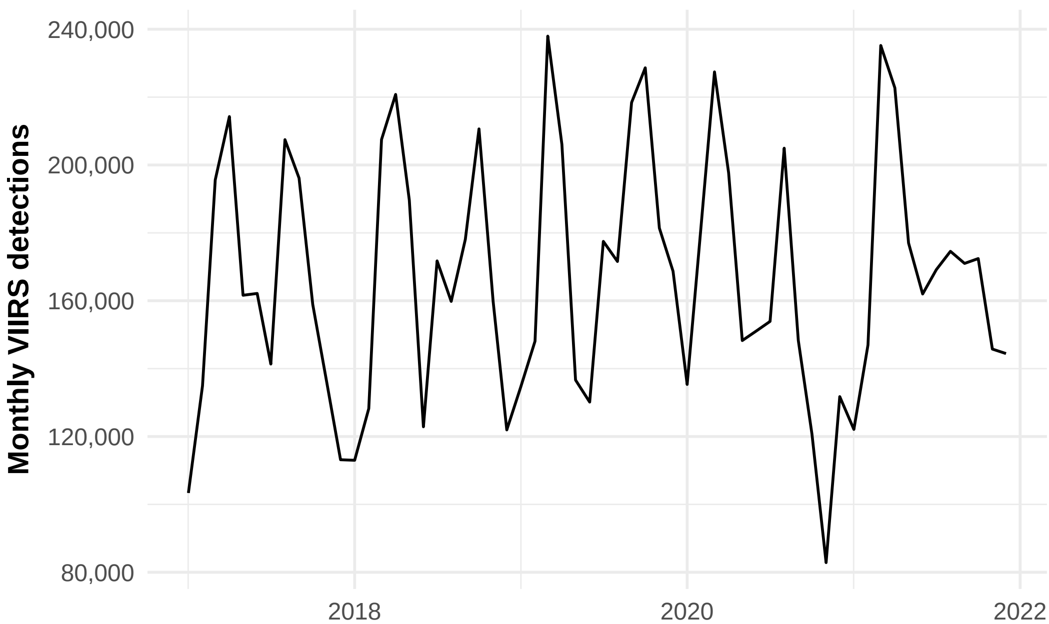


Figure 2.8: Monthly VIIRS detections.

Next we can look at at a map of these VIIRS detections (Figure 2.9), aggregating across time for each pixel across the entire processed time series (January 2017 through December 2021). The general spatial patterns seem to be consistent with those seen using AIS-based fishing effort data (Figure 2.7).

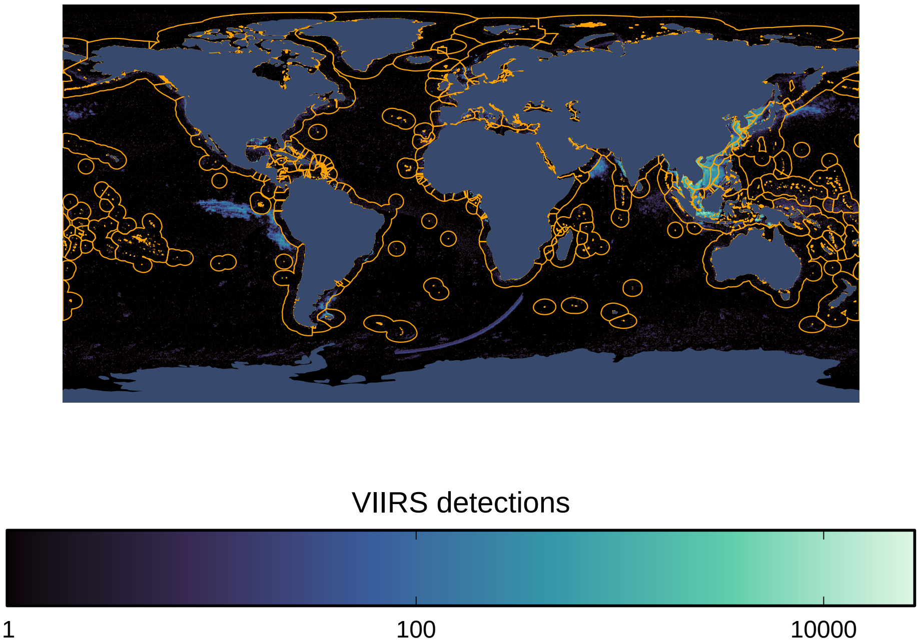


Figure 2.9: Map of VIIRS detections, aggregating across time for each pixel. EEZ boundaries from Marine Regions V12 are shown in orange.

2.6 Comparing AIS-based fishing effort and VIIRS detections

We first compare AIS-based fishing effort and VIIRS detections by looking at a time series of global total effort and detections (and only looking at those months that appear in both datasets) (Figure 2.10). Both datasets show a peak occurring in spring and a dip occurring in winter. They both also show a smaller peak occurring in fall, although this peak is much more pronounced in the VIIRS data.

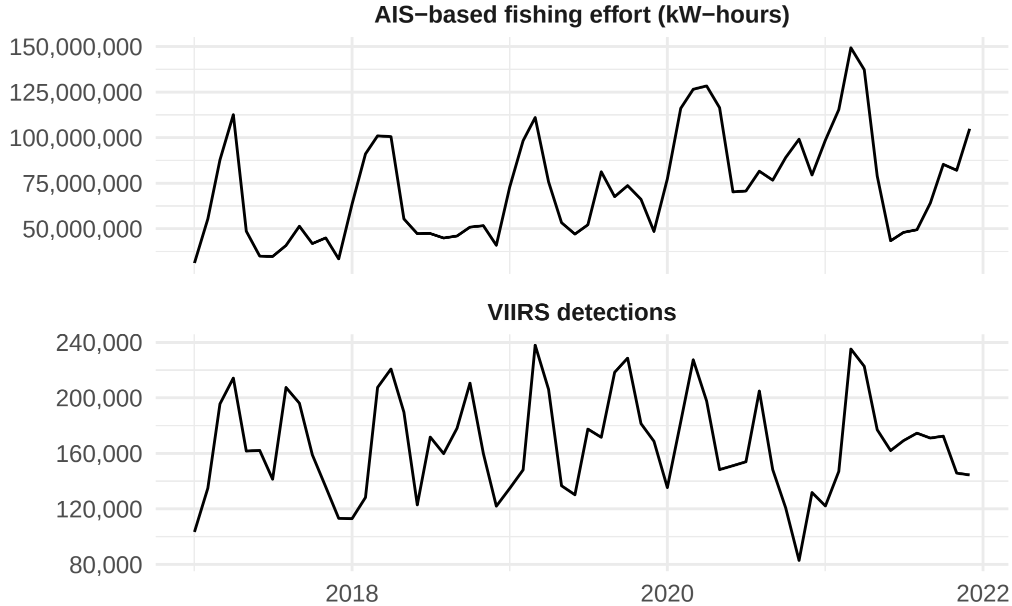


Figure 2.10: Comparison of monthly time series of AIS-based fishing effort and VIIRS detections.

We next compare the datasets by aggregating effort and detections across each month and pixel. There appears to be a generally strong relationship between the two, although there are many outliers that appear to have very low AIS-based fishing effort but actually have a very high number of VIIRS detections.

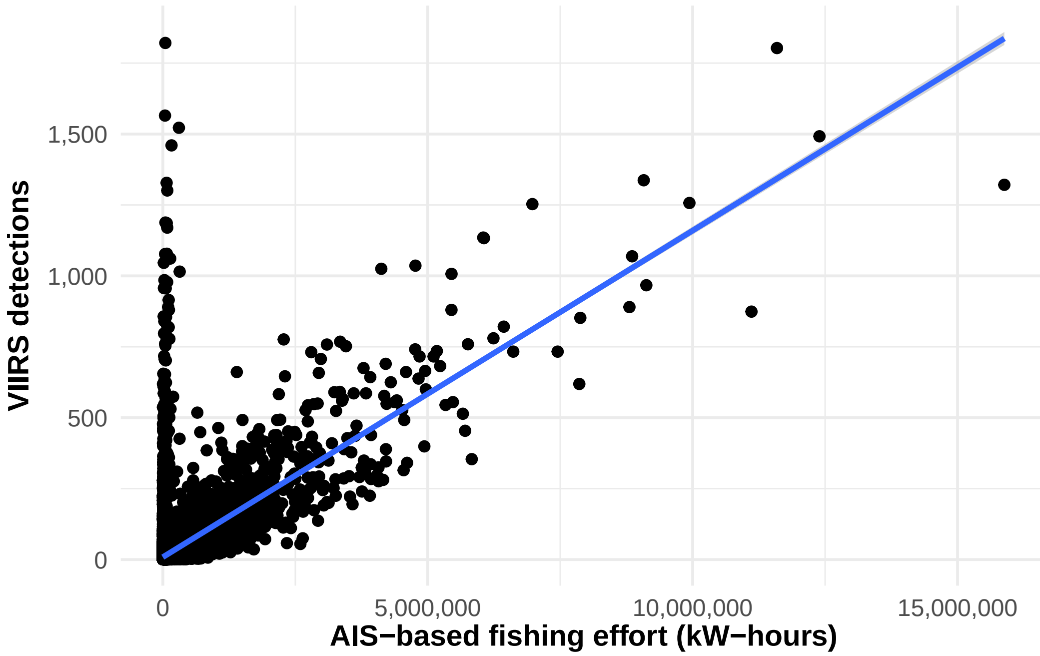


Figure 2.11: Comparison of AIS-based fishing effort (x-axis) and VIIRS detections (y-axis) for each pixel and month. A linear regression line fit is shown in blue.

We can fit a simple linear regression to VIIRS detections against fishing effort and look at the residuals (Figure 2.12). We see that the residuals are generally fairly evenly spaced around 0, although for very low AIS-based effort there are many very high residuals, indicating pixel-months that have much more VIIRS detections than expected.

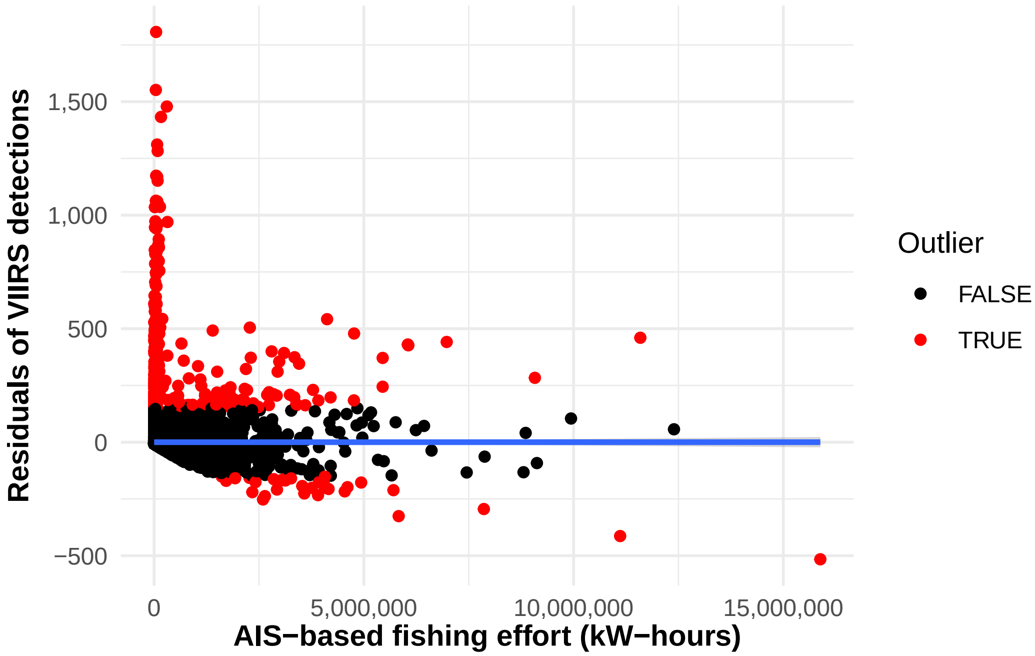


Figure 2.12: Residuals of VIIRS detections when regressed against AIS-based fishing effort. Points that fall outside of 3 standard deviations of residuals are marked in red.

3 Results

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