Quantifying Greenhouse Gas (GHG) Emissions Associated with Global Seafood Production

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1 About

Global fisheries are heavily reliant on fossil fuels, contributing significantly to the rise in global greenhouse gas (GHG) emissions driving climate change. While satellite technology is commonly used to monitor land-based emissions (and ocean-based emissions of shipping vessels), studies primarily estimating ocean-based emissions remain limited in the fishing sector. In collaboration with the Environmental Markets Lab (emLab) and Global Fishing Watch (GFW), this project leverages novel, high-resolution, satellite-based datasets to provide precise insights into the GHG emissions associated with global fisheries. We develop a reproducible, extensible, and open-source data processing pipeline to connect emissions data with seafood production data, along with an interactive dashboard to explore the resulting dataset. Our findings will enable novel research opportunities, offer actionable data to identify major GHG contributors, and facilitate new policy and market-based interventions to reduce fisheries-related emissions at scale.

This analysis was conducted as a part of UC Santa Barbara's Bren School of Environmental Science & Management Master of Environmental Data Science Capstone project.

1.1 Objectives

The primary objective of this project is to develop a reproducible pipeline to quantify GHG emissions associated with global seafood production, linking fishing vessel emissions data to species-specific FAO seafood production statistics. This dataset aims to provide emissions estimates for 9 GHG and non-GHG pollutants by FAO region, year, country, and species. Additionally, the project seeks to enhance the usability and accessibility of these data through an interactive dashboard, enabling targeted regulatory, policy, and market-based interventions to reduce the carbon footprint associated with global seafood production.

Products & Deliverables

- Emissions Processing Pipeline: Reproducible, extensible, and open-source data processing pipeline to estimate GHG emissions from global seafood production by harmonizing emLab's high-resolution vessel emissions data, including both AIS-broadcasting and non-broadcasting vessels, with FAO catch records.
- Seamissions Dashboard: Interactive public dashboard to visualize the relationships between GHG emissions and fishing vessel type, flag, catch species, and FAO region.

- Results Report: Comprehensive written assessment comparing the project's emissions estimates with existing published data.

1.2 Authors

We are a team of environmental data scientists working to quantify and demystify the emissions contributed through commercial fishing fleets.

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2 FAO Data Assembly

This chapter describes the process used to assemble FAO Seafood Catch data.

2.1 Datasets

FAO Global Capture Production data was downloaded as .csv files in a zipped folder. The following .csv files were used in this analysis:

- `Capture_Quantity.csv` (catch quantity)
- `CL_FI_COUNTRY_GROUPS.csv` (country information)
- `CL_FI_SPECIES_GROUPS.csv` (species information)

At the time of this analysis (Spring 2025), FAO data was only avaialable through 2022.

2.2 Packages

- {tidyverse}
- {janitor}

2.3 Methods

2.3.1 Remove non-target species

Prior to joining the .csv files, "PISCES", "CRUSTACEA", "MOLLUSCA", and "INVERTEBRATA AQUATICA" were filtered out of the major groups represented in the `CL_FI_SPECIES_GROUPS.csv`. Additionally, ISSCAAP group 82 (Corals) was removed. These species were assumed not to be the target species of the fishing gear types ("fishing", "squid_jigger", "drifting_longlines", "pole_and_line", "other_fishing", "trollers", "fixed_gear", "pots_and_traps", "set_longlines", "set_gillnets", "trawlers", "dredge_fishing", "seiners", "purse_seines", "tuna_purse_seines", "other_purse_seines", "other_seines", and "driftnets") represented in the broadcasting emissions dataset. This, however, does have implications for the non-broadcasting dataset (**see...**).

ISSCAAP groups 41 and 51, representing freshwater crustaceans and freshwater molluscs respectively, as well as the species "River eels", were filtered out because any emissions associated with freshwater collection are eliminated during the intersection of the FAO regions shapefile and the emissions grid. Therefore, it is assumed that none of the resulting emissions can be attributed to fishing for freshwater species.

2.3.2 Add species information

The analysis is conducted with species distinguished by a unique numeric code in the `identifier` column, and then additional species information is joined back to the final table. Species information was obtained from a modified version of the `data-keys/master_species_key.csv` created by Danielle Ferraro and Gordon Blasco and provided by emLab. Some species in the resulting FAO dataset were not represented in the master_species_key.csv, so the missing species were added from the `FAO CL_FI_SPECIES_GROUPS.csv`.

3 Merge Emissions Datasets

This chapter describes the process used to merge emissions datasets.

3.1 Datasets

Two emissions datasets, obtained from emLab, were used in this analysis:

- Broadcasting emissions: `meds_capstone_ais_emissions_data_v20241121.csv`
- Non-broadcasting emissions: `meds_capstone_non_broadcasting_emissions_data_v20250116.csv`

The data were pre-filtered by emLab from a larger emissions dataset to select for fishing vessels.

The following columns are required:

- `month`
- `flag`
- `vessel_class`
- `lon_bin`
- `lat_bin`
- `emissions_{pollutant}_mt`

define broadcasting vs. non-broadcasting?

3.2 Packages

- {tidyverse}
- {janitor}
- {lubridate}

3.3 Methods

3.3.1 Join Emissions Data

Emissions datasets (datasets 1 and 2 above) were read into the pipeline, the column names were converted to snake case, and a new `year-month` column was created for both datasets. In the broadcasting dataset, NA values in the `flag` column were filled with "UNK" to represent flag unknown, and `vessel_class` was filtered for gear types identified with a high degree of confidence (i.e. "squid_jigger", "drifting_longlines", "pole_and_line", "trollers", "pots_and_traps", "set_longlines", "set_gillnets", "trawlers", "dredge_fishing", "tuna_purse_seines", "other_purse_seines", "other_seines"). This eliminated gear types such as "passenger" that were likely mis-identified as "fishing" or as "passenger" by GFW's machine learning algorithm.

```
 [1] "trawlers"           "set_longlines"      "drifting_longlines"
 [4] "trollers"           "squid_jigger"       "pots_and_traps"
 [7] "other_seines"       "pole_and_line"      "other_purse_seines"
[10] "tuna_purse_seines"  "set_gillnets"       "dredge_fishing"
[13] NA
```

In the non-broadcasting dataset, emissions estimate columns for each of the 9 pollutants (CO2, CH4, N2O, NOX, SOX, CO, VOCS, PM2.5, PM10) are renamed to match the broadcasting dataset, and a `flag` column is created and populated with "DARK" to distinguish non-broadcasting emissions from the broadcasting emissions. Then, the datasets were concatenated.

A `year` column was created, and the combined dataset was filtered to 2016 and beyond to match the available data for the non-broadcasting dataset. Emissions estimates are then aggregated (summed) by year and flag for each one-by-one degree pixel (distinguished by `lat_bin` and `lon_bin`).

3.3.2 Assumptions

By filtering out certain gear types,... implications for non-broadcasting

4 Intersection by FAO Region

This chapter describes the process of spatially allocating emissions among FAO Major Fishing Area (Region).

4.1 Datasets

The following shapefile was downloaded from Marineregions.org:

- `World_Fao_Zones.dbf`
- `World_Fao_Zones.prj`
- `World_Fao_Zones.sbn`
- `World_Fao_Zones.shp`
- `World_Fao_Zones.shx`

4.2 Packages

- {tidyverse}
- {sf}

4.3 Methods

4.3.1 Intersection

Spatial attributes (points) were created for each `lat_bin` and `lon_bin` in the native WGS coordinate reference system (unit: degrees). An empty grid was generated from the point geometry, the emissions data were joined back to the empty grid, and the geodataframe was transformed to Equal Earth projection. Every grid cell was assigned a unique ID. Using the FAO shapefile (dataset 3), an intersection was run on the emissions grid cells to assign each to an FAO region. Some grid cells overlapped multiple regions, resulting in multipolygons for those grid cell IDs. Multipolygons were broken down into individual sub-polygons. The area was calculated for each sub-polygon, and the individual sub-polygon areas were summed for each grid cell ID.

4.3.2 Partition

Emissions from each grid cell ID were partitioned out based on the proportion of sub-polygon area to total grid cell area associated with each grid cell ID. The emissions partitioning was validated using a check to trigger a warning if more than 0.001% of emissions were lost in comparing the total emissions estimates before and after partitioning. Some emissions are expected to be lost due to floating point error and rounding, and 0.001% was arbitrarily selected as a threshold (though the actual number of lost emissions is likely much smaller).

4.3.3 Assumptions

This assumes a uniform distribution of emissions within the 1 x 1 degree pixel.

5 Emissions Allocation

This chapter describes the method used to allocate non-broadcasting emissions in order to link the emissions and seafood catch datasets.

5.1 Datasets

5.2 Packages

5.3 Methods

For each year, total **non-broadcasting** emissions were calculated for each FAO region and divided among *all* fisheries that reported catch in that region (proportionally by the weight of catch in each fishery). These partitioned non-broadcasting emissions were then join with the assigned broadcasting emissions.

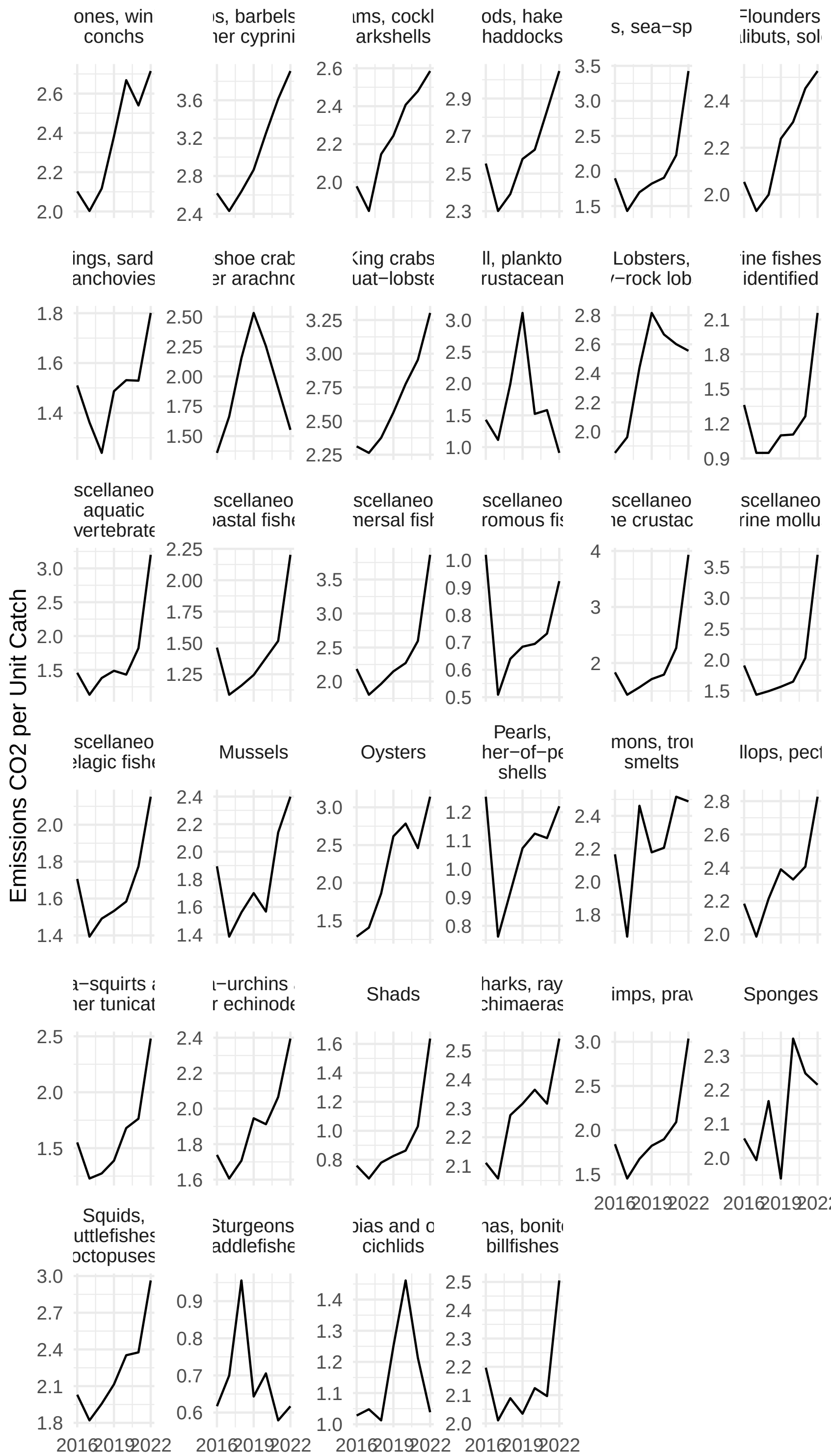
5.3.1 Assumptions:

Non-broadcasting emissions are partitioned out to FAO reporting fisheries (flag-species combinations) under the assumption that they are actively emitting in the region since they are reporting catch, but that they may not necessarily be using AIS on all (or any) of their fishing vessels. Additionally, this assumes that non-broadcasting emissions are directly proportional to the proportion of catch weight (in tons) by fishery (species-flag combo) and that the different gear types used to target the various fisheries have the same rate of emissions-per-unit-catch. For broadcasting emissions that are divided out proportionally among reported catch (by weight), we assume that all of a country's catch is reported and that emissions rates are the same for each species (when in reality, emissions estimates may vary the different gear types used to target individual fisheries).

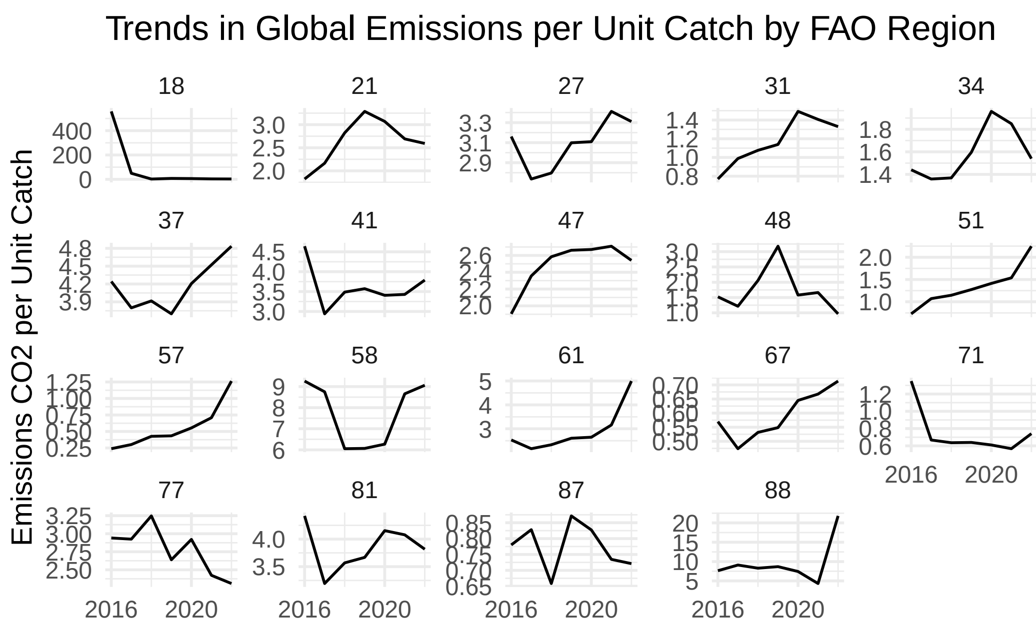
6 Results

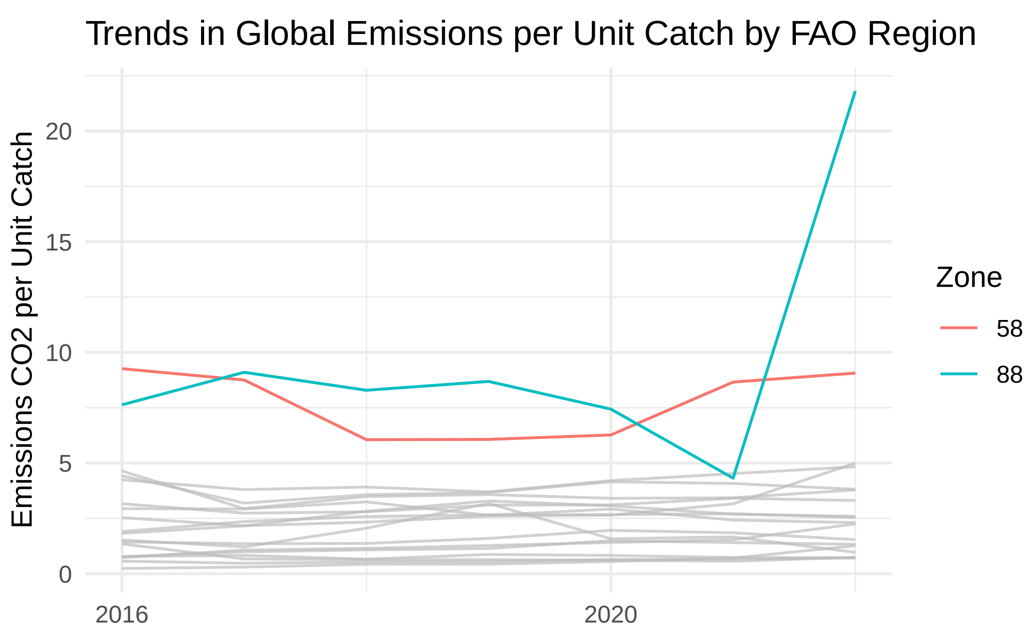
This chapter details the results from the primary analysis.

6.1 Trends in emissions-per-unit-catch by ISSCAAP species group



6.2 Trends in emissions-per-unit-catch by FAO region





6.3 Species Spotlight: Region 77 Salmons, Trouts, Smelts

7 SAU Validation

This chapter describes how we validated our findings by comparison with Sea Around Us catch data.

7.1 Datasets

Sea Around Us data was downloaded for each FAO Region (18, 21, 27, 31, 34, 37, 41, 47, 48, 51, 57, 58, 61, 67, 71, 77, 81, 87, and 88).

7.2 Packages

- {tidyverse}
- {janitor}

7.3 Methods

Sea Around US (SAU) data was prepped using the same methods as FAO catch data (see "FAO Data Assembly").

check that SAU doesn't contain mammals, plants, etc. *need to filter for human consumption and industrial*

7.4 Results

7.4.1 Overall Comparisons

```
[1] "FAO Catch Total: 329363271 MT."
```

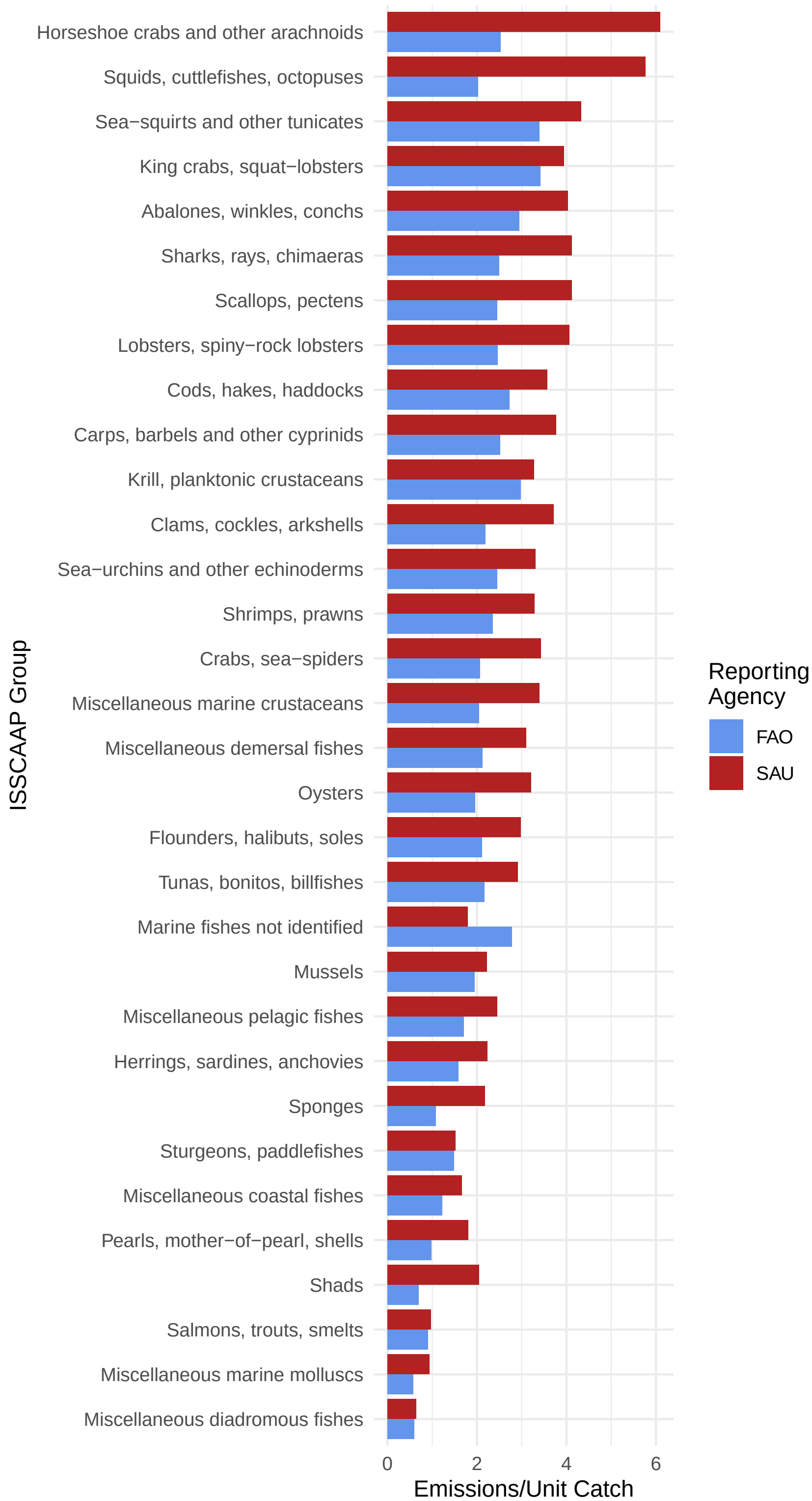
```
[1] "SAU Catch Total: 208274226 MT."
```

```
[1] "SAU reports -121089045 more MT of catch."

[1] "FAO emissions-per-unit-catch: 4.56."

[1] "SAU emissions-per-unit-catch: 7.21."
```

7.4.2 Comparisons by ISSCAAP Group



8 Flag ID

This chapter details the results of our flag analysis.

8.1 About

The following analysis looks into the relationship between a vessel's AIS-registered flag and its top-visited (home port) country using data from emLab and Global Fishing Watch.

8.2 Datasets

`meds_meds_capstone_annual_vessel_flag_country_emissions_v20241121.csv`

- `ssvid`: unique vessel ID
- `flag`: AIS-registered country
- `top_visited_country_iso3`: country the vessel visited the most number of times; home port
- `year`: year
- `emissions_co2_mt`: annual CO emissions (MT)

8.3 Packages

- {tidyverse}
- {kableExtra}

8.4 Methods

8.4.1 1. Full Dataset Mismatch

To give a high level sense of just how much of an issue flags of convenience could be, we assessed AIS-registered flag and top-visited country mismatch for the dataset as a whole.

Table 8.1: Flag Mismatch by Vessel

match	percent
FALSE	21
TRUE	75
NA	4

Table 8.2: Flag Mismatch by Emissions

Match	Percentage	Total
FALSE	71.13	6835022045
TRUE	28.56	2784977001
NA	0.30	29475094

To do this, we created a `match` column, populated with the following values:

- `TRUE`: match
- `FALSE`: mismatch
- `NA`: no value in AIS-flag, cannot determine.

8.4.2 2. Full Dataset Emissions

Next, we looked at how much emissions (MT), on aggregate, could be affected by this flagging issue. We summarized emissions by match (TRUE), mismatch (FALSE), and NA for each year and overall.

8.4.3 3. Overestimating Emissions

To quantify overestimation, or emissions attributed to a AIS-flag that visit different top-country, we assessed the fraction of emissions that end up in a different country (mismatch/FALSE) for each flag by year.

Ex. If for the flag of Panama (PAN) 75% of emissions are from vessels that have a different home port country, this could mean that we are *overestimating* emissions for Panama by upwards of 75% due to flagging issues.

8.4.4 4. Underestimating Emissions

To quantify underestimation, we assessed emissions for each top-visit country that come from a different AIS-flag.

Table 8.3: Overestimation of Emissions

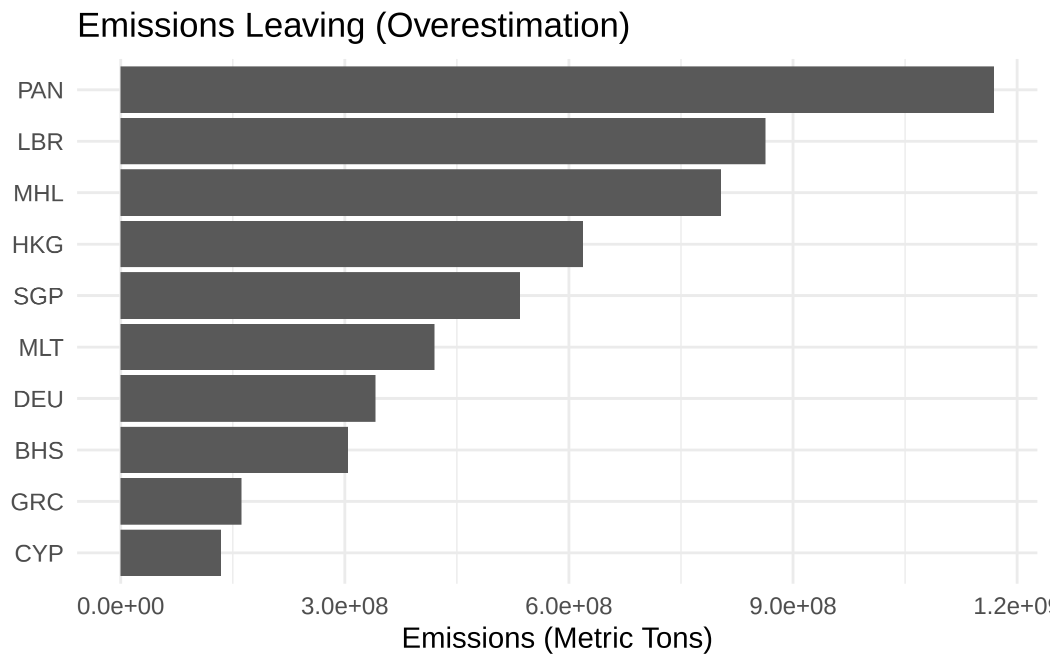
flag	total_emissions	percent_emissions_leaving_by_flag
PAN	1206570122	96.9
LBR	864314868	99.9
MHL	804641557	99.9
HKG	624671969	99.0
SGP	563593064	94.9
MLT	424942851	98.8
DEU	398070016	85.6
BHS	307567222	98.9
GRC	193952596	83.2
CYP	136205494	98.7

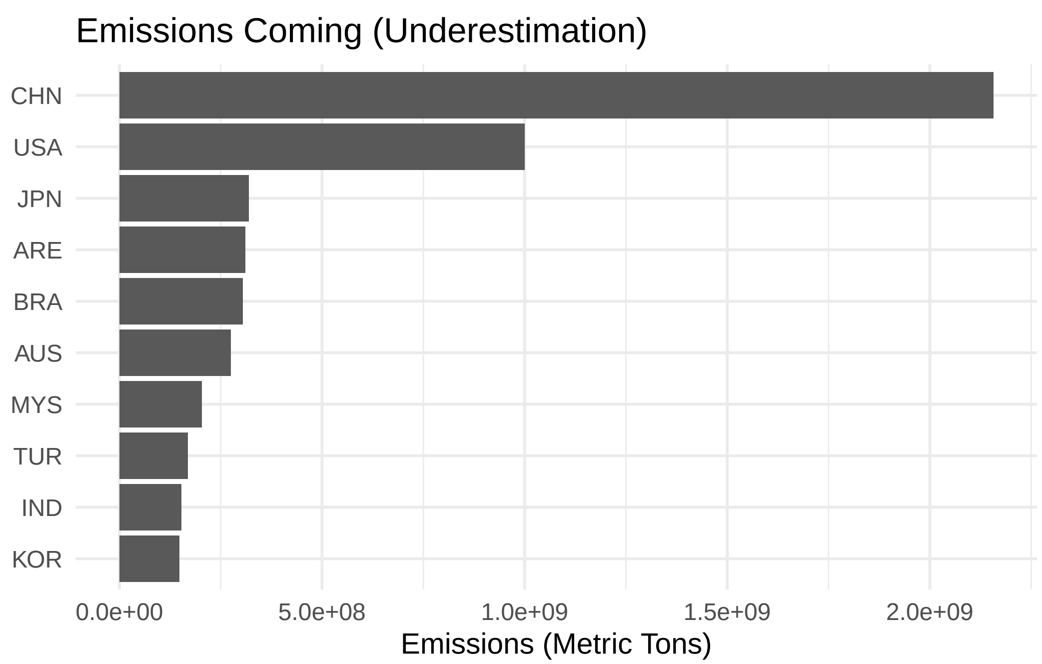
Table 8.4: Underestimation of Emissions

flag	total_emissions	percent_emissions_coming_by_flag
CHN	2873213170	75.0
USA	1263414706	79.1
JPN	576401931	55.3
ARE	319120513	97.2
BRA	331487795	91.7
AUS	329806075	83.2
MYS	232364455	87.3
TUR	246145472	68.5
IND	194510391	78.1
KOR	248005266	59.6

Ex. If for the country of China 25% of emissions are from vessels that have a different AIS-flag, this could mean that we are *underestimating* emissions for China by upwards of 25% due to flagging issues.

8.4.5 Visualize





8.4.6 Assumptions

Where top-visited country is NA, it was filled with AIS-flag value (assumes proper registration).

Vessels are assumed to land catch in their top-visited country, and that catch gets reported to the FAO by that country.

9 Comparison Report

This chapter is a comparison between historical estimates of global fishing emissions to those discovered by Global Fishing Watch (GFW) and emLab. There are two sections. The first is a report detailing what our team found during our project and comparing that to historic estimates, particularly the year 2016. The second works as living report that will automatically update as new data is uploading to the pipeline.

9.1 Report

9.1.1 Introduction

The carbon footprint of marine fisheries plays a crucial role in global ocean sustainability. Our study examines CO emissions from fishing activities, incorporating FAO data, Sea Around Us estimates, and original calculations derived from AIS and Sentinel-1 satellite data. By integrating satellite-based tracking, we aim to enhance emissions estimates, particularly for vessels that do not use AIS, which may have been underrepresented in previous assessments. This research builds upon previous studies, including Fuel Use and Greenhouse Gas Emissions of World Fisheries by Parker et al. (2018), which used a global fuel-based approach to estimate CO emissions, and Global Trends in Carbon Dioxide (CO) Emissions from Fuel Combustion in Marine Fisheries from 1950 to 2016 by Greer et al. (2018), which reconstructed effort-based emissions calculations. By incorporating an updated perspective that connects vessels to fishing based on tracking, our study provides a refined analysis of the emissions footprint of global fisheries

9.1.2 Background

The Sea Around Us study (Greer et al. 2018), estimated CO emissions from marine fisheries using a bottom-up reconstruction approach based on fishing effort data rather than reported catch alone. They did this based on:

- Fishing Effort Data - They reconstructed the number of fishing vessels per country, categorized by fleet type, gear, length class, and motorization. Engine capacity and days at sea were used to estimate total effort.

- Fuel Consumption Estimates – They calculated fuel use based on engine power (kW), fuel efficiency trends, and hours of engine operation per fishing trip.
- CO Emissions Calculation – They applied specific fuel consumption rates and emissions factors to estimate total CO emissions from fuel combustion.
- Comparison with Other Studies – Their estimates included both reported and unreported fisheries, leading to a higher total CO emissions figure compared to previous studies that relied on catch-based fuel use intensity.

The Fuel Use study (Parker et al., 2018) estimated CO emissions using a fuel-based approach rather than relying on catch data or reconstructed fishing effort. Here's how they did it:

- Global Fisheries Energy Use Database (FEUD) – They compiled data on fuel consumption from various fisheries worldwide, categorizing vessels based on gear type, species targeted, fleet characteristics, and region.
- Fishing Effort Data – They estimated fishing effort based on engine power (gross tonnage) and days at sea, using sources like FAO, the European Union, and regional tuna-management bodies.
- Fuel Use Intensity (FUI) – They assigned fuel consumption rates to different fisheries based on past case studies and adjusted them using weighted averages.
- CO Emissions Calculation – They applied fuel combustion emission factors and included non-fuel emissions such as vessel construction, refrigerant loss, and gear production to estimate total CO emissions.
- Comparison with Agriculture & Livestock – They contextualized fishery emissions by comparing them to emissions from land-based food production, highlighting the relatively lower carbon footprint of small pelagic fisheries compared to livestock.

9.1.3 Results

Comparing Global Trends in Carbon Dioxide (CO) Emissions from Fuel Combustion in Marine Fisheries from 1950 to 2016 by Greer et al. (2018) The Greer et al. (2018) study analyzed global CO emissions from small-scale and industrial fisheries between 1950 and 2016, using Sea Around Us catch and effort data to estimate emissions trends. Their findings showed that industrial fishing emitted 159 million tonnes of CO in 2016, a sharp increase from 39 million tonnes in 1950, while small-scale fisheries emitted 48 million tonnes, compared to 8 million tonnes in 1950. They also assessed emissions intensity, determining that industrial fishing produced 2.0 tCO tcatch−1, meaning 2 tonnes of CO were emitted for every 1 tonne of fish caught, whereas small-scale fisheries had an intensity of 1.8 tCO tcatch−1. In our study, we estimated total CO emissions from marine fisheries in 2016 at 146 million tonnes, about 9%

lower than industrial fishing, with an emissions intensity of 1.87 tCO tcatch−1 using FAO data, and 1.49 tCO tcatch−1 using Sea Around Us (SAU) data

These differences in emissions estimates and intensities likely arise from variations in data sources and methodology. We used FAO and SAU catch data but also incorporated AIS and Sentinel-1 satellite tracking, which allowed for more precise emissions estimates by identifying vessels that do not use AIS. This approach may have resulted in lower emissions intensity compared to the effort-based reconstruction used by Sea Around Us, which estimated fishing effort based on fleet characteristics rather than direct vessel tracking. Additionally, Sea Around Us separated industrial and small-scale fisheries, leading to higher total emissions estimates for industrial fleets, whereas we did not explicitly differentiate these categories in our analysis. The methodological differences in tracking fuel consumption also played a role, as Sea Around Us estimated fuel use based on engine power, efficiency trends, and fishing effort, which may have yielded a higher intensity figure for industrial fleets compared to our direct tracking approach.

Lastly, The Greer et al. (2018) study also compared total catch (tonnes) to total CO emissions from 1950-2011 as shown in Figure 2. (Greer et al., 2018). According to the study, the graph shows "CO emissions in both sectors continued to increase after the mid-1990s, despite declining global catches" (Greer et al., 2018)

Our study's analysis of Sea Around Us (SAU) catch data found a total global catch of 101,194,604 tonnes in its most recent year, 2019, compared to 108,000,000 tonnes in 2011 as reported by Greer et al. (2018). These numbers are even lower, 80,000,000 tonnes when looking at FAO catch. This decline aligns with the broader consensus that global fish catch has been decreasing since the late 1990s, when wild fish landings seem to have peaked. According to the Food and Agriculture Organization (FAO, 2024), total seafood production has increased due to aquaculture expansion, whereas wild capture fisheries have experienced stagnation or decline possibly due to factors such as overfishing, habitat degradation, and climate-related impacts. The lower catch estimate observed in our study supports the trend that many fisheries are struggling to maintain previous harvest levels, reinforcing concerns about the sustainability of marine resources.

In 2019, our analysis estimated 146 million tonnes of total emissions, whereas Greer et al. (2018) reported 159 million tonnes for the industrial sector alone. This discrepancy makes it difficult to determine whether emissions are genuinely rising or if the variation stems from differences in methodologies and underlying assumptions. Differences in data sources, estimation techniques, and classifications of fishing activity may contribute to these variations, highlighting the complexity of accurately assessing global emissions trends. Comparing Fuel Use and Greenhouse Gas Emissions of World Fisheries by Parker et al. (2018) Parker et al. (2018) estimated that global fishing fleets burned 40 billion liters of fuel in 2011, emitting 179 million tonnes of CO -equivalent (CO e) greenhouse gases into the atmosphere. Despite relatively stable fish landings, emissions from the industry increased by 28% between 1990 and 2011. Additionally, the study found that the average emissions per tonne of landed fish rose by 21%, reaching 2.2

Table 9.1: FAO Species Emissions Analysis

Year	Total CO2 MT	Total Catch (Tonnes)	Emissions per Catch	CO2 Percent Change	Catch Percent
2016	146238920	79,586,274	1.84	-	
2017	130148861	82,775,510	1.57	-11%	
2018	139017519	85,508,559	1.63	7%	
2019	145326671	81,492,928	1.78	5%	
2020	146114275	79,632,775	1.83	1%	
2021	158836613	81,612,999	1.95	9%	
2022	199511890	81,075,117	2.46	26%	
2023	223914218	0	Inf	12%	
2024	213189276	0	Inf	-5%	

tonnes CO e per tonne landed in 2011. The primary driver of this increase was the expansion of fuel-intensive crustacean fisheries, which had an emissions intensity of 7.9 tonnes CO e per tonne landed, significantly higher than small pelagic fisheries (0.2 tonnes CO e per tonne landed).

Our study does not extend back to 2011 but examines CO e emissions from 2016 to 2024 using 20-year Global Warming Potential (GWP) factors. We observed a notable 52.6% increase in emissions from 2016 to 2023, rising from 148 million tonnes CO e to 226 million tonnes CO e, a much steeper rate of increase compared to the 28% growth from 1990 to 2011 reported by Parker et al.

Furthermore, emissions per tonne of landed fish in our study increased from 1.86 tonnes CO e in 2016 to 2.47 tonnes CO e in 2022, representing a 32.8% increase over six years. This is based on FAO catch since SAU catch only ranges from 2016-2019. By 2022, our emissions intensity exceeded the 2011 global average of 2.2 tonnes CO e per tonne landed, highlighting a possible shift toward more fuel-intensive fishing methods, similar to trends observed in Parker et al.'s study. If this pattern persists, emissions from global fisheries could more than double by 2032, underscoring the urgent need for improved fuel efficiency and sustainable fishing practices to mitigate the environmental impact of the industry.

9.2 Future

9.2.1 What do emissions look like now?

10 Dashboard

This chapter describes how we built the Seamissions-Explorer dashboard.

11 References

11.1 Government and Organizational Reports

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