Transportation sector: Emissions From Non Broadcasting Vessels

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1. Introduction

Global Fishing Watch (GFW) and the Environmental Markets Lab (emLab) team at the University of California, Santa Barbara (UCSB) are contributing new information to the shipping sector emissions estimates, in collaboration with OceanMind. This work provides emissions estimates for all vessels, including estimates for vessels with low information availability, as well as an emissions reduction strategy focused on port loitering. There are two types of low information vessels: 1) vessels that transmit activity through the Automatic Identification System (AIS) but have little information publicly available on vessel characteristics such as size and engine power, and 2) vessels without detectable AIS signals, often called "dark" vessels because they are not detectable through traditional means of detection. At the time of this work, this is the first time that emissions have been estimated for the ocean-going dark fleet, allowing us to quantify a previously undisclosed source of emissions.

Please note that the methodology and results presented in this document represent emissions estimates based on the July 1, 2025 version of the model. The GFW and UCSB team are actively refining and improving the model's methodology and emissions estimates. To see the most up-to-date version of the methodology and results, and also to read in more detail about the methods and data, please refer to our GitHub notebook which we update regularly (please note that the methods and results in the GitHub notebook may be different than what are presented in this document, and should be considered preliminary and subject to change).

This methodology document presents a high level summary of the data used, methodology, and resulting greenhouse gas (GHG) and non-GHG air pollutant emissions estimates produced by the GFW and emLab team. OceanMind's methodology "*Domestic and International Shipping Emissions*", hosted in the Climate TRACE GitHub methodology repository, describes how results from each organization were integrated to produce the overall shipping sector emissions estimates. Furthermore, introduced in November 2025 by the Climate TRACE coalition, emissions reduction solutions (ERS) for each emitting sector. For shipping, loitering outside ports contributes to 'wasted' emissions was researched to understand ways to reduce emissions for this behavior. Additionally, how alternative fuels and energy sources can be employed to reduce shipping emissions. Refer to OceanMind's methodology for more information on the ERS applied to this sector.

2. Methodology

The following section describes the datasets and methodology used to estimate GHG emissions from the shipping industry. The methodology used in this work is presented in more detail in [*Quantifying Ocean-based Greenhouse Gas Emissions*](#) (2025). The methodology is presented in two parts (and visualized in Figure 1): 1. the AIS-based emissions model and 2. the "dark" vessels emissions model which uses Sentinel-1 synthetic aperture radar imagery to identify these vessels.

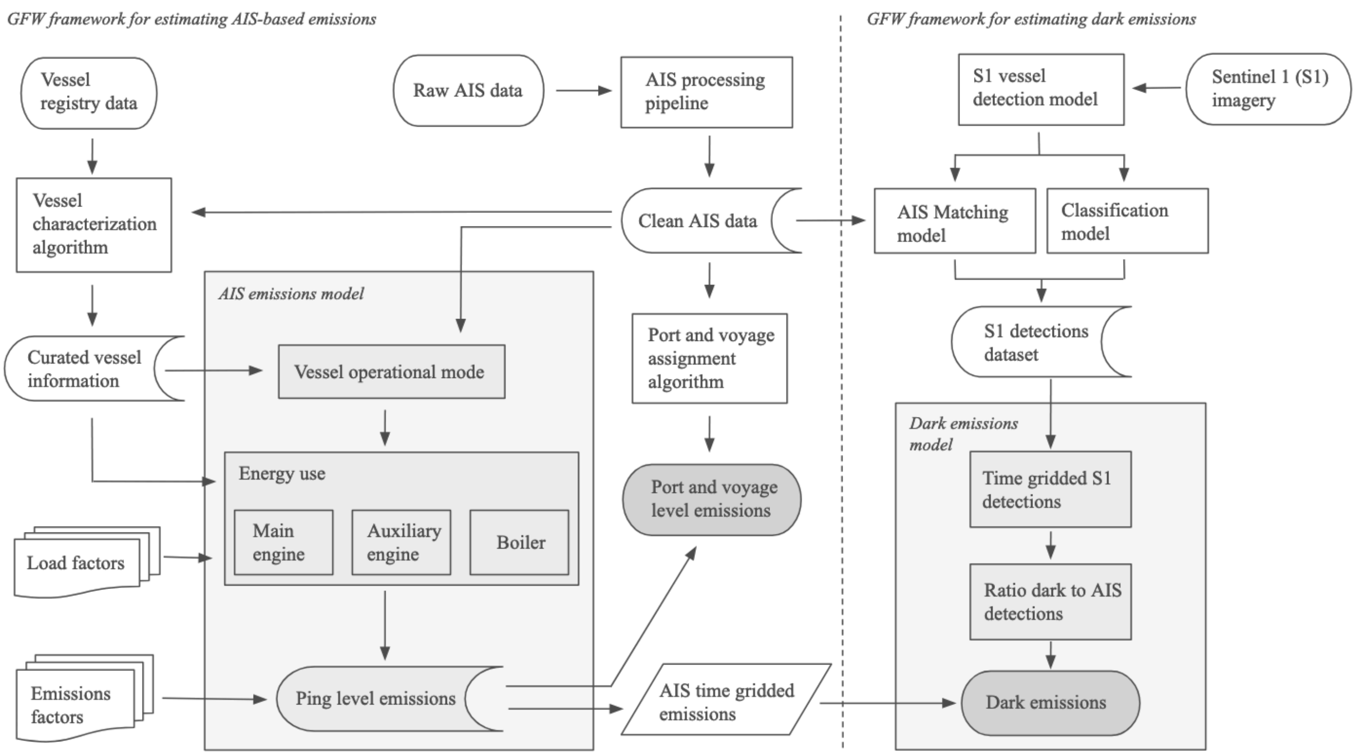

Figure 1. GFW framework for estimating emissions using the AIS-based emissions model and the dark vessel emissions model.

2.1 AIS-based emissions model description

The methodology uses an engineering bottom-up approach, based on vessel activity data from ships' automatic identification system (AIS), which is required as a safety feature for most large vessels. Compliance issues and inadequate message reception can limit the availability of AIS data on vessel activity. Models also rely on vessel characteristic information, such as vessel type and main engine power, which is obtained from a variety of sources (see notebook), and a range of emission factors. Here we describe the model, how it is applied to GFW activity and vessel characteristics data, and any deviations made from the published methodologies. This approach closely follows the methodology described in the 2020 International Maritime Organization's

(IMO) “Fourth Greenhouse Gas Study” (Faber et al. 2020) and the 2017 ICCT “Greenhouse Gas Emissions From Global Shipping” study (Olmer et al. 2017). Here, in overview, is how emissions using AIS data, where available, are calculated:

1. For each individual AIS message (i.e., each ping that broadcasts the vessel’s location, identity information, and a timestamp), we calculate the main engine power use and auxiliary engine power use for the time elapsed since the previous ping.
2. Using emissions factors (EFs) for main, auxiliary, and boiler engines for seven pollutants, including carbon dioxide (CO_2), methane (CH_4), nitrogen oxides (NOx), sulfur oxides (SOx), carbon monoxide (CO), nitrous oxide (N_2O), particulate matter (PM), and volatile organic compounds (VOC) we calculate the estimated emissions of each pollutant for each AIS ping for the main, auxiliary, and boiler engines. Emissions factors are corrected for reduced engine efficiency and increased emissions at low main engine loads, and lower sulfur fuel required by regulations after Jan. 1, 2020.
3. For each pollutant and each AIS ping, we sum the emissions estimate across the main, auxiliary, and boiler engines.
4. With ping-level estimated emissions, we are then able to aggregate emissions estimates by vessel, by voyage, by port visit, by time, by space, etc.

These data are then delivered to OceanMind to be directly integrated into their dataset before final delivery to Climate TRACE.

2.2 AIS-based emissions model data

2.2.1 Individual AIS messages

For AIS data, GFW relies on an automated process for parsing, cleaning, augmenting, and publishing of raw AIS data (Kroodsma et al. 2018). This process provides data from 2015 to present. We currently leverage the most advanced V3 version of GFW data processing pipeline from August 2024 (GFW 2024). Using these data as our starting point, we are able to estimate emissions from all analyzed pollutants for every single AIS message. These ping-level emissions can then later be aggregated as desired (e.g., by vessel, by voyage, by destination or arrival port, by time, by space, etc.).

2.2.2 Vessel characteristics

GFW has a comprehensive vessel characteristics database. These data were used by the IMO in their 4th GHG Study (Olmer et al. 2018). The GFW vessel database provides metadata for all vessels detected by GFW. The information for each vessel is based on: 1) data purchased from S&P Global; 2) where S&P Global data are not available, official registry information when available (Park et al. 2023); or 3) algorithm-derived vessel characteristics such as vessel class, engine power, maximum speed, and gross tonnage, when S&P or registry data are not available (Kroodsma et al. 2018). The GFW vessel characteristics database leverages extensive work that has been done to scrape and aggregate many publicly available vessel registries (Park et al. 2023). We are currently using a cutting edge version of this database, which uses a new random forest algorithm for inferring certain vessel characteristics when they are not available in S&P data or official vessel registries (vessel type, main engine power, maximum speed, length, and gross tonnage).

2.2.3 Voyages and port stays

GFW also produces a dataset that contains information for port-to-port voyages made by vessels. This table leverages extensive work done by the GFW team to: 1) define ports, 2) determine when vessels arrive at or depart from a port, 3) determine port stays that are defined as the period between a port arrival and port departure, and 4) determine voyages that are defined by a port departure and a port arrival (Global Fishing Watch 2021). From 2015-01-01 to 2025-06-30, we have 109,617,280 unique port visits across 835,196 unique vessels. These port visit trips occurred in 14,431 unique ports across 209 unique countries.

2.3 Dark fleet emissions model

We have developed a new model to estimate emissions from so-called "dark" vessels that do not broadcast AIS signals, and therefore are not captured in AIS-based datasets (Rowlands et al. 2019). These vessels have not been included in previous shipping emissions estimates, including Climate TRACE's database, and their activity and emissions are now revealed with this new model. The dark vessel model uses Sentinel-1 (S1) synthetic aperture radar (SAR) data to estimate emissions. S1 carries a microwave SAR instrument to provide an all-weather, day-and-night supply of imagery of the entire Earth's surface every 12 days. S1 can detect vessels using SAR, as it is sensitive to the metal/side of the ship and creates a right angle to the water. No vessel AIS broadcasting is required for detection. The full methodology used in this dark vessel emissions model is presented in detail in the GitHub notebook in this section.

To estimate emissions from the dark fleet, we spatiotemporally extrapolated our AIS-based emissions estimates to the dark fleet based on spatiotemporal vessel detections from S1. For every S1 detection, GFW has determined whether or not the vessel is matched to an AIS vessel that was broadcasting at the same location and time, allowing us to determine the number of broadcasting and non-broadcasting (i.e., dark) vessels in a given location and time. We are also able to make this extrapolation disaggregated by vessel type and size, since the GFW S1 model can determine if each dark fleet detection is a fishing or non-fishing vessel, and can also estimate the length of the detected vessel.

Our approach for estimating emissions from the dark fleet are as follows (see Figure 2 below for a visual):

1. Grid the ocean to 1x1 degree pixels.
2. Use a monthly temporal aggregation unit.

3. For each vessel type (fishing and non-fishing), use length percentiles from the distribution of S1 vessel detections to bin vessels into one of ten size classes.
4. For each 1x1 degree pixel, month, vessel type (fishing or non-fishing), and vessel size class, use our AIS-based emissions model to determine the amount of AIS-based emissions for each pollutant (CO_2, CH_4, N_2O, NOX, SOX, CO, PM, VOC).
5. For each 1x1 degree pixel, month, vessel type, and vessel size class, S1 data was used to determine: 1) the number vessel detections that are matched to an AIS-broadcasting vessel, 2) the number vessel detections that are not matched to an AIS-broadcasting vessel (i.e., the number of dark vessels), and 3) the ratio of dark vessels to AIS-broadcasting vessels.
6. S1 does not map the entire ocean globally, so for each vessel type and size class we can also calculate the monthly ratio of dark vessels to AIS-broadcasting vessels. Using an optimized k-nearest-neighbor value of k (8), the dark-to-broadcasting ratios inside and outside the S1 footprint are used to spatially extrapolate to all locations not covered by S1 in a given month;
7. Using the ratios generated in Steps 5-6, we multiply our AIS-based emissions estimates by the ratio of dark vessels to AIS-broadcasting vessels, for each pollutant by month and pixel location. We use a hierarchy for which ratio to use: 1) monthly pixel-level if available; 2) monthly global ratio pixel-level ratio if 1) is not available.
8. This then gives us, for every month and location for which we have AIS-based emissions estimates, corresponding dark fleet estimates. Adding these two numbers together gives us monthly gridded total emissions estimates from across the AIS-broadcasting and dark fleets.

As an example, we can look at a hypothetical 1x1 degree pixel, in a hypothetical month, representing the S1 detections corresponding to a specific vessel size bin (Figure 2). We can see detections for fishing vessels and non-fishing vessels (e.g., cargos, tankers, etc). First, we consider fishing vessels (left panel). Here we can see that S1 had 2 detections that we were able to match to AIS-broadcasting vessels, and 8 detections which were unmatched (e.g., these are from non-broadcasting vessels). Therefore, the ratio of dark-to-broadcasting vessels is 8/2 = 4. For this pixel, month, vessel type, and size bin, we would therefore take our AIS-broadcasting emissions and multiply it by 4 to obtain our non-broadcasting emissions estimate. If our observed AIS-broadcasting emissions for fishing vessels was 5 metric tonnes of CO_2, our non-broadcasting emissions would be 5*4 = 20 metric tonnes of CO_2. This calculation is done for each of the nine pollutants.

Next, we consider non-fishing vessels (FIgure 2, right panel). Here we can see that S1 had 15 detections that we were able to match to AIS-broadcasting vessels, and 5 detections which were unmatched (e.g., these are from non-broadcasting vessels). Therefore, the ratio of dark-to-broadcasting vessels is 5/15 = 0.33. For this pixel, month, size bin, we would therefore take our AIS-broadcasting emissions and multiply it by 0.33 to obtain our non-broadcasting emissions estimate. If our observed AIS-broadcasting emissions were 45 metric tonnes of CO_2 for non-fishing vessels, our non-broadcasting emissions would be 45*0.33 = 15 metric tonnes of CO_2. This calculation is done for each of the nine pollutants.

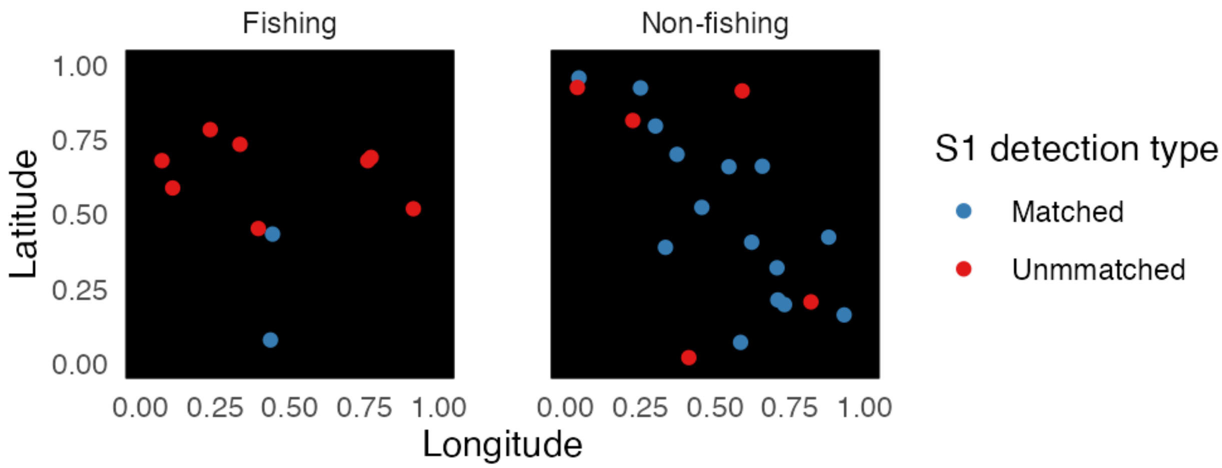

Figure 2: Hypothetical example showing the Sentinel-1 detections in a given 1x1 degree pixel, month, and for a vessel size bin, disaggregated by vessel type (fishing or non-fishing). For fishing vessels, we observe 2 matched detections, 8 unmatched detections, and therefore have a dark-to-broadcasting ratio of 8/2=4. For nonfishing vessels, we observe 15 matched detections, 5 unmatched detections, and therefore have a dark-to-broadcasting ratio of 5/15=0.33.

These data are shared directly with Climate TRACE as a single global non-broadcasting emissions estimate for each of our nine pollutants (unlike our AIS-broadcasting emissions estimates, which are first delivered to OM, who combines our estimates with theirs before delivering the final AIS-broadcasting emissions estimates to CT).

2.4 Dark fleet data

To identify the dark, non-broadcasting vessels, we used the European Space Agency (ESA) Copernicus Sentinel-1 SAR satellites (Paolo, et al. 2024). The images are sourced from two satellites (S1A and, formerly, S1B, which stopped operating in December 2021) that orbit 180° out of phase with each other in a polar, sun-synchronous orbit. Each satellite has a repeat cycle of 12 days, so that—together—they provide a global mapping of coastal waters around the world approximately every 6 days. The number of images per location, however, varies greatly depending on mission priorities, latitude and degree of overlap between adjacent satellite passes.

2.5 Emissions Reduction Strategy

The emissions reduction strategy for this sector is focused on port loitering activities and the potential emissions benefits derived from "Just in Time Arrivals", which could decrease global emissions by as much as 5%. See OceanMind methodology for more information.

3. Results

Detailed results are presented in the GitHub notebook. An overview of our results is presented below.

3.1 AIS emissions model validation

To validate the model used to estimate emissions from AIS-broadcasting vessels, we used the CO_2 emissions data from maritime transport provided by the European Maritime Safety Agency (EMSA 2025), which is part of the monitoring, reporting, and verification program of carbon emissions from maritime transport, set by the Regulation (EU) 2015/757. Vessels with certain characteristics and certain trips made by such vessels operating in the sea ports of the European Economic Area (EEA), must report their emissions on an annual basis. Our model generally aligned with the voyage-level EU validation data, achieving an R^2 of 0.8. Validation results from the EU data are presented in more detail in the GitHub notebook in this section.

3.2 Dark fleet emissions model validation

There is not an existing validation dataset for measured emissions from the dark fleet (i.e., those vessels that do not use AIS). However, using AIS data, we run simulations to attempt to assess the likely performance of the S1 dark fleet emissions model. More details can be found in the GitHub notebook. Generally, model performance is quite high (0.98 R^2).

3.3 AIS-broadcasting fleet time series trend

First, we look at the total global number of active vessels that are detected broadcasting AIS for which we estimate emissions, per year from 2015-2024 (corresponding to GitHub notebook figure 1.9 and table 1.8).

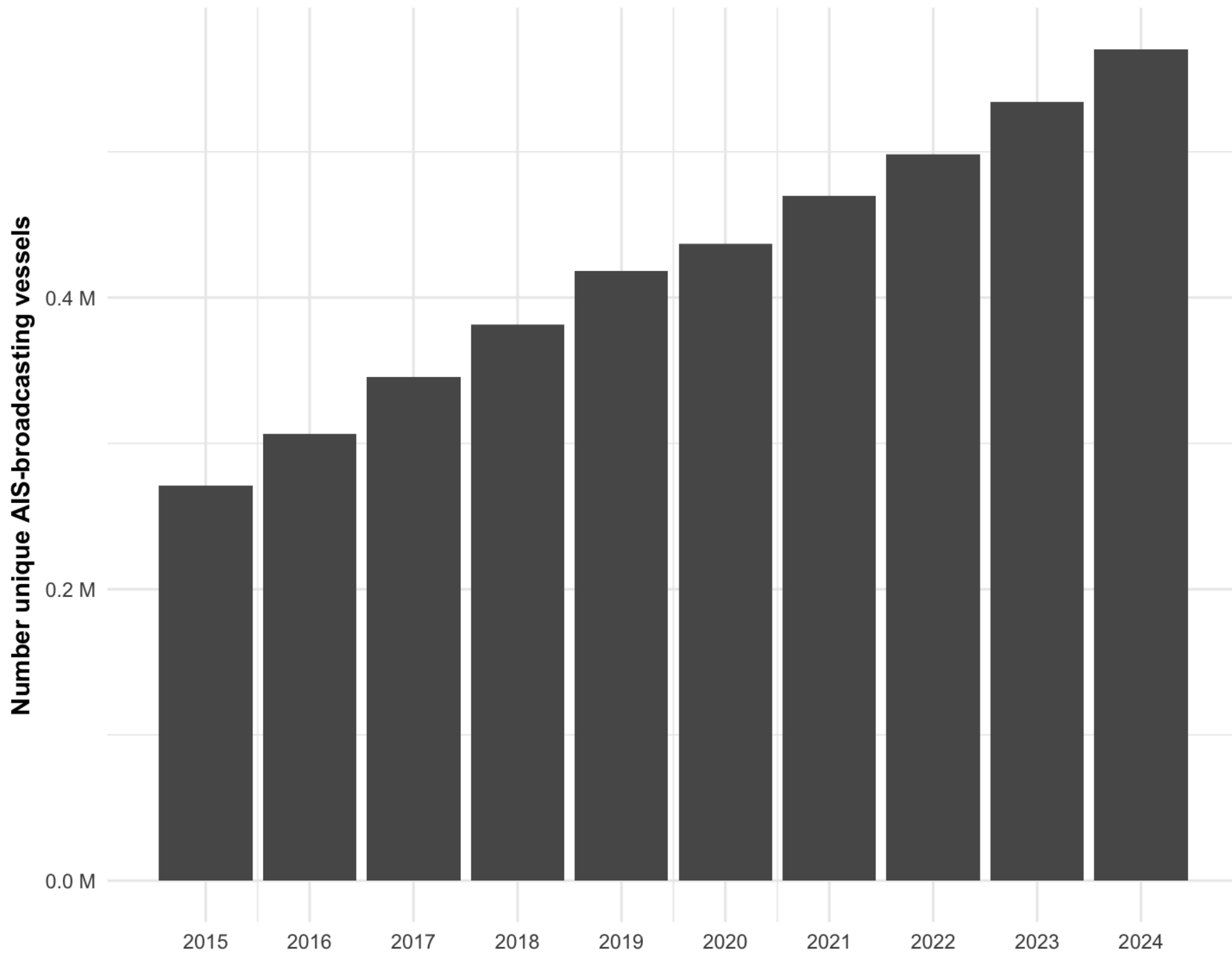

Figure 3. Total number of AIS-broadcasting vessels, by year, for which we estimate emissions.

Next, we look at total annual global emissions (metric tonnes, MT) for each pollutant from 2015-2024 (corresponding to GitHub notebook figure 1.12 and table 1.11).

Table 1. Summary of total global annual emissions estimates (MT) by pollutant.

year	CO2	NOX	SOX	CH4	CO	N2O	PM	PM10	PM2_5	VOCS
2015	718,722,836	12,625,854	4,449,919	11,869	591,766	35,229	653,820	1,330,165	1,223,017	809,033
2016	780,889,103	13,573,763	4,833,909	12,720	635,914	38,215	704,985	1,442,282	1,326,103	874,026
2017	846,501,499	14,529,395	5,238,889	13,572	680,694	41,352	757,432	1,560,024	1,434,361	941,607

year	CO2	NOX	SOX	CH4	CO	N2O	PM	PM10	PM2_5	VOCS
2018	876,809,809	14,897,047	5,425,214	14,011	701,399	42,854	780,849	1,618,553	1,488,175	979,887
2019	899,209,924	15,139,576	5,562,484	14,423	718,367	44,028	798,821	1,666,298	1,532,073	1,015,842
2020	889,302,629	14,816,298	1,099,983	14,223	706,586	43,569	161,981	340,080	312,686	1,009,692
2021	965,566,238	15,989,880	1,194,266	15,130	757,245	47,143	174,550	367,212	337,632	1,079,482
2022	1,038,855,368	17,138,169	1,284,752	16,388	817,252	50,812	187,859	396,442	364,507	1,172,586
2023	1,085,212,897	18,017,603	1,342,122	17,532	866,996	53,299	197,934	416,908	383,325	1,247,819
2024	1,167,605,666	19,156,424	1,443,761	18,503	920,275	57,199	210,961	446,935	410,933	1,329,062

3.4 Estimates with dark fleet emissions included

Total annual global emissions for each pollutant over time for all detected vessels, including AIS detections and S1 dark fleet detections are shown in Figure 4, (corresponding to GitHub notebook figure 3.4 and table 3.2). We observe an increase in total emissions over time, as shown by the sum of emissions for AIS-detected vessels and dark vessels detected only by S1 SAR.

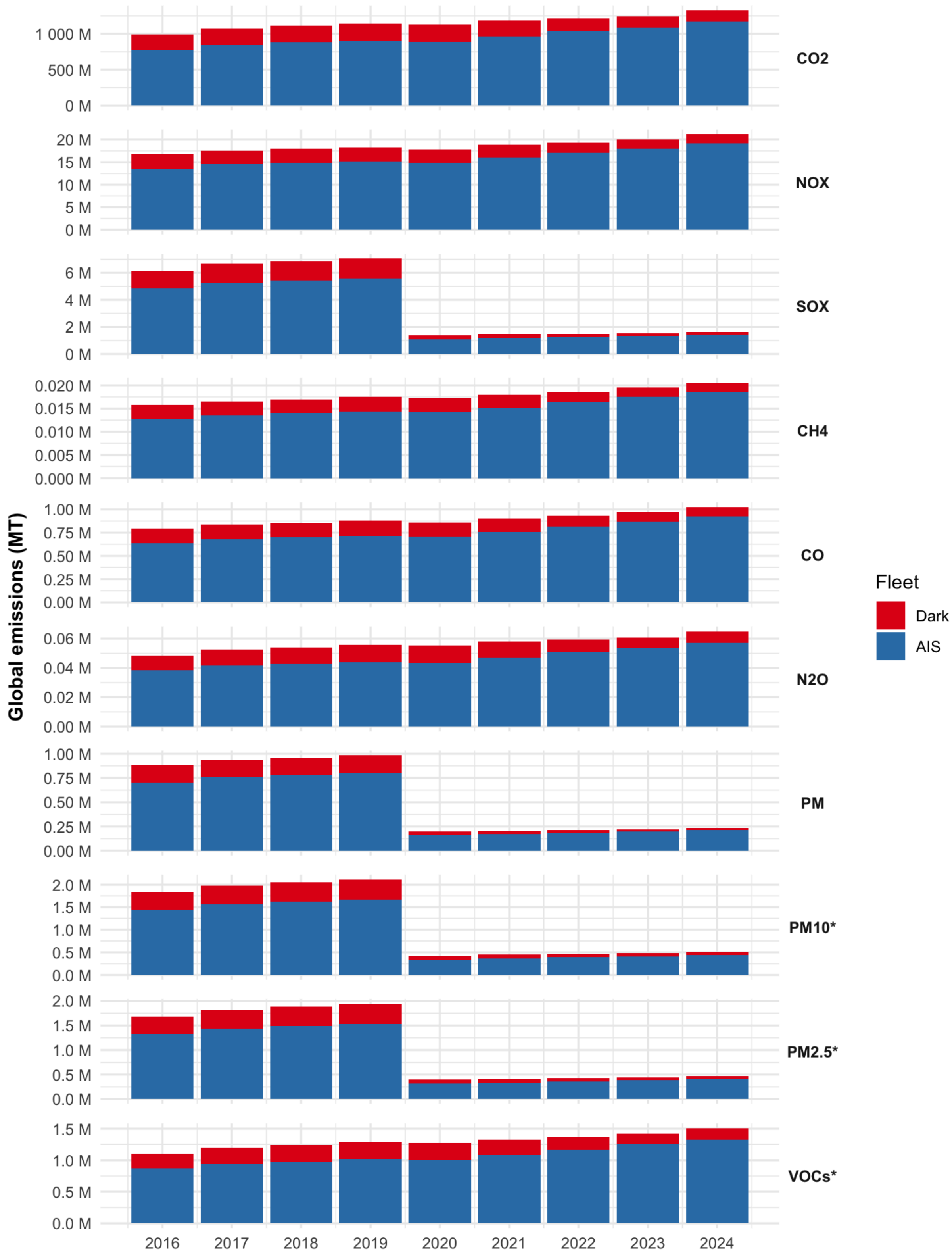

Figure 5. Summary of total global annual emissions over time, by pollutant and fleet. All emissions units are in metric tonnes, disaggregated by the AIS-broadcasting fleet and the dark fleet as detected by S1.

The total CO_2 emissions estimate for 2024 is 1.33 billion metric tonnes, including 1.17 billion metric tonnes from AIS-broadcasting vessels and 163 million metric tonnes from dark vessels detected by S1.

3.5 Spatial maps of emissions

Figure 5 shows spatial maps showing the CO_2 emissions globally by the AIS-broadcasting fleet and by the dark fleet. For each 1x1 degree pixel (the spatial resolution of the dark fleet model), we aggregate emissions separately for each pollutant for 2024. Global maps for all pollutants estimated by GFW can be found here.

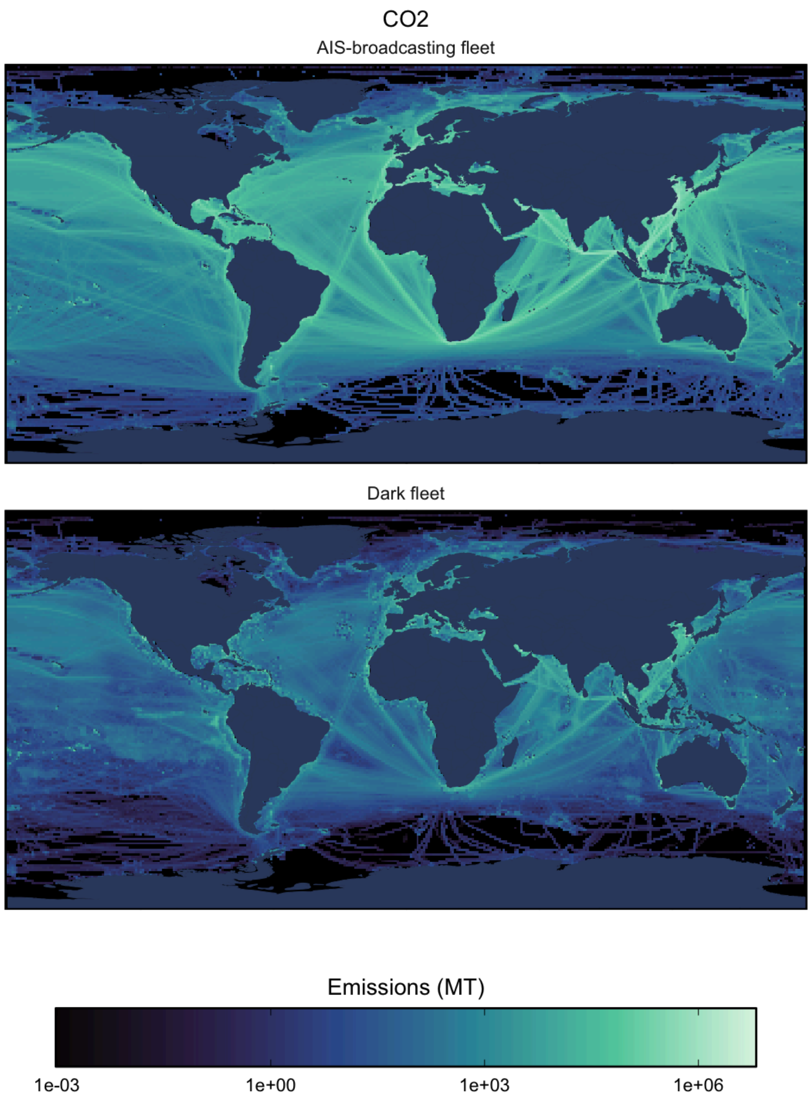

Figure 5. Map of 2024 CO_2 emissions, aggregated across all vessel classes, at 1x1 degree spatial resolution, disaggregated by the dark fleet and AIS-broadcasting fleet.

4. Discussion and Conclusion

Our model provides unprecedented coverage of global shipping, including vessels with little information publicly available. This includes vessels that broadcast AIS but are not found in public vessel information databases, and vessels that are not detected using AIS (“dark” vessels). Our model can provide results in near real time for vessels broadcasting AIS, and our sector-leading vessel characteristics database allows maximal coverage of low information vessels. Future refinements discussed below should improve the accuracy and vessel coverage of estimated emissions.

Some of our key findings so far include:

- Shipping GHG emissions have grown about 18% since 2016, increasing about five times faster than global carbon dioxide (CO_2) emissions from fossil fuels.
- The vessels we detected and modeled were responsible for about 1.3 billion tons of CO_2 emissions in 2024. That is about 3% of global fossil fuel emissions.
- The vast majority of emissions were by vessels that use AIS to broadcast their positions (87% in 2024), but understanding dark vessel activity is critical to estimating the total emissions and especially to estimating the change in emissions. Emissions from dark vessels – those not mapped by AIS – decreased by about 22% over 2016-2024, while emissions from vessels with AIS increased by about 50% over the same time period. The reason is that more vessels started using GPS devices, and technology to receive and record AIS messages improved.

4.1 AIS-based model, areas of potential model refinement

We have identified a number of areas for potential model refinement. They are all related to the need for improved vessel characteristics metadata:

1. Draft (draught) correction factor: Currently, we use the same correction factor for draft (the vertical distance from the waterline to the lowest point of the ship's hull) for all vessels. This single draft correction factor is currently an average of vessel class-specific correction factors, weighted by the total emissions by each vessel class. Future model iterations may want to use vessel class-specific draft factors.
2. Size units conversion: The inclusion of the four operational phases requires the use of auxiliary engine and boiler energy demand values by vessel operational phase and vessel size. As described earlier, this entails setting unit conversion expressions for the different measures of vessel size, such as deadweight, gross tonnage, TEU, cubic meters, etc. These conversion expressions can be refined to better capture energy demand, especially those for CBM conversion.

4.2 Dark fleet model-areas of potential refinement

We have identified an area for potential refinement of the dark fleet emissions model

1. Sentinel-2 data: Currently, we use S1 SAR data for our dark fleet emissions estimates. We tested extending this methodology to also incorporate Sentinel-2 (S2) optical imagery data. However, differences in detection capacity, coverage and noise, prevent a direct integration of S2 with S1. Future work should focus on combining both datasets to complement each other's strengths.

Supplemental Metadata

Table 2: General dataset information for Emissions From Vessels With Low Information Availability. There are two types of low information vessels: 1) vessels that transmit activity through the Automatic Identification System (AIS) but have little information publicly available on vessel characteristics such as size and engine power, and 2) vessels without detectable AIS signals, often called "dark" vessels because they are not detectable through traditional means of detection.

General Description	*Definition*
Sector Definition	*Shipping*
UNFCCC sector equivalent	*1.A.3.d Domestic Navigation, 1.C.3 Other, International Navigation*
Temporal Coverage	*AIS-based emissions: Jan 1, 2015-June 30, 2025; Dark vessel emissions: Jan 1, 2016-June 30, 2025*
Temporal Resolution	*Monthly*
Data format(s)	*CSV*
Coordinate Reference System	*EPSG:4326, decimal degrees*
Number of vessels available for download and percent of global emissions (as of 2024)	*AIS-broadcasting vessels: 925,682 unique vessels across 235 unique flags and 109,617,280 distinct trips or port visits. Dark fleet emissions estimates are global and cannot be disaggregated by vessel, flag, trip, or port visit.*
Total emissions for 2024	*AIS transmitting vessels: 1,167 million tons CO_2; Dark vessels: 163 million tons CO_2*
What emissions factors were used?	*Olmer, et al., 2017*
What is the difference between a "null/none/nan" vs "0" data field	*"0" values are for true non-existent emissions. If we know that the sector has emissions for that specific gas, but the gas was not modelled, this is represented by "NULL/none/nan"*
total_CO2e_100yrGWP and total_CO2e_20yrGWP conversions	*Climate TRACE uses IPCC AR6 CO2e GWPs. CO2e conversion guidelines are here:https://www.ipcc.ch/report/ar6/wg1/downloads/report/IPCC_AR6_WGI_FullReport_small.pdf*

Table 3: AIS-based estimates, confidence, and uncertainty. Low and high information vessels described in table 2 legend.

Data attribute	Confidence	Uncertainty
asset_identifier	Very high	NULL
asset_name	Very high (high-information vessels) Low (low-information vessels)	NULL
type	Very high (high-information vessels) Low (low-information vessels)	NULL
capacity	Very high (high-information vessels) Low (low-information vessels)	Standard deviation
capacity_factor	Very high (high-information vessels) Low (low-information vessels)	Standard deviation
activity	Very high	Standard deviation
CO2_emissions_factor	Medium (high-information vessels) Very low (low-information vessels)	Standard deviation
CH4_emissions_factor	Medium (high-information vessels) Very low (low-information vessels)	Standard deviation
N2O_emissions_factor	Medium (high-information vessels) Very low (low-information vessels)	Standard deviation
S OX_emissions_factor	Medium (high-information vessels) Very low (low-information vessels)	Standard deviation
NOX_emissions_factor	Medium (high-information vessels) Very low (low-information vessels)	Standard deviation

Data attribute	Confidence	Uncertainty
CO_emissions_factor	Medium (high-information vessels) Very low (low-information vessels)	Standard deviation
CO2_emissions	Medium (high-information vessels) Very low (low-information vessels)	Standard deviation
CH4_emissions	Medium (high-information vessels) Very low (low-information vessels)	Standard deviation
N2O_emissions	Medium (high-information vessels) Very low (low-information vessels)	Standard deviation
SOX_emissions	Medium (high-information vessels) Very low (low-information vessels)	Standard deviation
NOX_emissions	Medium (high-information vessels) Very low (low-information vessels)	Standard deviation
CO_emissions	Medium (high-information vessels) Very low (low-information vessels)	Standard deviation
total_CO2e_100yrGWP	Medium (high-information vessels) Very low (low-information vessels)	Standard deviation
total_CO2e_20yrGWP	Medium (high-information vessels) Very low (low-information vessels)	Standard deviation

Data citation format:

McDonald, G. and Kroodsma, D., Carbo-Mestre, P., Powell, M., and Wei, Z. (2024). *Transportation sector: Emissions From Vessels With Low Information Availability.* Global Fishing Watch, USA, Climate TRACE Emissions Inventory. https://climatetrace.org [Accessed date]

Geographic boundaries and names (iso3_country data attribute): The depiction and use of boundaries, geographic names and related data shown on maps and included in lists, tables, documents, and databases on Climate TRACE are generated from the Global Administrative Areas (GADM) project (Version 4.1 released on 16 July 2022) along with their corresponding ISO3 codes, and with the following adaptations:

- HKG (China, Hong Kong Special Administrative Region) and MAC (China, Macao Special Administrative Region) are reported at GADM level 0 (country/national);
- Kosovo has been assigned the ISO3 code 'XKX';
- XCA (Caspian Sea) has been removed from GADM level 0 and the area assigned to countries based on the extent of their territorial waters;
- XAD (Akrotiri and Dhekelia), XCL (Clipperton Island), XPI (Paracel Islands) and XSP (Spratly Islands) are not included in the Climate TRACE dataset;
- ZNC name changed to 'Turkish Republic of Northern Cyprus' at GADM level 0;
- The borders between India, Pakistan and China have been assigned to these countries based on GADM codes Z01 to Z09.

The above usage is not warranted to be error free and does not imply the expression of any opinion whatsoever on the part of Climate TRACE Coalition and its partners concerning the legal status of any country, area or territory or of its authorities, or concerning the delimitation of its borders.

Disclaimer: The emissions provided for this sector are our current best estimates of emissions, and we are committed to continually increasing the accuracy of the models on all levels. Please review our terms of use and the sector-specific methodology documentation before using the data. If you identify an error or would like to participate in our data validation process, please contact us.

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