Transportation sector:
Shipping

Mark Powell[1], Dan Knights[2], Max Schofield[1] and Ted Mackereth[1]
1) OceanMind, 2) University of Minnesota

Updated on April 7th, 2023

1. Introduction

1.1 The significance of greenhouse gas emissions from global shipping

Greenhouse gas (GHG) emissions from global shipping are estimated to be just below 3% of total anthropogenic GHG emissions (Fourth IMO GHG Study 2020). Despite the significance of this level of emissions, international shipping, along with international aviation, is exempt from the legally binding Paris Climate Agreement (UNFCCC 2016). This exemption means that other authorities must be responsible for decarbonizing shipping. The International Maritime Organization (IMO) is the United Nations (UN) body with authority to regulate international shipping. Efforts to date by the International Maritime Organization to reduce GHG emissions from shipping have been widely criticized as too slow and not compatible with Paris Agreement temperature targets, and unless current efforts are dramatically accelerated, global shipping's share of emissions could climb to 17% of anthropogenic GHG emissions by 2050 (Halim et al., 2018).

Some shipping companies are demonstrating leadership and taking steps towards decarbonization, despite the lack of any binding requirement to reduce emissions. Voluntary actions include disclosure of GHG emissions, decarbonization pledges, and development of tools and approaches to support decarbonization. But not all shipping companies are proactive and binding requirements may be necessary to achieve shipping emissions reduction consistent with the Paris Accord. The current lack of transparency regarding shipping emissions hinders efforts by those outside the industry to promote emissions reduction for shipping.

Transparency regarding GHG emissions from individual vessels and company fleets could provide opportunities for investors and customers of shipping companies, and others, to support leading companies that are voluntarily reducing emissions. The Ship it Zero campaign is an example of efforts to support low emissions shipping (Ship It Zero, 2021). Such mechanisms have been effective in providing tangible benefits for industry leaders in other industries that implement socially beneficial policies that may increase costs in the short term (Virdin et al., 2022).

There is no public disclosure of emissions from individual vessels for most of the world's commercial shipping fleet. Studies of emissions from global shipping include comprehensive estimates of total shipping emissions commissioned by the IMO, the UN body that regulates international shipping (Third IMO GHG Study 2014; Fourth IMO GHG Study 2020) and studies by others (Olmer et al., 2017). In addition, the European Union has created a monitoring, reporting and verification program and publishes ship emissions data annually for ships that call on EU ports (European Commissions 2020). Results from these studies include global emissions totals for all ships and by shipping subsector (e.g. container ships, oil tankers, vehicle carriers, etc.). These studies also included emissions by operational phase (cruising speed, berth, anchor, maneuvering) and analysis of factors that can influence emissions such as vessel speed. None of these studies provide emissions estimates for individual vessels.

The best current source of emissions from individual vessels is the European Union Monitoring, Reporting, and Validation (EU MRV) database that includes publicly accessible data on emissions from individual vessels that call on EU ports. That includes about 25% of the world's commercial shipping fleet each year. It is the only large-scale published record of individual vessel emissions, but gaps remain for the about 75% of vessels that do not call on EU ports. The MRV data is part of the EU effort to encourage decarbonization by monitoring emissions and potentially establishing a cost for carbon emissions from shipping. To date, the EU MRV has published 3 years of emissions data and is moving towards imposing a price on carbon for ship traffic that departs or arrives from EU ports and loads or offloads cargo or passengers, providing new insight into emissions from shipping.

Information on shipping emissions has also been produced to inform decarbonization and investment decisions. The results of these emissions evaluations have been presented as carbon efficiency levels aggregated at the level of sectors or transit routes (Clean Cargo Working Group 2017; Poseidon Principles 2021; RightShip GHG Rating). However, these studies also lack ship-specific emissions estimates, and have not driven accountability of shipping for GHG emissions. As an alternative, an approach has been developed by OceanMind that addresses the current gap in monitoring shipping emissions.

1.2 Summary of ship GHG emissions model

Recent advances in machine learning, increased access to ship data via Automatic Identification System (AIS), and cloud processing allow for improved estimation of ship emissions for greater transparency. OceanMind has developed an approach that makes use of readily available data and modeling to close the gap in ship emissions reporting. We used the EU MRV data and published emissions models from studies by the IMO and International Council on Clean Transportation to develop our model (Third IMO GHG Study 2014; Olmer et al. 2017; Fourth IMO GHG Study 2020). Our model relied on two components. First, a machine learning (ML) model was developed using the EU MRV data that predicted the emissions capacity of a ship in

$kgCO_2$/nautical mile (nm) traveled based on ship characteristics such as vessel size, engine power, year built, and other factors (see section 2.2 below). Second, ship activity data from AIS was used to estimate distance traveled during time intervals between AIS transmissions and an empirical model was used to estimate emissions based on time elapsed between AIS transmissions and ship speed.

Together, these models were used to estimate emissions by ship type and reported on the Climate TRACE website after aggregation by flag country, or reported as individual vessel emissions.

2. Materials and Methods

2.1 Datasets employed

The following datasets were employed in the OceanMind shipping model to estimate emissions.

Ship GHG emissions data from the European Union's Monitoring, Reporting, and Validation (EU MRV) dataset. The dataset is available at this link: https://mrv.emsa.europa.eu/#public/emission-report. At the time of writing (March 2022), data are available for 2018, 2019, and 2020.

The EU MRV dataset includes emissions totals for all voyages in a calendar year that originate or terminate in EU ports and involve the loading or offloading of cargo or passengers. Listed separately are all emissions that occurred in EU ports. GHG emissions from voyages without EU port calls or with EU port calls for other purposes (such as crew rotation, fueling, repairs, etc.) are not included in the EU MRV data. This record of individual vessel emissions is very useful in understanding GHG emissions from ships and producing emissions models that estimate emissions in subsequent voyages. One challenge with the EU MRV data is the difficulty in knowing which voyages were included in the data. This difficulty arises because of the requirement that emissions from voyages were only included if the voyages included loading or unloading of cargo or passengers in an EU port. This port stop qualification makes it difficult to link data from other sources to the MRV dataset. The emissions capacity of a ship in $kgCO_2$/nm traveled based on ship characteristics such as vessel size, engine power, year built, and other factors were generated from this dataset with the employed ML model.

Data from Third and Fourth IMO Greenhouse Gas Studies. These studies developed "bottom up" mechanistic models of emissions that could be applied to individual ships. The term "bottom up" is from the IMO GHG studies, and it refers to models that combine data on vessel characteristics and activity into a model that relies on engineering principles of the forces involved in ship propulsion and resistance to travel. No results were published for emissions from individual ships. Instead, the focus of these studies was to produce estimates of emissions from shipping sectors (container ships, oil tankers, passenger ships, etc.) to inform thinking about emissions trends and potential for emissions reduction. Several types of data were included in the OceanMind model from the Third and Fourth IMO GHG Study:

- Auxiliary engine power demand by ship type, size, and operational phase (cruising, anchor, berth)
- Boiler power demand by ship type, size, and operational phase

Vessel operational data. We obtained data including measured vessel emissions from vessel owners and from Siglar, a company that provides “actionable insights leading to substantial reduction in CO_2 emissions in the shipping industry.” These measured emissions data included three ship sectors, container ships, oil tankers, and chemical tankers. These three sectors account for almost half of total shipping emissions. This dataset was used to develop the speed adjustment portion of our model. Two thirds of the vessel data was used to develop the speed adjustment, and one third was used to validate the model.

Vessel activity data from Automatic Identification System (AIS). Vessel activity was monitored using AIS transmissions from ships as detected by satellite and terrestrial receivers and provided by Spire, a private company that sells this data. AIS technology was developed for ship safety and subsequently adapted as a tool for tracking the movements of ships at sea. The frequency of AIS transmissions received for most vessels ranges from about once each minute to about once each hour, with occasional gaps of longer duration. In some cases, gaps occur when vessels fail to transmit for hours while traveling in ocean areas of concern such as the South China Sea. Activity data obtained from AIS included position (latitude/longitude), timestamp, speed over ground, heading, and distance traveled. The typical number of vessels detected and modeled each week was about 37,000.

2.1.1 Sector Inventory data/Ground truth data

To assess the accuracy of our modeled shipping emissions, we compared modeled estimates to the following:

Vessel operational data from ship owners and other sources. We obtained ship data from the owner of 2 container ships and 3 fishing vessels, including vessel characteristics, activity data, and measured GHG emissions. This information was obtained under the condition that it remain confidential. We used this information to inform our thinking, to assist model development, and to examine emissions during different operational phases and at different vessel speeds. This dataset hereafter is referred to as “vessel ground truth data”.

Additionally, we obtained vessel operational data from Siglar, an “independent provider of actionable insights leading to substantial reduction in CO2 emissions in the shipping industry” (https://www.siglarcarbon.com/). Two thirds were reserved for model development and one third was reserved for validation. In addition, we discussed model results with Siglar to identify opportunities for model improvements.

Lastly, we obtained mechanistic "bottom up" emissions model results from an anonymous source under the condition that it remain confidential. The source's "bottom up" emissions estimates were compared to our model results.

Shipping sector inventory data. To verify the OceanMind modeled ship emissions, the emission results were compared to the United Nations Framework Convention on Climate Change (UNFCCC), the Fourth IMO GHG study, CarbonMonitor.org, and The Emissions Database for Global Atmospheric Research (EDGAR). These inventories vary in their coverage of the shipping sector, including differences in the national fleets included, vessel types included, operating area of ships (domestic vs. international), and level of information about vessels required for inclusion.

Each inventory's annual emissions totals for the entire shipping sector were compared to OceanMind modeled shipping emissions aggregated to the shipping sector level to provide another assessment to validate our results. This comparison required adjusting the inventories to account for differences in coverage described above.

2.2 Model Development and Deployment

Our shipping emissions model was an empirical model that estimated individual vessel emissions. Aggregated totals by sector, country, or other criteria were obtained as the sum of emissions for individual vessels by category. Emissions were modeled for 12 sectors of the global shipping industry, including: bulk carrier, chemical tanker, container, gas carrier (LPG), general cargo, LNG carrier, oil tanker, passenger, refrigerated cargo carrier, roll on-roll off/passenger, roll-on/roll-off carrier, and vehicle carrier.

Model development and steps to estimate shipping emissions:
Our emissions model for global shipping has the goal of including all commercial vessels larger than 500 gross tonnes. We obtained information on vessel identities, types, and other characteristics included in the emissions model from Lloyd's List Intelligence (https://www.lloydslistintelligence.com/), a commercial provider of information about ships including characteristics such as size, type of ship, engine power, country of registration, owner identity, and other characteristics. The process for development and deployment of the model is shown in figure 1.

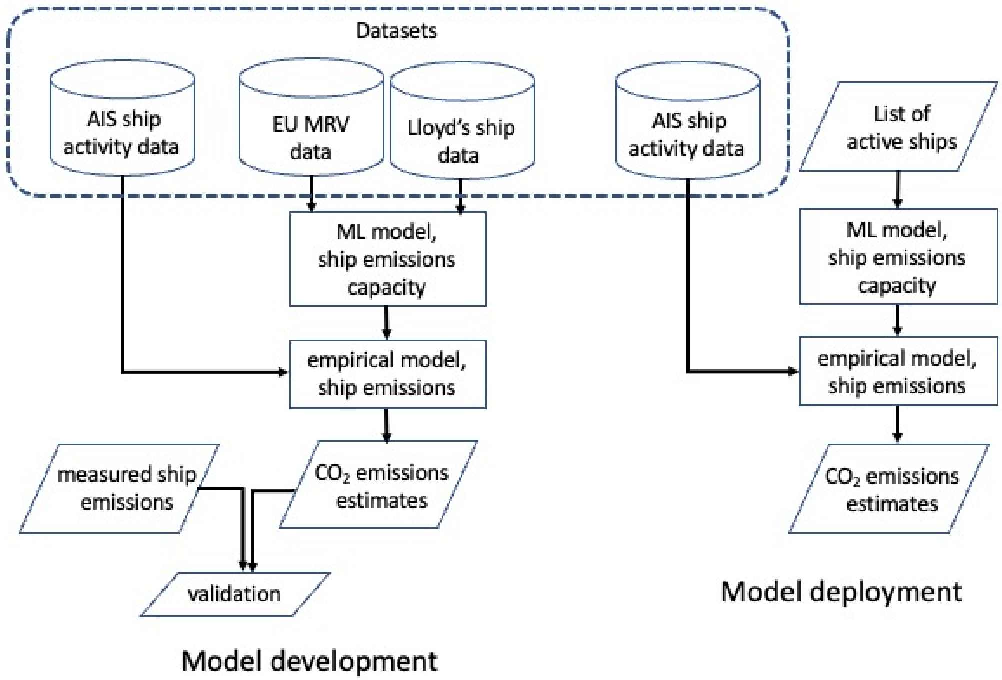

Figure 1 Flowchart depicting OceanMind's approach to estimate ship emissions**.** Description of the approach is provided in the text below.

Due to data limitations and modeling difficulties, there were some minor sectors that were not modeled in the current version of the model. These sector gaps include: military, fishing vessels, tugs, supply vessels, small vessels, and vessels that did not broadcast AIS. Our best estimate of the percentage of global emissions that were not included is:

- Vessels with insufficient information: 6.4% of emissions
- Sectors not included: 9.6% of emissions
- Military: unknown

Estimates for the emissions attributable to these groups of vessels were derived from the 4th IMO GHG study figures for emissions from these types of vessels.

Our model relied on two key components:

- **Step 1–ML model, estimation of emissions capacity** for each vessel, in kgCO_2/nautical mile traveled. This was done with an ML model developed using the EU MRV dataset.
- **Step 2–Empirical model, estimation of emissions in tonnes CO_2** produced by combining vessel activity data (elapsed time, and speed over ground) with the emissions capacity produced in step 1.

We used input data from the following sources:

- Vessel kgCO_2/nm from the EU MRV dataset

- Vessel characteristics (metadata) from Lloyd's List Intelligence
- Vessel activity data from Spire AIS

2.2.1 Machine learning model of emissions capacity

Emissions capacity was estimated using a machine learning model trained and validated on the EU MRV dataset that provided annual average kgCO_2/nautical mile traveled for vessels making qualifying EU port stops. This dataset included about 12,000 vessels each year for 2018 through 2020, with annual updates expected about 6 months after the year of data collection. Just over 7,000 vessels were present in all three years, 2018-2020, and the total number of unique vessels reported at least once in these three years was over 16,000.

Data preprocessing for machine learning models

For the machine learning model preprocessing, we began with 36,180 unique entries comprising 16,665 unique ships who reported fuel efficiency and emissions data to the EU in 2018, 2019, or 2020. We were able to obtain metadata for 16,516 of these ships from Lloyd's List Intelligence (https://www.lloydslistintelligence.com/). We also used location data from Spire to estimate time-at-sea, total annual distance traveled, and average speed for all ships. These three continuous variables were only used to remove ships with low-quality data from the training set, not for building and assessing the predictive model, because they must be derived from the location data.

To avoid using invalid training examples, we dropped 1799 ship entries with N/A, non-positive, or inadmissible value for continuous variables, including removing those with Time at sea < 1 week or > 1 year, Annual distance traveled < 1000km. Outlier detection was performed with a univariate basis using the following continuous variables, rejecting ships with values greater than three times the interquartile range above the 75th percentile, or less than three times the interquartile range below the 25th percentile: reported fuel efficiency, deadweight, gross tonnage, breadth, maximum engine power, auxiliary engine power, calculated average speed, reported cruising speed, and calculated distance traveled. This resulted in removing 329 additional entries, leaving 33,853 entries from 15,855 unique ships, with 11,198, 11,709, and 10,946 ships reporting fuel efficiency in 2018, 2019, and 2020, respectively. Once the data has been processed, the following engineered features for predictive modeling were created for the remaining data (Table 1):

- FlagNameBin, containing the registered country names for ships from the 15 most common countries, and an "Other" category for the remaining flagnames;
- ShipTypeEU, a binned version of the ship type derived from the Lloyd's List Intelligence ship type data category mapped to the vessel type category of our supplied metadata e.g., all types of bulk carrier mapped to category 'Bulk carrier';
- Length, ship length taken as the maximum of the value of LengthOverallLOA or LengthRegistered in our supplied metadata.

Missing values in continuous variables were imputed using the random forests machine learning algorithm, by training on samples with non-missing values for a given field using other fields as the predictors, and then using known values for those other fields to predict the missing values, with the *mice* (van Buuren S, Groothuis-Oudshoorn K 2011) package in *R* (R Core Team (2020). Because imputed values for one missing field can be used to impute values for another missing field, the process is iterated several times (determined by the value of the *mice* parameter "maxit") to attempt to improve the imputations. The entire imputation process is also restarted multiple times (*mice* parameter "nreps") to account for variance in the estimates of imputed values. We ran the *mice* imputation function with the “nreps” parameter to 20 and the “maxit” to 2, after evaluating the predictive accuracy of different values on a subset of test data.

Table 1 List of predictors used to train and evaluate machine learning models.

Predictor Name	Description	Example	% imputed
FlagName	Flag State	Japan	
FlagNameBin	Top 15 flags, with remainder grouped as OTH (other)	JPN	
ShipTypeEU	High level ship type group	Oil tanker	
YearOfBuild	Year vessel built	2009	
Deadweight	Vessel Deadweight	63,800 tons	2.2 %
GrossTonnage	Vessel GrossTonnage	50,300 tons	0 %
Speed	Vessel Service Speed	12.1 knots	14.3 %
Length	Vessel length	96 m	1.6 %
Breadth	Vessel width	16.61 m	10.5 %
Draught	Vessel Draught	7.41 m	2.9 %
PowerKwMax	Power of main engines	1,491 Kw	20.1 %
PowerKwAux	Power of auxiliary engines	830.8 Kw	65.3 %

Machine learning models

Several machine learning models were tested to generate emissions capacity: random forests, extreme gradient boosting, ridge-penalized regression on continuous variables, and linear regression on maximum engine power, using the RStudio randomForest, xgboost, caret, and base packages, respectively.

For the regression models, a separate model was constructed within each ship type category. During model tuning, we performed parameter sweeps on the following parameters for each model: for random forests, parameters mtry and nodesize (values can be seen in the function "my.rf.tune" in "lib/rf.r" in RStudio); for extreme gradient boosting, parameters max_depth, eta, subsample, and nround (values can be seen in the function "my.xgb.cv.tune" in "lib/xgb.r" in RStudio); and for ridge regression, using the default parameter sweep in the caret package. Model tuning for random forests was performed using out-of-bag error estimates; model tuning for extreme gradient boosting and ridge regression was performed using 5-fold cross-validation. Tuning was performed on all models with root-mean-squared error as the objective function. Model evaluation was performed by holding out 1/3 of all ship data as test data. We ensured that ships with entries for multiple years were contained entirely within the test set or the training set, to avoid information leak. The entire tuning/evaluation process was repeated five times to obtain estimates of the generalization accuracy. The final random forests model was created using all ships as training data with parameters mtry=15, nodesize=8, and 2,000 trees.

Empirical Model - Estimation of tons CO_2 emitted

Emissions were estimated by combining emissions capacity, distance traveled, and a speed adjustment factor that compensated for the known relationship between vessel speed and emissions (Fourth IMO GHG Study, 2020; Olmer et al., 2017). For each time interval in the AIS activity data, distance traveled was obtained with Eq.1:

Distance (nm) = speed over ground (nm/hr) × time (hr) (Eq.1)

This distance figure is subject to errors for long time intervals because the likelihood of speed changes increases for longer time intervals. For time intervals greater than 12 hours, distance was obtained from the starting and ending latitude and longitude.

Distance and speed were used to estimate emissions in Eq.2:

tCO_2 = *(distance (nm) × emissions capacity (tCO2/nm) - auxiliary engine emissions at sea) × speed adjustment factor + auxiliary engine emissions at sea.* (Eq. 2)

Where the emissions capacity (tCO_2/nm) was derived from the ML model. The speed adjustment factor (Eq. 3) was a dimensionless ratio that varies from 0-1.

Speed adjustment factor = (speed over ground/reference speed)^2 (Eq. 3)

The purpose of the speed adjustment factor was to model the effect of vessel speed on emissions. A vessel that traveled at a speed below maximum cruising speed had lower power output from main engines and lower emissions per distance traveled. The speed adjustment factor adjusted the emissions attributed to maine engine power output according to the known relationship of lower vessel emissions per distance traveled at speeds below maximum cruising speed (Degiuli et al., 2021). Auxiliary engine power output (and emissions) did not show the same decrease with ship speed as main engine demand (Fourth IMO GHG Study 2018), so auxiliary engine demand was not adjusted by the speed adjustment ratio.

The speed adjustment factor relationship was derived from high resolution data provided by a ship owner and this approach was informed by review of the bottom-up mechanistic modeling approach in the Third and Fourth IMO GHG Studies, and Olmer et al. (2017). Eq.3 was used to draw a smooth line through the data. The speed adjustment factor used here provided a good match to the high resolution data of emissions at the full range of vessel speeds. We used an exponent of 2 rather than 3 as used in the Third and Fourth IMO GHG Studies and Olmer et al. (2017) based on findings from Adland et al. (2020), and Berthelsen and Nielsen (2021).

In the speed adjustment factor, we defined a term, "reference speed" for use as the denominator in the speed adjustment factor. Reference speed was an empirically-determined speed close to maximum cruising speed (known as "service speed") that produced the best fit of the model to measured emissions. This factor was developed based on the high resolution data from vessel owners that showed emissions capacity of vessels (kgCO_2/nm) at a range of vessel speeds.

In our model, emissions at reference speed and faster speeds were obtained from activity data and kgCO_2/nm from EU MRV data for each vessel. Reference speed was determined for each vessel type for which we had sufficient validation data, and reference speed was estimated as 87% of service speed for other vessel types.

Emissions at zero speed, defined as Speed Over Ground (SOG) less than or equal to 0.5 nm/hr, were estimated from auxiliary engine power demand estimates in the Fourth IMO GHG Study. For our zero speed auxiliary engine demand, we used the average of anchoring demand and berth demand, based on our finding that anchor time and berth time were approximately equal for our validation vessel sample. For many sectors, anchorage demand and berth demand were approximately equal.

Model deployment

Our model was deployed to estimate global shipping emissions for years 2018-2021. Years 2015, 2016 and 2017 were backfilled with 2018 emissions data that were adjusted for yearly trends in the Fourth IMO GHG Report (2020). We used our ML model described above to predict emissions capacity (kg CO_2/nm) for all commercial ships above 500 gross tons that were active and identifiable in our AIS data from Spire. We used AIS activity data to predict CO_2 tonnes emitted by each ship as described above. Emissions estimates were typically made for one week time intervals, although some estimates used longer or shorter time periods. The flowchart in Figure 1 illustrates this process.

The results of this process were about 37,000 or more distinct vessel emissions estimates for each period analyzed (typically 1 week). Vessel emissions were attributed to categories for reporting, including vessel flag state (country of vessel registration), ship type, location of vessel operation, or other relevant categories. Individual vessel emissions, reported by flag state, are accessible on the Climate TRACE website, https://www.climatetrace.org/.

Vessels that had no AIS transmissions for a time period were not modeled, and presumed to be inactive.

2.3 Verifying modeled emissions estimates

We have found no publicly available source of independent emissions data that was usable for model validation at a large scale. In the absence of a large validation dataset, we relied on three approaches to confirm aspects of our modeling approach.

Assessment 1 - Measured emissions compared to estimated emissions.

We used measured emissions results for 33 vessels provided by Siglar to develop and validate our model. We divided the emissions data into two groups randomly, and used data from 21 vessels as inputs to our model and data from 12 vessels to validate our model. These measured emissions are for one voyage for each vessel, voyage duration ranged from 7-60 days. This validation is presented in Table 1.

Assessment 2 - Time-series analysis

Another type of validation was examining emissions estimates to evaluate whether notable events were captured by our model. The most dramatic emissions change we found was the decrease in cruise ship emissions that occurred when the World Health Organization declared COVID-19 a global pandemic. At that time, cruise ship traffic declined dramatically, falling to a standstill in some regions (March et al., 2021). Our emissions estimates describing this event are reported in the Results section below.

Assessment 3 - OceanMind emissions compared to existing inventories

We compared total OceanMind modeled emissions to other emission inventories for shipping, after correcting for differences in coverage. These inventories include:

- United Nations Framework Convention on Climate Change (UNFCCC) - 1.A.3.d Domestic Navigation, plus 1.C.3 Other, International Navigation. This inventory covers all shipping sectors for 2018, and is a definitive source that is widely used.
- Carbonmonitor.org - total shipping, domestic and international. This inventory has the most up to date information, covering Jan. 2019 to April 2021. This is the only inventory that covers shipping through early 2021.

- Emissions Database for Global Atmospheric Research (EDGAR) - 1.A.3.d. Water-borne navigation (domestic), plus 1.A.3.e. Other Transportation, international navigation (bunker fuel). This inventory covers shipping for 2019 and is widely respected and used.
- Fourth IMO Greenhouse gas study- International and Domestic Navigation. This inventory for 2018 will be used by OceanMind in validating results. It is the official inventory of the UN chartered international management body for shipping.

3. Results

3.1 Emissions capacity model results

We implemented a machine learning model that learns from the ships with known emissions capacity (kgCO_2/nm) to predict the emissions capacity of unknown ships on a per-ship basis using available ship metadata. The code and a fully trained model is available in section 6.

These results provide emissions capacity estimates for large commercial ships of the 12 types covered by our model, based on vessel metadata. These estimates are step one in a two step process of estimating vessel emissions.

3.1.1 Measured emissions compared to estimated emissions.

Emissions capacity estimates were combined with vessel activity data from AIS as described above to produce estimates of tons CO_2 emitted for selected periods of vessel activity for years 2018 to 2021.

Results of the comparison between estimated and measured emissions for the validation group of vessels provided by Siglar are shown in Table 2. These results compare measured emissions for a single voyage for each of the 12 vessels in the validation set. Predictions from OceanMind's current model (model 2.0) and, for comparison, predictions from OceanMind's 2021 model (model 1.0) are included in the results. Model 2.0 has a lower normalized root mean square error (nRMSE) than model 1.0, 13.9% and 22.1%, respectively. This indicates that version 2.0 is providing slightly more accurate emission estimates when compared to the validation dataset.

Table 2 Validation of OceanMind's models, version 1 and 2, to Siglar measured emissions. nRMSE shown are for the 12 vessels included in the validation.

Vessel #	Siglar measured tonnes CO_2	Model 2.0 tonnes CO_2	Difference: Model 2.0 - Siglar	nRMSE model 2.0	Model 1.0 tonnes CO_2	Difference: Model 1.0 - Siglar	nRMSE model 1.0
1	4999	5333	334	13.9%	5,673	674	22.1%
2	4641	5116	475		5,543	902	
3	587	598	11		403	-184	
4	1581	1165	-416		1,253	-328	
5	2018	1816	-202		2,363	345	
6	1254	923	-331		1,404	150	
7	1483	1291	-192		1,973	490	
8	2845	2732	-113		2,737	-108	
9	1112	1068	-44		1,234	122	
10	261	344	83		274	13	
11	223	279	56		265	42	
12	205	265	60		331	126	

Figure 2 presents a box and whiskers plot for the comparison of OceanMind model 2.0 and model 1.0 to measured emissions. The boxes include values from the 2nd and 3rd quartiles, and the whiskers show the minimum and maximum values. The "x" inside the boxes are mean values and the lines inside the boxes are median values. Model 2.0 has lower variance and the mean and median for model 2.0 are closer to measured emissions, highlighting the improved accuracy of model 2.0 over model 1.0.

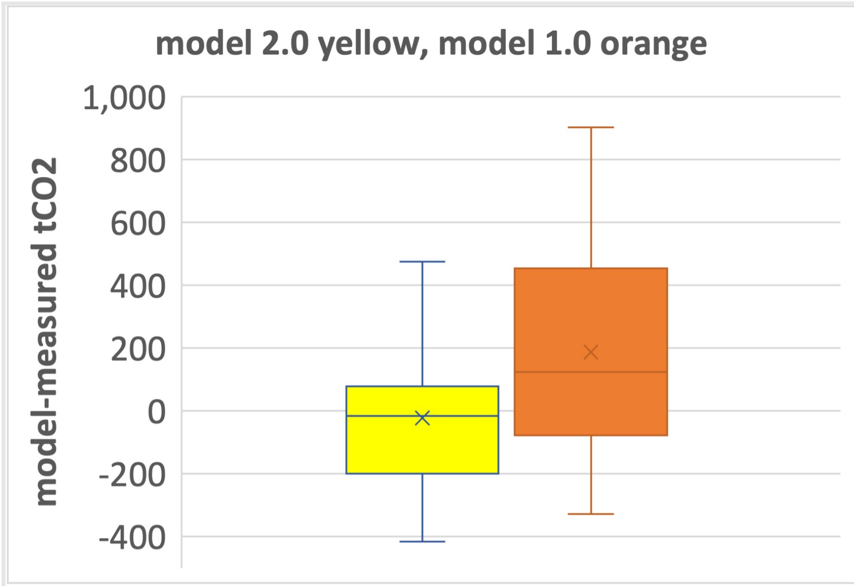

Figure 2 Difference between model emissions estimate and measured emissions for 12 vessels. Yellow: OceanMind model 2.0, orange: OceanMind model 1.0.

3.1.2 Time-series analysis

The OceanMind model was used to track changes in cruise ships emissions during the period when the COVID-19 pandemic caused rapid decreases in activity of cruise ships (March et al., 2021). Figure 3 shows emissions estimates for the cruise ship industry overall and for three cruise ship fleet owners. The dotted line shows the week of March 16-22, 2020, the date of the World Health Organization (WHO) pandemic declaration and the date when much of the cruise industry halted or greatly reduced activity of cruise ships (Washington Post, 2020). Our estimates showed time resolution capable of identifying a decrease in emissions of over 50% in one week, coincident with most cruise ships being brought to port. This result demonstrated the accuracy of our activity data to identify significant events that can impact the shipping sector.

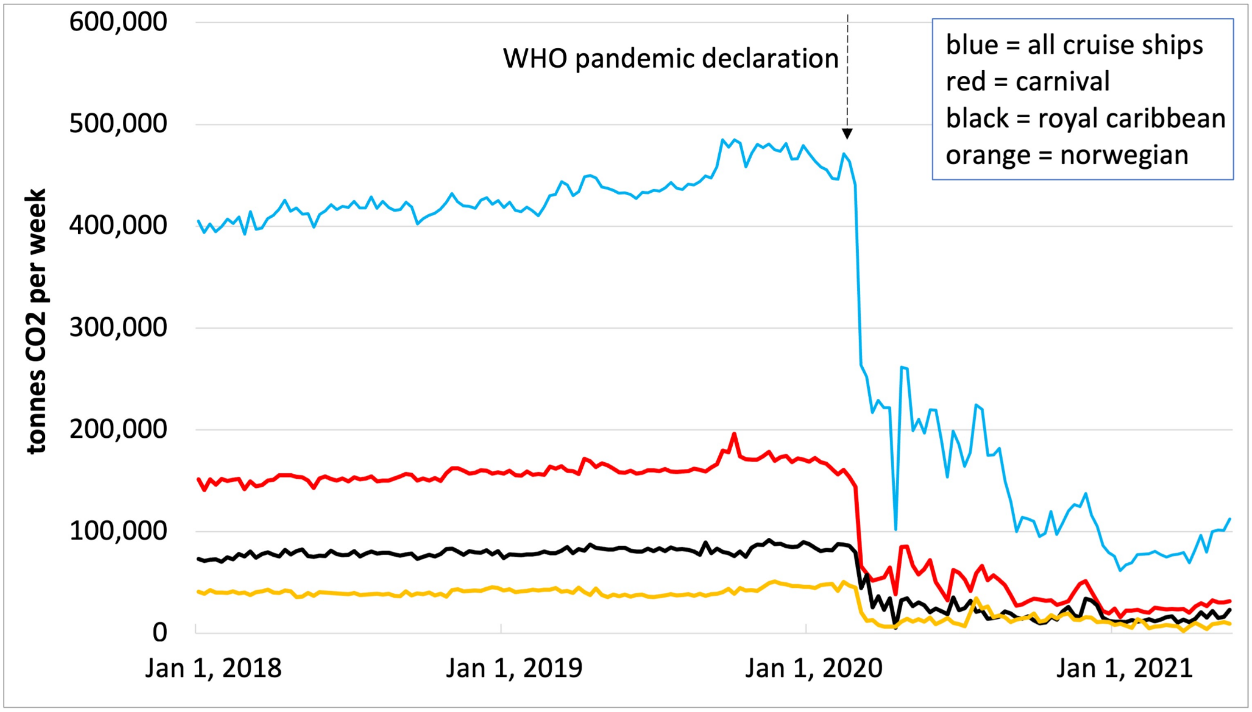

Figure 3 Weekly estimates of CO_2 tonnes per week for the cruise industry fleet overall (blue line) and for the fleets of three large cruise ships owners - carnival (red line), royal caribbean (black), and norwegian (orange). Dotted arrow indicates the week of March 16-22, 2020, the date when WHO declared COVID-19 a global pandemic.

3.1.3 OceanMind emissions estimates compared to existing inventories

The OceanMind model 2.0 currently covers emissions from global shipping for commercial vessels larger than 500 gross tons. Total emissions estimates for all vessels showed an increase of 4.6% from 2018 to 2019, and an increase of 3.1% from 2019 to 2020.

To compare similar emission estimates from other sources, the following inventories and categories were selected. Most recent years available were selected for each inventory. The results of these comparisons are shown in Figure 4.

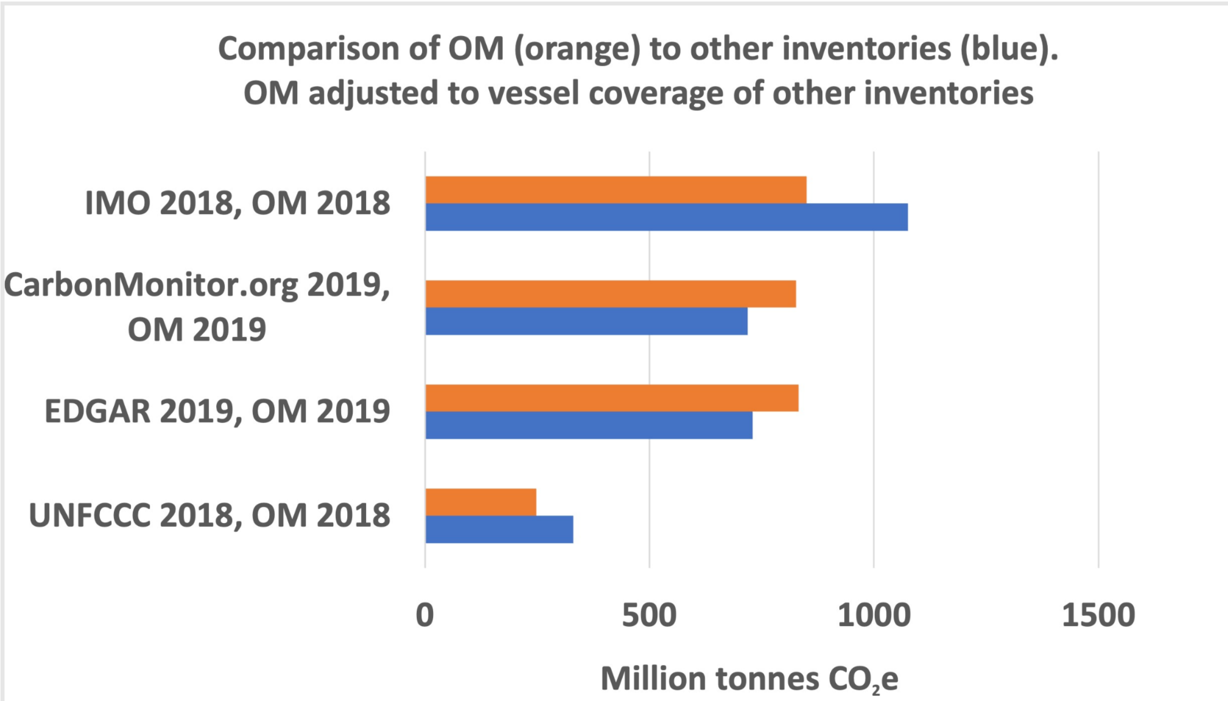

Figure 4 Comparison of OceanMind estimates (orange bars) to other GHG inventories (blue bars), OceanMind estimates adjusted to match vessel coverage of other inventories. See below for the year of comparison and specific adjustments for each inventory (e.g., UNFCCC is for Annex I countries only).

Results overviews for each inventory in Figure 4:

- UNFCCC, *annex I countries only*, 2018: 330 million metric tons.
- EDGAR, *international shipping only*, 2019: 730 million metric tons.
- CarbonMonitor.org, *international shipping only*, 2019: 718 million metric tons.
- IMO, 2018: 1,076 million metric tons.
- Climate TRACE, *international and domestic shipping*, some sectors not included (see below for details). 2018: 632 million metric tons; 2019: 703 million metric tons; 2020: 776 million metric tons. Climate TRACE totals are compared to other inventories after adjustment to match shipping sectors covered by each inventory.

The results of these comparisons, after adjusting for coverage as described above, are that the Climate TRACE inventory estimate is 75% of UNFCCC, 79% of IMO, 114% of EDGAR, and 115% of CarbonMonitor.org. The Climate TRACE inventory is within the range of the other inventories and nearly in the center of the range.

4. Discussion of model limitations

Despite the success of our model in matching a number of available emissions inventories, and it's good comparison with the small set of ground truth data available to us, our model, like any, does have known limitations, which have been highlighted in this document. It is possible that OceanMind's emissions are over- or under-estimated for individual vessels, due to a variety of factors (including, but not limited to, those outlined here) and model uncertainty. Our best estimation of the average uncertainty is 14%, but outliers are present in our predictions which will continue to be improved upon over time. In summary:

- Our model of vessel characteristics is trained using data from EU vessels. It is possible that the EU MRV dataset is not representative of global shipping, and so the model may be extrapolating into areas of the data space where the model was not trained. The Fourth IMO GHG study carefully examined this possible source of bias and concluded that the MRV was representative of global equivalents. However, some care should be applied when using results for vessels outside of the EU fleet.
- The effects of weather, ocean currents and other external factors on vessel emissions are implicit in the MRV data set, which provides aggregated emissions over many journeys in different conditions - and so are included 'on average' in our modelling. However, these effects are not explicitly modelled on an individual vessel level. Our inclusion of the 'averaged' effects of weather, currents and other factors is an albeit simpler, yet effective way to include these effects.
- The training outputs used to fit the model for vessel characteristics (including emissions capacity) come from aggregate emissions data from the EU MRV. This data provides the average emissions over a calendar year of vessel activity and so these numbers include port stays of varying lengths. This induces an artificial scatter in training data (which is contained within the total error of about 10%) which is reflected in the final results.
- We cannot, at present, infer the activity of vessels that remain in port for extended periods of time. In-port emissions are likely overestimated by the model at present, since it is not possible to know whether vessels are waiting in-port with engines turned on or off. Our current assumption is that emissions accrue from auxiliary engines for the entire time a vessel is in port. Users should be wary of results for vessels with long port stays. Future iterations of the model may flag or remove these results, but this is not implemented at present.
- In the absence of a large set of ground-truth data, the validation of the details of the speed adjustment in the model is based on a small set of daily emissions from 33 vessels, and detailed emissions from only 2 vessels and supported by reference to the similar speed adjustment factors in models in the 3rd and 4th IMO GHG Studies and Olmer et al. (2017). In most cases, our model is extrapolating beyond the training data.

Despite the items above, we are confident that the data derived from our model is reliable in demonstrating the trends in emissions from global shipping. In general, any side effects are captured by our estimate of uncertainty at the level of 14%.

5. Discussion

Our model made use of the EU MRV database of vessel emissions data and other sources to develop a predictive model applicable to nearly all large commercial ships and to global shipping in aggregate. We obtained measured emissions data from vessel owners and others, and used this information in a split sample design to develop and validate the emissions estimates. Our validation results show that our model is capable of modeling emissions with reasonable accuracy for individual vessels during individual voyages. We continue to seek additional measured emissions data to improve the model and validate the model with a larger set of vessels.

Shipping emissions are exempt from the Paris Accord (UNFCCC 2016), and the international regulatory system for global shipping, the International Maritime Organization, has not implemented mandatory measures capable of reducing shipping emissions. Our results show significant increases in GHG emissions from global shipping in recent years. From 2018 to 2019, emissions increased 4.6% and for 2019 to 2020, emissions increased 3.1% despite the economic slowdowns caused by the COVID-19 pandemic. Such increases are inconsistent with the goals of the Paris Accord and make future pathways more difficult by requiring much more drastic reductions in the future (Comer 2021). Unilateral action by the EU to put a price on carbon emissions for global shipping may be necessary to stimulate action to reduce emissions by the industry (Wettestad and Gulbrandsen 2022).

Emissions estimates for the cruise industry during the period when the WHO declared COVID 19 as a global pandemic demonstrate the accuracy and resolution of our ship activity data. Our estimates showed a drop of over 50% in emissions during the week March 16-22, 2020. This coincides with public reports of voluntary and mandatory stoppage of cruise ship activities (Washington Post 2020).

6. Conclusion

The OceanMind's GHG global shipping emissions model is intended to support efforts to reduce emissions. Our model is the first free and publicly available tool that estimates emissions for the tens of thousands of individual ships that carry out most of the world's commercial shipping. Another unique aspect of our model is that it provides flexible attribution to individual vessels, vessel owners, flag states, areas of operation, or other aspects of shipping. This allows data users to customize emissions estimates to suit their purpose. Our estimates have fewer coverage gaps than most other inventories and provide emission estimates that are not years out of date.

To improve our model, next steps include providing estimates in near real time, improved accuracy in estimates for individual ships, and developing new ways to provide the full details of model results to data users. This includes weekly updates of emissions for over 30,000 large commercial vessels. Model accuracy will be improved through acquisition of more training and validation data to improve the reliability and accuracy of the shipping model.

7. Link to data repository and model code

The code and a fully trained model is available here: https://github.com/knights-lab/climate-trace-shipping

8. Citations

1. Adland, Cariou and Wolff 2020. Optimal ship speed and the cubic law revisited: Empirical evidence from an oil tanker fleet. Trans. Res. Part E, 140 (2020). 101972. https://doi.org/10.1016/j.tre.2020.101972
2. Berthelsen and Nielsen 2021. Prediction of ships' speed-power relationship at speed intervals below the design speed. Transp. Res. Part D, 99 (2021), 102996. https://doi.org/10.1016/j.trd.2021.102996
3. Clean Cargo Working Group 2017. 2016 Global Maritime Trade Lane Emissions Factors. https://www.bsr.org/reports/BSR_CCWG_2016_Global_Maritime_Trade_Lane_Emissions_Factors.pdf
4. Comer 2021. Zero-Emission Shipping and the Paris Agreement: Why the IMO Needs to Pick a Zero Date and Set Interim Targets in it's Revised GHG Strategy. ICCT blog https://theicct.org/zero-emission-shipping-and-the-paris-agreement-why-the-imo-needs-to-pick-a-zero-date-and-set-interim-targets-in-its-revised-ghg-strategy/#:~:text=International%20shipping%20emissions%20pathways%20consistent,zero%20by%202040%20or%202050.
5. Degiuli, Martic, Farkas & Gospic 2021. The Impact of Slow Steaming on Reducing CO2 Emissions in the Mediterranean Sea. Energy Reports, 7, 8131; https://doi.org/10.1016/j.egyr.2021.02.046
6. EU MRV dataset. https://mrv.emsa.europa.eu/#public/eumrv
7. European Commission 2020. Reducing Emissions from the Shipping Sector. https://ec.europa.eu/clima/eu-action/transport-emissions/reducing-emissions-shipping-sector_en
8. Fourth IMO GHG Study 2020; International Maritime Organization (IMO) London, UK 2020; https://www.imo.org/en/OurWork/Environment/Pages/Fourth-IMO-Greenhouse-Gas-Study-2020.aspx
9. Halim, Kirsten, Merk and Martinez (2018). Decarbonization Pathways for International Maritime Transport: A Model-Based Policy Impact Assessment. Sustainability 10(7), 2243; https://doi.org/10.3390/su10072243.

10. March et al. 2021. Tracking the global reduction of marine traffic during the COVID-19 pandemic. Nature Communications. https://doi.org/10.1038/s41467-021-22423-6
11. Olmer et al. 2017. Greenhouse Gas Emissions from Global Shipping, 2013-2015; (International Council on Clean Transportation, 2017). https://theicct.org/sites/default/files/publications/Global-shipping-GHG-emissions-2013-2015_ICCT-Report_17102017_vF.pdf
12. Poseidon Principles 2021; Annual Disclosure Report. https://www.poseidonprinciples.org/finance/wp-content/uploads/2021/12/Poseidon-Principles-Annual-Disclosure-Report-2021.pdf
13. R Core Team, 2020. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/
14. RightShip GHG Rating; https://rightship.com/resources/knowledge-base/?section=rightship-s-ghg-rating
15. Ship It Zero, 2021; https://shipitzero.org/
16. Third IMO GHG Study 2014; International Maritime Organization (IMO) London, UK, April 2015; https://www.imo.org/en/OurWork/Environment/Pages/Greenhouse-Gas-Studies-2014.aspx
17. UNFCCC, 2016; Shipping Aviation and Paris; https://unfccc.int/news/shipping-aviation-and-paris
18. van Buuren S, Groothuis-Oudshoorn K 2011, "mice: Multivariate Imputation by Chained Equations in R." Journal of Statistical Software, 45(3), 1-67. doi: 10.18637/jss.v045.i03
19. Virdin, Vegh, Ratcliff, Havice, Daly and Stuart 2022; Combating illegal fishing through transparency initiatives: Lessons learned from comparative analysis of transparency initiatives in seafood, apparel, extractive, and timber supply chains. Marine Policy, 138:104984. https://doi.org/10.1016/j.marpol.2022.104984
20. Washington Post, 2020, All major cruise lines halt sailings temporarily in response to coronavirus.https://www.washingtonpost.com/travel/2020/03/12/princess-viking-cruise-lines-halt-all-sailings-temporarily-response-coronavirus/
21. Wettestad and Gulbrandsen 2022. On the Process of Including Shipping in EU Emissions Trading: Multi-Level Reinforcement Revisited. Politics and Governance, 10, 2022. https://doi.org/10.17645/pag.v10i1.4848