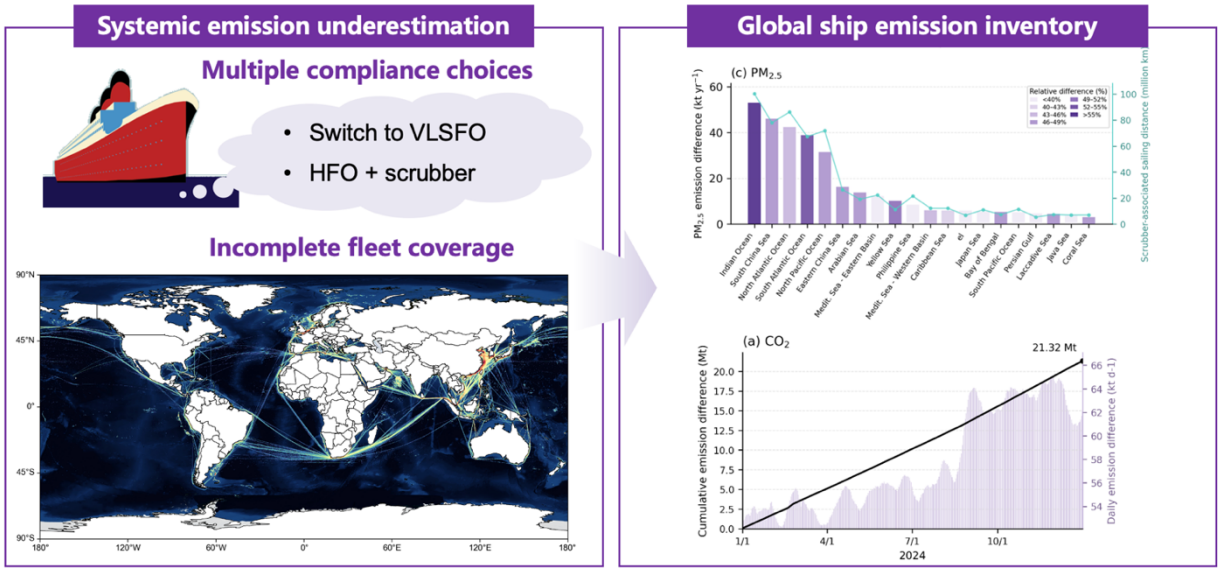
Addressing systematic underestimation in global ship emission inventories through improved fleet representation and fuel compliance characterization

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Abstract. As a sector with high energy demand, long-lived assets, and limited near-term low-carbon alternatives, global shipping is considered difficult to decarbonize and is subject to stringent emission controls. To evaluate emission control effects and conduct rapid response air quality simulations, accurate and timely ship emission inventories are indispensable. However, existing inventories face challenges from incomplete fleet representation and large uncertainties in $PM_{2.5}$ emissions after the global sulfur regulation. Here, we established a dynamically updated Ship Emission Inventory Model that allows near-real-time emission calculation within several days after AIS data acquisition. Ship activity and technical database are updated daily instead of yearly to obtain a more complete and rapid description of the global ship fleet. Fleet's multiple choices to comply with fuel sulfur regulation were considered, including switching to very low sulfur fuel and utilizing scrubbers to keep consuming heavy fuel oil. The daily expansion of ship technical database uncovered 8% and 6.2% of the total gross tonnage of active bulk carrier and container fleets, unveiling up to 5.4% of global ship CO_2 emissions. The resulting emission discrepancies gradually accumulated over 2024, demonstrating the persistent impact of delayed fleet information updates on ship emission estimates. Meanwhile, assuming that all ships switch to low-sulfur fuels after 2020 would lead to underestimation of $PM_{2.5}$ and BC emissions by approximately 43% and 15%. Although South China Ocean had the most absolute underestimation, the Indian Ocean had the highest underestimated portion, reaching 56% and 15% of its total $PM_{2.5}$ and BC emissions.



1 Introduction

As one of the hard-to-abate sectors (Sharmina et al., 2021), global shipping experienced a threefold increase in cargo turnover and a 1.7-fold increase in carbon dioxide (CO_2) emissions from 1970 to 2021 (Wang et al., 2025). Growing ship emissions have brought adverse impacts on the air quality and public health of coastal regions (Liu et al., 2016; Liu et al., 2019; Anenberg et al., 2019; Zhang et al., 2021). In 2018, global shipping was responsible for 2.9% of anthropogenic CO_2 emissions, 11% of sulfur oxides (SO_x), and 15% of nitrogen oxides (NO_x) (IMO, 2020). Under a business-as-usual scenario without additional mitigation measures, international shipping was projected to account for approximately 17% of global CO_2 emissions by 2050 (Cames et al., 2015), which reflects both the future development of international shipping emissions and the emission trajectories of other sectors. To restrain ship emissions, international and regional regulations have been implemented. Previous research showed that after the International Maritime Organization (IMO) low sulfur regulation came into force in 2020, ship SO_2 emissions dropped by 81.3% globally (Yi et al., 2024a) and by 71% in Southern China (Feng et al., 2023). Studies evaluating regional sulfur regulations have demonstrated their effectiveness in reducing ship-related SO_2 emissions. The sulfur emission control measures implemented in the Marmara Sea and Turkish Straits since 2006 reduced SO_2 concentrations by 90% in Istanbul (Viana et al., 2015) while China's Domestic Emission Control Area (DECA) policy, implemented progressively during 2016–2019, achieved an emission reduction by 33% within 200 nautical miles away from the Chinese mainland's territorial sea baseline (Wang et al., 2021).

Accurate and timely emission inventories are key to evaluating air quality and climate impacts and facilitating future policymaking (Im et al., 2018; Luo et al., 2024; Liu et al., 2024; Goldsworthy et al., 2019; Huang et al., 2020; Li et al., 2024). Bottom-up models using Automatic Identification System (AIS) have substantially improved the spatial and temporal

representation of shipping emissions by combining ship activity with ship-specific technical characteristics, engine-load calculations, and emission factors. However, converting ship activity into emissions requires information beyond vessel movements, including fuel consumption, technical specifications, and voyage-specific compliance pathways, which are not directly provided by AIS records. Therefore, existing models such as STEAM, MariTEAM, and MoSES generally rely on vessel characteristics, fleet statistics, regulatory assumptions, or predefined scenarios to estimate fuel use and emission-control practices (Schwarzkopf et al., 2021; Jalkanen et al., 2009; Kramel et al., 2021). These assumptions introduce two major uncertainties in global ship emission inventories: incomplete representation of the evolving fleet and insufficient characterization of fuel compliance pathways. In particular, distinguishing Heavy Fuel Oil (HFO) use with scrubbers from low-sulfur fuel switching remains challenging at the global ship level, despite their substantially different implications for $PM_{2.5}$, and BC emissions.

Among these uncertainties, the representation of sulfur compliance pathways became particularly important after the implementation of the IMO 2020 sulfur regulation. From January 1, 2020, the global sulfur limit for ship fuel oil was reduced from 3.50% to 0.50%, while a stricter limit of 0.10% applies within ECAs. Ships can comply with this regulation either by switching to low-sulfur fuels such as Very Low Sulfur Fuel oil (VLSFO) and Marine Gas Oil (MGO) or by continuing to use HFO with scrubber systems. However, globally complete ship-level information on scrubber installation is rarely available, limiting the ability of emission inventories to explicitly represent HFO-with-scrubber pathways. Some previous shipping emission inventories assumed that ships previously using HFO switched to VLSFO or MGO after 2020 without explicitly considering scrubber-based compliance (Yi et al., 2024a; Yi et al., 2024b).

Nevertheless, multi-source evidence indicates that HFO-based compliance pathways remained important after 2020. IMO fuel statistics showed that the broad HFO category still accounted for approximately 65% of ship fuel consumption after 2020 (IMO, 2024), while regional bunker data indicated that HFO remained an important fuel category in major maritime hubs, with reported shares ranging from 21.4% to 37.2% in Singapore and Rotterdam. Moreover, Lunde Hermansson et al. (2024) identified more than 800 scrubber-equipped ships operating in the Baltic Sea after 2020, demonstrating the continued use of scrubbers in regional fleets. However, these statistics provide indirect evidence of HFO consumption or regional scrubber presence rather than globally representative ship-level compliance information. Therefore, neglecting HFO-with-scrubber pathways may introduce substantial uncertainty into post-2020 estimates of $PM_{2.5}$, and BC emissions.

Another challenge facing ship emission inventories is the timely incorporation of newly identified ships into ship technical databases. In this study, newly identified ships include both newly delivered vessels and existing vessels absent from the original static database. Ships built after 2016 contributed 10.2% of global ship emissions in 2021 (Yi et al., 2024a), indicating that recently delivered vessels already represent a non-negligible fraction of shipping activity. Unlike ship activity data that can be processed at daily resolution, ship technical databases are generally updated with substantial delays (Yi et al., 2024a). Newly identified ships often lack key technical specifications and are represented by proxy values, which may affect engine power estimation, load-factor correction, and emission factor assignment. Previous studies have extracted ship parameters from AIS data (Wang et al., 2021; Huang et al., 2020; Schwarzkopf et al., 2021) and supplement missing

parameters with machine learning methods (Yang et al., 2022; Huang et al., 2024; Yang et al., 2024; Raman et al., 2025). However, an integrated framework that simultaneously updates ship activity and technical information with quality control remains lacking.

Here, we developed SEIMv2.3, a dynamically updated ship emission inventory model based on Shipping Emission Inventory Model (SEIM) (Liu et al., 2016; Wang et al., 2021; Yi et al., 2024a). SEIMv2.3 improves the representation of ship activity, fleet composition, and sulfur compliance pathways through three methodological developments. First, AIS activity records are processed at a daily temporal resolution with an enhanced preprocessing framework to support near-real-time emission updates. Second, newly identified ships are dynamically detected from AIS activity records and incorporated into the static ship technical database, with missing specifications supplemented through AIS-derived information and machine-learning-based reconstruction. Third, the fleet low sulfur compliance choice module (FLSCCM) is introduced to reconstruct post-2020 sulfur compliance pathways by integrating ship-level scrubber installation records with constrained gap filling. Using SEIMv2.3, we calculated global ship emissions from 2022 to 2024 at daily resolution and quantified the effects of improved fleet representation and sulfur compliance pathway characterization on emission estimates.

2 Method

SEIM was first established by (Liu et al., 2016) based on the idea of the disaggregated dynamic method. Driven by AIS data and ship technical information, SEIM realized vessel-by-vessel ship emission simulations, suitable for the establishment of multi-scale shipping emission inventories with applications in regions (Liu et al., 2016; Wang et al., 2021; Zhang et al., 2025b) and ports (Fu et al., 2017). The specific formula used in this study to calculate ship emissions are identical to those reported by (Yi et al., 2024a) and provided in Supplementary Information. Emission factors for different ship types and fuels are listed in Table S2-S4, primarily based on the IMO Fourth Greenhouse Gas Study (IMO, 2020) and U.S. Environmental Protection Agency reports (Starcrest Consulting Group, 2022). Engine-load effects were explicitly considered by estimating the main-engine load for each AIS record and applying pollutant-specific low-load adjustment factors when the load was below 20%. Detailed factors are provided in Fig. S4.

Similar to other AIS-based bottom-up models, SEIM reconstructs ship activity at high spatial and temporal resolution but cannot directly observe fuel consumption or compliance technologies used during each voyage. Therefore, emission estimation depends on both accurate fleet representation and appropriate characterization of fuel compliance pathways. To improve the timeliness and completeness of these key inputs, SEIMv2.3 introduces three methodological improvements: (1) Daily AIS-based activity processing. AIS records are processed at a daily temporal resolution rather than annual aggregation, enabling ship activity reconstruction and emission estimation with a short delay and providing the technical basis for near-real-time emission updates. Detailed methods are provided in Sect. 2.1. (2) Daily identification of previously missing ships. In SEIMv2.2, ship activity records were matched with our Ship Technical Specifications Database (STSD), which may become incomplete as new ships enter operation or previously unrecorded ships become active. SEIMv2.3 uses daily AIS

activity records to identify previously missing ships and update the STSD, with detailed procedures described in Sect. 2.2. (3) Fleet low sulfur compliance choice module (FLSCCM). SEIMv2.3 incorporates multiple sulfur compliance pathways, including low-sulfur fuel switching and HFO use with scrubbers, to better represent post-2020 sulfur compliance choices. Detailed methods are provided in Sect. 2.3.

2.1 From daily AIS to near-real-time emissions

This study established a daily AIS pre-processing framework specifically designed to handle anomalies in daily signals. AIS data consist of both dynamic data and static data. Dynamic AIS offers ship activity information encompassing timestamps and latitude-longitude coordinates, and are subject to multi-stage cleaning to establish a well-cleaned daily ship activity database. Static AIS contains ship technical information including ship type, length, width, and draft and are used for daily identification and characterization of new ships. In this study, we collected global daily AIS data from 2022 to 2024, comprising approximately 113 million dynamic signals and 14 million static signals per day. The daily AIS processing resulted in approximately 45 billion processed signals annually. AIS data contain anomalies and inaccuracies due to various reasons. Therefore, rigorous pre-processing was necessary especially for daily near-real-time emission calculation.

For the daily AIS dataset, firstly, to ensure the stability of daily input data, the model reads AIS signals from the three days preceding and following the target date when calculating daily emissions. Unlike annual AIS preprocessing, the daily framework explicitly accounts for transmission delays because daily AIS data received on a given day may contain signals with timestamps from both the current and previous days. As demonstrated in Fig. 1 (a), the total AIS signals received in one day generally comprised of about 90% of signals with timestamp of the current day and 10% of signals with timestamp of the previous day. Secondly, three-stage cleaning was performed to remove low-quality signals, temporal anomaly, and spatial anomaly. Fig. 1(c) and (d) present the spatial anomaly which leads to the abnormal AIS signal surge during February 21 and 29, 2024 in Fig. 1 (b), when the signal count exceeded 200 million per day. If unprocessed, the abnormal surge would result in up to 2 times of emission overestimation. The cleaning criteria in this study is the same as the work by (Yi et al., 2024a). Signals with invalid geographic coordinates, excessively long-time intervals, or ground speed exceeding 50 knots were discarded in this process. Thirdly, linear interpolation and route restoration was employed to reconstruct the actual sailing trajectory of ships. In the previous step, we removed signals located on land. Additionally, although some signals are not located over land themselves, the connecting lines with adjacent signals may cross over land. In this step, we reconstructed the sailing trajectory between the starting and ending points of those signals based on a global shipping route network using the Dijkstra shortest path algorithm (Wang et al., 2021; Aulinger et al., 2016; Johansson et al., 2017; Cherkassky et al., 1996). Interpolation was performed segment by segment at fixed time intervals, and emissions are calculated accordingly. Besides, as shown in Fig. 1 (e) and (f), the delayed signals contributed to a considerable part of the entire shipping routes, indicating the necessity of three-day AIS processing to the reconstruction of actual sailing trajectories. This preprocessing window is required for trajectory reconstruction from delayed AIS transmissions, while SEIMv2.3 enables near-real-time emission updates with a short delay after AIS data acquisition. The overall effect of pre-processing

framework on global AIS signals from 2022 to 2024 is illustrated in Fig. S1. Figure 1 (g) and (h) display the improvement in coastal regions along China and western Europe on February 22, 2024.The framework managed to reduce inland signals by 46% and 51% in the two regions, where spatial anomalies were removed while signals on inland rivers were kept.

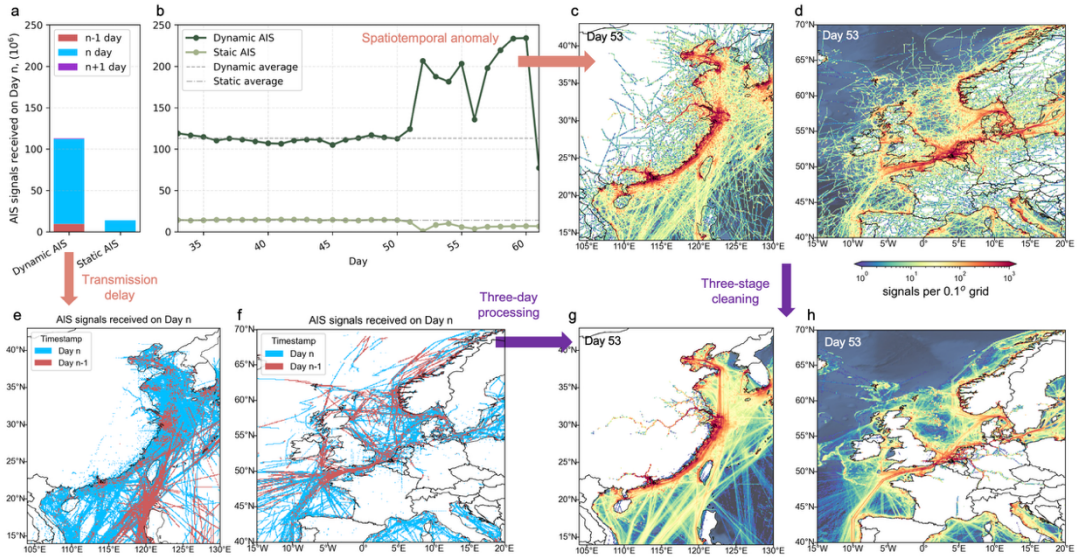


Figure 1: Anomalies and transmission delays of daily AIS signals. Timestamp of dynamic and static AIS signals received on Day n (a) and their spatial distribution in coastal areas along China (e) and western Europe (f). Example of daily signal count anomaly during February 21 to 29, 2024, Day 52 to Day 60 of 2024 (b). Spatial distribution of AIS signals received on Day 53 of 2024 in coastal areas along China (c) and western Europe (d). Spatial distribution of AIS signals of Day 53 after pre-processing in coastal areas along China (g) and western Europe (h).

2.2 Daily identification and characterization of previously missing ships

The STSD in SEIM describes ship attributes such as ship type, deadweight tonnage (DWT), and main engine power, and is originally updated once every two years. In our previous work, we updated the STSD with new-built ships from 2019 to 2021 obtained from Lloyd's Register (Yi et al., 2024a). To keep up with the update frequency of ship activity database and mitigate emission underestimation brought by delayed STSD update, a dynamic framework utilizing daily static AIS to promptly update the STSD has been established.

First, we identified newly detected ships by filtering IMO number that were not yet included in STSD from daily static AIS signals. Before utilizing static AIS to update the STSD, two major challenges need to be solved: (1) the classification of cargo ships in static AIS is overly broad, which does not align with the 14-type ship classification required by SEIMv2.3. While static AIS assign values 70–79 uniformly to cargo ships, SEIMv2.3 further subdivides cargo ships into auto carriers, bulk carriers, container ships, and general cargo ships, each with distinct emission factors. (2) Static AIS lacks main engine power and DWT information, which is also critical for matching emission factors. Without additional parameter completion, these missing specifications would have to be represented by proxy values, which may introduce considerable uncertainties in engine power estimation and subsequent emission factor assignment. Through extensive literature review, we selected

machine learning algorithms and feature sets that have demonstrated strong fitting performance to supplement and refine these missing or coarse parameters (Baek et al., 2024; Huang et al., 2024; Raman et al., 2025; Yang et al., 2024). The final models, features, and hyperparameters used are listed in Table S1. Cargo ships were further subdivided into auto carriers, bulk carriers, container ships, and general cargo ships based on geometric features such as ship length and width using the XGBoost, achieving an accuracy of 0.82. XGBoost and Random Forest were applied to predict DWT (r^2 = 0.92, RMSE = 4.9 ktons, MAE = 1.9 ktons) and main engine power (r^2 = 0.80, RMSE = 1.7 kW, MAE = 0.9 kW), significantly improving data completeness. Figure S2 demonstrates the performance of key ship parameter prediction. Ultimately, the reconstructed technical information of newly identified ships was merged with the original STSD, forming a dynamically updated STSD as shown in Fig. 2.

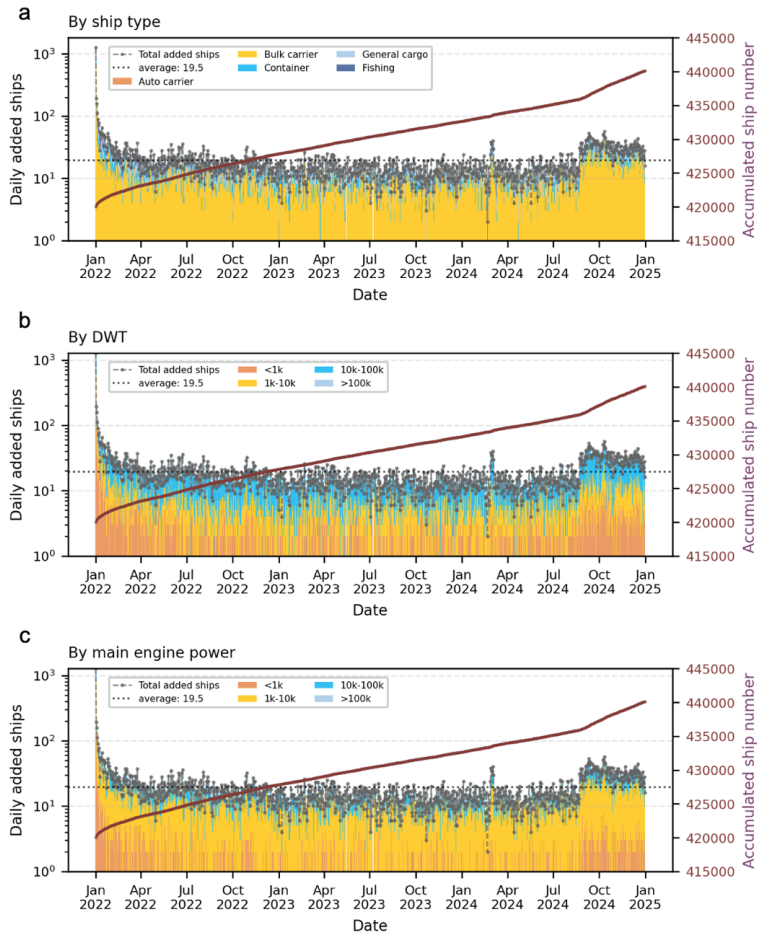


Figure 2: The composition of ship types (a), deadweight tonnage (b), and main engine power (c) for daily newly detected ships. The ship categories shown here represent the dominant categories identified from processed AIS static information for newly identified ships and do not correspond directly to the 14 emission categories used in SEIMv2.3.

2.3 Fleet low sulfur compliance choice module (FLSCCM)

In response to the IMO low sulfur regulation, ships primarily have three compliance options (Chu Van et al., 2019; Deng et al., 2021; Ji and El-Halwagi, 2020), with different implications for fuel consumption, SO_2 emissions, $PM_{2.5}$, and BC emissions: (1) Switching to low-sulfur fuels (e.g., MGO, VLSFO). This straightforward option directly lowers fuel sulfur content, resulting in sharp reduction in SO_2, $PM_{2.5}$ and BC emissions. As shown in Table S2 and Table S4, the emission factors for HFO (2.43% sulfur) are 0.051 gSO_2/g fuel and 1.39 $gPM_{2.5}$/kWh for the main engine, whereas for VLSFO (0.5% sulfur) they are 0.0098 gSO_2/g fuel and 0.31 $gPM_{2.5}$/kWh. Assuming other operational factors remain constant, this switch reduces SO_2 by 81% and reduces $PM_{2.5}$ and BC emissions by approximately 77%. (2) Continuing to use cheap HFO with a scrubber. Scrubbers remove SO_2 from exhaust but are less effective against $PM_{2.5}$. Studies reported the $PM_{2.5}$ removal efficiency ranging only from about 16% to 37% and no significant BC removal efficiency for ship scrubbers (Yang et al., 2021; Kuittinen et al., 2024). Therefore, compared to option (1), this option yields similar SO_2 emissions but results in relatively higher $PM_{2.5}$ and BC emissions. (3) Using alternative fuels such as LNG, which can substantially reduce emissions but currently represent a limited share of global marine fuel consumption. Therefore, FLSCCM focuses on the allocation of the two dominant sulfur compliance pathways: low-sulfur fuel switching and HFO with scrubbers.

Because globally complete ship-level compliance information is unavailable, FLSCCM reconstructs fleet sulfur compliance pathways by combining ship-level scrubber installation records with constrained statistical gap filling. First, scrubber-equipped ships recorded in the Clarksons Research database are identified and matched with the SEIM fleet using ship MMSI. Ships were considered to have observed scrubber capability only when they were identified as fitted with scrubbers and the installation was effective before the corresponding emission calculation period. These records indicate scrubber installation availability rather than voyage-level operation. In this study, ships with effective installations were assumed to follow the HFO-with-scrubber pathway during the corresponding period.

For ships without available scrubber installation records, FLSCCM applies structurally constrained gap filling based on characteristics derived from scrubber-equipped vessels identified from the installation database. Analysis of the scrubber installation database in Supplementary Information showed that scrubber adoption was concentrated among major cargo ship categories and larger vessels. Bulk carriers, containers, and tankers together accounted for approximately 79.5% of identified installations (Fig. S7). Therefore, gap filling was restricted to bulk carriers, containers, oil tankers, and chemical tankers. In addition, ship size and construction year were introduced as screening criteria because scrubber installation is economically favoured for ships with higher fuel consumption and sufficient remaining service life. Database-unmatched ships were considered eligible candidates only when they had a DWT of at least 50,000 tonnes and a construction year later than 2006 when reliable information was available. These criteria were applied only to ships without scrubber installation records during the residual gap-filling procedure and did not affect ships with confirmed scrubber installations. The threshold settings were determined based on the characteristics of the observed scrubber-equipped fleet. For vessels identified or assigned as following the HFO-with-scrubber pathway, SEIMv2.3 applies a baseline $PM_{2.5}$ removal efficiency of 37% and a

BC removal efficiency of 30% in the emission calculation. Uncertainties associated with scrubber assignment criteria and removal efficiencies are further evaluated through sensitivity analyses in the Supplementary Information and the Discussion section.

The reconstructed fleet-level fuel structure was evaluated against IMO fuel consumption statistics for the post-2020 period (Fig. 3). SEIMv2.3 reproduced the major transition from HFO-dominated fuel use before IMO 2020 to increased adoption of low-sulfur fuels and HFO-with-scrubber pathways afterward. The remaining differences between modelled and IMO-reported fuel shares are likely attributable to differences in fuel classification, fleet coverage, and the explicit separation of HFO-with-scrubber pathways in SEIMv2.3. Therefore, IMO statistics were used as an independent fleet-level reference to assess the plausibility of reconstructed compliance pathways rather than as a direct constraint for model calibration.

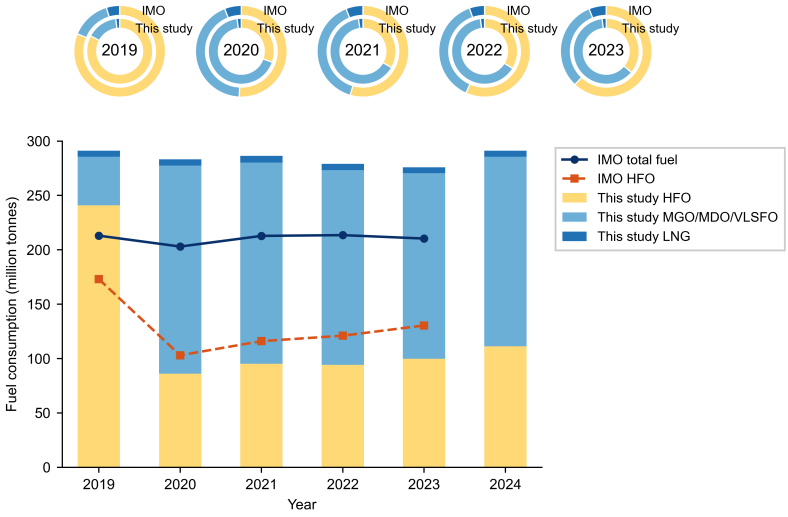


Figure 3: Fuel consumption validation with IMO statistics

3 Results

3.1 Enhanced description of global shipping fleet

The daily identification and characterization mechanism enables the model to effectively capture newly-detected ship activity. An average of 20 ships (identified by MMSI number) previously absent from the STSD are detected per day, their characteristics are presented in Fig. 2. Bulk carriers constitute the primary category among these newly added ships, accounting for approximately 57% of the total. Regarding DWT range, newly identified vessels were predominantly distributed within the 10,000–100,000 DWT range, accounting for about 59% of newly identified vessels by number. Meanwhile, main engine power was largely concentrated in the 1,000–10,000 kW range, which included approximately 58% of newly identified vessels by number. The daily identification and characterization mechanism also led to a continuous expansion of our STSD, as illustrated in Fig. S5. Over the study period, the number of ships (identified by unique MMSI) in

the STSD increased from 418,000 to 440,000, representing a growth of 5.3%. If we identified ship number by unique IMO number (primarily for oceangoing ships), the STSD exhibited more significant growth, expanding from 105,000 to 126,000 ships—a notable increase of 20.0%, underlining that dynamic update of STSD effectively enhanced the coverage of oceangoing ships.

The expansion of the STSD have enabled SEIMv2.3 to provide a more comprehensive characterization of the global active fleet. In 2024, SEIMv2.3 captured activities from 132,000 ships, including 68,000 IMO-identified ships. Compared with SEIMv2.2, the number of active bulk carriers, container ships, general cargo ships, and fishing ships increased by 22.9%, 6.8%, 8.0%, and 14.6%, respectively. Bulk carriers and container ships showed the largest increases in fleet tonnage, with gross tonnage increases of 8.0% and 6.2%, respectively. Newly identified ships were primarily constructed between 2000 and 2010, indicating that the update mainly supplemented missing information for existing vessels (Fig. 4). DWT distribution reveals that while the ship number increase in SEIMv2.3 was dominated by ship whose DWT was less than 10 kt, the growth in total fleet tonnage was driven predominantly by ship DWT between 60 to 80 kt. The newly identified ships accounted for approximately 10.3% of all active ships annually and contributed about 11.3% of the total annual sailing distance in 2024. Their activities exhibited the highest signal density in major maritime hubs, notably in East Asia and Europe, with their activity widely distributed across global shipping routes, as shown in Fig. 5. This geographical pattern reflects the higher rate of new ship deployment in these key shipbuilding and operational regions, such as China, South Korea, and the major ports of Northern Europe.

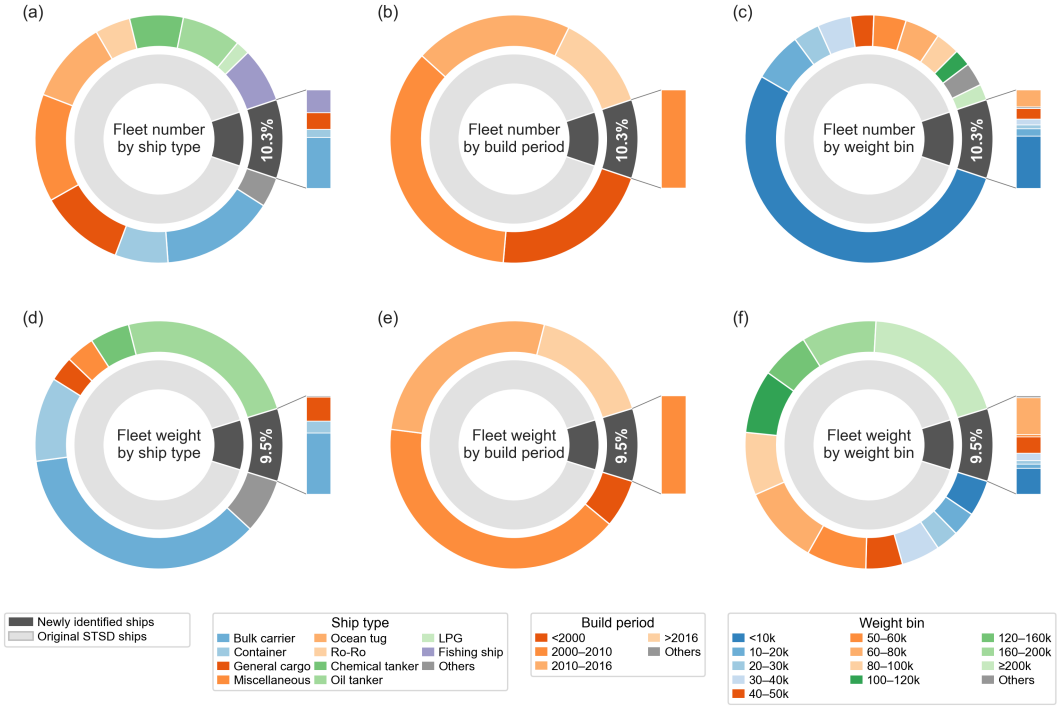


Figure 4: The composition of ship number and total weight of the active global fleet by SEIMv2.3 and SEIMv2.2. Panels (a–c) show fleet number by ship type, build period, and weight bin; panels (d–f) show the corresponding distributions of total fleet weight. The inner ring distinguishes ships contained in the original STSD (light grey) from ships newly identified through the dynamic STSD updating procedure (dark grey). The outer coloured ring shows the category composition of the original STSD fleet, and the linked stacked bar shows the composition of newly identified vessels using the same colour scheme.

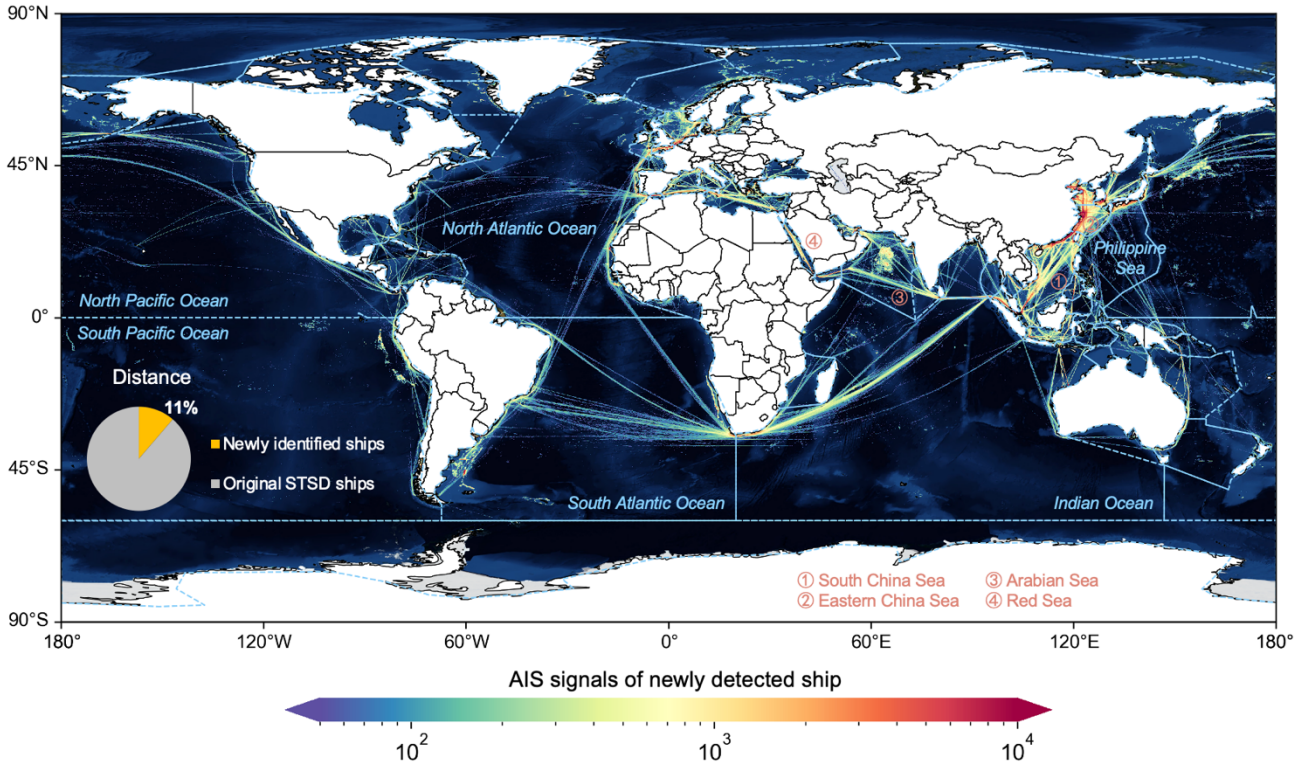


Figure 5: Spatial distribution of newly detected ship signals.

3.2 Annual ship emissions and comparison with other studies

Following our previous global ship emission estimates for 2016–2021 (Yi et al., 2024a), SEIMv2.3 extends the inventory to 2022–2024. To improve the representation of emission changes before and after the IMO 2020 sulfur regulation, historical emissions from 2019 to 2021 were recalculated using the revised SEIMv2.3 framework. Figure 6 shows the global ship emissions of nine atmospheric pollutants and greenhouse gases (GHG), including CO_2, CH_4, and N_2O, calculated using different models from 2019 to 2024. For comparison, available international shipping emission estimates from the Emissions Database for Global Atmospheric Research (EDGAR) and the Community Emissions Data System (CEDS) were used as independent global references to evaluate the temporal consistency of SEIMv2.3. For EDGAR, international shipping emissions were derived using the Ship Traffic Emission Assessment Model (STEAM3) framework (Crippa et al., 2024).Comparisons were limited to pollutants with available and comparable estimates.

From 2019 to 2020, ship SO_2 emissions dropped sharply from 12,215 kt to 2,212 kt, consistent with the results from EDGAR and CEDS. $PM_{2.5}$ emissions showed a substantial but less pronounced reduction than SO_2 because the implementation of sulfur regulations affected not only fuel sulfur content but also the selection of compliance pathways. In SEIMv2.3, global ship $PM_{2.5}$ emissions decreased by 60.2%, from 1,725 kt in 2019 to 686 kt in 2020, and remained relatively stable at 703–768 kt during 2021–2024. In comparison, SEIMv2.2, which did not represent HFO-with-scrubber pathways after 2020, estimated only 393 kt $PM_{2.5}$ emissions in 2020, corresponding to a 42.7% underestimation relative to SEIMv2.3. BC emissions exhibited a comparable but weaker response. SEIMv2.3 estimated that global ship BC emissions decreased by 30.3%, from 98 kt in 2019 to 68.3 kt in 2020, followed by relatively stable emissions between 67.2 and 70.6 kt during 2021–2024. In contrast, SEIMv2.2 estimated 58 kt BC emissions in 2020, corresponding to a 15.1% underestimation relative to SEIMv2.3 and indicating the importance of representing HFO-with-scrubber pathways for BC emission estimation. For other atmospheric pollutants and GHGs, the improvement mainly results from daily identification and characterization of newly observed ships. Comparison between SEIMv2.3 and SEIMv2.2 shows that the absence of daily ship technical database updates would underestimate CO_2 emissions by 5.4% in 2023 and 2.6% in 2024. Although the proportion of underestimated emissions relative to total shipping emissions was relatively low, the inclusion of newly identified ships enabled us to capture emission changes caused by fluctuations in maritime trade and provided a more complete basis for monitoring shipping decarbonization and evaluating mitigation policies.

To distinguish the contributions of daily STSD updates and the FLSCCM, numerical experiments were conducted for the 2024 inventory. Experiment (i) applied SEIMv2.2 without daily STSD updates or FLSCCM; experiment (ii) applied the updated STSD without FLSCCM; and experiment (iii) applied the complete SEIMv2.3 framework. The difference between experiments (iii) and (ii) represents the contribution of FLSCCM, whereas the difference between experiments (ii) and (i) represents the contribution of daily STSD updates. The results indicate that emission underestimation sources differ among pollutants: STSD updates mainly improve CO_2 and gaseous pollutant estimates by increasing fleet completeness, while FLSCCM remains particularly important for $PM_{2.5}$ and BC because these pollutants are directly affected by fuel sulfur content and scrubber-related removal efficiencies.

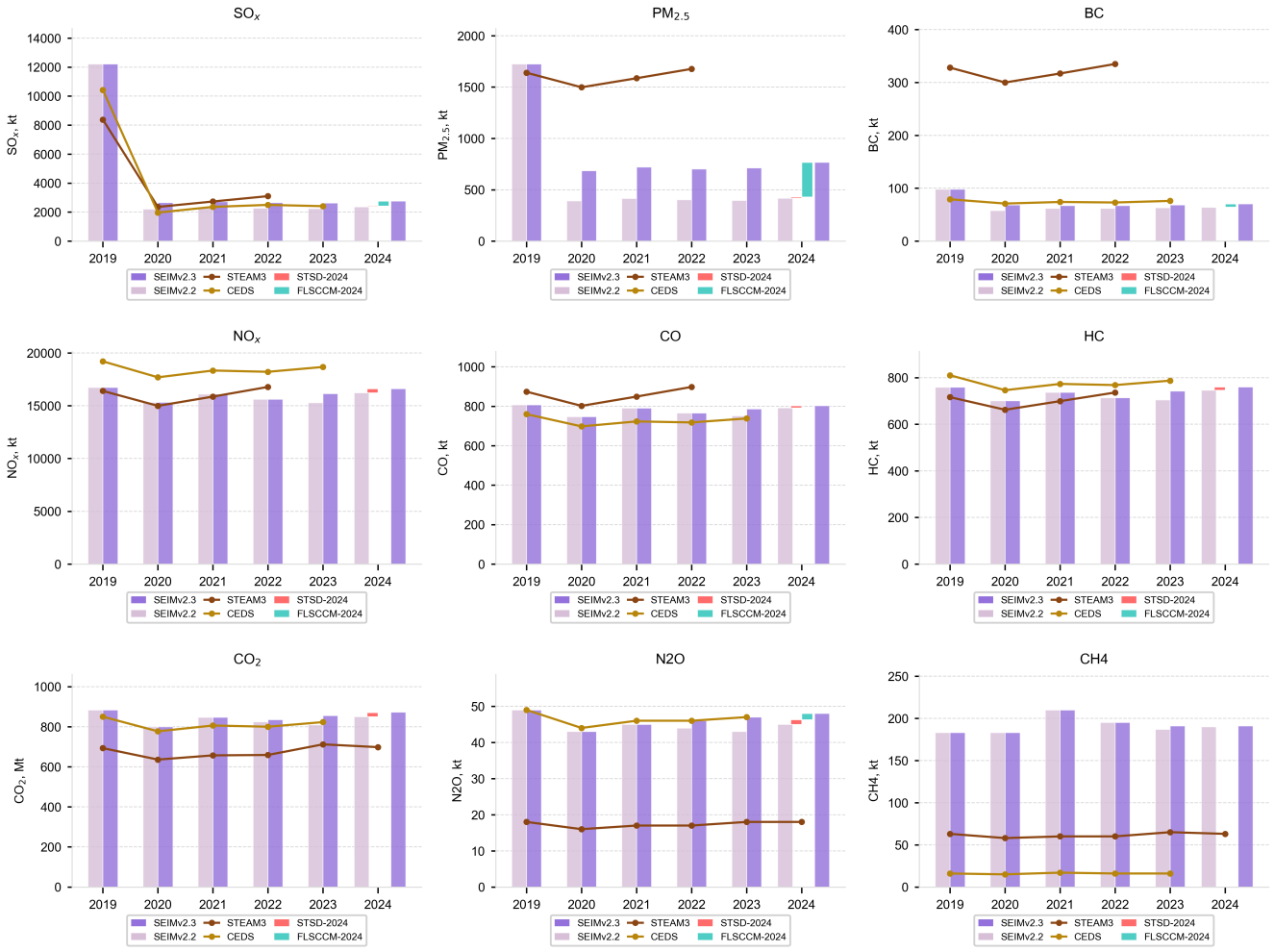


Figure 6: Comparison of annual global ship emissions results from SEIMv2.3, SEIMv2.2, and other emission inventories from 2019 to 2024. SEIMv2.2 results were sourced from (Yi et al., 2024a). SEIMv2.3 represents the method presented in this paper. STEAM3 represents the emission results from EDGAR (Crippa M., 2025), whose shipping emission results are based on STEAM3. CEDS represents the emission results from Community Earth atmospheric Data Systems, sourced from (Hoesly, 2025). STSD-2024 and FLSCCM-2024 denote configurations incorporating updated fleet information and reconstructed sulfur compliance pathways, respectively.

3.3 Spatiotemporal heterogeneity in ship emission underestimation

Emission underestimation showed distinct spatial patterns among pollutants (Fig. 7). The major discrepancies were concentrated in the South China Sea, North Atlantic Ocean, Indian Ocean, and North Pacific Ocean. Figure 7 compares regional emission discrepancies with sailing distances of newly identified ships and scrubber-equipped ships to identify potential sources of underestimation. For CO_2 and NOx, the largest discrepancies were primarily associated with incomplete

fleet representation. The South China Sea contributed the largest shares of global CO_2 and NOx underestimation, accounting for 14.2% and 14.4%, respectively, followed by the Indian Ocean and North Atlantic Ocean. These regions also exhibited relatively high STSD-added vessel sailing distances, indicating the important contribution of incomplete fleet representation to CO_2 and NOx discrepancies. In contrast, $PM_{2.5}$ and BC underestimations were more strongly associated with incomplete representation of sulfur compliance pathways. The Indian Ocean showed the largest contributions to global $PM_{2.5}$ and BC underestimation, accounting for 15.1% and 14.7%, respectively. These regions also showed substantial scrubber-associated sailing distances, indicating that incomplete representation of HFO-with-scrubber pathways was a major contributor to particulate emission discrepancies.

The relative impact of underestimation on individual regions was further evaluated by normalizing emission differences against regional total emissions. For CO_2, the relative differences were relatively small across major shipping regions, reaching 3.0% in the South China Sea, 2.9% in the Indian Ocean, and 2.8% in the South Atlantic Ocean. Similarly, NOx underestimation ratios ranged from 2.7% to 4.6%, with the highest value observed in the South China Sea. In contrast, particulate emissions exhibited substantially larger relative differences. The relative underestimation of $PM_{2.5}$ reached 56.1% in the Indian Ocean, 53.7% in the South Atlantic Ocean, and 48.5% in the South China Sea. For BC, the corresponding values were 14.5%, 12.8%, and 10.8%, respectively. These results highlight the stronger influence of compliance pathway assumptions than fleet completeness on regional $PM_{2.5}$ and BC estimates.

The differences between SEIMv2.3 and SEIMv2.2 accumulated throughout 2024 due to differences in fleet representation and sulfur compliance pathway characterization. The daily emission discrepancies remained consistently positive throughout 2024. As shown in Fig. 8, the daily emission discrepancies between SEIMv2.3 and SEIMv2.2 increased from 52.8 kt CO_2 d^{-1}, 1.52 kt NOx d^{-1}, 0.93 kt $PM_{2.5}$ d^{-1}, and 0.017 kt BC d^{-1} at the beginning of 2024 to 62.1 kt CO_2 d^{-1}, 1.79 kt NOx d^{-1}, 0.95 kt $PM_{2.5}$ d^{-1}, and 0.018 kt BC d^{-1} at the end of 2024. The corresponding cumulative emission discrepancies reached 21.3 Mt CO_2, 615.8 kt NOx, 350.3 kt $PM_{2.5}$, and 6.5 kt BC by the end of 2024.

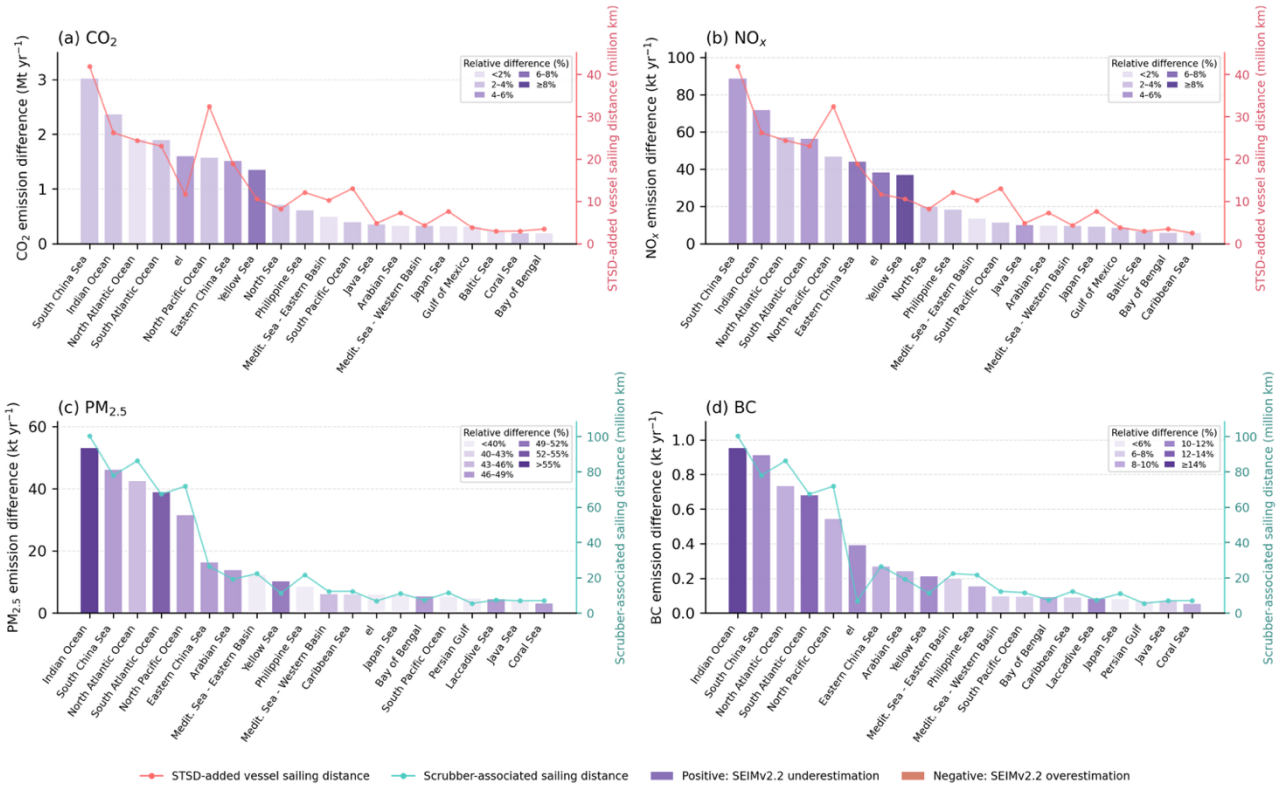


Figure 7. Ship $PM_{2.5}$, BC, CO_2, and NOx emission underestimation mitigated by SEIMv2.3 in different ocean regions in 2024.

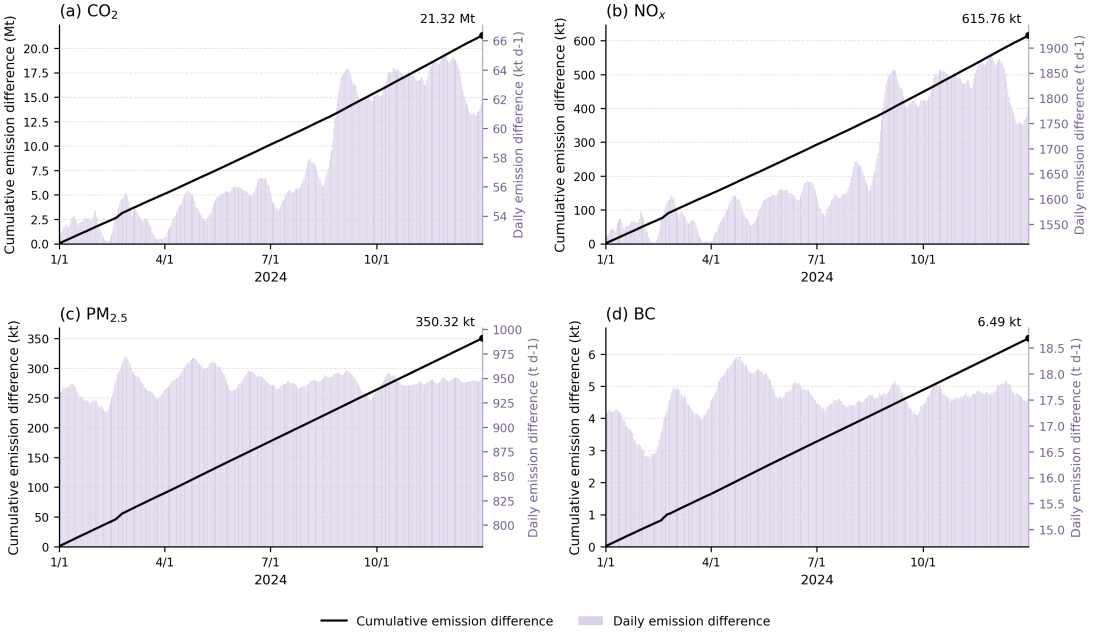


Figure 8. Temporal accumulation of emission discrepancies between SEIMv2.3 and SEIMv2.2 during 2024.

4 Summary

In this study, we introduced SEIMv2.3, which features daily updated ship activity database and STSD to support near-real-time ship emission calculation. With fleet low sulfur compliance choice module, it can simulate fleet's multiple choices to comply with emission control regulations, which forms the fuel consumption structure that aligns well with the actual situation. On average, 23 newly detected ships were supplemented to the STSD daily. From 2022 to 2024, ships included in our STSD rose from 105,000 to 126,000, an increase of 20.0%. The daily expansion of the STSD unveiled an important proportion of the global maritime transport capacity, about 8.0% and 6.2% of the total gross tonnage of the active bulk carrier and container fleets. Those newly-detected ships contributed to 11.3% of the total sailing distance and 10.3% of active ship fleet, uncovering 5.4% and 2.6% of the CO_2 emissions in 2023 and 2024. For $PM_{2.5}$ and BC emissions, the neglect of HFO-with-scrubber pathways after 2020 would lead to underestimations of approximately 43% and 15%, respectively. Our results suggest a decrease of 60.2% in $PM_{2.5}$ emissions from 2019 to 2020, compared with the 77.2% reduction estimated by SEIMv2.2. The South China Sea contributed the largest shares of global CO_2 and NOx underestimation, accounting for 14.2% and 14.4%, respectively, while the Indian Ocean showed the largest contributions for $PM_{2.5}$ and BC underestimation, accounting for 15.1% and 14.7%, respectively. When normalized by regional total emissions, the Indian Ocean and South Atlantic Ocean exhibited the largest relative underestimations. For $PM_{2.5}$ and BC emissions, the underestimated portion reached 56.1% and 14.5% of regional emissions in the Indian Ocean, respectively, compared with 48.5% and 10.8% in the South China Sea. Without the methodological improvements in SEIMv2.3, emission differences accumulated throughout 2024. The daily CO_2 emission difference increased from about 0.053 Mt/d to 0.062 Mt/d, while the daily $PM_{2.5}$ emission difference increased from about 0.93 kt/d to 0.95 kt/d.

5 Discussion

Overall, our study establishes a dynamically updated framework for global ship emission estimation and reveals substantial emission underestimation associated with incomplete fleet representation and simplified sulfur compliance assumptions in previous SEIM configurations. Near-real-time emission inventories enable tracking of short-term emission changes and provide a data foundation for emission reduction policies (Xu et al., 2023). The underestimation addressed in this study may affect assessments of the environmental and health impacts of global shipping. Underestimated $PM_{2.5}$ and SO_2 emissions may bias estimates of shipping-induced aerosol–cloud interactions and radiative forcing (Chen et al., 2017; Goldsworthy et al., 2019; Yuan et al., 2024; Zhang et al., 2025a). Such underestimation may also affect assessments of atmospheric deposition impacts in coastal and marine environments (Shi et al., 2023). The additional contribution to population exposure and health burdens may be limited, because the additional emissions identified in this study were mainly in open-ocean regions, distant from populated coastal areas.

Our conclusions are also supported by independent evidence from IMO fuel consumption statistics, scrubber installation records, and ambient particle observations. IMO fuel statistics indicate that HFO-based pathways remained important after

2020 (IMO, 2024), while (Lunde Hermansson et al., 2024) identified continued operation of scrubber-equipped ships after the sulfur regulation, supporting the necessity of explicitly representing HFO-with-scrubber pathways. (Song et al., 2022) analyzed $PM_{2.5}$ concentrations near Busan Port before and after the IMO 2020 sulfur regulation and found limited changes in ambient $PM_{2.5}$, highlighting the complexity of evaluating shipping impacts based solely on particle mass concentrations.

In addition to $PM_{2.5}$ mass emissions, particle number (PN) emissions deserve further attention because ship exhaust contains large numbers of ultrafine particles that are not fully represented by particle mass. Previous studies demonstrated that shipping remains an important source of anthropogenic PN emissions after 2020 (Kuittinen et al., 2021). Measurements in the Baltic Sea sulfur emission control area showed that reducing fuel sulfur content from 1.5% to 0.1% decreased plume PN concentrations by 27% and ambient PN concentrations by 32% (Seppälä et al., 2021). However, the influence of scrubbers on PN is complex and depends on particle size and scrubber configuration. Onboard measurements of a modern cruise ship showed that a hybrid scrubber reduced total PN and nonvolatile PN, whereas particles larger than 50 nm, which may include BC and metal-containing particles, were not significantly reduced (Kuittinen et al., 2024). These findings indicate that future ship emission inventories should extend beyond $PM_{2.5}$ mass emissions and incorporate PN size distributions and scrubber-specific particle removal characteristics.

Despite the improvements introduced in SEIMv2.3, several uncertainties remain. First, missing vessel specifications supplemented through machine learning may introduce errors at the individual-ship level, although these uncertainties are expected to decrease after aggregation at regional and global scales. Second, FLSCCM reconstructs sulfur compliance pathways using vessel-level scrubber records combined with constrained statistical allocation because global ship-specific fuel-use observations are unavailable. Third, FLSCCM does not distinguish ULSFO and MGO, and fuels of 0.1% sulfur are represented using MGO emission factors. This simplification is expected to have limited influence on SO_2, but it may lead to some underestimation of $PM_{2.5}$ and BC emissions where residual-type ULSFO is used. Therefore, uncertainties may arise from incomplete scrubber records, assumed scrubber operation, and simplified representation of ULSFO using MGO emission factors. These uncertainties mainly affect $PM_{2.5}$ and BC estimates, while their influence on SO_2 remains limited.

To quantify the influence of scrubber-related uncertainty on particulate emission estimates, we conducted sensitivity analyses using different scrubber removal efficiency assumptions. Under the low-, baseline-, and high-removal scenarios, corresponding to $PM_{2.5}$ removal efficiencies of 10%, 37%, and 70% and BC removal efficiencies of 10%, 30%, and 60%, global $PM_{2.5}$ emissions varied by +26.6% and −32.6% relative to the baseline case, while BC emissions varied by +11.5% and −17.3%. Despite this uncertainty, all scenarios consistently show higher particulate emissions than inventories that neglect or incompletely represent HFO-with-scrubber pathways, indicating that the identified underestimation is robust to plausible variations in scrubber removal performance.

Future reductions in uncertainty require improved ship-specific technical databases, broader sharing of scrubber installation records and fuel-use data, and additional validation datasets such as onboard measurements, EU MRV, or ship bunkering records. Direct single-ship validation remains challenging because such data are rarely publicly available. Nevertheless,

comparisons with independent inventories and sensitivity analyses indicate that these uncertainties are unlikely to alter the main conclusions regarding the magnitude and characteristics of global shipping emissions.

Code and data availability

Python codes used during the current study are available from the corresponding author on reasonable request.

Author contributions

Weiwei Zhang developed the model, performed the simulations, and prepared the manuscript. Zhaofeng Lv managed the project and edited the manuscript. Bensheng Xiao collected the data. Wen Yi, Tingkun He, and Feng Sun validated the results and reviewed the manuscript. Huan Liu and Qiang Zhang conceptualized the research aim, supervised the project and acquired the financial support.

Competing interests

One of the co-authors is member of the editorial board of Atmospheric Chemistry and Physics.

Acknowledgements

This work was supported by the National Key R&D Program of China (No. 2023YFC3705604) and COSCO SHIPPING Co., Ltd. (No. 2025-4-Z001-03).

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