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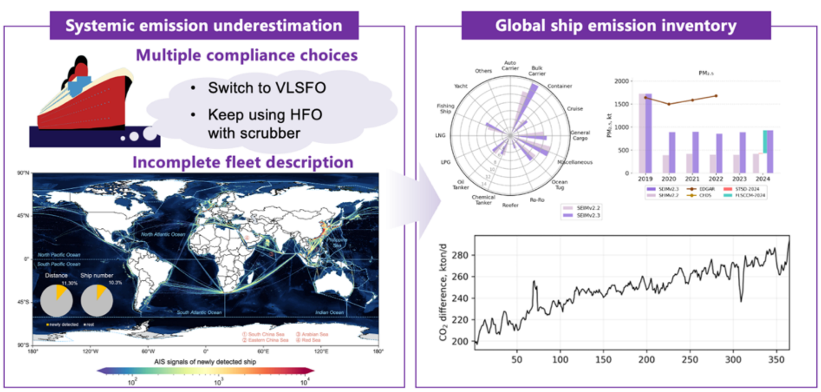
Addressing systemic underestimation in global ship emissions from fleet growth and fuel compliance

Weiwei Zhang[1,2], Zhaofeng Lv[1], Wen Yi[1,2], Tingkun He[1,2], Bensheng Xiao[1], Qiang Zhang[3], Huan Liu[1,2]

[1] State Key Laboratory of Regional Environment and Sustainability, School of Environment, Tsinghua University, Beijing 100084, China
[2] Institute for Carbon Neutrality, Tsinghua University, Beijing 100084, China
[3] Ministry of Education Key Laboratory for Earth System Modeling, Department of Earth System Science, Tsinghua University, Beijing 100084, China

Correspondence to: Huan Liu (liu_env@tsinghua.edu.cn)

Abstract. As a hard-to-abate sector, global shipping is under international and regional emission control regulations. To evaluate emission control effects and conduct rapid response air quality simulations, accurate and timely ship emission inventories are indispensable. However, current ship emission inventory models face multiple challenges, including incomplete and delayed global ship fleet description and significant divergence in $PM_{2.5}$ emissions after global low sulfur regulation came into effect. Here, we established a dynamically updated Ship Emission Inventory Model that allows near-real-time emission calculation. Ship activity and technical database are updated daily instead of yearly to obtain a more complete and rapid description of 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. Without the expansion, the daily underestimation would enlarge over time from about 0.20 Mt CO_2 /d to 0.29 Mt CO_2 /d throughout 2024. On the other hand, the single compliance choice assumption and ignorance of heavy fuel oil use after 2020 would lead to underestimation of $PM_{2.5}$ and BC emissions by approximately 55% and 27%. Although South China Ocean had the most absolute underestimation, the Indian Ocean had the highest underestimated portion, reaching 75% and 39% of its total $PM_{2.5}$ and BC emissions.



https://doi.org/10.5194/egusphere-2026-1935
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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 rise by 1.7 times in atmospheric 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 carbon dioxide (CO_2) emissions, 11% of sulfur oxides (SO_x), and 15% of nitrogen oxides (NO_x) (Imo, 2020). If unregulated, the contribution to total CO_2 emissions would surge to 17% in 2050 (Cames et al., 2015). 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 regulations found that sulfur emission control areas (ECA) in Marmara Sea and Turkish Straits reduced SO_2 concentration by 90% in Istanbul (Viana et al., 2015) while China's Domestic Emission Control Area (DECA) policy achieved an emission reduction by 33% within 200Nm 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). However, the accuracy of existing emission inventories is systemically constrained by the incomplete and delayed technical data (Hu et al., 2025; Huang et al., 2021; Ye et al., 2025), especially for the global maritime transportation sector (Liu et al., 2022; Baek et al., 2024). First, the fuel choice assumption after the implementation of IMO low sulfur regulation by existing ship emission inventory model do not align with the actual situation. IMO low sulfur regulation requires that, from January 1, 2020, the global cap on the sulfur content of ship fuel oil be reduced from 3.50% to 0.50%. Within ECAs, the sulfur content cap is 0.10%. Previous ship emission inventory models assumed that after 2020, all ships using heavy fuel oil (HFO) had switched to very low sulfur fuel oil (VLSFO) or marine gas oil (MGO) (Yi et al., 2024a; Yi et al., 2024b). Yet, multi-source data suggest that using HFO with scrubber to comply with IMO regulation is a mainstream choice for global ship fleets. IMO fuel statistics showed that HFO still accounts for 65% of the ship fuel consumption even after 2020 (Imo, 2024). HFO also constituted of 21.4% - 37.2% of the marine bunker fuel in Singapore and Rotterdam (https://shipandbunker.com/). Lunde Hermansson et al. (2024) found that after 2020 there were over 800 ships in the Baltic Sea equipped with scrubbers to comply with IMO regulation. As the choice of HFO with installation of scrubber would be cost-competitive to the choice of VLSFO for over 95% of the ships within five years after installation(Lunde Hermansson et al., 2024), ship scrubber use would maintain the mainstream choice for ship fleets in the short or middle term.

Another challenge facing ship emission inventories is to include newly built or newly identified ships into ship technical database. Ships built after 2016 contributed to 10.2% of global ship emissions in 2021 (Yi et al., 2024a). With the number and gross tonnage of ships on order rising (Eirik Ovrum, 2024), newly built ships will amount to even larger percentage. Unlike ship activity data, which can be updated daily, ship technical database are generally supplemented at least one year

https://doi.org/10.5194/egusphere-2026-1935
Preprint. Discussion started: 26 May 2026

later (Yi et al., 2024a), resulting in the failure to combine ship activity data to proper emission factors. Although scholars have managed to extract ship parameters from Automatic identification systems (AIS) data (Wang et al., 2021; Huang et al., 2020) and supplement missing parameters with machine learning methods (Yang et al., 2022; Huang et al., 2024; Yang et al., 2024; Raman et al., 2025), there is currently no established framework where activity data and technical data are updated simultaneously with quality control.

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 updates both activity data and ship technical data on a daily basis. On one hand, ship activity data went through pre-processing framework specifically designed to handle anomalies in daily signals. On the other hand, ship technical parameters of newly identified ships were extracted from AIS data to supplement the ship technical database. The fleet low sulfur compliance choice module was added to identify HFO and scrubber use. We calculated global ship emissions from 2022 to 2024 day-by-day and evaluated the improvement by SEIMv2.3 on global fleet description, and daily and annual emission calculation.

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., 2025) and ports (Fu et al., 2017). The specific formula used in this study to calculate ship emissions were largely consistent with that of (Yi et al., 2024a) and provided in Supplementary Information.

Compared to previous versions (Wang et al., 2021; Yi et al., 2024a), this dynamically updated version, SEIMv2.3, features three key improvements: (1) AIS data are collected, preprocessed, and calculated daily instead of yearly. Emission inventories with a rapid response capability are crucial for pollution control and air quality simulation. In SEIMv2.3, we collected daily AIS data and enhanced the pre-process accordingly to enable near-real-time ship emission calculation. Detailed methods are provided in Sect. 2.1. (2) Daily identification and characterization of new ships. The number of active ships identified by SEIMv2.2 dropped markedly in recent years, from 108,000 in 2021 to 104,000 in 2023 while global fleet data from UNCTAD showed an increase by 9.2 % from 99,800 ships 2021 to 109,000 ships in 2023(Unctad, 2021, 2024). To obtain a more complete description of global ship fleet, we promptly updated the STSD with daily AIS data, which is discussed in detail in Sect. 2.2. (3) The fleet low sulfur compliance choice module. We simulated the multiple choices of fleet to comply with IMO low sulfur regulation to generate more accurate emission calculation. Detailed methods are provided in Sect. 2.3.

https://doi.org/10.5194/egusphere-2026-1935
Preprint. Discussion started: 26 May 2026

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 daily AIS from 2022 to 2024, which comprised of approximately 113 million dynamic signals and 14 million static signals, reaching a total of 45 billion 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.

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 data, due to transmission delays, daily AIS data consist of signals from both the current day 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. 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.

https://doi.org/10.5194/egusphere-2026-1935
Preprint. Discussion started: 26 May 2026

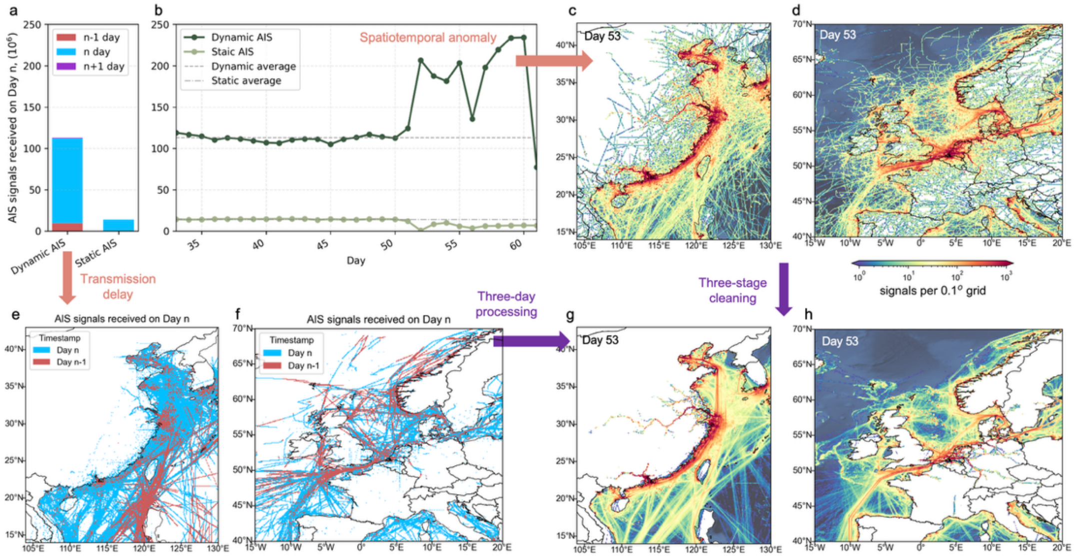

Figure 1: Anomalies and transmission delays of daily AIS signals. Timestamp of dynamic and static AIS signals received on Day n (a) and their spatial distribution in coastal areas along China (e) and western Europe (f). Example of daily signal count anomaly during February 21 to 29, 2024, Day 52 to Day 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 new ships

The Ship Technical Specification Database (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 lack main engine power and DWT information, which is also critical for matching emission factors. 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,

https://doi.org/10.5194/egusphere-2026-1935
Preprint. Discussion started: 26 May 2026

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 supplemented information of newly detected ship was merged with the original STSD, forming a daily updated STSD as shown in Fig. 2. Daily static AIS data from 2022 to 2024 were used to enhance our description of the global ship fleet.

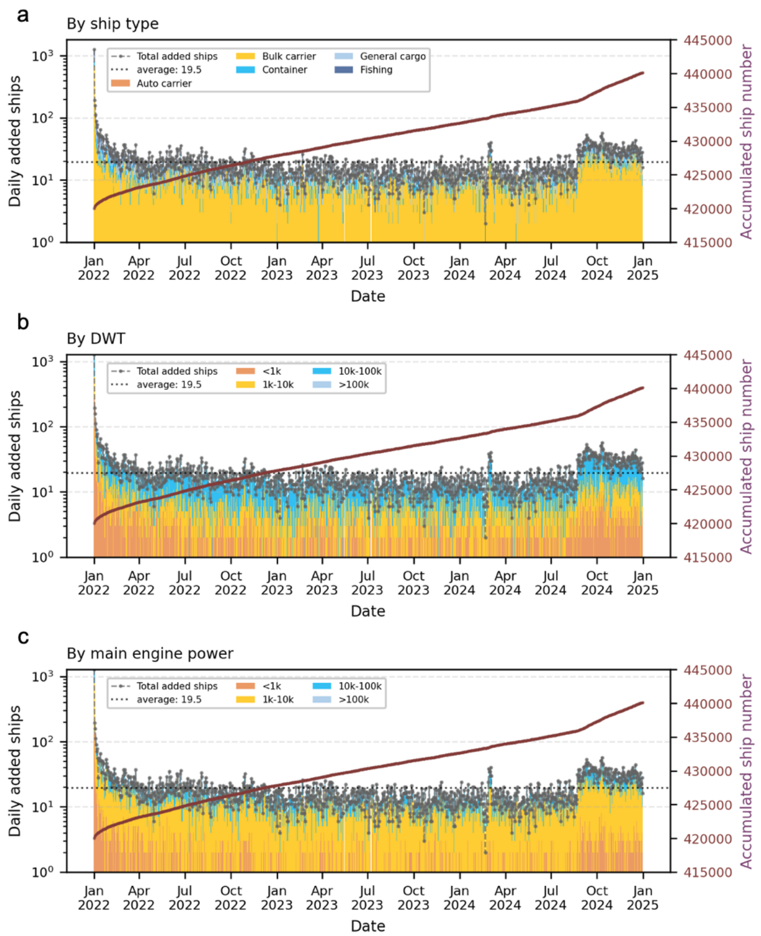

Figure 2: The composition of ship types (a), deadweight tonnage (b), and main engine power (c) for daily newly detected ships.

2.3 Fleet low sulfur compliance choice module

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 S3, 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 MGO (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

https://doi.org/10.5194/egusphere-2026-1935
Preprint. Discussion started: 26 May 2026

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. This option drastically reduces most air pollutants, as the emission factors are negligible compared to HFO. However, the current ship LNG consumption is minimal relative to HFO, VLSFO, or MGO. Consequently, the fleet low sulfur compliance choice module only considers the allocation of option (1) and (2).

Due to the lack of global, ship-specific data on actual compliance choices, this study developed a proxy method based on vessel type and size to assign the compliance choice to each ship. Analysis of IMO fuel consumption statistics by ship type and DWT revealed that bulk carriers, container ships, and tankers accounted for nearly 90% of global HFO consumption (Imo, 2024). Within these categories, the proportion of HFO use increases significantly with vessel size (Fig. S3). Based on this pattern, a DWT threshold was established for these three key ship types. Ships exceeding the threshold are assigned to option (2) as the economic incentive for scrubber installation is stronger for larger, higher-fuel-consumption ships. Ships at or below the threshold are assigned to option (1). The DWT threshold was calibrated by testing a range of values (e.g., 40,000–60,000 DWT) against the IMO fuel consumption data. The threshold that minimized the difference between the modeled and reported HFO consumption share in 2021 was selected. For this study, a threshold of 40,000 DWT was applied (Fig. S4). The module was validated by comparing its fuel consumption results with IMO statistics of 2020, 2022 and 2023. SEIMv2.3 successfully reproduced the dramatic fuel shift: the HFO share of total consumption fell sharply from 82.8% in 2019 to 52.2% in 2020, matching the IMO-reported values of 81.2% and 50.7%, respectively (Fig. 3). The absolute HFO consumption estimates for the post-2020 period also align with the statistics. Admittedly, uncertainties and limitations exist in the fleet low sulfur compliance choice module. They will be explained in detail in Discussion section.

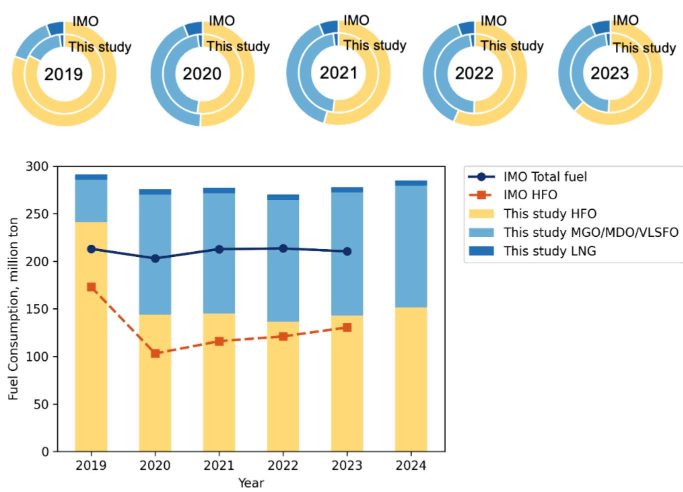

Figure 3: Fuel consumption validation with IMO statistics

https://doi.org/10.5194/egusphere-2026-1935
Preprint. Discussion started: 26 May 2026

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, the newly detected ships are predominantly distributed within the 10k–100k ton range, representing about 59% of the total. Meanwhile, the main engine power is largely concentrated in the 1k–10k KW interval, comprising roughly 58% of the newly detected ships. 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. Using 2024 as an example, SEIMv2.3 captured the activities of 132,000 ships, including 68,000 ships identified by IMO number. As illustrated in Fig. 4, compared to SEIMv2.2, the number of active bulk carriers, container ships, general cargo ships, and fishing ships identified by SEIMv2.3 increased by 22.9%, 6.8%, 8.0%, and 14.6%, respectively. Regarding transport capacity, bulk carriers remained the primary contributor to total fleet tonnage, with SEIMv2.3 reporting an 8.0% increase in gross tonnage for bulk carriers, while container ship tonnage grew by 6.2%. In terms of age distribution, SEIMv2.3 primarily supplemented activities of ships constructed between 2000 and 2010, both in ship number and gross tonnage. 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 detected ships represent a significant and active component of global shipping activity. These ships accounted for approximately 10.3% of all active ships annually and contributed about 11.3% of the total annual sailing distance in 2024. Without the dynamic update of the STSD, this substantial portion of maritime activity would either be omitted or be inaccurately estimated using generalized default emission factors. Spatially, the newly detected ships 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.

https://doi.org/10.5194/egusphere-2026-1935
Preprint. Discussion started: 26 May 2026

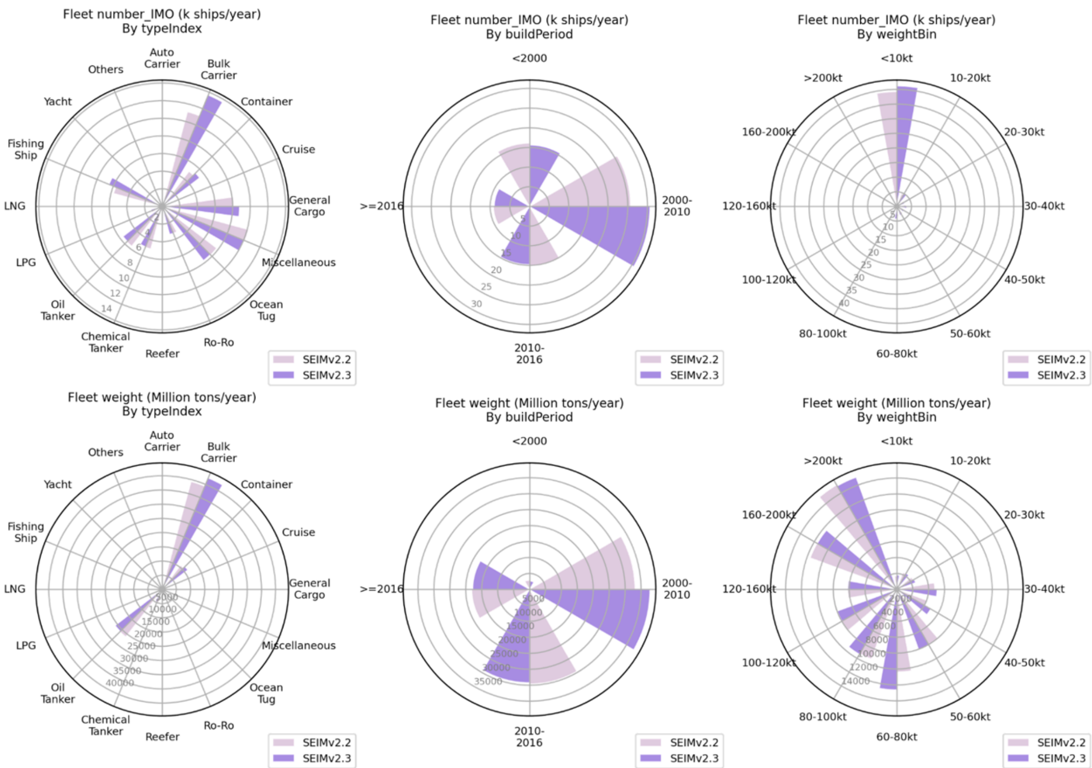

Figure 4: The composition of ship number and total weight of the active global fleet by SEIMv2.3 and SEIMv2.2.

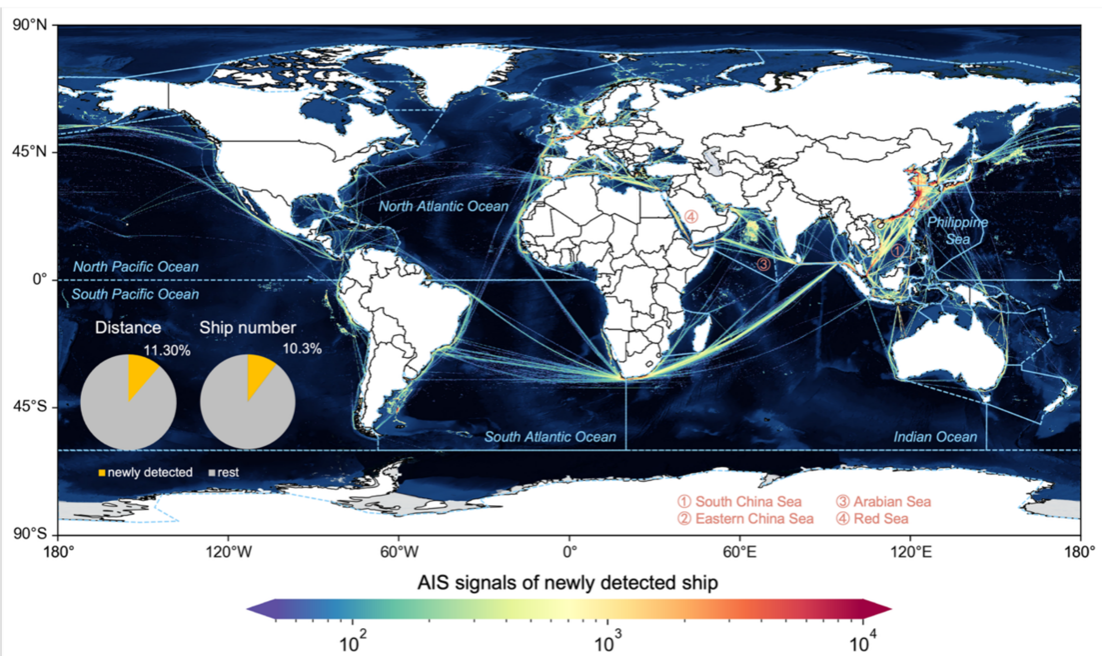

Figure 5: Spatial distribution of newly detected ship signals.

https://doi.org/10.5194/egusphere-2026-1935
Preprint. Discussion started: 26 May 2026

3.2 Annual ship emissions and comparison with other studies

Building on our previous work of ship emission from 2016 to 2021(Yi et al., 2024a), this study further presents global ship emissions from 2022 to 2024. To obtain more accurate emission results before and after IMO low sulfur regulation, we calculated historical ship emissions from 2019 to 2021 using SEIMv2.3. Figure 6 shows the global ship emissions of nine atmospheric pollutants and greenhouse gases (GHG) calculated using different models from 2019 to 2024. The emissions in 2024 were analyzed to illustrate the impact on emission calculation by daily identification and characterization of new ships (denoted as STSD-2024) and the fleet low sulfur compliance choice module (denoted as FLSCCM-2024).

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. For $PM_{2.5}$ emissions, the results from SEIMv2.3 show that from 2019 to 2020, ship $PM_{2.5}$ emissions decreased from 1,725 kt to 893 kt, a reduction of approximately 48.2%, and then fluctuated slightly between 856 kt and 932 kt from 2021 to 2024. SEIMv2.2 did not consider HFO use after 2020 and underestimated $PM_{2.5}$ emissions to be 393 kt in 2020, representing a decrease of about 77.2% compared to 2019. EDGAR results do not reflect the control effect of IMO's sulfur regulations on $PM_{2.5}$ emissions. Although there was also a decrease by 8.6% in ship $PM_{2.5}$ emissions from 2019 to 2020 in EDGAR results, this can be attributed to reduced ship activity due to the pandemic in 2020. BC emissions show a similar pattern to $PM_{2.5}$ emissions. Results SEIMv2.3 show that from 2019 to 2020, ship BC emissions decreased from 98 kt to 83 kt, a reduction of approximately 15.3%, and then fluctuated between 83 kt and 88 kt from 2021 to 2024, highly consistent with CEDS results. SEIMv2.2 underestimated BC emissions to be 58 kt in 2020, representing a decrease of about 40.8% compared to 2019. Comparison between SEIMv2.3 and SEIMv2.2 shows that the ignorance of HFO use after 2020 would lead to an underestimation of $PM_{2.5}$ and BC emissions by approximately 55% and 27%, 97% of which can be mitigated by fleet low sulfur compliance choice module. For other atmospheric pollutants and GHGs, the emission underestimation was mitigated by daily identification and characterization of new ships. Comparison between SEIMv2.3 and SEIMv2.2 shows that the absence of daily identification and characterization of new ships would lead to CO_2 emission underestimation by 5.4% in 2023 and 2.6% in 2024. Although the proportion of underestimated emissions to total emissions was relatively low, the inclusion of them allowed us to capture emission changes caused by fluctuations in maritime trade.

https://doi.org/10.5194/egusphere-2026-1935
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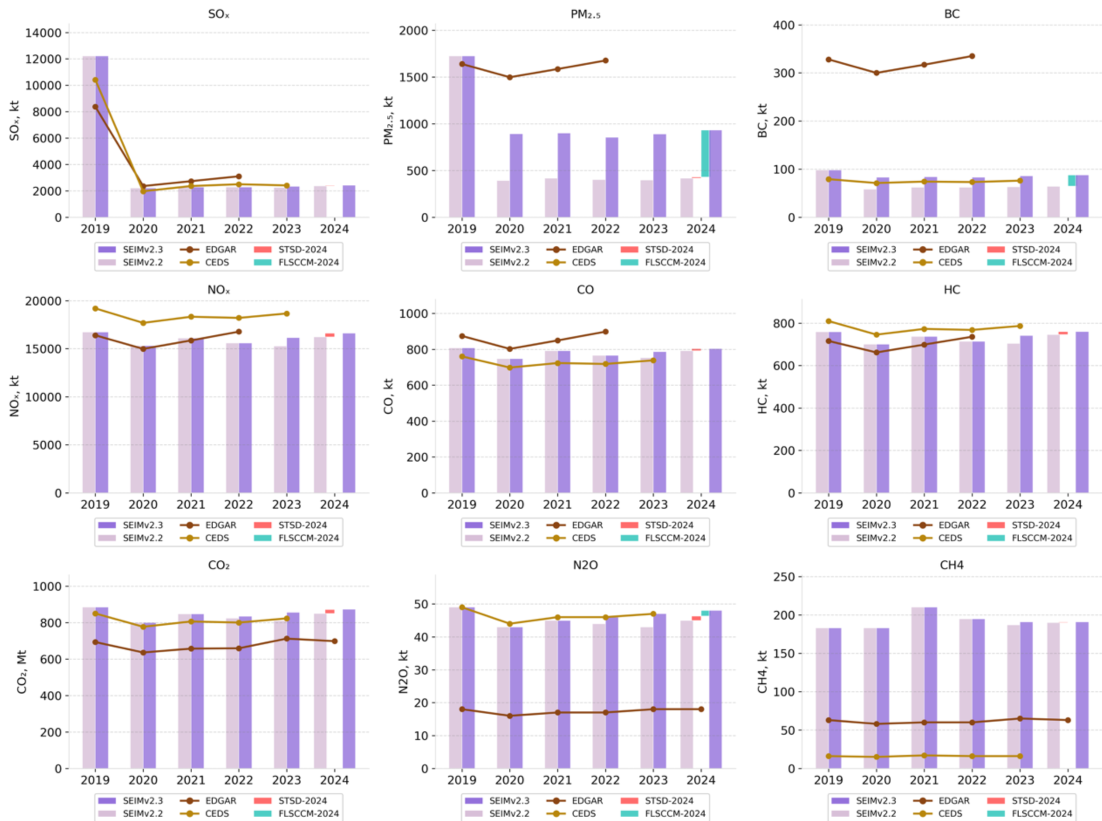

Figure 6: Comparison of annual global ship emissions results from SEIMv2.3, SEIMv2.2, and other studies. SEIMv2.2 results were sourced from (Yi et al., 2024a). SEIMv2.3 represents the method presented in this paper. EDGAR represents the emission results from Emissions Database for Global Atmospheric Research, sourced from (Crippa M., 2025). CEDS represents the emission results from Community Earth atmospheric Data Systems, sourced from (Hoesly, 2025).

3.3 Spatiotemporal heterogeneity in ship emission underestimation

For different air pollutants and GHGs, the underestimated emissions were concentrated in the South China Sea, North Atlantic Ocean, Indian Ocean, and North Pacific Ocean, consistent with the spatial distribution of newly added ship signals shown in Fig. 5. Figure 7 illustrates the ocean regions with the top 20 underestimated emissions derived by subtracting SEIMv2.2 results from the SEIMv2.3 results, most of which appeared in South China Sea, accounting for 13.4% to 15.2% of the total underestimation. However, in terms of the percentage of underestimated emissions relative to the total emissions of each region, the Indian Ocean and the South Atlantic Ocean exhibited the highest proportions of underestimation. For CO_2 and NOx emissions, the underestimation in the Indian Ocean and the South Atlantic Ocean accounted for 8.1% and 7.5% of their respective total regional emissions, whereas the underestimation in the South China Sea was relatively lower at 5.7%. A more pronounced discrepancy is observed in $PM_{2.5}$ and BC emissions, whose underestimation was dominantly mitigated by FLSCCM. For $PM_{2.5}$ emissions, the underestimated portion reached 75% and 73% of the total emissions in the Indian Ocean

https://doi.org/10.5194/egusphere-2026-1935
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and South Atlantic Ocean, respectively, compared to 69% in the South China Sea. For BC emissions, the underestimated portion reached 39% and 38% of the total emissions in the Indian Ocean and Red Sea, respectively, compared to only 29% in the South China Sea. The spatial heterogeneity of the underestimated proportions indicates that overlooking the daily expansion of the STSD and the multiple choices of fleet low-sulfur compliance would lead to significantly more substantial emission underestimations in the Indian Ocean and the South Atlantic Ocean.

By increasing the update frequency of the STSD from yearly to daily, we managed to include emissions previously omitted or miscalculated due to delayed update of ship parameters. The average supplemented daily emissions are 1.52 kt $PM_{2.5}$, 6.07 kt NOx, 0.62 kt SO_2, 0.22 kt CO, 0.24 kt HC, 0.25 Mt CO_2, 0.01 kt N_2O, 0.01 CH_4, and 0.07 kt BC. Those emissions account for 58 % of daily $PM_{2.5}$ emissions and 28% of daily BC emissions. For other air pollutants and GHG, the proportion is smaller, from 2% to 12.6%. Figure 8 shows the temporal variations in calculated ship $PM_{2.5}$ and CO_2 emissions throughout 2024, derived by subtracting SEIMv2.2 results from the SEIMv2.3 results. Despite some fluctuations, the daily emission differences show an increasing trend over time. The daily $PM_{2.5}$ emission difference climbed from about 1.45 kt/d at the start of 2024 to 1.58 kt/d at the end of 2024. The same was true with other emissions. The daily CO_2 emission difference climbed from about 0.20 Mt/d at the start of 2024 to 0.29 Mt/d at the end of 2024. The findings highlight the major advantage of SEIMv2.3 in its accuracy in daily emission calculation.

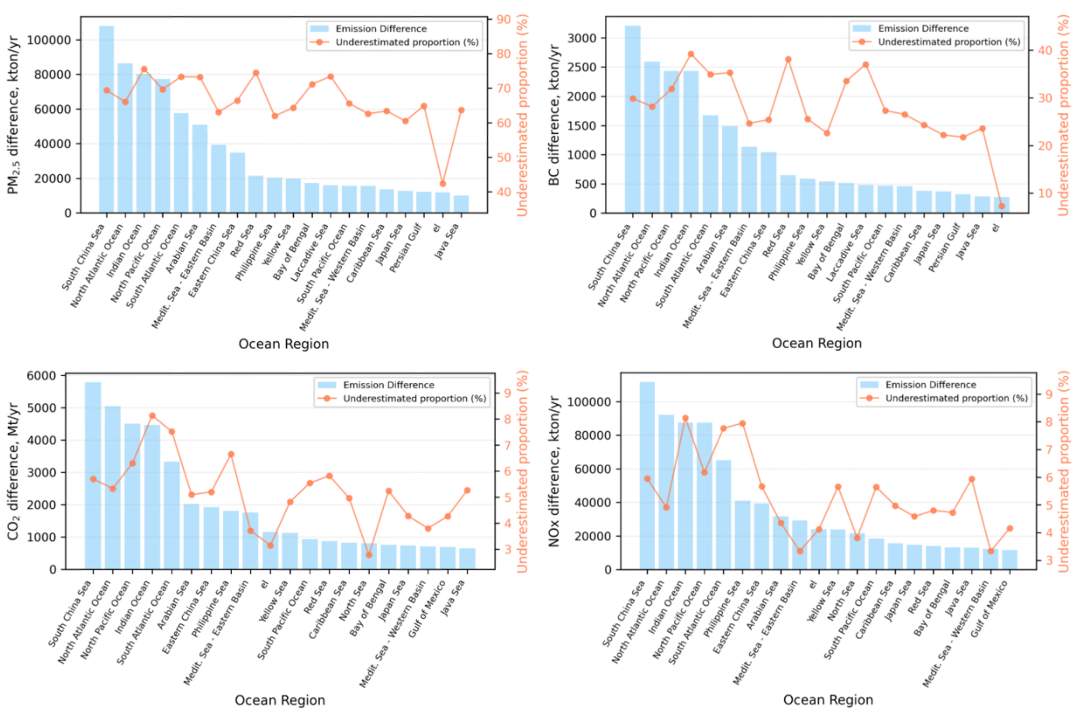

Figure 7. Ship $PM_{2.5}$, BC, CO_2, and NOx emission underestimation mitigated by SEIMv2.3 in different ocean regions.

https://doi.org/10.5194/egusphere-2026-1935
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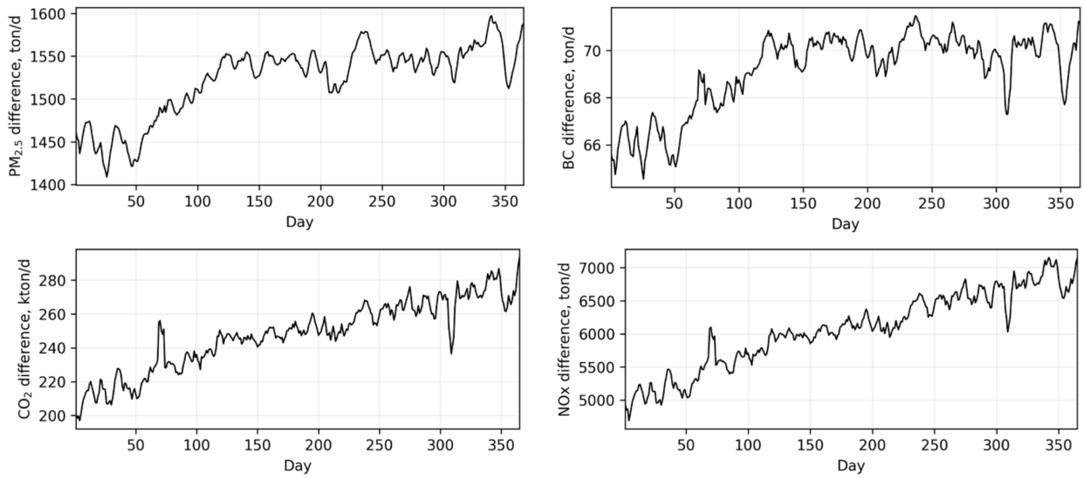

Figure 8. Temporal variations in daily ship PM$_{2.5}$, BC, CO_2, and NOx emission underestimation.

4 Summary and Discussion

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 ignorance of HFO use after 2020 would lead to an underestimation of PM$_{2.5}$ and BC emissions by approximately 55% and 27%. Our results suggest a decrease by 48.2% in PM$_{2.5}$ emission from 2020 to 2019, instead of by 77.2% by previous bottom-up method. Most underestimation happened in South China Sea, accounting for 13.4% to 15.2% of the total underestimation. However, in terms of the percentage of underestimated emissions relative to the total emissions of each region, the Indian Ocean and the South Atlantic Ocean exhibited the highest proportions of underestimation. For PM$_{2.5}$ and BC emissions, the underestimated portion reached 75% and 39% of the total emissions in the Indian Ocean respectively, compared to 69% and 29% in the South China Sea. Without the dynamic update framework proposed in SEIMv2.3, the emission underestimation would enlarge over time. The daily CO_2 emission difference climbed from about 0.20 Mt/d to 0.29 Mt/d throughout 2024. The daily PM$_{2.5}$ emission difference climbed from about 1.45 kt/d to 1.58 kt/d throughout 2024.

Overall, our study pioneers in its near-real-time framework to calculate global ship emissions and its discovery of the systemic emission underestimation in previous emission inventory studies. Near-real-time emission inventories enable

https://doi.org/10.5194/egusphere-2026-1935
Preprint. Discussion started: 26 May 2026

tracking of short-term emission changes and provide a data foundation for emission reduction policies (Xu et al., 2023). Among these, $PM_{2.5}$ emission results serve as essential precursor data for cloud formation and radiative forcing, forming the basis for air quality simulation, which is crucial for achieving timely air quality responses (Chen et al., 2017; Goldsworthy et al., 2019; Yuan et al., 2024). Yet, existing research has neither reached a consensus regarding ship $PM_{2.5}$ emissions after 2020 nor provided satellite-based concentration inversion study for verification. In this study, we addressed the systemic underestimation in global ship emissions and proposed a rapidly responsively emission calculation framework to support air quality simulation and policy evaluation. Our conclusions align well with IMO fuel consumption statistics, fleet installation of scrubbers by (Lunde Hermansson et al., 2024), and $PM_{2.5}$ concentration observational research. (Song et al., 2022) analyzed the $PM_{2.5}$ concentrations near Busan Port, South Korea, before and after 2020. His findings indicated that the IMO low sulfur regulation did not affect $PM_{2.5}$ emissions. Additionally, (Kuittinen et al., 2021) also argued that ship emissions remain a significant source of anthropogenic PN emissions after 2020.

Admittedly, certain limitations exist in our methodology. First, although our emission inventory results went through multi-source verification on global level, its accuracy on single-ship level has not been verified. Uncertainties appear when we applied machine learning algorithm to supplement missing ship parameters, which performs well on global and regional scale. Moreover, the fleet low sulfur compliance choice module was based on a combination of top-down fuel consumption statistics and bottom-up fuel choice allocation, which may cause issues such as emission structural mismatches and spatial misalignments.

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 and Tingkun He 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.

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