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SUPPLEMENTARY INFORMATION

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# Emissions and health impacts from global shipping embodied in US–China bilateral trade

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# Supplementary Information

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## Supplementary References

# Supplementary Methods

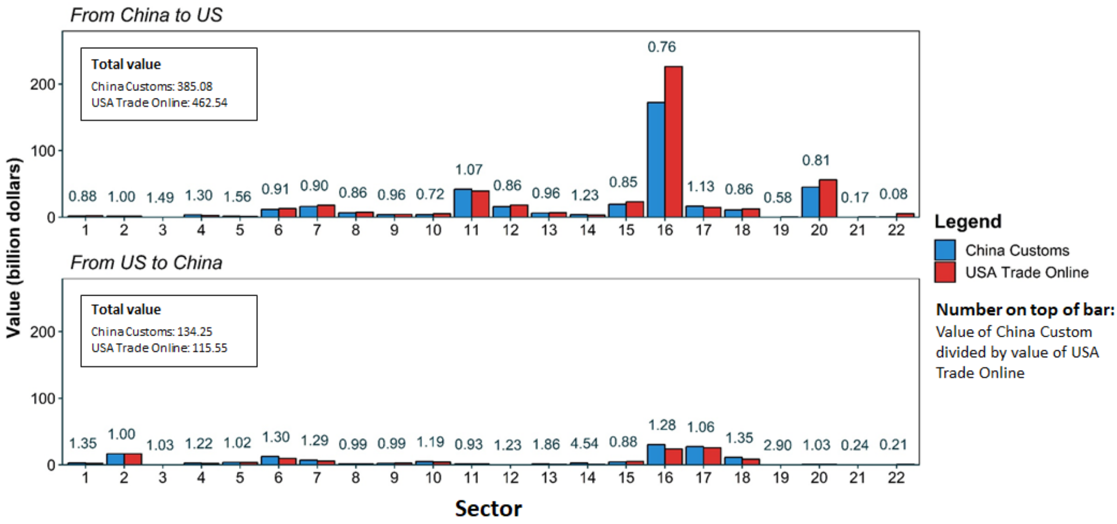
## 1. Trade Database and Verification

### *1.1 Data Source and Categories for US-China Bilateral Trade Database (BTD)*

In this study, to make linkages between the trade commodity and ship categories, a detailed Bilateral Trade Database (BTD) was established. The trade data between China and the US in 2016 was acquired from the "China Customs Statistics Yearbook 2016", which was published by the "China Customs Magazine" (http://www.ccmag.cn/index.php). This yearbook was authorized by China's General Administration of Customs, including the data on the value and weight of trade commodities. The trade commodities were classified based on the Harmonized Commodity Description and Coding System code (HS code)[7] formulated by the World Customs Organization. The commodity statistics of US-China bilateral trade was in 8-digit numbers, including 22 sections, 98 chapters and 12,346 commodity subcategories of US-China trade in total. The whole BTD used in this research is provided in this Supplementary Information for more details on the value, weight. All commodity information is country level data, without specific to ports/regions level.

### *1.2 QA/QC of the Bilateral Trade Database*

As the data was from the official department, we consider it reliable. In addition, it was compared with the data collected from USA Trade Online in 2016[8], as shown in Supplementary Fig.1. The total commodity values of US-to-China and China-to–US trade in the BTD were 134.3 and 385.1 billion dollars, respectively, while that in the USA Trade Online were 115.5 and 462.5 billion dollars, respectively). The value ratios of the BTD to USA Trade Online for US-to-China and China-to-US trade were 1.16 and 0.83, respectively.




**Supplementary Fig. 1 |** Comparison between USA Trade Online data and Chinese Customs data in 22 sectors.

## 2. Ship Database and Verification

### *2.1 Ship Technical Specifications Database (STSD)*

As each ship has different technical specification information, a combined Ship Technical Specification Database (STSD) from our previous research[1] was expanded and used in this study. The database combined data from Lloyd's Register, the China Classification Society and technical information included in the static AIS data. The STSD provides data that describes ship properties including dead weight tonnage (DWT), maximum continuous rating (MCR) of the engine, vessel type, etc. In this research, vessel information from the static AIS data was also included in the STSD, and it was enlarged to include over 120,000 vessels. Supplementary Table 1 compares the ship identified (referring to ships have both AIS data and STSD data) in this study and the world vessel fleet data. The number of identified ships was 65,180. Compared with the world vessel fleet, the total DWT of identified ships from the STSD for each vessel type was similar to that of the world vessel fleet, which means that our STSD covered most of the world vessel fleet.

**Supplementary Table 1** | Ships identified in this study and comparison to the world fleet.

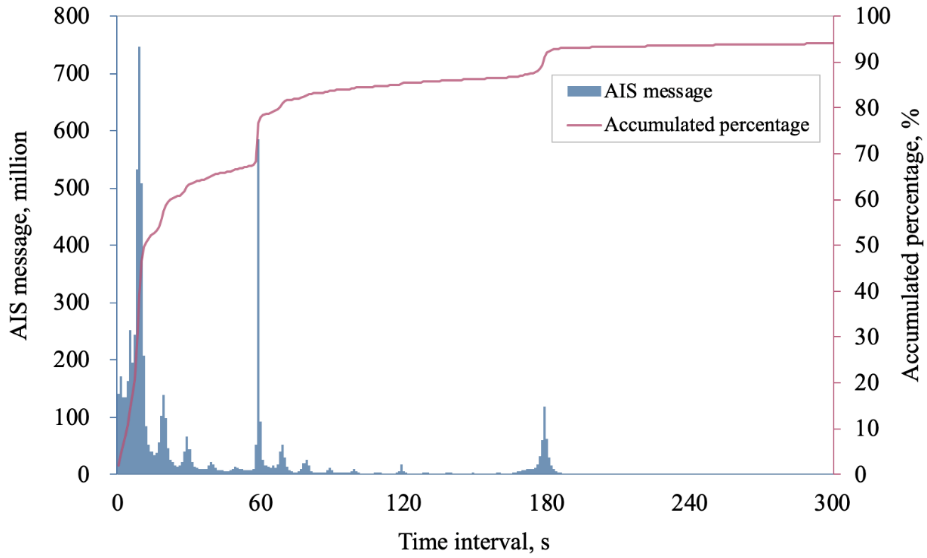
| No. | Vessel type | Ships identified in both AIS and STSD | AIS messages ($10^3$) | Total DWT of ships in this study (kt) | Total DWT of the world fleet[a] (kt) |
|---|---|---|---|---|---|
| 1 | Auto Carrier | 591 | 6,882 | 9,184 | - |
| 2 | Bulk Carrier | 12,110 | 1,536,930 | 744,883 | 778,890 |
| 3 | Container Ship | 5,336 | 950,066 | 210,142 | 244,274 |
| 4 | Cruise Ship | 704 | 35,684 | 833 | 5,950 |
| 5 | General Cargo Ship | 9,042 | 721,717 | 116,995 | 75,258 |
| 6 | Miscellaneous | 15,213 | 1,562,316 | 118,751 | - |
| 7 | Oceangoing Tug/Tow | 5,898 | 559,315 | 29,118 | - |
| 8 | RORO | 3,670 | 467,142 | 30,677 | - |
| 9 | Refrigerated Ship | 793 | 36,836 | 5,017 | - |
| 10 | Chemical Tanker | 4,356 | 400,316 | 91,581 | 44,347 |
| 11 | Oil Tanker | 7,467 | 585,242 | 529,029 | 557,812 |
| | Other[b] | - | - | - | 100,120 |
| | **Total** | **65,180** | **6,862,445** | **1,886,210** | **1,806,651** |

a: Data from the report of the United Nations Conference on Trade and Development (UNCTAD)[2],which was based on data from Clarksons Research.

b: Vessel category of "Other", which was in the UNCTAD report but not in our STSD data.

### *2.2 Ship Automatic Identification System Data (AIS)*

High quality Automatic Identification System (AIS) data from January to December of 2016 was used in this research. AIS was introduced by the IMO for safety at sea and provides a message every few seconds to every few minutes. The AIS data includes dynamic information can be potentially used for trade transport vessel identification, such as the vessel position (longitude and latitude), real-time speed, Maritime Mobile Service Identity (MMSI) code and technical information. International ships over 300 GT are mandated by IMO to install AIS, so we assumed that the AIS data includes most of the ships for US-China bilateral trade transport. Supplementary Fig. 2 shows the time interval statistics for our AIS data. In all, 94% of our AIS data have a time interval of less than 5 minutes. To identify vessels traveling between the US and China, a time interval of less than 5 minutes should be short enough to figure out the continuous position and activity mode of vessels, which ensures the accuracy of the identification and emissions calculation results.

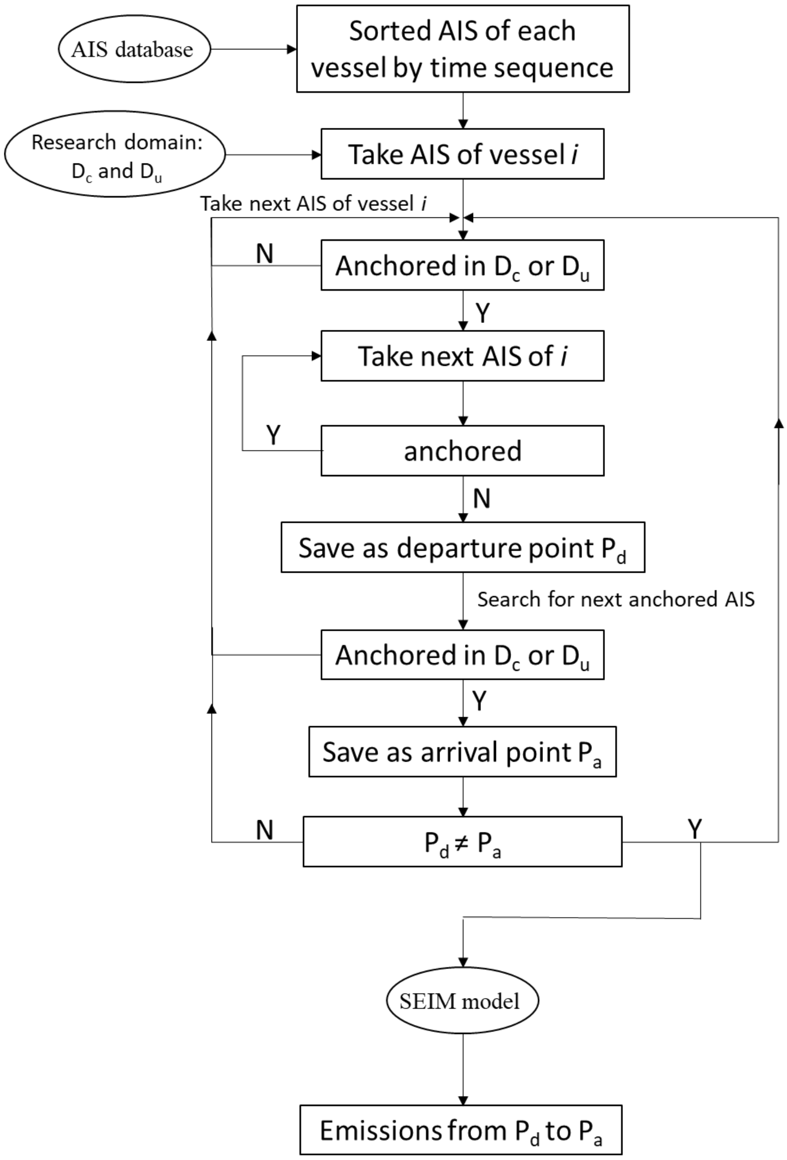



**Supplementary Fig.2** | Time interval distribution frequency of AIS data.

## 3. Bilateral Trade-related Vessel Call Identification

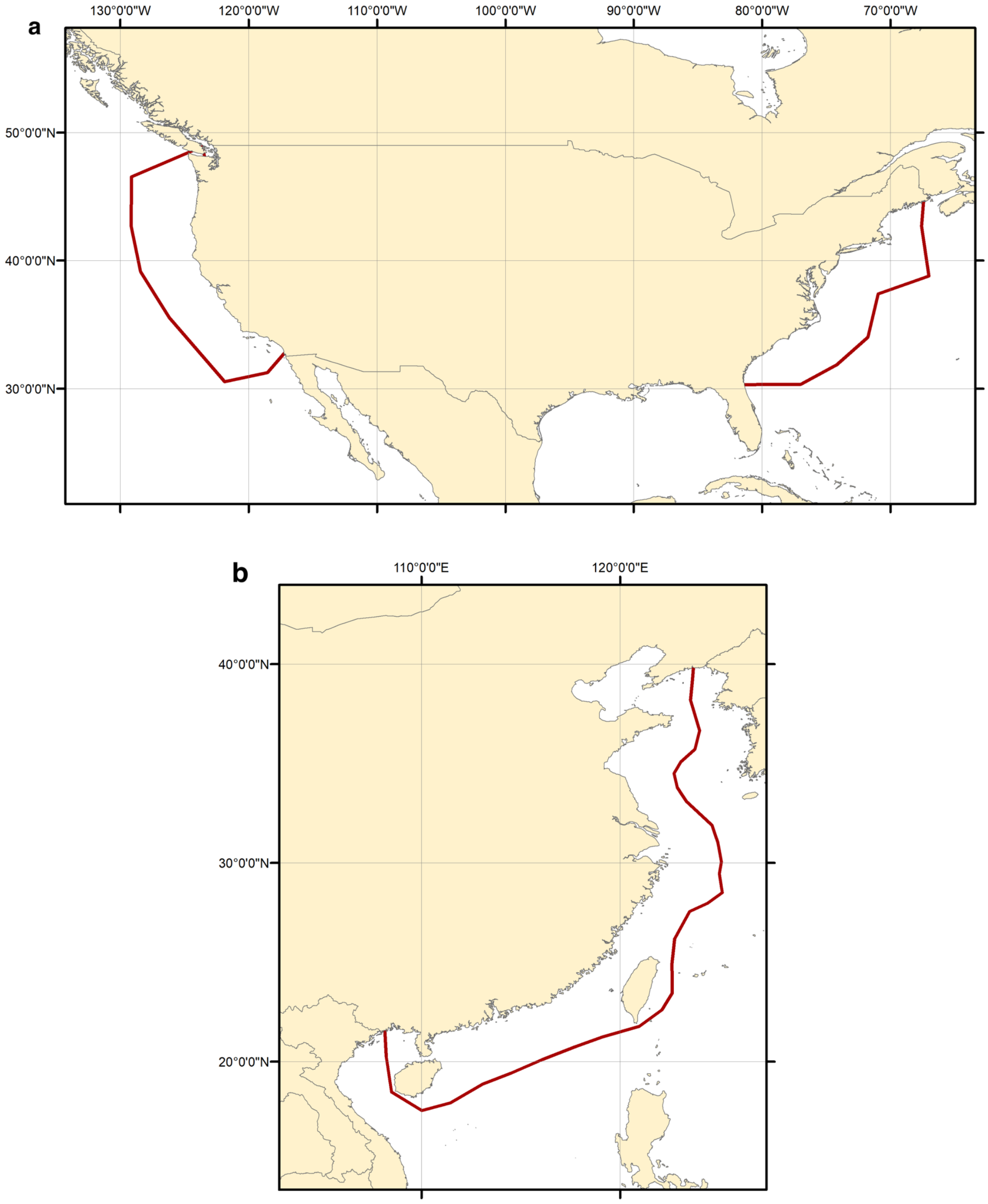
### *3.1 Voyage Identification Approach*

Trade-related shipping emission was calculated based on trade related vessel calls. A non-stop trip directly between the US and China was defined as a vessel call (all possibilities on vessel call classification and uncertainties are introduced in the next section). The identification standards for the vessel calls from China to the US were as follows, and vice versa: (1) the departure point and arrival point were in Chinese research domain and the US research domain, respectively; (2) vessels after departure did not sail back into the Chinese research domain before arriving in the US research domain; and (3) vessel departure was defined as being anchored (with a sailing speed less than one knot) in last AIS message and not anchored in current AIS message. Vessel arrival was defined similarly to the vessel departure (not anchored in last AIS message and anchored in current AIS message). By this identification standard, the stopping-over situation was excluded. Here we summarized the algorithmic portrayal process of any single vessel $i$ in Supplementary Fig.3.




**Supplementary Fig.3 |** Flowchart for bilateral trade related voyage identification.

We set the ECA region as the US identification domain and the exclusive economic zone (EEZ) as the Chinese identification domain. The research domains are shown in Supplementary Fig. 4. The reasons for the choice of research domains are as follows: (1) A port-based approach may neglect a lot of vessel calls and cause underestimation, since the uncertainty of AIS-data is considered larger than the port range (the least research set a $\pm 2^{\circ}$ error during the AIS-based identification period)[3]. Defining a larger zone could amend the underestimation without increasing the total emission uncertainty. Based on the ship AIS data[4,5], the emissions in the whole trip were counted, including the voyage to the port. (2) The ECA requires vessels to use fuels with lower sulfur content, which is much more expensive than bunker oil; so it is reasonable to assume that a vessel would not sail into the ECA unless it has to sail to US ports for trade or any other task. EEZs were prescribed by the United Nations Convention on the Law of the Sea and represent sovereign rights; so it is reasonable to assume that vessels would sail through but not anchor, unless these ships anchor in a port for trade or another task.




**Supplementary Fig.4** | Research domain in voyage identification. a, US. b, China.

When a vessel finished a trip from the US to China or from China to the US, this trip was named as a vessel call. 4,482 trade vessel calls between China and the US were identified and selected by the above method. When a vessel was identified as a trading vessel between China and the US, its AIS data between the starting point and destination was extracted and saved. Then, all the identified vessels' deadweight tonnage (DWT) was retrieved from our ship technical specifications database (STSD)[1], from which the total capacity of vessel transport was estimated. The results of vessel calls and the total DWT of each vessel category are shown in Supplementary Table 2.

**Supplementary Table 2 |** Vessel call identification results

| Trip | Vessel category | Vessel amount | Vessel calls | Total DWT/ton |
|---|---|---|---|---|
| China to US | Auto Carrier | 17 | 20 | 279355 |
| | Bulk Carrier | 693 | 828 | 57680847 |
| | Container Ship | 398 | 1326 | 114728922 |
| | General Cargo Ship | 115 | 168 | 6153310 |
| | Miscellaneous | 9 | 11 | 323614 |
| | Oceangoing Tug/Tow | 1 | 2 | 976 |
| | Refrigerated Ship | 1 | 1 | 5360 |
| | Chemical Tanker | 36 | 41 | 1645797 |
| | Oil Tanker | 38 | 44 | 3859791 |
| US to China | Auto Carrier | 46 | 53 | 884029 |
| | Bulk Carrier | 608 | 721 | 49766364 |
| | Container Ship | 373 | 1041 | 94062480 |
| | General Cargo Ship | 92 | 138 | 4630056 |
| | Miscellaneous | 10 | 11 | 358930 |
| | Oceangoing Tug/Tow | 1 | 1 | 488 |
| | Chemical Tanker | 27 | 38 | 1439444 |
| | Oil Tanker | 30 | 38 | 2643275 |

### *3.2 Uncertainty of the Identification Method*

Supplementary Table 3 discusses several possibilities for freight transport and their related uncertainties.

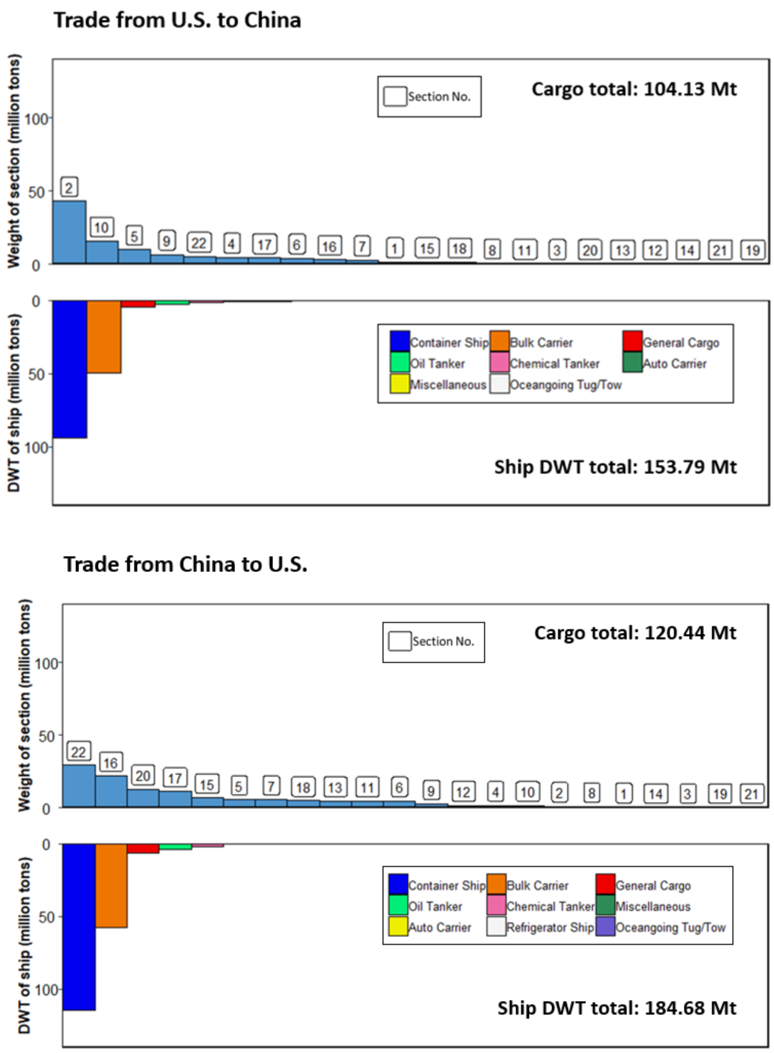
**Supplementary Table 3** | Detailed description and error evaluation of vessel calls considered as the bilateral trade related voyage.

| | | Cargo | Emission calculation | Error (emissions vs. trade) | Reason | Overall error evaluation |
|---|---|---|---|---|---|---|
| Single-trip Voyage | Non-stop (A to B) | Not empty | Yes | accurate | | Errors were balanced, because:<br>Some counted ships are empty and some cargos are delivered by uncounted ships.<br>The total ship DWT is a little bit higher than the total delivered cargos. This is reasonable because ships could be not fully loaded. |
| | | empty | Yes | accurate | The emission is accurate, but not directly related to trade in count. | |
| | With stop (A to C to B) | Not empty | No | undercount | If parts of the cargos are from A to B, the emissions were undercounted. | |
| | | empty | No | accurate | | |
| | With stop (A to B to C) | | Yes | Over count | Part of the cargos may from A to C, but all emissions between A and B were counted as A-B trade related. | |
| Round-trip voyage | A-B-A (669 vessels) | Not empty | Round-trip | accurate | | Error is small for the following reasons:<br>empty return emissions were calculated in this study;<br>AIS results show that less than 1/3 of total vessels have a direct return voyage.<br>Even with a return voyage, the chance for empty return was not high, because China and US trade are balanced on weight, and our calculation on ship DWT matches with cargo weight. |
| | | Return empty | Round-trip | Accurate emission, but not match with one-side trade. | B-A emissions were counted, but was related to B-A trade, which is not true. That return emissions should be related to A-B trade. However, the possibility for this is low. | |
| | A-B-C (1157 vessels) | Second trip not empty* | One way | accurate | | |
| | | Second trip empty* | One way | accurate | The voyage B-C is not related to A-B bilateral trade. | |

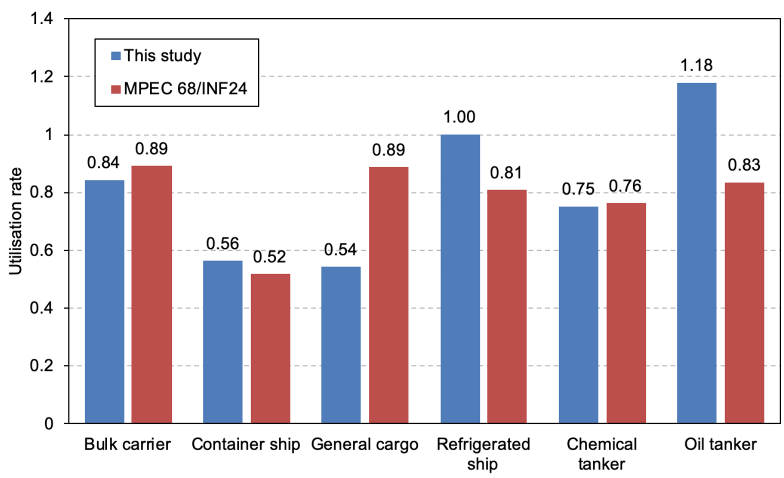
*Here A and B refer to China or US, and C refer to other countries.

Uncertainties may originate mainly from “full loading”, “more-than-bilateral trade related voyage”, and “domestic voyage prior to international journeys”.

The total magnitude of error was evaluated using the identified DWT of vessel fleet (388.5 Tg) compared to the realist weight of commodities (224.6 Tg) (Supplementary Fig. 5). The utilization rate is 66%, which is close to the results reported by IMO MEPC 68/INF 24[8] (The vessel fleet-wide average utilization rate was 73.7% for 2013 and 66% for 2012). This ratio is higher but not too much, than the differences between US and China import and export trade weight. This is reasonable as some of the returning voyage cannot get cargo due to the trade surplus (13% weight difference, see Supplementary Fig. 5), and some of the capacities were wasted due to other reasons, e.g. poor dispatch. We also compared our calculated capacity utilizations with the payload utilization rates in MEPC 68/INF 24 by each vessel category, as shown in Supplementary Fig. 6. The capacity utilizations of the bulk carrier, container ship and chemical tanker showed great consistent with the MEPC 68/INF 24 report. As the container ship and bulk carrier together constituted the majority of the trade (83% in vessel numbers, 87% in vessel calls and 93% in total dead weight tonnages), we considered our vessel call identification results reliable because our utilization rates for these vessel types were close to reported rates. For those vessel categories with only few vessels recognized, they were generally assumed full load, e.g., refrigerated ship (2 vessel calls). In addition, inevitable discrepancies still exist due to a small proportion of mismatched commodity-ship linkage or imperfect identification of vessel fleets, which could be inherent uncertainties of this method. By and large, the detailed comparison of the capacity utilizations for each vessel category showed our vessel call identification results acceptable, and this identification method was generally applicable to other studies.




**Supplementary Fig.5** | Comparison of transport weight between trade statistics and ship fleet identification results.




**Supplementary Fig.6** | Comparison of utilization rates to MEPC 68/INF 24[8], by vessel category.

For the full loading and empty return voyage issue, the IMO MEPC 68/INF 24[6] figured out that certain ships operated some of the voyages loaded and some of the voyages in the ballast condition, which meant the ships may be empty and return to pick up cargo from another port. If the "return" voyage is a non-stop trip, whether it's empty or not, it was included in our calculation because we calculate based on AIS data. In our calculation, we cannot know whether a ship is empty or not, but from the statistic results in our study, there are 34% capacity wasted.

Stop-over situations (i.e., a vessel from China first trades with another country and then travels from that country to the US) were excluded from the calculation. Although the situation that the vessel carried a part of cargos of US-China trade and some cargos of other countries' trade exists, especially for container ships, the proportion of this kind of situation and the proportion of the cargos of US-China trade in this situation were both difficult to figure out. To figure out how much would be potentially missing or incorrect if the stopping over condition was ignored, we carried out another run of model which did not exclude the stopping over situation. This time we identified 5,629 vessel calls from US to China and 5,819 from China to US, which would be more than twice as much as before. In terms of the total DWT, it would be 385 and 394 million tons, over three times as big as the weight of trade commodity (Supplementary Fig. 5). This means, if all these ship emissions were counted as China-US bilateral trade responsible for, it's highly overestimated. So we keep our original identification method to exclude the stopping over ships. The underestimation from excluding stop-over ships was balanced by the overestimation from including ships which take US or China as interim stop. By excluding these stopping over voyage, we could avoid overlap when assess multiple pairs of bilateral trade, which make this method applicable globally. Because these stopping over conditions would be calculated for each non-stop trip, the total emission would match with global total on shipping.

Another uncertainty here was that we ignored the movements between domestic ports prior to international journeys, which may result in a downward bias. The reason was that we could not figure out whether a movement was resulted from international trade or domestic trade. But considering the much longer distance between US and China than the domestic trip, the downward bias is very small.

## 4. Linking Trade with Ship Fleets

### *4.1 Transport Mode Split*

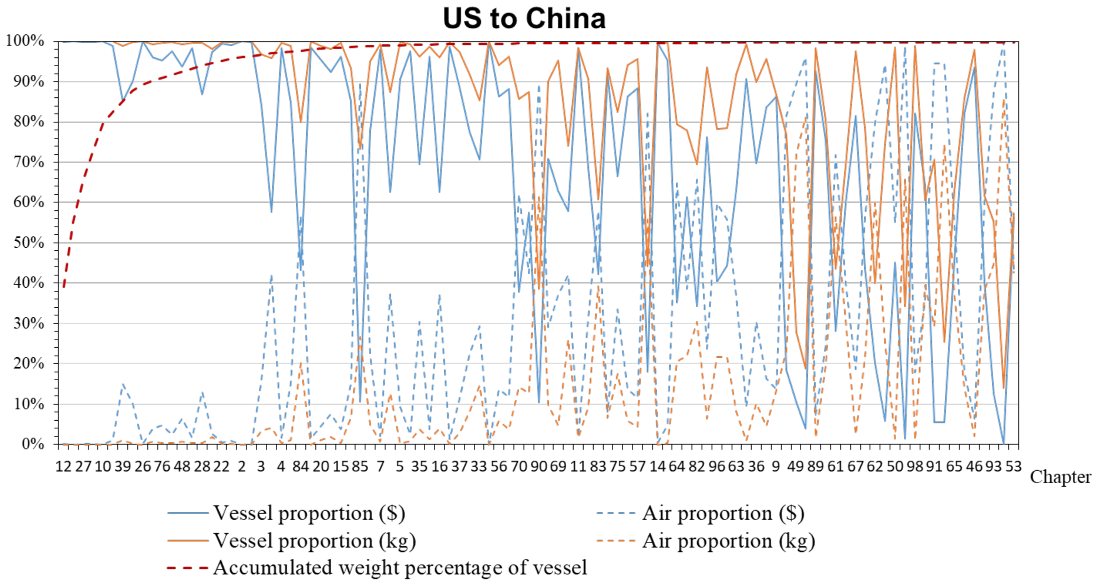
US-China bilateral trade includes trade in goods, trade in services (in terms of tourism, education, movies, technology, cultural products and service outsourcing) and two-way investment, in which only trade in goods requires freight transport via sea or air. Other than that, it is the weight of goods that determines the amount of vessels, not the value of goods. Thus, weight is a much better proxy to build the link between trade and ships, by matching the vessel fleet DWT with the commodity weight.

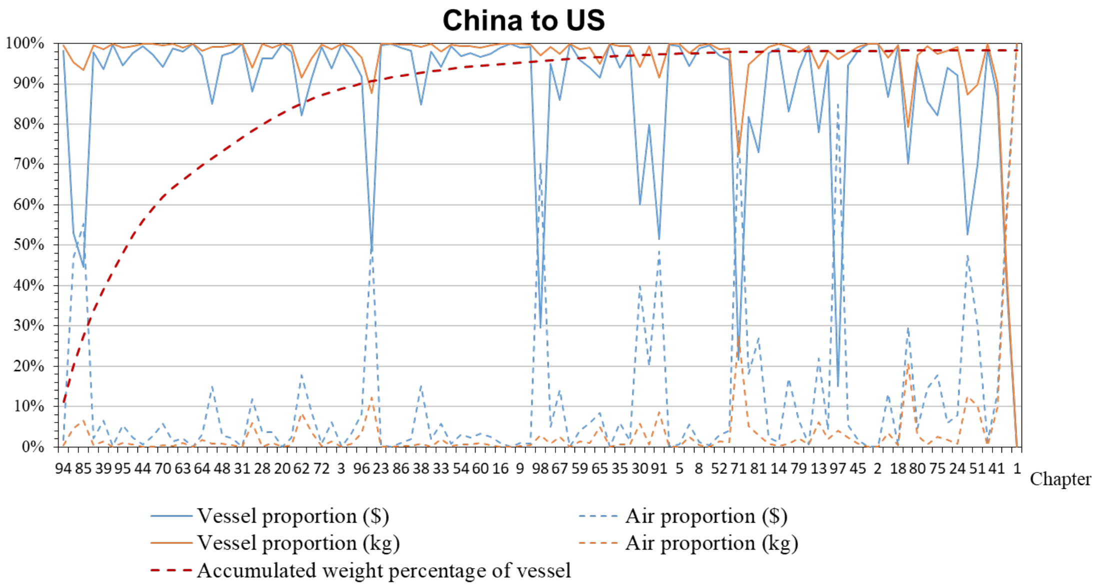
As the geographic position of China and the US is separated by the Pacific, US-China trade commodities are mainly transported via sea or air. Our research assumed that all weights are transported via sea. USA Trade Online[8] shows that although commodities transported from the US to China via air account for 29% of the total value, they only account for 0.3% of the total weight and vice versa (Supplementary Table 4). This is because only high-value low-weight products are cost-effective when transported via air.

Supplementary Fig. 7 shows the detailed breakdown for the mode share by 98 cargo chapters[8]. When sorting the commodity chapters by weight (from left to right), we found that the weight carried by sea reached over 90% of the top chapters. Although in some chapters, the proportion of commodity weight carried by air was over 50%, the commodity weights in these chapters were quite low (indicated by accumulated weight percentage of vessel). Thus, neglecting the commodity weight carried by air was acceptable.

**Supplementary Table 4** | Transport mode split between sea transport and air transport[8]

| | Vessel proportion (by $) | Air proportion (by $) | Vessel proportion (by kg) | Air proportion (by kg) |
|---|---|---|---|---|
| US to China | 57.7% | 29.0% | 99.7% | 0.3% |
| China to US | 64.3% | 28.4% | 98.2% | 1.8% |



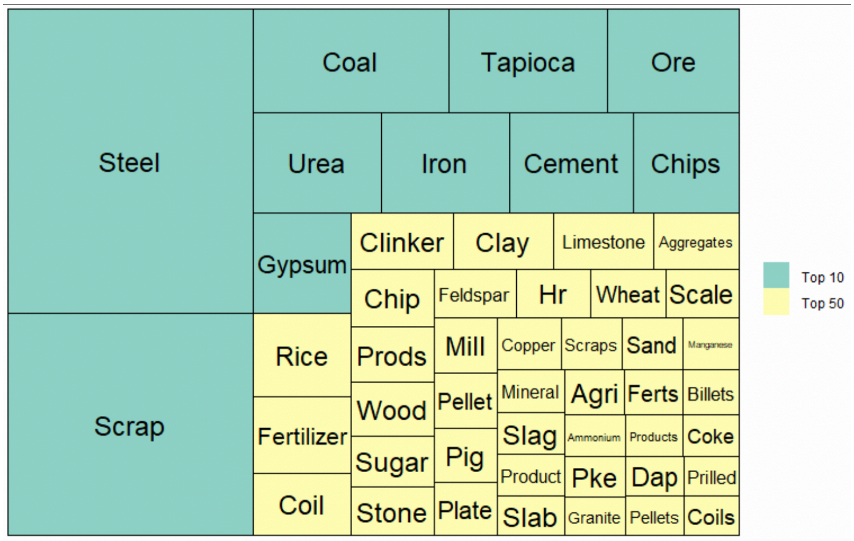




**Supplementary Fig. 7** | Transport mode split between sea transport and air transport, broken down by 98 commodity chapters.

### *4.2 Linkage between Transport Vessel Fleets and Commodities*

A report by the International Chamber of Shipping (ICS)[9] summarized the characteristics of vessels by category and that the commodities carried by each vessel category are diverse. Within different vessel types, the commodity type carried by auto carriers, refrigerated ships, chemical tankers and oil tankers was relatively clear because of their unique characteristics, wherefore these vessels were matched with commodities at first. (Refrigerated ships, for instance, are mainly used to carry perishable commodities, which are easy to distinguish from trade data.)

However, commodity match is difficult for bulk carriers and container ships. We collected over 10,000 real logistics information on commodity types carried by bulk carriers from the marine logistics information platform website (http://company.shipping.jctrans.com/AskOfferList) to summarize the commodities carried by bulk carriers (Supplementary Fig. 8). According to Supplementary Fig. 8, ore, wood, gypsum, cement, base metals, waste such as steel scrap, and large-sized machinery were all matched to bulk carriers. Some commodities with relatively low value but high amounts, such as cereals, plastics, steel plates, etc., were matched to bulk carriers, container ships and general cargo ships considering the high total transport capacity of container ships from the identification results. The remaining commodities were matched to container ships and general cargo ships.




**Supplementary Fig.8** | Frequency of commodities carried by bulk carriers.

Supplementary Table 5 summarizes the list of matched commodities carried by each vessel type, and the attached excel database shows more details on each commodity subcategory and transport vessel type.

**Supplementary Table 5** | Matched commodities with vessel types.

| No. | Vessel type | Commodity description |
|---|---|---|
| 1 | Auto Carrier | Vehicles, associated transport equipment, parts and accessories thereof |
| 2 | Bulk Carrier | Raw materials and primary products without packing, including coal, coke, pitch, cereal, mineral, sand, cement, plaster, timber, base metal and product thereof, fertilizer, plastic, large machinery and appliances, waste, etc. |
| 3 | Container Ship | Almost all commodity types, except large machinery and appliances larger than the container size, |
| 4 | Cruise Ship | No commodities |
| 5 | General Cargo Ship | Mainly carried commodities with packing, also large machinery and appliances |
| 6 | Miscellaneous | No commodities |
| 7 | Oceangoing Tug/Tow | No commodities |
| 8 | RORO | Similar to container ships |
| 9 | Refrigerated Ship | Perishable items that need refrigeration such as seafood, meat, entrails, fresh flowers, etc. |
| 10 | Chemical Tanker | Liquid chemical products |
| 11 | Oil Tanker | Petroleum and fuel products, liquefied petroleum gas, liquefied natural gas |

In overlap situations, we assumed that the commodity amount was distributed in each vessel category by weighting the total DWT of each vessel category. For commodity *i*, the weight matching vessel categories *j*, *k*, and *l* in an overlap situation can be described by the equation below:

$$W_{i,jt} = W_i \times \frac{DWT_{jt}}{DWT_{j1}+DWT_{j2}+\cdots+DWT_{jn}} \quad (1 \leq t \leq n, n > 1) \qquad \text{equation (1)}$$

where $W_{i,jt}$ represents the commodity weight *i* carried by vessel category $j_t$; $W_i$ represents the total weight of commodity *i*; $DWT_{j1}$, $DWT_{j2}$, $\cdots DWT_{jn}$ represent the total DWT of the identified vessel fleets in vessel categories $j_1$, $j_2$, ••• $j_n$, respectively.

The details of the connection between each subcategory and vessel types are shown in the attached database file.

*4.3 Uncertainty of ship-commodity matching*

Even though both the ICS report[9] and realistic shipping manifest information platform were applied for the commodity-ship matching, there are still uncertainties on the matching results. The quantitive assessment is difficult when not all shipping manifest information is available. However, the total shipping emissions calculation was based on AIS data but not the matching process. So the uncertainty in this step would not be transferred to the emissions.

The $CO_2$/$ results could be affected by the commodity-ship matching process. To evaluate the impacts from uncertainty on this commodity-ship matching process, a comparison between emissions per ton for multiple ship categories was made. The largest uncertainty is from the mismatching to bulk carrier, container ships and general cargo ships. The difference of $CO_2$ emissions per capacity among these vessel categories is small (0.03-0.09 ton $CO_2$/ ton capacity). However, the difference on $CO_2$/$ for different commodities is larger by several magnitudes (0.1-2492.7 g/$). Thus, even there's mismatching, it would not influence the relative rank and the magnitude of $CO_2$/$.

Comparing to the latest research about Brazil exports shipping emissions based on shipping waybill, the results were comparable[3]. In the Brazil study, the $CO_2$ emission per weight is 32,000 to 113,000 g/t, and our results is 36,000 to 173,344 g/t. The ratios between the maximum and minimum value were similar (3.53 and 4.82). The $CO_2$ emission per tonnage per nautical mile in the Brazil study was 18 to 24 g/t/nautical mile. The result in our research is 17.1 g/t/nautical mile which is quite comparable to the sea-waybill-based study.

## 5. Emission Modeling

*5.1 Emission Modeling Approach*

In the identification process, we extracted and saved the AIS data between the starting point and destination of each vessel trip (Supplementary Fig.3). Then these AIS data were applied to calculate shipping emissions by the Shipping Emission

Inventory Model (SEIM) established in our previous research[1]. This model was similar to the method used in the Third IMO GHG Study but was updated using a time interval calculation to improve the regional accuracy[5,10,11]. The emissions of commodity *i* carried by vessel category *j* are described by the equation below:

$$E_{i,j} = E_j \times \frac{W_{i,j}}{W_j} \qquad \text{equation (2)}$$

where $E_{i,j}$ represents the emissions of commodity *i* carried by vessel category *j*; $W_{i,j}$ represents the weight of commodity *i* carried by vessel category *j*; $E_j$ represents the total emissions of vessel category *j*; and $W_j$ represents the total commodity weight carried by vessel category *j*.

The SEIM model used in this research was a disaggregated bottom-up model to calculate shipping emissions[1]. Basic modeling parameters in SEIM are accordant with the IMO 3rd GHG Study. The difference between SEIM model and method used in IMO 3rd GHG Study is that SEIM model puts AIS data of one ship together according to the time sequence and calculate emissions of each single ship to avoid the overestimation due to duplicate AIS data or underestimation due to the loss of AIS signal. The advantage of SEIM model on better spatial allocation has been approved1. The validation of the SEIM model was also done in previous study1, with global total similar to the IMO study. The latest estimate of global health impact of vessels also compared their results with the result of SEIM model and found the model is reliable[10].

## *5.2 Detailed Shipping Emission Results Embodied in US-China Trade*

Supplementary Table 6 summarizes the shipping emissions embodied in US-China trade. Shipping emissions from China to the US were all higher than those from the US to China due to the higher commodity weight exported from China to the US.

**Supplementary Table 6** | Detailed emission results of trade related shipping activities.

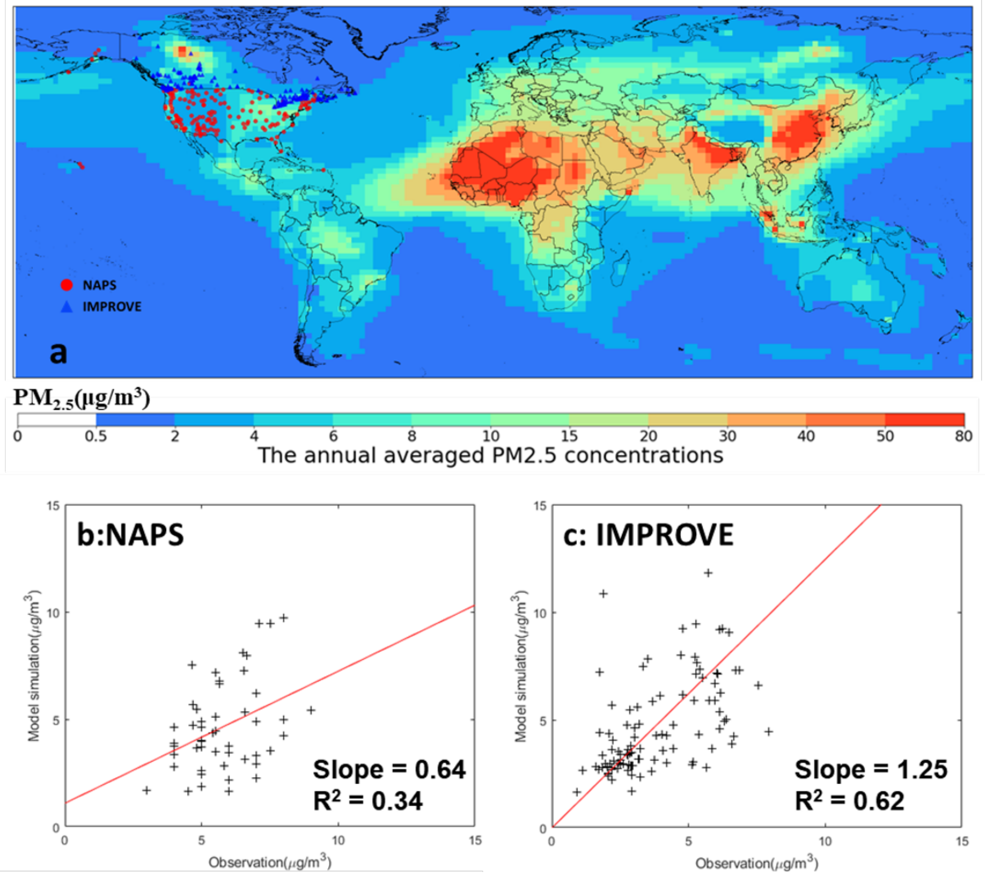
| Trip | Vessel category | PM | NOx | $SO_2$ | CO | HC | $CO_2$ | $N_2O$ | $CH_4$ |
|---|---|---|---|---|---|---|---|---|---|
| | Unit | Ton | Ton | Ton | Ton | Ton | $10^3$ Ton | Ton | Ton |
| China to US | Auto Carrier | 132.1 | 1612.0 | 970.1 | 55.7 | 55.7 | 66.2 | 3.4 | 1.1 |
| | Bulk Carrier | 3436.5 | 39042.2 | 26177.1 | 1435.3 | 1356.8 | 1776.2 | 91.8 | 27.1 |
| | Container Ship | 19342.0 | 216129.0 | 153488.2 | 8661.4 | 7926.5 | 11415.4 | 630.0 | 158.5 |
| | General Cargo Ship | 484.9 | 5520.0 | 3636.4 | 206.8 | 196.9 | 251.0 | 13.0 | 3.9 |
| | Miscellaneous | 62.2 | 669.3 | 476.2 | 26.0 | 24.0 | 32.0 | 1.6 | 0.5 |
| | Oceangoing Tug/Tow | 0.3 | 16.8 | 0.7 | 0.7 | 0.6 | 0.9 | 0.0 | 0.0 |
| | Refrigerated Ship | 5.3 | 56.4 | 42.6 | 2.2 | 1.9 | 2.8 | 0.1 | 0.0 |
| | Chemical Tanker | 184.4 | 2149.9 | 1402.5 | 79.1 | 74.5 | 98.4 | 5.1 | 1.5 |
| | Oil Tanker | 229.4 | 2826.3 | 1724.8 | 97.3 | 96.1 | 120.1 | 6.4 | 1.9 |
| US to China | Auto Carrier | 277.9 | 3422.9 | 2066.2 | 121.8 | 119.2 | 147.1 | 7.6 | 2.4 |
| | Bulk Carrier | 2382.8 | 26966.7 | 18090.1 | 998.2 | 945.1 | 1222.7 | 63.3 | 18.9 |
| | Container Ship | 13585.2 | 145004.4 | 108030.5 | 5955.6 | 5507.7 | 7539.6 | 421.1 | 110.2 |
| | General Cargo Ship | 274.1 | 3069.5 | 2109.8 | 115.5 | 104.9 | 144.5 | 7.5 | 2.1 |
| | Miscellaneous | 24.4 | 254.0 | 151.6 | 12.6 | 13.8 | 10.8 | 0.6 | 0.3 |
| | Oceangoing Tug/Tow | 0.0 | 0.9 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| | Chemical Tanker | 164.4 | 1873.8 | 1250.6 | 68.2 | 64.7 | 84.1 | 4.3 | 1.3 |
| | Oil Tanker | 136.4 | 1687.0 | 1031.8 | 57.9 | 56.7 | 72.1 | 3.8 | 1.1 |

## 6. Air Quality

The atmospheric chemical transport model is driven by meteorological data to calculate variations in atmospheric concentrations due to emission, chemistry and deposition through complex chemical reactions and transport mechanisms. GEOS-Chem is one of the most widely used atmospheric chemical transport models and is used by research groups around the world to analyze atmospheric composition problems, especially in recent years for $PM_{2.5}$-related research[13-17]. The model is managed and supported by the Atmospheric Chemistry Simulation Team at Harvard University and Dalhousie University (http://acmg.seas.harvard.edu/geos/index.html). In this work, we used GEOS-Chem model to estimate the impacts of US-China trade shipping emissions on the global surface $PM_{2.5}$ concentration for the base year of 2016 with a zero-out method. Briefly, the difference between the simulation results with and without US-China-trade shipping emissions with other parameters set the same was used in our air quality analysis. The model was run with full Ox-NOx-CO-VOC-HOx chemistry and online aerosol calculations[18,19], on a 2.5° longitude × 2° latitude grid with 47 vertical layers and driven by the 3-D meteorological fields assimilated by the Goddard Earth Observing System (GEOS).

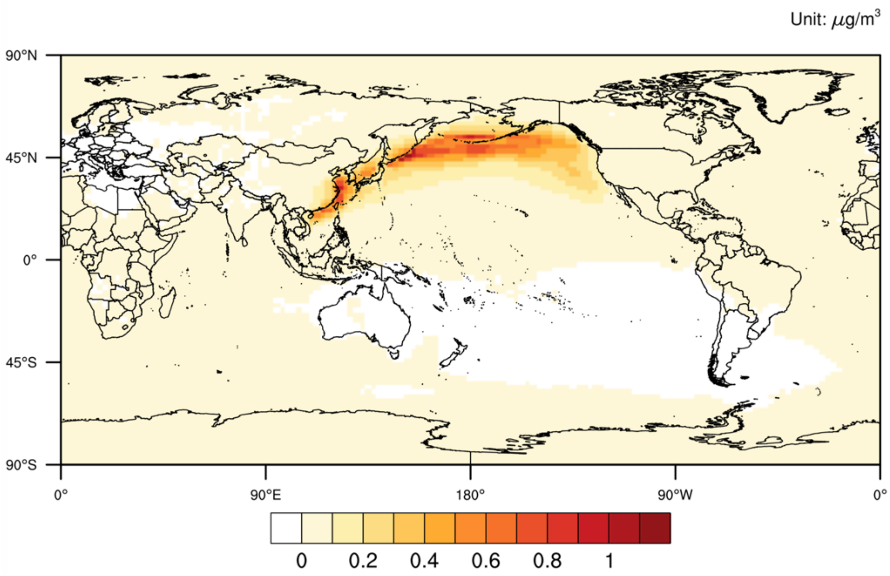
In this work, GEOS-Chem (version 11–01) was driven by MERRA-2, a reanalysis data product from NASA/GMAO (http://wiki.seas.harvard.edu/geos-chem/index.php/MERRA-2). The global shipping emissions for 2016 were calculated using our SEIM model[1] and were used as an input for the GEOS-Chem. In addition to shipping emissions, the global anthropogenic emissions used here were from the Community Emissions Data System (CEDS)[20], and the latest 2014 emissions were used. For anthropogenic emissions over China, we updated the available data, using the Multi-Resolution Emission Inventory of China for the year 2016 (MEIC, http://meicmodel.org). In addition, GFED4 biomass burning (v4.1)[21], sea salt[22], MEGAN biogenic emissions[23], $NO_X$ from lightning[24,25], and NO from soils/fertilizers[26], aircraft[27] and the DEAD dust model[28] were included in the simulation. To generate more accurate initial conditions for simulation, 6 months of spin-up time for each case was used. In the model, the sum of sulfate, nitrate, ammonium, BC and OC represented $PM_{2.5}$ and the bottom 24-hour average $PM_{2.5}$ concentration from the model was selected to represent the surface concentration.

We used the surface measurement $PM_{2.5}$ concentration to evaluate the model simulated $PM_{2.5}$ concentration. Following method of the Zhang et al.[12], the average annual $PM_{2.5}$ concentration from the National Air Pollution Surveillance network (NAPS, http://maps-cartes.ec.gc.ca/rnspa-naps/data.aspx) from Canada and the Interagency Monitoring of Protected Visual Environments network (IMPROVE, http://vista.cira.colostate.edu/improve/Data/data.htm) from the US were used. The comparison of $PM_{2.5}$ concentrations between the observations and the model simulation is shown in Supplementary Fig. 9. Overall, the model simulation was in accordance with the US observation, though slightly lower than the Canadian observations. This underestimation may be due to an underestimation of the Canadian emission inventory and the coarse model resolution.




**Supplementary Fig.9** | Comparison of annual average PM2.5 concentrations simulated by GEOS-Chem and observations. a, GEOS-Chem results; b, comparison with surface observations in Canada; c, comparison with observations in the US. Red circles and blue triangles represent the NAPS and IMPROVE sites used in this study, respectively.

With GEOS-Chem model, Supplementary Fig.10 showed the distribution of $PM_{2.5}$ impacts from vessel emissions embodied in US-China trade. The shipping emissions influenced the $PM_{2.5}$ not only along the sea lanes but also in the inland areas due to the air mass from sea to land. The distribution reflected that the US-China trade mainly impacted the coastal region of China, Japan and some countries in Southeast Asia. The US would avoid the $PM_{2.5}$ impacts because of the low sulphur fuel used within ECA region. On the one hand, low sulphur fuel can reduce the new particle formation in the combustion process, causing less primary PM. On the other hand, less sulfate in the secondary PM would be formed in the air during the oxidation process because of the reduction in $SO_2$ emissions.




**Supplementary Fig.10** | Impacts on $PM_{2.5}$ concentrations from US-China trade related shipping emissions.

## 7. Health Impacts

Changes in health impacts from long-term exposure to $PM_{2.5}$ due to shipping emissions from US-China trade were calculated in this research. In addition to the model results obtained above, the integrated exposure-response (IER) function developed by Burnett, et al. [29] was selected, which has been widely used, namely, in the GBD study, to estimate premature deaths from outdoor $PM_{2.5}$ exposure. The global population data was from the Gridded Population of the World version 4 (GPWv4) (http://sedac.ciesin.columbia.edu/data/collection/gpw-v4/sets/browse) developed by NASA's Socioeconomic Data and Applications Center (SEDAC). The original spatial resolution of the population data was 2.5′ × 2.5′, while the resolution of the GEOS-Chem model result was 0.1° × 0.1°. Therefore, we downscaled the population data to 0.1° × 0.1° to enable integration with the estimated $PM_{2.5}$ result. Cause-specific baseline mortality rates and the distribution of different age groups for each nation were obtained from Global Burden of Disease Study 2016 (GBD 2016) results (http://ghdx.healthdata.org/gbd-results-tool). With these data and results, the premature mortality for five leading causes of death: ischemic heart disease (IHD), cerebrovascular disease (stroke), chronic obstructive pulmonary disease (COPD), lung cancer (LC) and acute lower respiratory (ALRI) were estimated.

The grid-based (0.1° $\times$ 0.1°) premature deaths associated with exposure to $PM_{2.5}$ were calculated with equation 3:

$$M = M_b \times P \times \mathrm{AF} \qquad \text{equation (3)}$$

where $M$ is the number of premature deaths due to $PM_{2.5}$; $M_b$ represents the cause–specific baseline mortality rate; $P$ is population; and AF represents the attributable fraction of deaths due to $PM_{2.5}$. AF can be described in terms of the relative risk (RR) as below:

$$\mathrm{AF} = (\mathrm{RR} - 1)/\mathrm{RR} \qquad \text{equation (4)}$$

In the IER model, RR is expressed by equation 5:

$$\mathrm{RR} = \begin{cases} 1 + \alpha(1 - e^{-\gamma(C - C_0)^{\delta}}, if C > C_0 \\ 1, else \end{cases} \qquad \text{equation (5)}$$

where $C$ represents the exposure to $PM_{2.5}$ obtained from the GEOS-Chem model; $C_0$ is the counterfactual concentration below which there is no additional risk; and $\alpha$, $\gamma$ and $\delta$ are parameters used to describe the different shapes of the exposure-response curve for various diseases, which were obtained from Burnett, et al. [29]. Considering the uncertainties of $\alpha$, $\gamma$ and $\delta$ in the IER function, 1000 sets of these parameters were used in 1000 simulations. The median and 95% Confidence Interval (CI) were provided in results. In addition to the IER parameters, the uncertainty in linking a given amount of $PM_{2.5}$ concentrations to premature mortality mainly comes from the statistical estimation and limited epidemiological evidence of the IER functions[29,30]. To calculate the premature deaths associated with US-China-trade shipping emissions, the annual mean $PM_{2.5}$ concentrations (on a 0.1° $\times$ 0.1° grid) estimated with and without US-China trade shipping emissions were applied to the IER model, respectively. The difference in these two results was the premature death associated with US-China trade shipping emissions. The overall health impacts of $PM_{2.5}$ were consistent with other published studies. For example, the IER model estimated the total worldwide premature death derived from $PM_{2.5}$ at 6.1 million (95% CI, 2.8-7.9 million) in 2016. The result of a recent study in the *Lancet* showed that exposure to $PM_{2.5}$ resulted in approximately 4.2 million premature deaths in 2015[31], which falls within the 95% confidence interval of our estimates.

The linear concentration-response function from Lepeule, et al. [32] was also used to estimate $PM_{2.5}$-related premature death due to two reasons: (1) IER may underestimate the excess relative risk over the exposure range experienced in developing countries with high exposure to $PM_{2.5}$, which was reported by a recent study based on a large national cohort in China[33]; (2) this equation provide estimates that are comparable with prior research on health impacts from shipping[10]. We focused on cardiovascular and lung cancer mortality corresponding to impacts on a population cohort aged 30 years or more. These national data were also from the GBD results described above. For our linear function, RR is defined as:

$$\mathrm{RR} = e^{\beta(C_1 - C_0)} \qquad \text{equation (6)}$$

where $C_0$ and $C_1$ represent $PM_{2.5}$ concentration levels for different scenario (simulations with and without US-China trade shipping emissions), and the coefficient $\beta$ is derived from Lepeule, et al. [32] and Sofiev, et al. [10] ($\beta$=0.023111 (95% CI, 0.013103-0.033647) for cardiovascular mortality, $\beta$=0.031481 (95% CI, 0.006766-0.055962) for lung cancer related deaths).

The global premature deaths due to shipping in US-China trade reached 5,700 (95% CI, 2,700-6,600) and 19,500 (95% CI, 9,900-29,400) using the IER model and linear model, respectively (Supplementary Table.7). Although the national ranking of mortality number was extremely similar in these two methods, the linear C-R function produced 3-5 times higher health burden estimates than those using the IER model, which was mainly because the linear model produced higher RR values at a high $PM_{2.5}$ exposure level.

**Supplementary Table 7 |** IER model and linear C-R function estimates of mortality in the global total, China, the US and the other five-highest countries due to US-China trade ships.

| Results from the IER Model | | Results from the Linear C-R Function | |
|---|---|---|---|
| Country | Mortality Estimate* (thousand, 95% CI) | Country | Mortality Estimate* (thousand, 95% CI) |
| China | 3.7 (1.9-4.2) | China | 16.6 (8.4-24.9) |
| United States | 0.1 (0.0-0.2) | United States | 0.3 (0.1-0.4) |
| Japan | 1.0 (0.5-1.1) | Japan | 1.2 (0.6-1.9) |

| | | | |
|---|---|---|---|
| South Korea | 0.2 (0.1-0.3) | South Korea | 0.6 (0.3-0.9) |
| Vietnam | 0.2 (0.1-0.3) | Vietnam | 0.3 (0.1-0.4) |
| Thailand | 0.1 (0.0-0.1) | North Korea | 0.2 (0.1-0.3) |
| North Korea | 0.1 (0.0-0.1) | Thailand | 0.1 (0.1-0.2) |
| Total | 5.7 (2.7-6.6) | Total | 19.5 (9.9-29.4) |

*Values for annual premature mortality are rounded to the nearest 100.

## 8. QA/QC

### *8.1 Summary of Uncertainties*

Supplementary Table 8 provides an overview of uncertainty and descriptions in each calculation step. The details are discussed in the previous sections.

**Supplementary Table 8** | Summary of uncertainties in each part.

| Research content | Source of uncertainty | Significance of uncertainty component |
|---|---|---|
| US-China Bilateral Trade Database | Trade data | Minor. The data was from Chinese Customs and was similar to the data from the US Census Bureau. |
| Transport Mode Split | Neglecting the commodity weight carried by air | Minor. In US-China trade, only 0.9% of the commodity weight was carried by air. |
| Ship Technical Specifications Database (STSD) | Assumption that the STSD represents most trade vessels | Minor. Compared to the total DWT of the world vessel fleet of each vessel category, the STSD showed nearly complete coverage. |
| Ship Automatic Identification System Data (AIS) | Quality of AIS data | Minor. In all, 94% of our AIS data had a time interval of less than 5 minutes, and this was enough for trade vessel identification. The coverage of AIS data was tested in our previous research[1] |
| Identification of Bilateral Trade Related Voyages | Excluding the stop-over situation | Minor. The comparison of total cargo weight with ship DWT is in a reasonable ratio as reported by IMO report[6]. This excluding can also avoid double counting for global level calculation. |
| | Ignoring the movements between domestic ports prior to international journeys | Minor. Domestic voyage could be related to domestic trade. Even part of the domestic voyage is related to US-China trade, compared to the long distance between the two countries, it's not significant on total emissions. |

| | | |
|---|---|---|
| Emission Modeling Approach | Emission factors | Minor. The SEIM model was the latest model based on AIS data which reflected the actual sailing process of ships. |
| Air Quality | Uncertainties in anthropogenic emissions, meteorological prediction and chemical mechanisms | Minor. The comparison between the simulated results and the observation showed our predicted $PM_{2.5}$ was reliable. |
| Health Impacts | Uncertainties in selected parameters and limited epidemiological studies | Large. Health impacts are quite different using these two methods, the range of 95% CI were provided for each method based on the estimation of uncertainties in their parameters. |

### *8.2 Summary of Results Validation*

Besides the bottom-up uncertainty analysis, SI-Table 9 provides a top-down validation from three aspects: transported weight (ship fleet capacity vs. trade commodity weight), trade value (Chinese data sources vs. US data sources), and the share of US-China trade in the global total (from trade value, shipping emissions, and shipping emission-related premature deaths).

**Supplementary Table 9** | Summary of results validation.

| Content | Results | Comparison data | Difference |
|---|---|---|---|
| Identification of vessels | Fleet capacity (Tg) | Trade commodity weight (Tg) | 33.6% |
| | 388.5 | 224.6 | |
| Trade database | Value from BTD (billion $) | Value from USA Trade Online (billion $) | 10.2% |
| | 519 | 578[8] | |
| Proportion of US-China bilateral trade in the global total | 3.4% (519/15460 billion $) | Trade value | |
| | 2.5% (23/938 Tg) | Vessel $CO_2$ emissions | |
| | 4.8% (19475/403300 premature deaths) | Premature deaths | |

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