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Quantifying the Source–Receptor Relationships of $PM_{2.5}$ Pollution and Associated Health Impacts among China, South Korea, and Japan: A Dual Perspective and an Interdisciplinary Approach

Jianzheng Liu,[1,2,3]* Fei Yao,[4,5]* Hongwen Chen,[6] and Hongyan Zhao[7]

[1]School of Public Affairs, Xiamen University, Xiamen, Fujian, China
[2]Fujian Key Laboratory of Sensing and Computing for Smart Cities, Xiamen, Fujian, China
[3]Xiamen Key Laboratory of Integrated Application of Intelligent Technology for Architectural Heritage Protection, Xiamen, Fujian, China
[4]National Centre for Earth Observation, University of Edinburgh, Edinburgh, UK
[5]School of GeoSciences, University of Edinburgh, Edinburgh, UK
[6]School of Tourism, Nanchang University, Nanchang, Jiangxi, China
[7]Center for Atmospheric Environmental Studies, School of Environment, Beijing Normal University, Beijing, China

Background: Transboundary particulate matter (PM) with aerodynamic diameter $\leq 2.5\ \mu m$ ($PM_{2.5}$) pollution is causing significant environmental conflicts among China, South Korea, and Japan. However, efforts to address these conflicts have been impeded by a lack of a comprehensive understanding of source–receptor relationships of $PM_{2.5}$ pollution and associated health impacts among these countries.

Objectives: We quantified the extent to which transboundary $PM_{2.5}$ pollution and associated health impacts are mutual among the three countries in 2015 and 2017 using three metrics (population-weighted mean $PM_{2.5}$ concentration, $PM_{2.5}$ population exposure, and $PM_{2.5}$-related premature deaths) and two accounting perspectives (production and consumption).

Methods: We adopted an integrated interdisciplinary analysis framework that links an environmentally extended multiregional input–output model, a GEOS-Chem chemical transport model, a population exposure model, and an exposure–response model.

Results: From a production perspective, China's contributions to population-weighted mean $PM_{2.5}$ concentrations in South Korea and Japan were considerable, whereas the contributions of South Korea and Japan to China were negligible. However, the contributions from South Korea and Japan to $PM_{2.5}$ population exposure and associated premature deaths in China were nonnegligible from both production and consumption perspectives. From a consumption perspective, the contributions of South Korea and Japan to $PM_{2.5}$-related premature deaths in China amounted to 6.96 [95% confidence interval (CI): 6.36, 7.56] and 9.79 (95% CI: 8.93, 10.64) thousand deaths in 2015, respectively, and 5.03 (95% CI: 4.55, 5.49) and 7.75 (95% CI: 7.02, 8.47) in 2017, respectively. These figures were generally larger than China's contributions to $PM_{2.5}$-related premature deaths in South Korea and Japan, which totaled 4.63 (95% CI: 3.97, 5.28) and 3.91 (95% CI: 2.78, 5.01) thousand deaths in 2015, respectively, and 4.43 (95% CI: 3.75, 5.1) and 3.69 (95% CI: 2.57, 4.79) in 2017, respectively.

Discussion: Our findings show that mutual contributions of $PM_{2.5}$ pollution and associated health impacts among the three countries varied considerably when different metrics and accounting perspectives were applied. A consumption perspective revealed narrower gaps in mutual contributions than a production perspective. Moreover, other countries outside Northeast Asia may have played a significant role in contributing to $PM_{2.5}$ pollution and associated health impacts in Northeast Asia, suggesting that Northeast Asian countries should look beyond this region and collaborate with the rest of the world to jointly develop effective $PM_{2.5}$ mitigation strategies. Our findings could help policymakers, scholars, and the public in China, South Korea, and Japan understand the intricacies involved in assigning environmental responsibilities and achieving environmental justice with respect to transboundary $PM_{2.5}$ pollution. https://doi.org/10.1289/EHP14550

Introduction

Transboundary fine particulate matter ($PM_{2.5}$) pollution has become an increasingly significant and sensitive environmental issue in China, South Korea, and Japan. The prevailing westerly winds from the west toward the east in the middle latitudes are causing transboundary $PM_{2.5}$ pollution originating from upwind countries (e.g., China and South Korea) to spread across borders into downwind countries (e.g., South Korea and Japan), which results in adverse impacts on human health in downwind countries. The transboundary $PM_{2.5}$ pollution has raised tremendous public concern and many debates and arguments on the allocation of environmental responsibilities in both academia and society in Northeast Asia (NEA). Driven by the increasing concern, there is a proliferation of studies focusing on the source–receptor relationship (SRR) of $PM_{2.5}$ pollution among these countries in recent years.[1,2] These studies allowed for an understanding of the source areas of transboundary $PM_{2.5}$ pollution in NEA and their source contributions to receptor countries via atmospheric transport.[3–7] However, most of these studies attributed the pollution to a country only by evaluating the direct air pollutant emissions produced in that country but overlooked the indirect air pollutant emissions embodied in cross-border trade caused by consumption in other countries. A typical anthropogenic emission process of air pollutants is not only executed by producers, but also stimulated by consumers,[8] which raises a critical question about the extent to which the consumer countries that have benefited from the emission process should be accountable for the emissions and the consequent air pollution. Therefore, it is recommended that future studies on the SRR of $PM_{2.5}$ pollution in NEA should consider both production and consumption perspectives.[1]

A production perspective views all emissions produced in a country as the responsibility of that country. Clearly, only the impact of atmospheric transport on the air quality in downwind countries will be considered when examining the SRR of $PM_{2.5}$ pollution from this perspective. By contrast, a consumption perspective regards all emissions induced by the consumption of a

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*These authors contributed equally to this work.

Address correspondence to Hongwen Chen. Email: hongwen_chen@ncu.edu.cn. And, Hongyan Zhao. Email: zhao-hy2021@bnu.edu.cn

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country via the trade of goods and services to be the responsibility of that country, irrespective of the countries where the emissions are produced.[9–12] In this sense, not only atmospheric transport relocates $PM_{2.5}$ pollution between countries, but also trade displaces $PM_{2.5}$ pollution by physically separating the production and consumption activities. The consumption perspective has been explored in air pollution studies both internationally[11,13] and nationally[14–16]; however, it has not been used to examine the SRR of $PM_{2.5}$ pollution in NEA, especially on the country level that is required to guide local actions. A related study examines the consumption-based health burdens of black and organic carbon in Asia,[17] but it neither investigates the lumped $PM_{2.5}$ nor provides a production-based analysis of concentrations of black and organic carbon or the associated health impacts. Therefore, the SRR of $PM_{2.5}$ pollution in NEA from a consumption perspective and their differences from those of a production perspective remain unknown.

Here, we adopted an integrated interdisciplinary analysis framework, consisting of an environmentally extended multiregional input–output (EE-MRIO) model,[18] a GEOS-Chem chemical transport model,[19] a population exposure model,[20,21] and an exposure–response model[22] to provide a contemporary, comprehensive, and quantitative analysis of the SRR of $PM_{2.5}$ pollution and associated health impacts among China, South Korea, and Japan in 2015 and 2017. For modeling purposes, we used the detailed sectoral emission dataset, the Emissions Database for Global Atmospheric Research v6.1 (EDGARv6.1).[23] EDGARv6.1 provided an extended time series (1970–2017) of anthropogenic emissions of air pollutants covering the globe. This extended time series allows us to capture possible changes over time in mutual contributions to $PM_{2.5}$ pollution and associated health impacts among China, South Korea, and Japan in recent years, which was not possible in prior studies due to data unavailability.[13,17] Our experimental design enables us to quantify the extent to which transboundary $PM_{2.5}$ pollution and associated health impacts are mutual among nations in NEA.

Methods

We adopted an integrated analysis framework that consists of four steps (Figure 1). First, we used an EE-MRIO model to develop the consumption-based emission inventories based on China's MRIO tables,[24] the Organisation for Economic Co-operation and Development (OECD) intercountry input–output (ICIO) tables,[25] and the production-based emission inventory EDGARv6.1.[23] Second, we used the GEOS-Chem chemical transport model[19] to simulate the surface $PM_{2.5}$ concentrations in China, South Korea, and Japan under a baseline and nine emission-reduction scenarios (Table 1). The simulation results of the nine emission-reduction scenarios were compared with that of the baseline scenario to determine the grid-level fractional contributions to $PM_{2.5}$ pollution from production- and consumption-based emissions in NEA countries. In the third and fourth steps, we used an exposure model and an exposure–response model to calculate the population-weighted mean (PWM) $PM_{2.5}$ concentrations, $PM_{2.5}$ population exposure, $PM_{2.5}$-related premature deaths, and contributions from source countries to these metrics in receptor countries. Additional details on each step are described below.

Multiregional Input–Output Model for Deriving Consumption-Based Emissions

We used an EE-MRIO model to calculate consumption-based emissions. The EE-MRIO model extends and augments the basic input–output model developed by Wassily Leontief[26] with additional environmental datasets to evaluate the environmental impacts of economic activities.[27] It is a well-established method in the fields of applied economics and industrial ecology to analyze the environmental footprints in the supply chains.[27,28] The core of the EE-MRIO model is a multiregional input–output (MRIO) model describing the transactions of products within and among countries/regions.[27,29] With the help of the EE-MRIO model, we calculated the consumption-based emissions via an input–output analysis of the economic output in monetary unit required to produce goods and services for consumption in a region, multiplied by emission intensities. We performed the input–output analysis on a sector and region basis using a MRIO model that combines China's MRIO tables obtained from the Carbon Emission Accounts and Datasets with the OECD ICIO tables (https://www.oecd.org/en/data/datasets/inter-country-input-output-tables.html).[25] China's MRIO tables were compiled based on provincial single region input–output tables constructed from survey data, provincial statistics yearbooks, and China's customs database.[24] The OECD ICIO tables were generated based on national input–output tables, annual national accounts, and bilateral trade data.[25] By capturing the economic processes among sectors and regions, the EE-MRIO model enables the tracing of the air pollutant emissions from the region of final consumption to its source region of production.[9]

To link China's MRIO tables with the OECD ICIO tables, we adopted a linking procedure outlined in previous studies.[15] Specifically, we used China's MRIO tables as the base and nested the OECD ICIO tables into China's MRIO tables by constraining the international exports and imports (including both intermediate and final demands) to those of China's MRIO tables (Table S1). The interprovincial trade among Chinese provinces remained unchanged. China's exports to other countries/regions and the exports from other countries/regions to China derived from the OECD ICIO tables were used as proxies to split Chinese provincial exports and imports with other countries/regions. The total output vectors of other countries/regions were constrained by the ratios of China's total output vectors in China's MRIO tables to those in the OECD ICIO tables. For

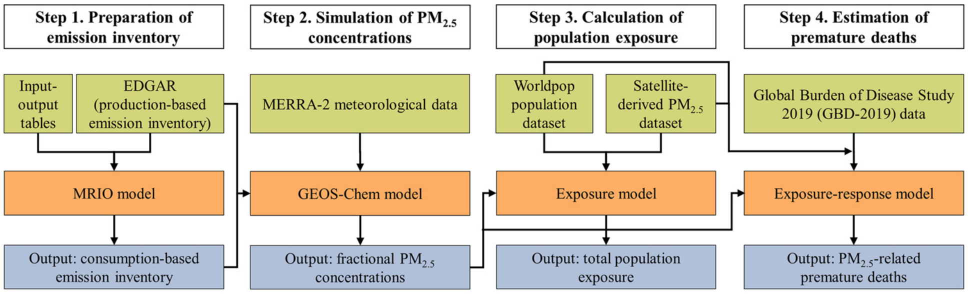

Figure 1. Analysis framework. Each column shows the purpose, input data, model, and output data of each step from top to bottom. Arrows indicate data flow. Note: EDGAR, the Emissions Database for Global Atmospheric Research; GBD, Global Burden of Disease; MERRA-2, Modern-Era Retrospective analysis for Research and Applications version 2; MRIO, multiregional input–output; $PM_{2.5}$, fine particulate matter with an aerodynamic diameter ≤ 2.5 µm.

interregional trade among other countries/regions, the trade structure remained constant, but the values were constrained by a total volume after deducting their intermediate and final demands by China from the total output vectors of other countries/regions. Finally, the linked MRIO model consisted of 97 regions, including 31 out of 34 province-level divisions in China (excluding Hong Kong, Macau, and Taiwan), and 66 countries/regions, including South Korea and Japan (Table S1). The linked MRIO model begins with the following equation for monetary flows:

$$\begin{pmatrix} x_1 \\ \vdots \\ x_r \\ \vdots \\ x_{97} \end{pmatrix} = \begin{pmatrix} A_{1,1} & \cdots & A_{1,s} & \cdots & A_{1,97} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ A_{r,1} & \cdots & A_{r,s} & \cdots & A_{r,97} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ A_{97,1} & \cdots & A_{97,s} & \cdots & A_{97,97} \end{pmatrix} \begin{pmatrix} x_1 \\ \vdots \\ x_r \\ \vdots \\ x_{97} \end{pmatrix} + \begin{pmatrix} \sum_s \sum_t y^t_{1,s} \\ \vdots \\ \sum_s \sum_t y^t_{r,s} \\ \vdots \\ \sum_s \sum_t y^t_{97,s} \end{pmatrix}, \quad (1)$$

where x_r $(r = 1, 2, \ldots, 97)$ is a vector of the total economic output for each sector in region r. The subscripts ranging from 1 to 31 indicate the 31 provinces of mainland China, and the subscripts ranging from 32 to 97 indicate the 66 countries/regions. $A_{r,s}$ $(r = 1, 2, \ldots, 97,$ and $s = 1, 2, \ldots, 97)$ represents the matrix of direct consumption coefficients in which the columns represent the amount of input from the sectors in region r required for one unit of output to be produced by each sector in region s. $y^t_{r,s}$ is the final demand in region s, which is satisfied by the goods produced in region r. t refers to different types of final demand, including consumption by rural and urban residents, government investment, fixed asset investment, and others. A simplified version of Equation 1 is as follows:

$$x = Ax + y, \quad (2)$$

where x is the matrix of the total economic output, A is the matrix of direct consumption coefficients, and y is the matrix of final demand.

If Equation 2 is solved for the total economic output, then it can be expressed as:

$$x = (I - A)^{-1} y, \quad (3)$$

where I is the identity matrix and $(I - A)^{-1}$ denotes the Leontief inverse matrix. By multiplying the economic output with the emission intensity,[27] the emissions induced by consumption in a given region can be calculated as:

$$E^r = \widehat{f}(I - A)^{-1} y^r, \quad (4)$$

where E^r represents the region- and sector-specific emissions of air pollutants induced by consumption in region r, y^r is the final demand vector for region r, and $\widehat{f}$ is a diagonal matrix of the region- and sector-specific emission intensities (pollutant emissions per unit of economic output), which can be calculated by dividing the production-based pollutant emissions derived from the EDGARv6.1 by the total economic output x on a region and sector basis. The EDGARv6.1 was produced using a bottom-up approach that compiled an inventory of equipment and estimated the emissions based on the amount of fuel combusted, distances traveled or similar activity data for that equipment in each sector.[30] Values of A, y, and y^r are available in the MRIO model.

The China's MRIO tables follow the Chinese national sector classification and have 42 sectors,[24] the OECD ICIO tables use the sector classification of OECD ICIO system and have 45 sectors,[25] and EDGARv6.1 dataset uses the sector classification from the 1996 Intergovernmental Panel on Climate Change guidelines and has 38 sectors.[23] To facilitate the MRIO analysis, we combined and matched the sectors in the China's MRIO tables, OECD ICIO tables, and the EDGARv6.1 dataset through a mapping process (Tables S2, S3, and S4) adapted from previous consumption-based studies.[15] We first aggregated sectors in the China's MRIO tables and the OECD ICIO tables, respectively, and formed a unified sectoral classification in the linked MRIO model (Table S2 and S3). Sectors in EDGARv6.1 were then mapped to the unified sectors in the linked MRIO model according to the products and usage categories (Table S4). In addition, consistent with previous studies,[15,31,32] we allocated the consumption-based emissions from regional to grid level by following the spatial distribution of the production-based emission inventory for each sector. For example, a portion of emissions physically produced in China is driven by consumption in Japan. To simulate the effect of the consumption-based emissions induced by Japan, this portion of emissions is still released in China and thus gridded according to the spatial distribution of production-based emissions in China.

GEOS-Chem Chemical Transport Model for Simulating $PM_{2.5}$ Concentrations

The GEOS-Chem model is a global three-dimensional chemical transport model of tropospheric chemistry driven by assimilated meteorological observations, which enables simulations of atmospheric composition on local to global scales.[19] We ran version 12.9.3 of the GEOS-Chem tropospheric chemistry ("tropchem") mechanism to provide surface $PM_{2.5}$ concentrations at a horizontal resolution of 0.5° latitude and 0.625° longitude for the months of January through December in 2015 and 2017 within a self-defined study domain (Figure S1, Excel Table S1). The study domain covered China, South Korea, and Japan, as well as potential source areas of $PM_{2.5}$ pollution in NEA, such as South and Central Asia, which include Mongolia, Russian Far East, Kazakhstan, Kyrgyzstan, Uzbekistan, Tajikistan, Afghanistan, Pakistan, India, Myanmar, Laos, Thailand, Vietnam, Cambodia, and Philippines. We performed two self-consistent global runs using GEOS-Chem to provide initial and time-dependent lateral boundary conditions at a horizontal resolution of 2° latitude and 2.5° longitude, which are necessary for regional runs. These two global runs covered the periods of July 2014 to December 2015 for the 2015 simulation and July 2016 to December 2017 for the 2017 simulation. The first 6 months of each run served as the model spin-up to obtain initial conditions that reflect the true atmospheric state. Both global and regional runs were driven by the meteorology from the Modern-Era Retrospective analysis for Research and Applications version 2 (MERRA-2).[33] We employed EDGARv6.1 anthropogenic emissions and other GEOS-Chem default emissions (Table S5). We turned off emissions in the latter that existed in the former, which included emissions from anthropogenic activities, agricultural soil nitrogen oxides (NO_x), agricultural waste burning, aviation, and shipping, to avoid double counting. In practice, we initially had an insufficiently high model performance for black carbon. We improved its simulation by redistributing its emissions in EDGARv6.1 to the spatial profile of black carbon emissions in the MIX Asian emission inventory[34] that can better represent regional characteristics.

We evaluated the model performance by comparing model simulation results against hourly $PM_{2.5}$ concentration measurements collected from *a*) the China National Environmental Monitoring Center (CNEMC); *b*) the AirKorea of the Korean Ministry of Environment; *c*) the Atmospheric Environmental Regional Observation System (AEROS), the Ministry of the Environment Government of Japan; and *d*) the Acid Deposition Monitoring Network in East Asia (EANET). In addition, we evaluated the model performance using ground measurements of $PM_{2.5}$ chemical components [sulfate, nitrate, ammonium, organic carbon (OC), and black carbon (BC)] collected from sources as listed in Table S6.

To ensure the accuracy of the evaluation of the model performance, we performed a comprehensive data quality check of the hourly $PM_{2.5}$ concentration measurements. This quality check involved removing any problematic data points using the data quality control procedures that have been established in previous studies.[35,36] Those steps are as follows:

1. Convert the time stamps of all hourly observation data to the Coordinated Universal Time (UTC).

   The air quality monitoring systems in different countries record hourly observation data using different time zone settings. For example, CNEMC records hourly $PM_{2.5}$ concentration measurements using China Standard Time (UTC+8:00), whereas AirKorea and AEROS use Korean Standard Time and Japan Standard Time (UTC+9:00), respectively. To facilitate the comparison between observed and modeled data, we converted the timestamps of all hourly observation data to UTC.
2. Set lower and upper limits of hourly $PM_{2.5}$ concentration measurements to $[0; 3{,}000]\ \mu g/m^3$.

   We considered hourly $PM_{2.5}$ concentration measurements $<0\ \mu g/m^3$ or exceeding $3{,}000\ \mu g/m^3$ as potential instrumental failures and therefore removed them from further analysis by setting their values to NaN (Not a Number). Missing data were also considered as NaN.
3. Remove $PM_{2.5}$ concentration measurements that exceed concurrently co-located PM_{10} concentration measurements.

   $PM_{2.5}$ concentration measurements are the mass of particles with an aerodynamic diameter $\leq 2.5\ \mu m$ per unit volume of air, whereas PM_{10} concentration measurements are the mass of particles with an aerodynamic diameter $\leq 10\ \mu m$ per unit volume of air. It is clear that at any given time and location, the $PM_{2.5}$ concentration measurements should never exceed those of PM_{10}.[35] Therefore, we considered $PM_{2.5}$ concentration measurements that exceeded concurrently co-located PM_{10} concentration measurements as problematic measurements, and subsequently removed them from further analysis by setting their values to NaN.
4. Eliminate any series of five consecutive hourly $PM_{2.5}$ concentration measurements that are identical in value.

   $PM_{2.5}$ measurements are typically volatile, so it is highly unlikely for an air quality monitoring instrument to record the same value for 5 consecutive hours.[35] As a result, we considered any such repeated measurements to be potential instrumental errors and marked them as invalid by setting their values to NaN.
5. Remove any extreme jumps in hourly $PM_{2.5}$ concentration measurements.

   Occasionally, meteorological events such as strong winds can cause dramatic changes in $PM_{2.5}$ concentration measurements. However, these events are usually accompanied by sustained high $PM_{2.5}$ concentrations either before or after their occurrence. As a result, it is unlikely for $PM_{2.5}$ concentrations to change abruptly without any connection to the measurements before or after.[36] To identify problematic abrupt changes in $PM_{2.5}$ concentration measurements, we adopted the method proposed by Jiang et al.[36] This process involved two steps: first, if the hourly change in $PM_{2.5}$ concentration at a given hour (t), relative to $t-1$ and $t+1$, was >15 times the hourly change in $PM_{2.5}$ concentration at $t-1$ relative to $t-2$, and >15 times the hourly change in $PM_{2.5}$ concentration at $t+1$ relative to $t+2$, then the $PM_{2.5}$ concentration at t was considered invalid and set to NaN. Second, if the hourly change in $PM_{2.5}$ concentration at a given hour (t) relative to $t-1$ was >20 times the hourly change in $PM_{2.5}$ concentration at $t-1$ relative to $t-2$, and the $PM_{2.5}$ concentration at $t+1$ was invalid, then the $PM_{2.5}$ concentration at t was considered invalid and set to NaN.
6. Check the continuity of hourly $PM_{2.5}$ concentration measurements at each air quality monitoring site.

   If more than 10% of the hourly measurements at an air quality monitoring site in a given year were missing or marked as invalid after applying the quality control steps described above, we removed that site's data from our analysis for that year.

After performing the data quality check, we compared *in situ* observations and model simulations of lumped $PM_{2.5}$ on a yearly scale. For $PM_{2.5}$ chemical components (sulfate, nitrate, ammonium, OC, and BC), we compiled the modeled values according to the monitoring period for each observation of $PM_{2.5}$ chemical components, because the monitoring periods for observation data of $PM_{2.5}$ chemical components can vary from several days to months.[37]

To describe the comparisons between *in situ* observations and model simulations, we used the Pearson correlation coefficients (R) (Equation 5), normalized mean bias (NMB) (Equation 6), normalized mean error (NME) (Equation 7), mean fractional bias (MFB) (Equation 8), and mean fractional error (MFE) (Equation 9) as follows[38]:

$$R = \frac{\sum_1^N (M-\overline{M})(O-\overline{O})}{\sqrt{\sum_1^N (M-\overline{M})^2 \sum_1^N (O-\overline{O})^2}}, \tag{5}$$

$$NMB = \frac{\sum_1^N (M-O)}{\sum_1^N O}, \tag{6}$$

$$NME = \frac{\sum_1^N |M-O|}{\sum_1^N O}, \tag{7}$$

$$MFB = \frac{1}{N}\sum_1^N \left(\frac{M-O}{O+M/2}\right), \tag{8}$$

$$MFE = \frac{1}{N}\sum_1^N \left|\frac{M-O}{O+M/2}\right|, \tag{9}$$

where M and O refer to modeled and observed values, respectively; $\overline{M}$ and $\overline{O}$ are the respective means of M and O, and N denotes the number of comparison points.

Table S7 shows the evaluation of concentrations of simulated $PM_{2.5}$ and its chemical components against ground measurements data. For the lumped $PM_{2.5}$, the Pearson correlation coefficients, *NMB, NME, MFB*, and *MFE* between modeled and observed values for the years of 2015 and 2017 were 0.71 and 0.75, 39.0% and 39.9%, 49.0% and 49.4%, 20.2% and 21.9%, and 28.7% and 29.1%, respectively. For model evaluation of concentrations of $PM_{2.5}$ chemical components in 2015, the Pearson correlation coefficients, *NMB, NME, MFB*, and *MFE* between modeled and observed values ranged from 0.48 to 0.69, −12.7% to 34.6%, 30.5% to 58.8%, −1.2% to 29.1%, and 23.9% to 44.2%, respectively. For model evaluation of concentrations of $PM_{2.5}$ chemical components in 2017, the Pearson correlation coefficients, *NMB, NME, MFB* and *MFE* between modeled and observed values ranged from 0.14 to 0.8, −9.0% to 46.7%, 27.0% to 79.6%, −3.8% to 38.6%, and 19.9% to 42.3%, respectively.

The above statistics show that our model performs reasonably well in simulating lumped $PM_{2.5}$ concentrations but has a common issue with currently available global emission inventories: overestimates in the east of model domain and underestimates in the west (Figure S2; Excel Table S2).[39] To address this issue, we followed an approach commonly adopted in the field[13] that uses the model output to calculate the fractional contributions of production- and consumption-based emission to surface $PM_{2.5}$ concentration (Equation 10).

We defined a total of 10 emission scenarios (Table 1) and used a zero-out contribution method[1] to estimate the contributions of each country to $PM_{2.5}$ concentrations in NEA from both production and consumption perspectives. In Scenario 1, we used the production-based emission inventory (EDGARv6.1) to simulate the baseline $PM_{2.5}$ concentrations. Suppose we defined C_{s1} as the baseline $PM_{2.5}$ concentrations simulated under the baseline scenario (Scenario 1) in which no emissions were excluded, C_{s2} as the simulated $PM_{2.5}$ concentration under the Scenario 2 in which the emissions in China were excluded. Therefore, the difference in simulated $PM_{2.5}$ concentrations between Scenario 1 and Scenario 2 ($C_{s1} - C_{s2}$) measured the contribution of production-based emissions in China to $PM_{2.5}$ concentrations in NEA. Similarly, Scenarios 3 and 4 set the production-based emissions in South Korea and Japan, respectively, to zero to derive the contributions of production-based emissions in South Korea ($C_{s1} - C_{s3}$) and Japan ($C_{s1} - C_{s4}$), respectively, to $PM_{2.5}$ concentrations in NEA. Scenarios 5, 6, and 7 set the consumption-based emissions induced by the consumption in China, South Korea, and Japan, respectively, to zero to derive the contributions of the consumption-based emissions in China ($C_{s1} - C_{s5}$), South Korea ($C_{s1} - C_{s6}$), and Japan ($C_{s1} - C_{s7}$), respectively, to $PM_{2.5}$ concentrations in NEA. Scenarios 8, 9, and 10 were additionally designed to decompose the contributions from China's production-based emissions to $PM_{2.5}$ concentrations in South Korea and Japan into parts induced by the consumption in South Korea, Japan, and other countries, excluding China, South Korea, and Japan, with the goal of examining to which extent the consumption in China, South Korea, Japan, and other countries were responsible for the transboundary $PM_{2.5}$ pollution and associated health impacts transported from China to South Korea and Japan. The part of transboundary contributions from emissions produced in China but induced by consumption in South Korea was calculated as the difference between baseline $PM_{2.5}$ concentrations and simulated $PM_{2.5}$ concentrations under Scenario 8: $C_{s1} - C_{s8}$. Similarly, the part induced by consumption in Japan was calculated as $C_{s1} - C_{s9}$. The part induced by consumption outside China was calculated as $C_{s1} - C_{s10}$. Therefore, the part induced by consumption in China was calculated as follows:

$$(C_{s1} - C_{s2}) - (C_{s1} - C_{s10}) = (C_{s10} - C_{s2}).$$

Finally, the part induced by consumption outside China, South Korea, and Japan was calculated indirectly as follows:

$$\begin{aligned}(C_{s1} - C_{s2}) - (C_{s1} - C_{s8}) - (C_{s1} - C_{s9}) - (C_{s10} - C_{s2})\\ = (C_{s1} - C_{s10}) - (C_{s1} - C_{s8}) - (C_{s1} - C_{s9}).\end{aligned}$$

The fractional contributions associated with the *i*th emission-reduction scenario over the simulation domain were calculated as follows:

$$F^i = (C_{s1} - C_{si})/C_{s1}, \tag{10}$$

where F^i ($i = 2, 3, \ldots, 10$) refers to the gridded fractional contributions attributable to the *i*th emission source associated with the *i*th emission-reduction scenario of which the gridded $PM_{2.5}$ concentrations were termed C_{si}. All the calculations were performed at the annual level. All maps were created using Python 3.7 with Cartopy 0.20.0. The basemap layer of country boundaries was derived from the Natural Earth datasets (http://www.naturalearthdata.com/).

Exposure Model for Calculating $PM_{2.5}$ Population Exposure

Exposure to $PM_{2.5}$ pollution is one of the leading risk factors contributing to disease burden worldwide.[40] We defined the $PM_{2.5}$ population exposure in a country as the total doses of $PM_{2.5}$ mass inhaled per day by the entire population in that country. To calculate the exposure, we used an exposure model that took into account the time–activity patterns, indoor/outdoor air quality, and human inhalation rates.[20,21] More specifically, we computed the baseline $PM_{2.5}$ population exposure in a country by summing the product of population, inhalation rate, outdoor/indoor $PM_{2.5}$ concentrations, and outdoor/indoor time fractions for all grid cells covering that country as follows:

$$Baseline\ PE = \sum_g \left[P_g \times IR \times \left(PM_{out_g} \times T_{out} + PM_{in_g} \times T_{in}\right)\right]/10^9, \tag{11}$$

and

Table 1. Definitions of the 10 emission scenarios for determining the source–receptor relationships of $PM_{2.5}$ pollution and related health impacts among China, South Korea, and Japan.

Categories	Scenarios	Definition
Base scenario	Scenario 1 (S1)	Baseline scenario in which production-based emissions from EDGARv6.1 is used, and no emissions are excluded
Production-based scenarios	Scenario 2 (S2)	A scenario in which emissions produced in China are excluded
	Scenario 3 (S3)	A scenario in which emissions produced in South Korea are excluded
	Scenario 4 (S4)	A scenario in which emissions produced in Japan are excluded
Consumption-based scenarios	Scenario 5 (S5)	A scenario in which emissions induced by final consumption in China are excluded
	Scenario 6 (S6)	A scenario in which emissions induced by final consumption in South Korea are excluded
	Scenario 7 (S7)	A scenario in which emissions induced by final consumption in Japan are excluded
Additional scenarios	Scenario 8 (S8)	A scenario in which emissions in China induced by final consumption in South Korea are excluded
	Scenario 9 (S9)	A scenario in which emissions in China induced by final consumption in Japan are excluded
	Scenario 10 (S10)	A scenario in which emissions in China induced by final consumption in all other countries except China are excluded

Note: EDGARv6.1, the Emissions Database for Global Atmospheric Research version 6.1; $PM_{2.5}$, fine particulate matter with an aerodynamic diameter ≤2.5 μm.

$$PM_{in_g} = PM_{out_g} \times IF, \tag{12}$$

where *Baseline PE* refers to the baseline $PM_{2.5}$ population exposure with a unit of kilograms per day, P_g refers to the population count at the gth grid cell, which was obtained from the Worldpop high-resolution population distribution dataset.[41] The Worldpop dataset provided a time series (2000–2020) of global gridded population distribution dataset at a spatial resolution of 1 km. It was produced based on subnational census and a number of gridded geospatial factors that correlate strongly with population density, including land use and land cover, elevation, temperature, night lights, and human settlement.[41] PM_{out_g} refers to the outdoor ambient $PM_{2.5}$ concentration at the gth grid cell, which was obtained from a newly available high-resolution (1 km × 1 km) satellite-derived $PM_{2.5}$ concentration dataset.[42] *IR* refers to the inhalation rate that measures the amount of air inhaled per day (m^3 per day) by people in that country or its different regions. T_{out} and T_{in} refer to the time fractions that people in that country or its different regions spend in outdoor and indoor environments, respectively. *IR*, T_{out}, and T_{in} were determined through resident surveys and obtained from the Chinese exposure factor handbook,[43] the updated exposure factors study in South Korea,[44] and the Japan exposure factors handbook,[45] respectively. They are listed in Tables S8 and S9. PM_{in_g} refers to the indoor $PM_{2.5}$ concentration at the gth grid cell. *IF* refers to the infiltration factors, which measure the equilibrium fractions of outdoor particles penetrating indoors and remaining suspended.[46] *IF* were obtained from the literature[21,47,48] and are listed in Table S10. The sum of all the combinations of these terms is expressed in µg because the unit of PM_{out_g} is $\mu g/m^3$. To obtain a unit of kg, we divided the sum by 10^9.

We computed the $PM_{2.5}$ population exposure in a receptor country contributed by the ith emission source by summing the product of population, inhalation rates, gridded fractional contribution calculated from Equation 10, outdoor/indoor $PM_{2.5}$ concentrations, and outdoor/indoor time fractions for all grid cells covering that receptor country as follows:

$$Source\ PE^i = \sum\nolimits_g \left[P_g \times IR \times F_g^i \times \left(PM_{out_g} \times T_{out} + PM_{in_g} \times T_{in} \right) \right] / 10^9. \tag{13}$$

The baseline PWM ambient $PM_{2.5}$ concentration in a country was calculated as follows:

$$Baseline\ PWM = \sum\nolimits_g \left(P_g \times PM_{out_g} \right) / \sum\nolimits_g \left(P_g \right). \tag{14}$$

The PWM ambient $PM_{2.5}$ concentration in a receptor country contributed by the ith emission source was then calculated as:

$$Source\ PWM^i = \sum\nolimits_g \left(P_g \times F_g^i \times PM_{out_g} \right) / \sum\nolimits_g \left(P_g \right). \tag{15}$$

With baseline and source *PWM* and *PE*, we quantified the relative contributions of $PM_{2.5}$ concentrations and associated population exposure in a receptor country attributable to the ith emission source as:

$$RC1^i = Source\ PWM^i / Baseline\ PWM, \tag{16}$$

and

$$RC2^i = Source\ PE^i / Baseline\ PE. \tag{17}$$

Exposure–Response Model for Estimating $PM_{2.5}$-Related Premature Deaths

Long-term exposure to $PM_{2.5}$ pollution is linked to premature deaths, particularly in people who have cardiovascular and respiratory diseases.[40] We used the Meta Regression-Bayesian, Regularized, Trimmed (MR-BRT) model, as developed in the Global Burden of Disease 2019 (GBD 2019) study,[22] to estimate $PM_{2.5}$-related premature deaths. The MR-BRT model characterizes the exposure–response relationship across a wide range of ambient $PM_{2.5}$ concentrations.[22] It is particularly well suited for studies focusing on Asia because it incorporated additional data from cohort studies conducted in high-pollution, low-income countries such as China. In this study, we estimated the number of premature deaths attributable to $PM_{2.5}$ pollution resulting from adult (25 y of age and older) ischemic heart disease, stroke, chronic obstructive pulmonary disease, type II diabetes, lung cancer, and childhood (younger than 5 y of age) and adult (25 y of age and older) acute lower respiratory infection. In addition, we calculated the 95% confidence intervals for our estimates of attributable premature deaths.

We estimated the number of premature deaths related to $PM_{2.5}$ pollution resulting from adult (25 y of age and older) ischemic heart disease, stroke, chronic obstructive pulmonary disease, type II diabetes, lung cancer, and childhood (younger than 5 y of age) and adult (25 y of age and older) acute lower respiratory infection, using the following equations:

$$M = \sum\nolimits_g \sum\nolimits_d \sum\nolimits_a M_{a,g}^d, \tag{18}$$

$$M_{a,g}^d = AF_{a,g}^d \times B_a^d \times P_{a,g}, \tag{19}$$

and

$$AF_{a,g}^d = \left(RR_a^d \left(PM_{out_g} \right) - 1 \right) / RR_a^d \left(PM_{out_g} \right), \tag{20}$$

where M is the total $PM_{2.5}$-related premature deaths in a receptor country, $M_{a,g}^d$ is the $PM_{2.5}$-related premature deaths for the ath age group due to the dth disease at the gth grid cell in that receptor country, and $AF_{a,g}^d$ is the attributable fraction to $PM_{2.5}$ pollution for the ath age group and the dth disease at the gth grid cell in that receptor country; B_a^d is the baseline death incidence due to the dth disease for the ath age group in that receptor country, with its values derived from the national average data in the GBD 2019 database.[49] $RR_a^d(PM_{out_g})$ is the relative risk (RR) for the ath age group and the dth disease due to exposure to ambient $PM_{2.5}$ pollution at the gth grid cell in that receptor country, which is further calculated using the MR-BRT model developed in the GBD 2019 study.[22]

The MR-BRT model describes the exposure-response relationship for a wide range of ambient $PM_{2.5}$ concentrations.[22] The relative risk at the gth grid cell for the ath age group and the dth disease was calculated as follows:

$$RR_a^d \left(PM_{out_g} \right) = \begin{cases} MRBRT\left(PM_{out_g} \right) / MRBRT(tmrel), PM_{out_g} > tmrel \\ 1 \qquad\qquad\qquad\qquad\qquad\qquad\quad , PM_{out_g} < tmrel \end{cases}, \tag{21}$$

where *tmrel* is the theoretical minimum risk exposure level (TMREL), $MRBRT(PM_{out_g})$ and $MRBRT(tmrel)$ refers to the estimates of risks for the ath age group and the dth disease when exposed to $PM_{2.5}$ concentrations of PM_{out_g} and tmrel, respectively. The GBD 2019 study generated 1,000 samples of TMREL estimates with a uniform distribution from 2.4 to $5.9\ \mu g/m^3$, and 1,000 risk estimates for each $PM_{2.5}$ exposure interval level, each age group, and each disease. These estimates, which are provided in the format of look-up tables,[50] enabled us to calculate the 95% confidence intervals of $PM_{2.5}$-related premature deaths.

To determine the number of premature deaths attributable to the ith emission source, we followed previous studies[14,31,51,52] and adopted the direct proportion approach, which assumes a linear relationship between the proportions of $PM_{2.5}$ concentration and the proportion of total $PM_{2.5}$-related premature deaths as follows:

$$Source\,M^i = \sum\nolimits_g \sum\nolimits_d \sum\nolimits_a \left(M^d_{a,g} \times F^i_g\right), \tag{22}$$

where $Source\,M^i$ is the number of $PM_{2.5}$-related premature deaths in a receptor country attributable to the ith emission source.

With total $PM_{2.5}$-related premature deaths M and $PM_{2.5}$-related premature deaths attributable to the ith emission source $Source\,M^i$, we calculated the relative contribution of $PM_{2.5}$-related premature deaths in a receptor country attributable to the ith emission source as follows:

$$RC3^i = Source\,M^i / M. \tag{23}$$

In addition, to verify whether there were statistically significant differences between these consumption-based estimates and production-based estimates, we calculated monthly scale values for PWM $PM_{2.5}$ concentration and $PM_{2.5}$ population exposure from both production and consumption perspectives and used these results to conduct paired Student t-tests at a significance level of 0.05. We did not calculate monthly scale $PM_{2.5}$-related premature deaths because the monthly baseline death incidence data were not available. Therefore, we did not conduct statistical tests for comparing the consumption-based $PM_{2.5}$-related premature deaths and production-based $PM_{2.5}$-related premature deaths.

Results

Local and Transboundary Contributions to $PM_{2.5}$ Concentrations in China, South Korea, and Japan

Figure 2 shows the gridded fractional contributions to $PM_{2.5}$ concentrations from production- and consumption-based emissions in NEA countries in 2017. Results from 2015 were similar (Figure S3). The fractional contributions are defined as the ratios of the differences between the baseline and nonbaseline $PM_{2.5}$ concentrations to the baseline $PM_{2.5}$ concentrations (see Equation 10). Table 2 shows the estimated contributions from source to receptor countries' PWM $PM_{2.5}$ concentrations in NEA in 2015 and 2017. The production perspective shows that the largest contributors to PWM $PM_{2.5}$ concentrations in China, South Korea, and Japan in 2015 were themselves, with local contributions of 72.2%, 38.9%, and 38.7%, respectively. This pattern persisted in 2017, with slightly decreased values of 70.7%, 37.3%, and 37.7% for China, South Korea, Japan, respectively. The consumption perspective shows that the results for China were similar because the largest contributor was China itself, but the largest proportions of PWM $PM_{2.5}$ concentrations in South Korea and Japan were contributed by the emissions driven by the consumption in other countries and natural sources of $PM_{2.5}$ (e.g., dust, sea salt, etc.), which contributed 47.2% and 48.9% to PWM $PM_{2.5}$ concentrations in South Korea and Japan in 2015, respectively, and 44.9% and 48.6% to PWM $PM_{2.5}$ concentrations in South Korea and Japan in 2017, respectively.

With respect to transboundary contributions, we found that, in 2015, the emissions produced (induced by consumption) in China contributed 35.0% (26.9%) and 22.1% (17.6%) to PWM

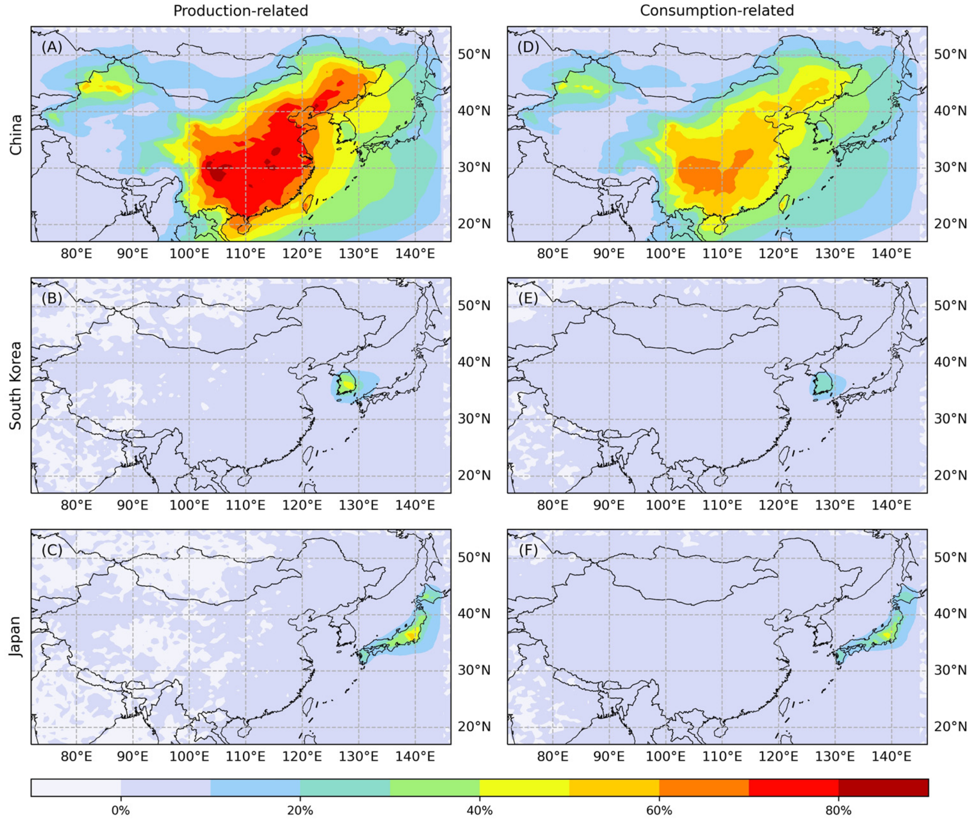

Figure 2. Annual gridded fractional contributions to $PM_{2.5}$ concentrations in 2017 in Northeast Asia from production-based emissions in (A) China, (B) South Korea, (C) Japan, and consumption-based emissions induced by the consumption in (D) China, (E) South Korea, and (F) Japan. A descriptive statistic of the data in this figure at country scale can be found in Table S11. Data for creating this figure can be found in the Supplemental netCDF File. Note: $PM_{2.5}$, fine particulate matter with an aerodynamic diameter ≤ 2.5 μm.

Table 2. Contributions from source to receptor countries' population-weighted mean $PM_{2.5}$ concentrations in Northeast Asia.

Year	Receptor country Source country	China ($\mu g/m^3$, %)		South Korea ($\mu g/m^3$, %)		Japan ($\mu g/m^3$, %)	
2015	Baseline PWM $PM_{2.5}$ concentration	49.86	100%	24.92	100%	12.24	100%
	Source country where pollution is emitted						
	China	36.01	72.2%	8.73	35.0%	2.71	22.1%
	South Korea	0.19	0.4%	9.69	38.9%	0.44	3.6%
	Japan	0.03	0.1%	0.22	0.9%	4.74	38.7%
	Others	13.63	27.3%	6.28	25.2%	4.35	35.6%
	Source country where goods are consumed						
	China	25.88	51.9%	6.71	26.9%	2.15	17.6%
	South Korea	0.25	0.5%	6.06	24.3%	0.31	2.5%
	Japan	0.35	0.7%	0.39	1.6%	3.79	31.0%
	Others	23.38	46.9%	11.76	47.2%	5.99	48.9%
2017	Baseline PWM $PM_{2.5}$ concentration	43.38	100%	22.62	100%	11.56	100%
	Source country where pollution is emitted						
	China	30.68	70.7%	8.39	37.1%	2.64	22.9%
	South Korea	0.08	0.2%	8.44	37.3%	0.48	4.1%
	Japan	0.01	0.0%	0.13	0.6%	4.35	37.7%
	Others	12.61	29.1%	5.66	25.0%	4.09	35.3%
	Source country where goods are consumed						
	China	22.13	51.0%	6.49	28.7%	2.14	18.5%
	South Korea	0.17	0.4%	5.68	25.1%	0.35	3.0%
	Japan	0.27	0.6%	0.31	1.3%	3.45	29.9%
	Others	20.81	48.0%	10.14	44.9%	5.62	48.6%

Note: The values in the rows of "Others" are residuals after deducting Chinese, South Korean, and Japanese contributions from the baseline. The GEOS-Chem chemical transport model and a satellite-derived $PM_{2.5}$ concentration dataset[42] are used to calculate the data in this table. $PM_{2.5}$, fine particulate matter with an aerodynamic diameter ≤ 2.5 µm; PWM, population-weighted mean.

$PM_{2.5}$ concentrations in South Korea and Japan, respectively. Contributions of the emissions produced (induced by consumption) in South Korea to PWM $PM_{2.5}$ concentrations in China and Japan were relatively low at 0.4% (0.5%) and 3.6% (2.5%), respectively. Contributions of Japan's production-based (consumption-based) emissions to PWM $PM_{2.5}$ concentrations in China and South Korea were even lower at 0.1% (0.7%) and 0.9% (1.6%), respectively.

We found that the consumption-based PWM $PM_{2.5}$ concentrations and production-based PWM $PM_{2.5}$ concentrations were significantly different (Table S12). We also found that consumption-related contributions from upwind countries to downwind countries (from China to South Korea and Japan, and from South Korea to Japan) were lower than the corresponding production-related contributions. Conversely, consumption-related contributions from downwind countries to upwind countries (from Japan to South Korea and China, and from South Korea to China) were higher than the corresponding production-related contributions.

Transboundary Contributions to $PM_{2.5}$ Population Exposure among China, South Korea, and Japan

Table 3 shows the SRR of $PM_{2.5}$ population exposure among China, South Korea, and Japan. From a production perspective, China's contributions to $PM_{2.5}$ population exposure in South Korea (3.79 and 3.72 kg/d) were 1.3 and 2.8 times those of South Korea to China (2.93 and 1.32 kg/d) in 2015 and 2017, respectively. China's contributions to $PM_{2.5}$ population exposure in Japan (2.11 and 2.07 kg/d) were 4.4 and 14.8 times those of Japan to China (0.48 and 0.14 kg/d) in 2015 and 2017, respectively. South Korea's contributions to $PM_{2.5}$ population exposure in Japan (0.34 and 0.37 kg/d) were 3.4 and 6.2 times those of Japan to South Korea (0.1 and 0.06 kg/d) in 2015 and 2017, respectively.

The results calculated from a consumption perspective show a different pattern. Particularly, China's contributions to $PM_{2.5}$ population exposure in South Korea (2.92 and 2.88 kg/d) were 0.7 and 1.1 times those of South Korea to China (3.9 and 2.74 kg/d) in 2015 and 2017, respectively. China's contributions to $PM_{2.5}$ population exposure in Japan (1.68 and 1.68 kg/d) were 31% and 39% those of Japan to China (5.48 and 4.26 kg/d) in 2015 and 2017, respectively. South Korea's contributions to $PM_{2.5}$ population exposure in Japan (0.24 and 0.27 kg/d) were 1.4 and 1.9 times those of Japan to South Korea (0.17 and 0.14 kg/d) in 2015 and 2017, respectively. In addition, from a consumption perspective, the largest contributor to $PM_{2.5}$ population exposure in South Korea and Japan were not themselves but the emissions driven by the consumption in the other countries and natural sources of $PM_{2.5}$, which contributed 47.2% and 48.9% to $PM_{2.5}$ population exposure in South Korea and Japan in 2015, respectively, and 44.9% and 48.6% to $PM_{2.5}$ population exposure in South Korea and Japan in 2017, respectively.

Once again, we found that there were significant differences between the consumption-based $PM_{2.5}$ population exposure and production-based $PM_{2.5}$ population exposure (Table S13). We generally found narrower gaps in mutual contributions of $PM_{2.5}$ population exposure among China, South Korea, and Japan from a perspective of consumption than production in both years (2015 and 2017). In addition, Table 3 shows that South Korea and Japan's contributions to $PM_{2.5}$ population exposure in China became larger than or comparable to that of China to South Korea and Japan, when switching from a perspective of production to consumption.

Transboundary Contributions to $PM_{2.5}$-Related Premature Deaths among China, South Korea, and Japan

The SRR of $PM_{2.5}$-related premature deaths among China, South Korea, and Japan (Table 4) largely follows the pattern of $PM_{2.5}$ population exposure. We reported that in 2015 and 2017, the ratios of China's contributions to $PM_{2.5}$-related premature deaths in South Korea and vice versa were 1.2 (6.02 vs. 5.22 thousand premature deaths) and 2.3 (5.73 vs. 2.47 thousand premature deaths) from a production perspective, and 0.7 (4.63 vs. 6.96 thousand premature

Table 3. Contributions from source to receptor countries' $PM_{2.5}$ population exposure in Northeast Asia.

Year	Receptor country / Source country	China (kg/d, %)		South Korea (kg/d, %)		Japan (kg/d, %)	
2015	Baseline $PM_{2.5}$ population exposure	768.24	100%	10.83	100%	9.56	100%
	Source country where pollution is emitted						
	China	557.61	72.6%	3.79	35.0%	2.11	22.1%
	South Korea	2.93	0.4%	4.21	38.9%	0.34	3.6%
	Japan	0.48	0.1%	0.1	0.9%	3.7	38.7%
	Others	207.22	26.9%	2.72	25.2%	3.4	35.6%
	Source country where goods are consumed						
	China	400.7	52.2%	2.92	26.9%	1.68	17.6%
	South Korea	3.9	0.5%	2.64	24.3%	0.24	2.5%
	Japan	5.48	0.7%	0.17	1.6%	2.96	31.0%
	Others	358.16	46.6%	5.10	47.2%	4.68	48.9%
2017	Baseline $PM_{2.5}$ population exposure	680.65	100%	10.04	100%	9.04	100%
	Source country where pollution is emitted						
	China	484.9	71.2%	3.72	37.1%	2.07	22.9%
	South Korea	1.32	0.2%	3.75	37.3%	0.37	4.1%
	Japan	0.14	0.0%	0.06	0.6%	3.4	37.7%
	Others	194.29	28.6%	2.51	25.0%	3.2	35.3%
	Source country where goods are consumed						
	China	349.43	51.3%	2.88	28.7%	1.68	18.5%
	South Korea	2.74	0.4%	2.52	25.1%	0.27	3.0%
	Japan	4.26	0.6%	0.14	1.3%	2.7	29.9%
	Others	324.22	47.7%	4.5	44.9%	4.39	48.6%

Note: The values in the rows of "Others" are residuals after deducting Chinese, South Korean, and Japanese contributions from the baseline. An exposure model that takes into account the time–activity patterns, indoor/outdoor air quality, and human inhalation rates is used to calculate the data in this table. Note: —, no data; $PM_{2.5}$, fine particulate matter with an aerodynamic diameter ≤2.5 μm.

deaths) and 0.9 (4.43 vs. 5.03 thousand premature deaths) from a consumption perspective. The ratios of China's contributions to $PM_{2.5}$-related premature deaths in Japan and vice versa in 2015 and 2017 were 5.7 (4.92 vs. 0.87 thousand premature deaths) and 15.7 (4.56 and 0.29 thousand premature deaths) from a production perspective, and 0.4 (3.91 vs. 9.79 thousand premature deaths) and 0.5 (3.69 vs. 7.75 thousand premature deaths) from a consumption perspective. The ratios of South Korea's contributions to $PM_{2.5}$-related premature deaths in Japan and vice versa in 2015 and 2017 were 5.3 (0.8 vs. 0.15 thousand premature deaths) and 9.3 (0.84 vs. 0.09 thousand premature deaths) from a production perspective, and 2.1 (0.56 vs. 0.27 thousand premature deaths) and 2.9 (0.61 vs. 0.21 thousand premature deaths) from a consumption perspective. In addition, the consumption perspective shows that the $PM_{2.5}$-related premature deaths in China, South Korea, and Japan were highly influenced by emissions driven by the consumption in other countries and natural sources of $PM_{2.5}$, which contributed 47.1%, 47.1%, and 48.8% to the $PM_{2.5}$-related premature deaths in China, South Korea, and Japan in 2015, respectively, and 48.0%, 44.7%, and 48.3% to the $PM_{2.5}$-related

Table 4. Contributions from source to receptor countries' $PM_{2.5}$-related premature deaths in Northeast Asia.

Year	Receptor country / Source country	China: thousand premature deaths (95% CI) and relative contribution (%)		South Korea: thousand premature deaths (95% CI) and relative contribution (%)		Japan: thousand premature deaths (95% CI) and relative contribution (%)	
2015	Total $PM_{2.5}$-related premature deaths	1,386.51 (1,263.53, 1,507.49)	100%	17.19 (14.74, 19.62)	100%	22.32 (15.89, 28.66)	100%
	Source country where pollution is emitted						
	China	995.47 (908.63, 1,081.18)	71.8%	6.02 (5.16, 6.87)	35.0%	4.92 (3.5, 6.32)	22.0%
	South Korea	5.22 (4.78, 5.66)	0.4%	6.69 (5.74, 7.64)	38.9%	0.8 (0.58, 1.02)	3.6%
	Japan	0.87 (0.79, 0.95)	0.1%	0.15 (0.13, 0.18)	0.9%	8.72 (6.25, 11.17)	39.1%
	Others	384.95 (349.34, 419.7)	27.7%	4.33 (3.71, 4.93)	25.2%	7.88 (5.56, 10.16)	35.3%
	Source country where goods are consumed						
	China	717.01 (654.28, 778.89)	51.7%	4.63 (3.97, 5.28)	26.9%	3.91 (2.78, 5.01)	17.5%
	South Korea	6.96 (6.36, 7.56)	0.5%	4.19 (3.59, 4.78)	24.4%	0.56 (0.41, 0.72)	2.5%
	Japan	9.79 (8.93, 10.64)	0.7%	0.27 (0.23, 0.31)	1.6%	6.96 (4.98, 8.93)	31.2%
	Others	652.75 (593.96, 710.4)	47.1%	8.10 (6.95, 9.25)	47.1%	10.89 (7.72, 14.01)	48.8%
2017	Total $PM_{2.5}$-related premature deaths	1,247.62 (1,129.81, 1,363.44)	100%	15.44 (13.07, 17.78)	100%	19.86 (13.75, 25.85)	100%
	Source country where pollution is emitted						
	China	881.06 (799.07, 961.94)	70.6%	5.73 (4.84, 6.59)	37.1%	4.56 (3.17, 5.91)	22.9%
	South Korea	2.47 (2.24, 2.7)	0.2%	5.78 (4.89, 6.65)	37.4%	0.84 (0.6, 1.07)	4.2%
	Japan	0.29 (0.26, 0.32)	0.0%	0.09 (0.07, 0.1)	0.6%	7.52 (5.22, 9.78)	37.9%
	Others	363.8 (328.25, 398.48)	29.2%	3.84 (3.26, 4.43)	24.9%	6.94 (4.76, 9.09)	35.0%
	Source country where goods are consumed						
	China	636.64 (577.24, 695.2)	51.0%	4.43 (3.75, 5.1)	28.7%	3.69 (2.57, 4.79)	18.6%
	South Korea	5.03 (4.55, 5.49)	0.4%	3.89 (3.29, 4.48)	25.2%	0.61 (0.43, 0.78)	3.1%
	Japan	7.75 (7.02, 8.47)	0.6%	0.21 (0.18, 0.24)	1.4%	5.95 (4.13, 7.75)	30.0%
	Others	598.2 (540.99, 654.28)	48.0%	6.91 (5.85, 7.96)	44.7%	9.61 (6.63, 12.53)	48.3%

Note: The values in the rows of "Others" are residuals after deducting Chinese, South Korean, and Japanese contributions from the baseline. An exposure–response model built based on the MR-BRT model in the GBD-2019 study is used to calculate the data in this table. Note: —, no data; CI, confidence interval; GBD, Global Burden of Disease; MR-BRT, meta regression-Bayesian, regularized, trimmed model; $PM_{2.5}$, fine particulate matter with an aerodynamic diameter ≤2.5 μm.

Table 5. Partition of China's transboundary contributions to $PM_{2.5}$ pollution and associated population exposure and premature deaths in South Korea and Japan.

	Receptor country	South Korea			Japan		
Year	Source country	Concentration ($\mu g/m^3$, %)	Population exposure (kg/d, %)	Premature death: thousand premature deaths (95% CI), %	Concentration ($\mu g/m^3$, %)	Population exposure (kg/d, %)	Premature death: thousand premature deaths (95% CI), %
2015	China's contribution from production perspective	8.73, 100%	3.79, 100%	6.02 (5.16, 6.87), 100%	2.71, 100%	2.11, 100%	4.92 (3.5, 6.32), 100%
	- part induced by China's consumption	6.56, 75.1%	2.85, 75.1%	4.52 (3.88, 5.16), 75.1%	2.04, 75.2%	1.59, 75.2%	3.7 (2.63, 4.75), 75.2%
	- part induced by South Korea's consumption	0.04, 0.5%	0.02, 0.5%	0.03 (0.02, 0.03), 0.5%	0.01, 0.5%	0.01, 0.5%	0.02 (0.02, 0.03), 0.5%
	- part induced by Japan's consumption	0.09, 1.0%	0.04, 1.0%	0.06 (0.05, 0.07), 1.0%	0.03, 1.0%	0.02, 1.0%	0.05 (0.04, 0.06), 1.0%
	- part induced by others' consumption	2.04, 23.4%	0.89, 23.4%	1.41 (1.21, 1.61), 23.4%	0.63, 23.3%	0.49, 23.3%	1.15 (0.82, 1.47), 23.3%
2017	China's contribution from production perspective	8.39, 100%	3.72, 100%	5.73 (4.84, 6.59), 100%	2.64, 100.0%	2.07, 100%	4.56 (3.17, 5.91), 100%
	- part induced by China's consumption	6.42, 76.5%	2.85, 76.5%	4.38 (3.7, 5.04), 76.5%	2.04, 77.1%	1.59, 77.1%	3.51 (2.44, 4.55), 77.1%
	- part induced by South Korea's consumption	0.04, 0.5%	0.02, 0.5%	0.03 (0.02, 0.03), 0.5%	0.01, 0.5%	0.01, 0.5%	0.02 (0.01, 0.03), 0.5%
	- part induced by Japan's consumption	0.08, 0.9%	0.03, 0.9%	0.05 (0.04, 0.06), 0.9%	0.02, 0.9%	0.02, 0.9%	0.04 (0.03, 0.05), 0.9%
	- part induced by others' consumption	1.85, 22.1%	0.82, 22.1%	1.27 (1.07, 1.46), 22.1%	0.57, 21.5%	0.45, 21.5%	0.98 (0.69, 1.27), 21.5%

Note: The percentages for concentration, population exposure, and premature deaths are slightly different but become identical after rounding. An exposure–response model built based on the MR-BRT model in the GBD-2019 study is used to calculate the data in this table. —, no data; CI, confidence interval; GBD, Global Burden of Disease; MR-BRT, meta regression-Bayesian, regularized, trimmed model; $PM_{2.5}$, fine particulate matter with aerodynamic diameter ≤2.5 μm.

premature deaths in China, South Korea, and Japan in 2017, respectively.

Table 5 shows the partition of transboundary contributions from China to $PM_{2.5}$ pollution and associated population exposure and premature deaths in South Korea and Japan. The results show that the emissions produced in China but induced by consumption in other countries outside Northeast Asia in 2015 contributed 23.4% and 23.3% to $PM_{2.5}$ pollution and associated population exposure and premature deaths in South Korea and Japan, respectively. The corresponding values for South Korea and Japan in 2017 were slightly lower but still nonnegligible at 22.1% and 21.5%.

Discussion

We provided a contemporary, comprehensive, and quantitative assessment of the SRR of $PM_{2.5}$ pollution and associated health impacts among China, South Korea, and Japan in 2015 and 2017. We found that China was the major contributing source country for transboundary PWM $PM_{2.5}$ concentrations in South Korea and Japan, whereas the contributions of South Korea and Japan to PWM $PM_{2.5}$ concentrations in China were negligible. This finding is consistent from both production and consumption perspectives, with the latter showing narrower gaps in mutual contributions than the former. This finding suggests that trade narrows the gaps in mutual contributions of PWM $PM_{2.5}$ concentrations among China, South Korea, and Japan, which becomes even more noticeable when we observe the $PM_{2.5}$ population exposure and associated premature deaths below. From 2015 to 2017, there were only minor changes in these values of transboundary contributions, suggesting that the results were fairly consistent despite any differences in emissions, meteorology, and other factors during the 2 y. The contributions from South Korea and Japan to $PM_{2.5}$ population exposure and associated premature deaths in China were nonnegligible from both production and consumption perspectives. From a consumption perspective, South Korea and Japan contributed to $PM_{2.5}$ population exposure and associated premature deaths in China at levels that were generally larger than China's contributions to South Korea and Japan. This reversed the relationship in mutual contributions of $PM_{2.5}$ population exposure and associated premature deaths when viewed from a production perspective. We assume that this reversed relationship primarily stems from the differences between the consumption-based emission inventory and production-based emission inventory, as well as the differences in the countries' population sizes. As shown in Figure 2, the footprint of the impacts on $PM_{2.5}$ concentrations attributable to consumption-based emissions was more widely distributed than that attributed to production-based emissions (Figure 2E,F vs. Figure 2B,C). This suggests that trade expands the extent to which atmospheric transport relocates $PM_{2.5}$ pollution among countries by separating production and consumption activities and allowing the production of emissions to occur far from where the goods are consumed. From a production perspective, the emissions produced in China are all China's responsibility. But, from a consumption perspective, Japan and South Korea are responsible for part of the emissions produced in China because that part of emissions is produced to meet the demand driven by the consumption in Japan and South Korea (see Table S14 on the contributions from source to receptor countries' NO_x emissions in Northeast Asia in 2015 for an illustration).

Comparisons with Prior Studies

Comparisons with prior analyses were limited by differences in study areas and periods as well as differences in data and models adopted. There have been quantifications of the SRR of $PM_{2.5}$ pollution and associated health impacts in Asia.[13,17] However, these analyses used coarse resolution models that have not been informed by local measurements and have not revealed country-to-country relationships, making them inadequate to guide local actions. In contrast to previous studies, we have employed regional models, which are informed by local measurements, to disclose the SRR of the $PM_{2.5}$ concentrations and associated population exposure and premature deaths among China, South Korea, and Japan in more detail. This improvement represents a significant advancement and will benefit local policymaking.

Decrease in China's Contributions to $PM_{2.5}$ Pollution in South Korea and Japan

Nonetheless, we selected and compared production-based studies (Tables S15 and S16) that have explicitly quantified China's contributions to $PM_{2.5}$ pollution in South Korea and Japan over a period no less than 1 year. Figure 3 shows reductions in China's contributions to $PM_{2.5}$ pollution in South Korea and Japan from 2008 to 2017, which roughly coincided with the decreasing emission trend in China from 2010 to 2017, suggesting the co-benefits of China's clean air actions for neighboring countries' air quality.

However, China's clean air actions mainly rely on the end-of-pipe pollution control measures of which the benefits will become mostly exhausted by 2030.[53] Although China's ambitious carbon neutrality goals will continuously improve its own and likely surrounding countries' air quality in the next couple of decades by entailing systematic changes in energy sources and industrial transformation,[54,55] consumption-side efforts can help boost the process. For instance, the implementation of the Regional Comprehensive Economic Partnership (RCEP) free trade agreement in 2022 presents an opportunity for China, South Korea, and Japan to jointly develop effective $PM_{2.5}$ mitigation strategies, particularly from a consumption side.

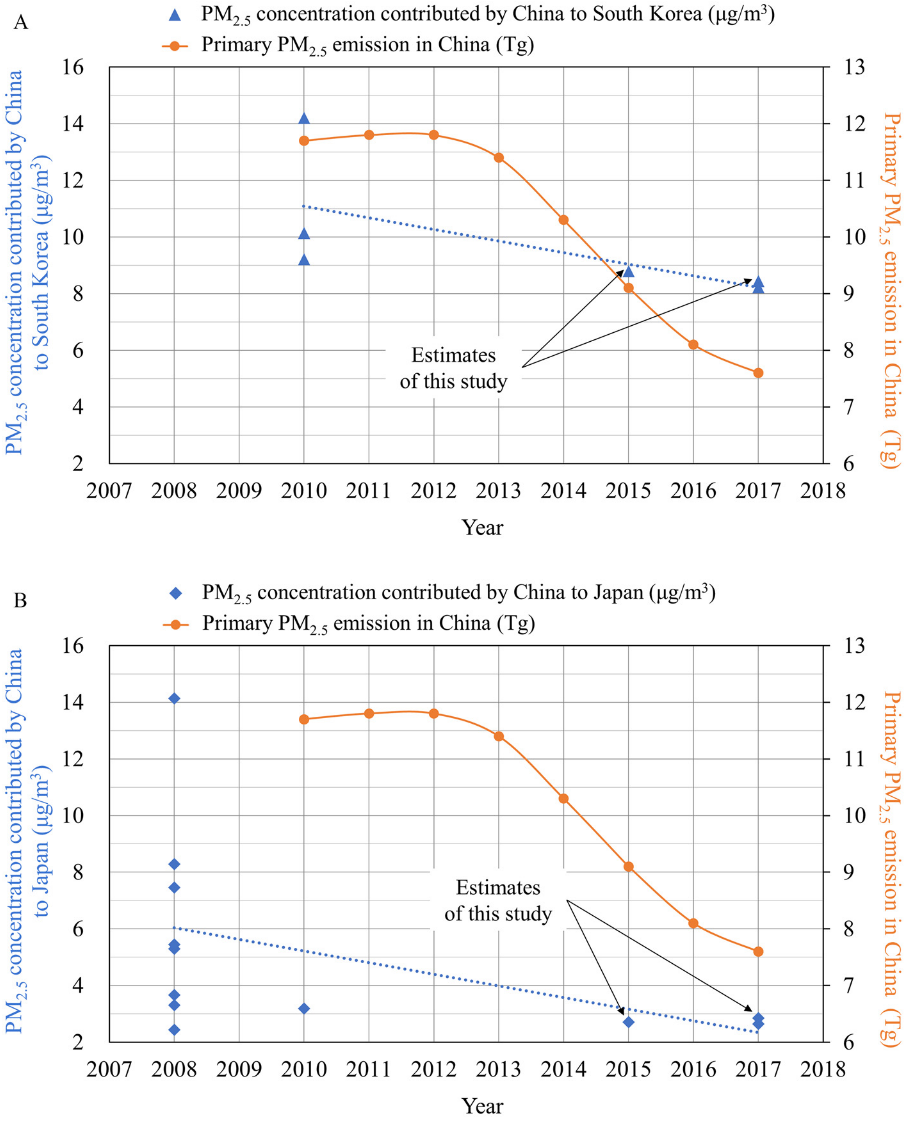

Figure 3. The estimated $PM_{2.5}$ concentrations contributed by China to (A) South Korea and (B) Japan from 2008 to 2017 and the primary $PM_{2.5}$ emission trend in China from 2010 to 2017. Each blue triangle represents an estimation of China's contribution to $PM_{2.5}$ concentrations in South Korea from the literature[3,5,69–71] and this study. Each blue diamond represents an estimation of China's contribution to $PM_{2.5}$ concentrations in Japan from the literature[3,6,69,72] and this study. The blue dash lines refer to the trend lines of China's contributions to $PM_{2.5}$ concentrations in South Korea and Japan. The orange line refers to the primary $PM_{2.5}$ emission trend in China from 2010 to 2017 based on data obtained from the study by Zheng, Tong.[73] Numerical data can be found in Table S15, Table S16, and Table S17 in the Supplemental Material. Note: $PM_{2.5}$, fine particulate matter with an aerodynamic diameter ≤ 2.5 μm.

Contributions Driven by the Consumption in Other Countries outside NEA to $PM_{2.5}$ Pollution and Associated Health Impacts in China, South Korea, and Japan

More important, the results for all three metrics from a consumption perspective consistently show that the $PM_{2.5}$ pollution and associated health impacts in all three countries are highly influenced by the consumption in other countries outside NEA and the natural sources of $PM_{2.5}$. Taking South Korea and Japan as an illustration, the consumption perspective shows that the largest proportion of $PM_{2.5}$ pollution and associated health impacts are from the emissions driven by the consumption in other countries and the natural sources of $PM_{2.5}$. Previous studies have shown that the contribution of the natural sources for $PM_{2.5}$ concentrations in China, South Korea, and Japan were 10% to 24%, 9.9% to 10%, and 16.1% to 42%, respectively.[56,57] We can infer that, after deducting the contributions from natural sources, other countries outside NEA may have played a significant role in contributing to the $PM_{2.5}$ pollution and associated health impacts in NEA from a consumption perspective. Moreover, as shown in Tables 2–4, when shifting the perspective from production to consumption, the contribution from China decreased, whereas the contribution in the "Others" category from other countries and natural sources of $PM_{2.5}$ increased. The changes in the "Others" category in Tables 2–4 from the production to the consumption perspective reflect the changes in other countries' contributions from production to consumption, because the contributions from natural sources of $PM_{2.5}$ are identical in both scenarios and hence were canceled out when we calculated the changes. Therefore, the general public, the media, and the governments in NEA should look beyond this region but focus on the rest of the world, especially those affluent countries with high consumption.[13,58]

In addition, to examine the extent to which the consumption in China, South Korea, Japan, and other countries are responsible for the transboundary $PM_{2.5}$ pollution and associated health impacts transported from China to South Korea and Japan, we constructed Scenarios 8, 9, and 10 (Table 1) to decompose the contributions from China's production-based emissions to $PM_{2.5}$ pollution and associated health impacts in South Korea and Japan into parts induced by the consumption in South Korea, Japan, and other countries. As shown in Table 5, although the consumption in China contributes mostly to transboundary $PM_{2.5}$ pollution and associated population exposure and premature deaths transported from China to South Korea and Japan, the roles played by the consumption in other countries were nonnegligible. The emissions produced in China but induced by consumption in other countries outside NEA in 2015 contributed 23.4% and 23.3% to $PM_{2.5}$ pollution and associated population exposure and premature deaths in South Korea and Japan, respectively. Once again, this finding highlights that an improved regional air quality requires joint efforts from all relevant countries.

Limitations and Uncertainties

Our work has several sources of uncertainties. First, the preparation of consumption-based emission inventories relied on the production-based emission inventory EDGARv6.1 and the input–output tables in the MRIO model, so uncertainties in these datasets may propagate to our results. The uncertainties in the EDGARv6.1 derived from the incomplete knowledge and inaccurate estimation of anthropogenic activities and emission factors. Studies have shown that the uncertainties of sulfur dioxide (SO_2), NO_X, carbon monoxide (CO), nonmethane volatile organic compound (NMVOC), ammonia (NH_3), BC, and OC in EDGARv4.3.2 were estimated as 14.4% to 47.6%, 17.2% to 69.4%, 25.9% to 64.6%, 32.7% to 73.6%, 186% to 294.4%, 46.8% to 92%, and 88.7% to 153.2%, respectively.[30] EDGARv6.1 likely have a similar but narrower range. The input–output tables were compiled based on national accounts, trade statistics, and survey data, but the quality of these data varied across countries and years. Trade data, for example, often have asymmetries and imbalances, where the sum of exports exceeds the sum of imports.[59] Therefore, a harmonization calculation process is usually performed to compile the input–output tables. Several global input–output databases are available, each using different data sources and harmonization and consolidation procedures, including Eora,[60] GTAP,[61] EXIOBASE,[62] the World Input –Output Database (WIOD),[63] and OECD ICIO.[25] Among these databases, the OECD ICIO database was compiled by OECD, whereas all other global input–output databases were compiled by academic researchers.[59] Therefore, we regarded OECD ICIO as the most authoritative, credible, and robust global input–output database currently available.[64] In addition, our study has combined the global OECD ICIO dataset with China's MRIO tables with details on 31 provinces of China, which provided more reliable estimations of the spatial distribution of the consumption-based emission inventory.

Second, the simulated surface $PM_{2.5}$ concentrations were affected by uncertainties in emission inventories and limitations in air quality modeling. The uncertainties in emission inventories are described above. The limitations in air quality modeling here refer to the imperfect representation of atmospheric chemistry and meteorological processes in the GEOS-Chem model. Our current understanding of many physicochemical mechanisms, such as the formation of secondary organic aerosols, deposition, and scavenging, remains to be improved. Due to the computational intensity of the GEOS-Chem model, it is not feasible to estimate the uncertainties through sensitivity analyses.[51] Instead, the impact of uncertainties in emission inventories and limitations in air quality modeling can be evaluated by comparing the simulated $PM_{2.5}$ concentrations against the ground measurements. As shown in the model performance evaluation, the simulated $PM_{2.5}$ concentrations generally agreed well with the ground observations, with R values ranging from 0.71 to 0.75 and NMB values ranging from 39.0% to 39.9% over different years. To further reduce the error and bias from the simulation process, the GEOS-Chem model output was only used to estimate the fractional contributions of production- and consumption-based emissions to the baseline simulated $PM_{2.5}$ concentrations. Then, by multiplying the fractional contributions and a high-resolution satellite-derived $PM_{2.5}$ concentration dataset with relatively small uncertainty,[42] we can obtain a more accurate estimation of the fractional $PM_{2.5}$ concentrations contributed by an emission source. Nonetheless, we acknowledge that the fractional contributions are still based on biased estimates, which points to a need to further improve GEOS-Chem modeling in future studies. In addition, this study used a zero-out contribution method to calculate the fractional contributions of regions' production- or consumption-based emissions. The zero-out contribution method may introduce additional bias due to the nonlinear relationship between the emissions and modeled pollutant concentrations. Studies have shown that the absolute biases due to the nonlinear effects ranged from $-2.0\ \mu g/m^3$ to $0.1\ \mu g/m^3$, and the relative biases ranged from -12.0% to 1.4%.[13] These findings indicate that the biases caused by the nonlinear effects are relatively small.

Third, the estimates of $PM_{2.5}$ population exposure was affected by uncertainties in the data on time–activity patterns, inhalation rates, and infiltration factors. These data were derived from the surveys provided in the exposure factor handbooks in China,[43] South Korea,[44] and Japan.[45] Many assumptions are made in calculating and applying these data. For example, although the time–activity survey in China has used representative and reliable samples from the population, it relied on the 24-h recall method to obtain detailed time–activity data from participants,[43] which is inevitably subject to memory errors. Unfortunately, these exposure handbooks did not provide sufficient information on the uncertainties of these data. The exposure factor handbook in Japan,[45] for example, provided only a short summary in Japanese and English that presented a single value for outdoor time and inhalation rate. One study focusing on China assumed a coefficient of variation of 5% for the time–activity patterns of Chinese residents,[21] but we have not found uncertainty information for Japan and South Korea. As a result, this study did not provide confidence intervals for $PM_{2.5}$ concentrations and $PM_{2.5}$ population exposure. Fortunately, thanks to the information on the distribution of parameters provided by the GBD-2019 study,[50] we have conducted a partial Monte Carlo simulation to quantify the uncertainties and provide the confidence intervals for $PM_{2.5}$-related premature deaths.

Last, the MR-BRT model may introduce additional uncertainties to our results. The MR-BRT model developed in the GBD 2019 study was built based on cohort studies from various countries.[22] However, very few cohort studies have examined the health outcomes of $PM_{2.5}$ pollution in China, South Korea, and Japan. The database of cohort studies in the GBD-2019 is still predominantly composed of western cohort studies. Nonetheless, the MR-BRT model is the most recent and widely used method for estimating health impacts of ambient air pollution. In comparison with the previous Integrated Exposure–Response (IER) model[65] and the Global Exposure Mortality Model (GEMM) model,[66] the MR-BRT model in the GBD-2019 study incorporated more recent cohort studies, including those in China and India, which provided more data at high $PM_{2.5}$ levels. In addition, existing concentration–response models generally assume that the composition of $PM_{2.5}$ pollution does not vary with countries and that the toxicity of $PM_{2.5}$ pollution at a given concentration level is equivalent across different components (sulfate, nitrate, ammonium, OC, and BC). However, the health impacts of $PM_{2.5}$ pollution in a region may differ from those in other regions due to variations in the toxicity of $PM_{2.5}$ sources.[67,68] This points to a need for future studies that take into account the varying toxicity of different $PM_{2.5}$ components.

Conclusion

Using an interdisciplinary framework that links an EE-MRIO model, a GEOS-Chem chemical transport model, a population exposure model, and an exposure–response model, the present study quantified the mutual contributions of transboundary $PM_{2.5}$ pollution and associated health impacts among China, South Korea, and Japan. We found that, from a production perspective, China contributed considerable PWM $PM_{2.5}$ concentrations to South Korea and Japan, amounting to $8.73\,\mu g/m^3$ and $2.71\,\mu g/m^3$ in 2015, respectively, and $8.39\,\mu g/m^3$ and $2.64\,\mu g/m^3$ in 2017, respectively, whereas the contributions of South Korea and Japan to China were negligible, measuring $0.19\,\mu g/m^3$ and $0.03\,\mu g/m^3$ in 2015, respectively, and $0.08\,\mu g/m^3$ and $0.01\,\mu g/m^3$ in 2017, respectively. However, in terms of $PM_{2.5}$ population exposure and $PM_{2.5}$-related premature deaths, the contributions from South Korea and Japan were nonnegligible from both production and consumption perspective. From a consumption perspective, South Korea and Japan contributed 6.96 (95% CI: 6.36, 7.56) and 9.79 (95% CI: 8.93, 10.64) thousand $PM_{2.5}$-related premature deaths to China in 2015, respectively, and 5.03 (95% CI: 4.55, 5.49) and 7.75 (95% CI: 7.02, 8.47) thousand $PM_{2.5}$-related premature deaths to China in 2017, respectively. These numbers were generally larger than China's contributions to South Korea and Japan.

Our study shows that the SRR varied substantially across different metrics and accounting perspectives. The relationships in mutual contributions were even reversed when switching different metrics and accounting perspectives. More importantly, countries outside NEA Asia may have contributed a significant proportion of $PM_{2.5}$ pollution and associated health impacts in NEA from a consumption perspective. Our study suggests that Northeast Asian countries should not squabble among each other but rather collaborate with each other and the rest of the world to jointly develop effective $PM_{2.5}$ mitigation strategies, encompassing not only production but also consumption perspective.

Acknowledgments

J.L. conceived the project. J.L. and H.C. prepared the emission inventory with contributions from F.Y. F.Y. performed and evaluated GEOS-Chem model simulations with contributions from J.L. J.L. performed the calculations of population-weighted mean $PM_{2.5}$ concentrations, $PM_{2.5}$ population exposure, and $PM_{2.5}$-related premature deaths with contributions from H.Z. J.L. and F.Y. analyzed and interpreted the results. J.L. and F.Y. wrote the manuscript, with contributions from H.C. and H.Z. H.Z. reviewed the manuscript. All authors contributed to the development of the manuscript and approved the final version for publication. J.L. and F.Y. have verified the underlying data and have full access to all the data in the study.

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