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Global health benefits associated with a substantial decrease in land transportation emissions during the COVID-19 period

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The changes in global air pollutant concentrations influenced by the COVID-19 lockdown have been widely investigated. The lack of clarity regarding the individual contributions to restricted human activities (i.e., transportation) has limited the understanding of the health impacts of the lockdown. In this study, an efficient chemical transport model (GEOS-Chem) was employed to simulate the concentration changes in air pollutants ($PM_{2.5}$, NO_2, and O_3) associated with emission reductions in land transportation and the corresponding health benefits. The simulated results suggested that transportation-related $PM_{2.5}$, NO_2, and O_3 reduced by 20%, 36%, and 55%, respectively. The reduction in O_3 concentrations presented regional variations, with percentages ranked as follows: China (67%) > India (56%) > Europe (−81%) > the US (−86%), indicating the various intensities of secondary transformations with spatial relevance. The health benefits were also simulated, and the all-caused mortalities were estimated to be 63,547 (95% CI: 47,597, 79,497), 52,685 (95% CI: 32,310, 73,059), and 231,980 (95% CI: 210,373, 253,586) for the reduced concentration of $PM_{2.5}$, NO_2, and O_3 globally, respectively. Transportation-related O_3 reduction contributed the largest proportion (~67%) to global health benefits, further emphasizing the global relevance and severity of O_3 pollution. Our study confirms that the health benefits of transportation emission reduction during the COVID-19 lockdown were considerable and provides relevant simulated data as supporting evidence. We suggest that further coordinated efforts to restrict certain pollutants worldwide should focus on controlling the global O_3 concentrations to protect people from severe O_3 exposure.

KEYWORDS

COVID-19, transportation emission, GEOS-Chem, health benefits, atmosphere pollutants

1 Introduction

Land transportation is a major global source of air pollutants. Numerous studies have demonstrated that emissions from road and rail transport sectors contribute significantly to acid deposition, air pollution, and climate change (AlKheder, 2024; Colvile et al., 2001; Rodríguez-Sánchez et al., 2024). For example, Li and Managi estimated that a 6.17 billion-kilometer (km) increase in on-road transportation per square kilometer could lead to a 1-μg/m³ increase in county-level $PM_{2.5}$ concentrations across the contiguous United States (Li and Managi, 2021). Mertens et al. quantified that land transport emissions contribute to 18% of ozone concentrations in North America (Mertens et al., 2018). Additionally, there is growing concern about the impact of land transportation on urban air quality and human health (Allaouat et al., 2024; Priyan et al., 2024; Rajagopal et al., 2024; Sang et al., 2022). Stevenson et al. estimated that private motor vehicles are responsible for 826 disability-adjusted life years (DALYs) per 100,000 population (Stevenson et al., 2016). Given these significant impacts, it is crucial to quantify the contribution of the land transportation sector to air quality and human health, which would enable local governments to develop targeted strategies to mitigate these public health risks (Di et al., 2017).

A growing body of research has focused on the contribution of land transportation to air pollution (Shen et al., 2024; Tong et al., 2020; Xu et al., 2024; Yan et al., 2022; Zara et al., 2024). Tong et al. assessed the impact of on-road vehicles on $PM_{2.5}$ emissions and human health in Beijing, finding that median vehicle-related $PM_{2.5}$ concentrations in the city exhibited significant weekly variations, with higher values (2.68 μg/m³) on weekdays and lower values (1.82 μg/m³) on weekends (Tong et al., 2020). Later, Yan et al. reported that the vehicle-related contribution to $PM_{2.5}$ levels increased from 34% to 63% between 2013 and 2020 (Yan et al., 2022). However, most current studies have focused primarily on the regional scale, with few exploring the global contribution of land transportation to air pollution (Bhardwaj et al., 2023; Jiang et al., 2022; Kim et al., 2024; Le Hong and Zimmerman, 2021). Quantifying the impact of land transportation on air quality at a global level is crucial for identifying hotspots and proposing stringent control measures to mitigate environmental and health damage.

The onset of the COVID-19 pandemic at the end of 2019 significantly reshaped normal social and economic activities through strict lockdown measures, including stay-at-home orders and road closures (Ansari and Ramachandran, 2024; Liu et al., 2021). These temporary lockdowns led to a substantial reduction in anthropogenic emissions, particularly those from land transportation. On a global scale, Hoang et al. confirmed that NO_X emissions showed a 20% decrease in early 2020 compared with the same period in 2019 (Hoang et al., 2021). Moreover, land transportation emissions experienced a 50%–80% decrease around the world, significantly higher than reductions observed in other sectors (Doumbia et al., 2021). Furthermore, human health was also greatly impacted by the concentration of pollutants, which was widely predicted and simulated (Chen and Hoek, 2020; Kyrychenko, 2024; Schraufnagel et al., 2019). However, the health benefits of COVID-19 lockdown-resulted air quality shifts were only investigated regionally (i.e., in Eastern Indo-Gangetic Plain and China (Jain et al., 2024; Ye et al., 2021)). The abrupt COVID-19 event provided an unprecedented chance to quantify the significant air quality and health benefits of land transportation emission reduction, which could provide a scientific basis for the proposal of future emission control measures (Berman and Ebisu, 2020; Li et al., 2021; Ma et al., 2024).

It should be noted that although the lockdown of COVID-19 has resulted in many consequences for the global economy, health benefits were benefitted from these restrictions. The reduction in pollutant emissions was particularly important when considering the long-term health benefits. Emission reductions from numerous sources reduced their contribution to global complex pollution, thus leading to fewer cases of death in relation to specific source emissions (Jain et al., 2024; Liu et al., 2021; Sacks et al., 2020). Therefore, the investigation of health benefits resulting from global emission reductions is necessary to better understand the health effects of pollutants, which should also be part of the long-term effects of COVID-19 (Ansari and Ramachandran, 2024; Li R. et al., 2023; Ling et al., 2023; Mueller et al., 2023; Tong et al., 2020; Zhang et al., 2021). In this study, a chemical transport model was used to quantify the concentrations of $PM_{2.5}$, NO_2, and O_3 associated with land transportation emissions from February to April in 2019 and 2020. Subsequently, the differences in absolute concentrations and health impacts of these air pollutants between 2019 and 2020 were calculated. Lastly, the health benefits resulting from the reduction in land transportation emissions were assessed.

2 Materials and methods

2.1 Field measurements

All the field measurements for atmospheric $PM_{2.5}$, NO_2, and O_3 focus on East Asia, India, Europe, and the United States. The hourly ambient $PM_{2.5}$, NO_2, and O_3 observations across China during 2019–2020 were downloaded from the website http://beijingair.sinaapp.com/. The observation network in China possesses more than 2000 monitoring sites, and these sites are mixed with urban, suburban, and rural regions (Supplementary Figure S1). The ambient $PM_{2.5}$, NO_2, and O_3 levels were measured using a continuous monitoring system, the chemiluminescence method (TEI Model 42i from Thermo Fisher Scientific Inc., USA), and the UV spectrophotometry method (TEI model 49i from Thermo Fisher Scientific Inc., USA). The monthly $PM_{2.5}$, NO_2, and O_3 concentrations in other countries of East Asia and Southeast Asia from 2019 to 2020 were collected from the Acid Deposition Monitoring Network in East Asia (EANET). The daily $PM_{2.5}$, NO_2, and O_3 datasets were collected from the Central Pollution Control Board (CPCB) database (https://app.cpcbccr.com/ccr/#/caaqm-dashboard-all/caaqm-landing). The ground-level $PM_{2.5}$, NO_2, and O_3 datasets in more than 100 sites across Europe during 2019–2020 were downloaded from the European Monitoring and Evaluation Programme (EMEP) (www.emep.int). The daily ambient $PM_{2.5}$, NO_2, and O_3 datasets in more than 200 sites during 2019–2020 across the United States were downloaded from the website https://www.epa.gov/.

2.2 GEOS-Chem simulation

GEOS-Chem (v13.4.0) was employed to estimate $PM_{2.5}$, NO_2, and O_3 concentrations during February–April in 2019 and 2020. This model comprises a detailed simulation of tropospheric NO_x–VOC–O_3–aerosol chemistry mechanism (Mao et al., 2010; Park et al., 2004). Wet deposition includes the processes of sub-grid scavenging in convective updrafts, in-cloud rainout, and below-cloud washout (Liu et al., 2001). Dry deposition was calculated on the basis of a resistance-in-series model (Wesely, 2007). This model was driven by MERRA-2 assimilated meteorological factors (Li L. et al., 2023; Ou et al., 2022; Su et al., 2023). A global simulation was conducted at a spatial resolution of 2 × 2.5 (Ling et al., 2023; Qiu et al., 2020; Weagle et al., 2018). The anthropogenic emission inventory, including land transportation emissions in 2019 (0.5°), was collected from the Community Emissions Data System (CEDS, https://github.com/JGCRI/CEDS). Afterward, the daily emissions during February–April 2020 were calculated based on the value in 2019 and updated adjustment factor (for each source) proposed by Doumbia et al. (2021). Natural emissions include open biomass burning, lightning, and soil emissions. Open fire emissions derived from the Global Fire Emissions Database (GFED) in 2019 and 2020 were used for simulations (Chen et al., 2023). Lightning NO_X emissions were estimated using the average of LIS/OTD satellite observations during 1995–2013 (Hudman et al., 2012; Murray et al., 2012). For the isolation of land transportation contribution, we calculated the total concentrations of air pollutants derived from all the sources and then subtracted the concentrations derived from all the sources excluding land transportation emissions. Finally, the concentrations derived from land transportation alone could be determined. The modeling performance of the contribution from individual sources cannot be validated, and thus, we only assessed the overall predictive accuracy of air pollutants from all the sources. In our study, some statistical indicators (supporting information) were applied to evaluate the predictive accuracy of the chemical transport model based on the ground-level observations.

2.3 Health effect assessment

In our study, the premature mortality associated with short-term $PM_{2.5}$, NO_2, and O_3 exposures was estimated. The premature mortality linked with excessive air pollutant exposure was calculated based on the following formula, as previously recommended by Manojkumar and Srimuruganandam (2021) and Sacks et al. (2020).

$$H = x_0 \left(1 - 1/\exp\left[\beta\left(C - C_0\right)\right]\right) \times Population, \quad (1)$$

$$RR = e^{\beta(C - C_0)}, \quad (2)$$

where H denotes the premature all-cause mortality, owing to excessive $PM_{2.5}$, NO_2, and O_3 exposures. x_0 represents the baseline mortality. β and RR represent the short-term exposure–response coefficient and relative risk for $PM_{2.5}$, NO_2, and O_3 pollution, respectively (Supplementary Table S1). C and C_0 are exposure concentration and theoretical minimum-risk exposure level, respectively. *Population* is the total population in each year. The log-linear exposure–response function was established using meta-analysis, which has been obtained from Chen et al. (2018); Hang et al. (2022); Song et al. (2023); and Yang et al. (2021).

3 Results and discussion

3.1 Model evaluation

The modeling performance of three pollutants—$PM_{2.5}$, NO_2, and O_3—was evaluated using observed concentrations from field measurements (Section 2.1) and simulated concentrations from GEOS-Chem (Section 2.2). Ground-level observations of $PM_{2.5}$, NO_2, and O_3 from over 2,000 cities worldwide were used to assess the predictive accuracy of the GEOS-Chem model. Notably, as there were insignificant differences between the correlations for February–April 2019 and 2020, the evaluation focused on each individual pollutant, with the results presented in Figure 1. The correlation coefficients (R values) between the observed and simulated concentrations for $PM_{2.5}$, NO_2, and O_3 were 0.61, 0.65, and 0.72, respectively, for the period of February–April in 2019 and 2020. Furthermore, the root mean square error (RMSE) values were 3.89 μg m^{-3} for $PM_{2.5}$, 6.68 μg m^{-3} for NO_2, and 34.3 μg m^{-3} for O_3, indicating good model performance. The mean absolute error (MAE) was calculated as 2.91 μg m^{-3} for $PM_{2.5}$, 3.52 μg m^{-3} for NO_2, and 28.2 μg m^{-3} for O_3. In addition, the mean bias (MB), mean normalized bias (MNB), and mean normalized error (MNE) were determined to be −0.06 μg m^{-3}, 0.05, and 0.42 for $PM_{2.5}$; −2.98 μg m^{-3}, −0.20, and 0.39 for NO_2; and −23.6 μg m^{-3}, −0.22, and 0.36 for O_3. The MNB and MNE values were well within the thresholds recommended by the Epa (2007), which are ±60% for MNB and 75% for MNE. This suggests that the model results are robust, and the predicted concentrations of $PM_{2.5}$, NO_2, and O_3 are reliable.

Moreover, the model's accuracy was comparable to previous studies. For instance, Balamurugan et al. reported an average R value of 0.55 for $PM_{2.5}$ between *in situ* measurements and GEOS-Chem simulations in 10 German cities before the COVID-19 pandemic (January–May 2019) (Balamurugan et al., 2022). Similarly, Kong et al. found an average R value of 0.67 for NO_2 in the North China Plain in 2010, while Lu et al. reported R values of 0.72 and 0.65 for NO_2 in China in 2019 and 2020, respectively (Kong et al., 2020; Lu et al., 2024). Although the correlation for O_3 was 0.53 from February to March 2019 over China, as simulated by Lu et al., this was likely due to the exclusion of significantly reduced NO_X emission sites and the limited number of ground observation stations (Lu et al., 2024). In comparison, the R value for O_3 in this study was higher, adding reliability to the model predictions. These results also surpass those of Sun et al. and Li et al., who reported R values of 0.65 (2019), 0.63 (2020), and 0.69 for O_3, respectively (Li R. et al., 2023; Sun et al., 2024a). Overall, the model-predicted concentrations of air pollutants were both credible and satisfactory.

3.2 Impact of land transportation emissions on air pollutants around the world

The $PM_{2.5}$, NO_2, and O_3 concentrations derived from land transportation emissions were estimated by subtracting the

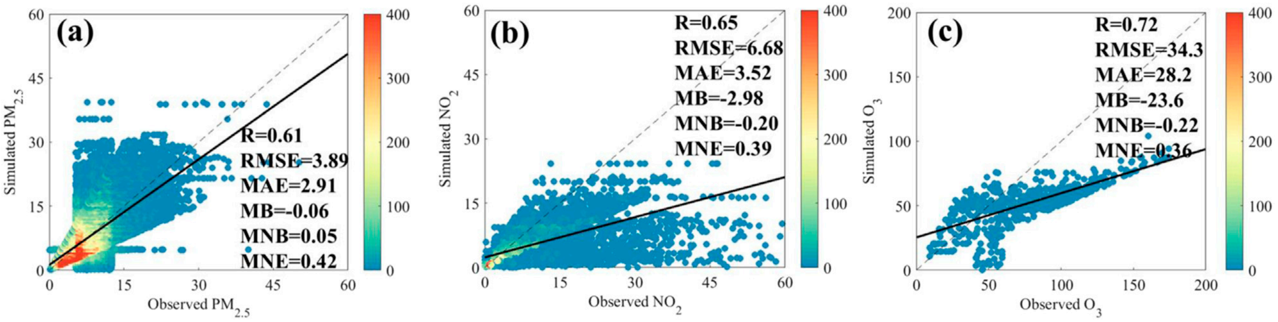

FIGURE 1
Modeling accuracy of estimated $PM_{2.5}$ **(A)**, NO_2 **(B)**, and O_3 **(C)** levels during February–April in 2019 and 2020 globally (Unit: μg/m^3).

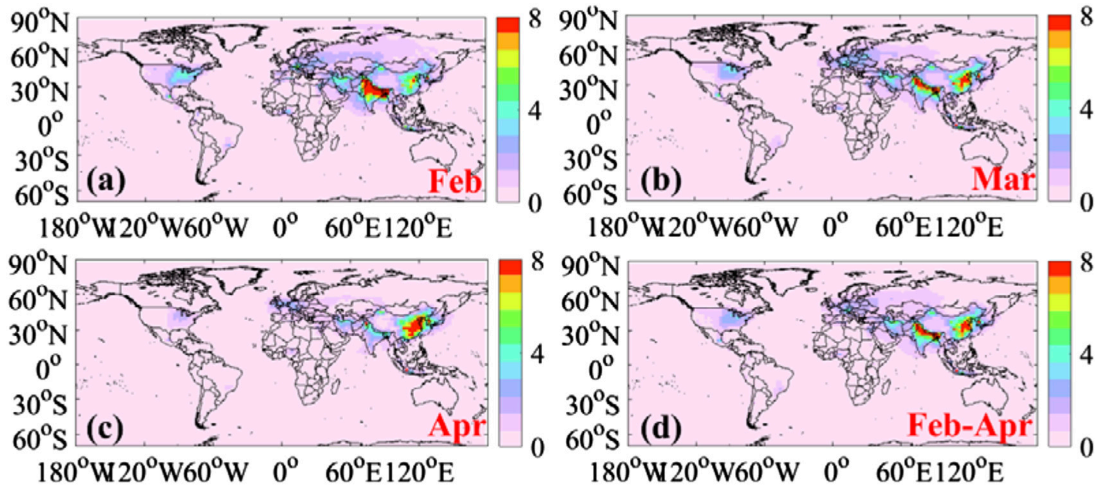

FIGURE 2
Spatial distributions of $PM_{2.5}$ levels from land transportation emissions in February **(A)**, March **(B)**, and April **(C)** in 2020. **(D)** Mean concentrations of $PM_{2.5}$ derived from land transportation emissions during February–April 2020.

concentrations excluding land transportation emissions from the total concentrations. The results indicated that the transportation-related $PM_{2.5}$ levels varied between 0.01 and 14.5 μg/m^3 with a median of 0.46 μg/m^3 during February–April 2019 (Supplementary Figure S2). The transportation-derived $PM_{2.5}$ concentrations varied between 0.01 and 13.3 μg/m^3 with a median of 0.28 μg/m^3 during February–April 2020 (Figure 2). The transportation-related NO_2 levels ranged from 0.02 to 9.66 μg/m^3 with a median of 0.15 μg/m^3 during February–April 2019 (Supplementary Figure S3). The transportation-related NO_2 concentrations varied between 0.01 and 7.34 μg/m^3 with a median of 0.09 μg/m^3 during February–April 2020 (Figure 3). The O_3 concentrations associated with land transportation ranged from 0.35 to 35.1 μg/m^3 with a median of 7.68 μg/m^3 during February–April 2019 (Supplementary Figure S4). The transportation-derived O_3 levels varied between 0.26 and 30.9 μg/m^3 with a median of 2.78 μg/m^3 during February–April 2020 (Figure 4).

The estimated transportation-derived $PM_{2.5}$, NO_2, and O_3 levels exhibited significant spatial variations on a global scale. At the spatial scale, the transportation-related $PM_{2.5}$ concentrations followed this order: India [4.19 ± 2.12 (2019) and 4.25 ± 2.66 (2020) μg/m^3] > China (3.69 ± 1.68 and 2.89 ± 1.45 μg/m^3) > Europe (3.54 ± 1.78 and 1.00 ± 0.48 μg/m^3) > the US (1.17 ± 0.65 and 0.72 ± 0.42 μg/m^3), which was in good agreement with the spatial distribution of total $PM_{2.5}$ concentrations (Lim et al., 2020). The transportation-related NO_2 levels in 2019 followed this order: Europe (1.47 ± 0.86 μg/m^3) > China (1.15 ± 0.66 μg/m^3) > India (1.06 ± 0.58 μg/m^3) > the US (0.57 ± 0.35 μg/m^3), while the transportation-derived NO_2 levels in 2020 followed this order: China (0.85 ± 0.52 μg/m^3) > India (0.83 ± 0.55 μg/m^3) > Europe (0.63 ± 0.42 μg/m^3) > the US (0.44 ± 0.28 μg/m^3). The results suggested that Europe suffered from serious NO_2 pollution derived from land transportation emissions during the business-as-usual period (Cooper et al., 2022; Sun et al., 2024b). This phenomenon is not surprising since the field measurements suggested that the NO_X control is not as efficient as once thought, especially in Europe, where the transportation contribution to NO_X concentrations is still dominant (Ntziachristos et al., 2016; Ramacher et al., 2020; Vestreng et al., 2009). Transportation-related O_3 levels in 2019 displayed the highest concentrations in the US (12.4 ± 6.58 μg/m^3), followed by India (11.1 ± 5.84 μg/m^3) and Europe (11.0 ± 6.42 μg/m^3), and the lowest concentration observed in China (10.1 ± 4.96 μg/m^3). However, the transportation-derived O_3 levels in 2020 showed the highest values in

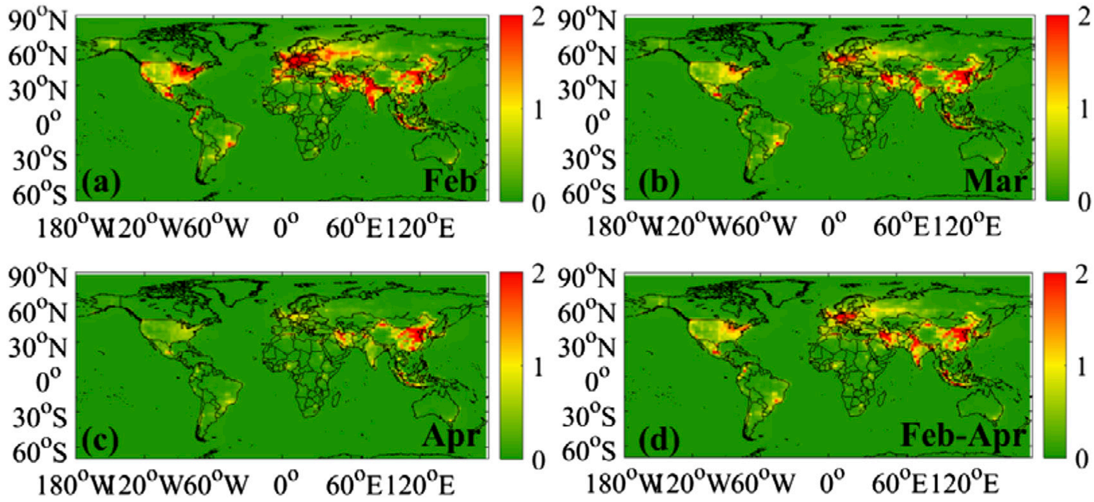

FIGURE 3
Spatial distributions of NO_2 levels from land transportation emissions in February **(A)**, March **(B)**, and April **(C)** in 2020. **(D)** Mean concentrations of NO_2 derived from land transportation emissions during February–April 2020.

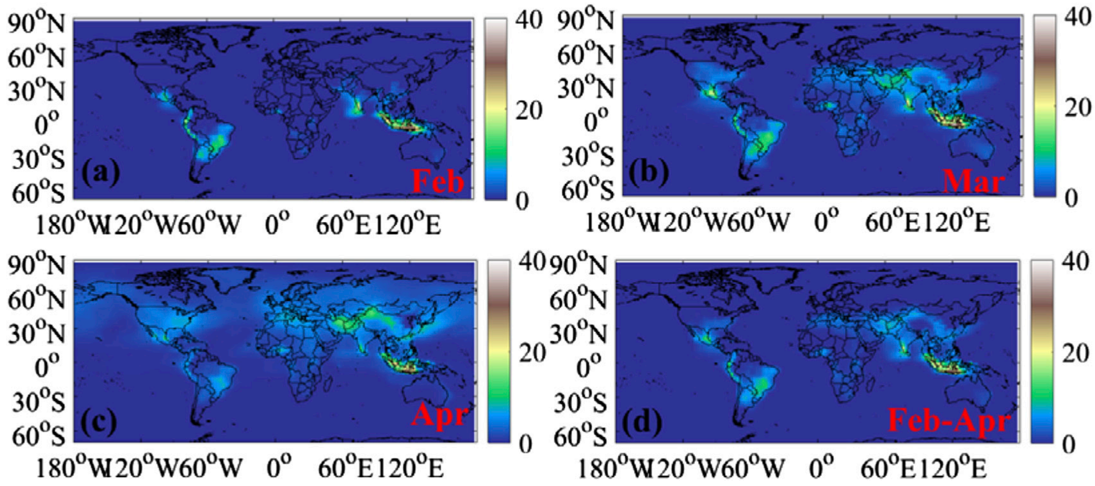

FIGURE 4
Spatial distributions of O_3 levels from land transportation emissions in February **(A)**, March **(B)**, and April **(C)** in 2020. **(D)** Mean concentrations of O_3 derived from land transportation emissions during February–April 2020.

India (4.84 ± 2.65 μg/m^3), followed by China (3.34 ± 2.12 μg/m^3) and Europe (2.09 ± 1.12 μg/m^3), and the lowest value in the US (1.74 ± 0.96 μg/m^3). The marked decrease in transportation-derived O_3 levels in the US compared with other countries during the COVID-19 lockdown might be contributed to more rapid decreases in NO_X and VOC emissions than in other regions (Shakoor et al., 2020; Sicard et al., 2020). As recommended by Mertens et al., the transportation contribution toward ozone net production has reached 21% in North America, higher than 13% globally (Mertens et al., 2018). Such research studies emphasized the importance of precursors on the secondary formation of ozone globally.

The transportation-related $PM_{2.5}$, NO_2, and O_3 concentrations not only displayed remarkable spatial differences but also suffered from marked variations during the COVID-19 period. The mean concentrations of transportation-derived $PM_{2.5}$, NO_2, and O_3 decreased by 20%, 36%, and 55%, respectively. Furthermore, the decreasing ratios of air pollutants in different regions often suffered from significant spatial discrepancies. In China, $PM_{2.5}$, NO_2, and O_3 concentrations reduced by 21%, 26%, and 67%, respectively. In India, $PM_{2.5}$, NO_2, and O_3 levels decreased by 1%, 21%, and 56%, respectively. In the United States and Europe, the transportation-related O_3 levels [−81% (Europe) and −86% (the US)] experienced more rapid decreases compared with $PM_{2.5}$ [−72% (Europe) and −38% (the US)] and NO_2 [−57% (Europe) and −23% (the US)]. More significant decreases in transportation-related air pollutant concentrations in the United States and Europe after the COVID-19 outbreak might be associated with dense road networks and land transportation emissions during the non-

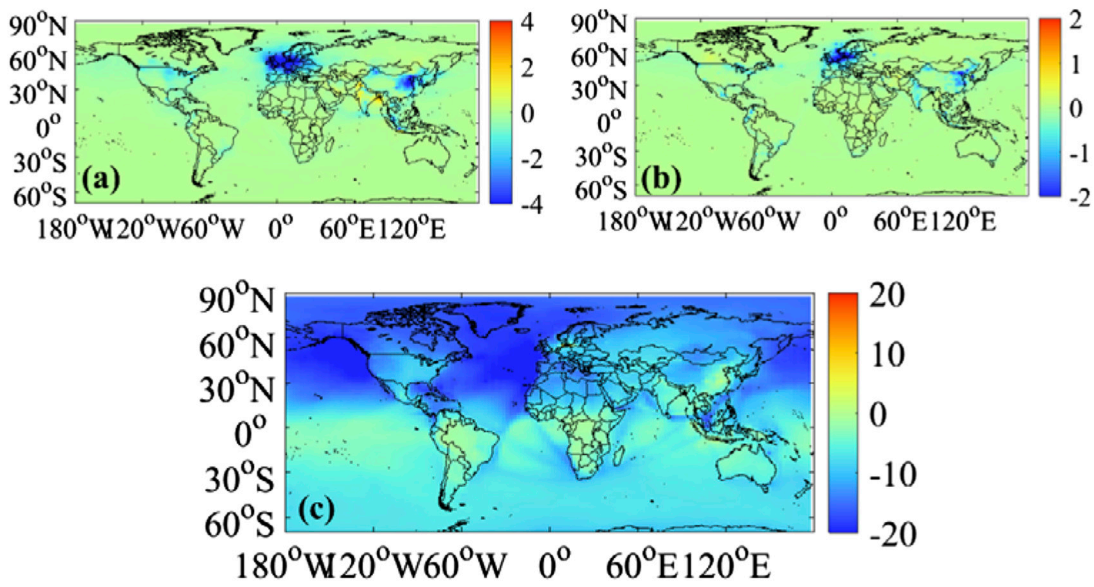

FIGURE 5
Spatial distributions of $PM_{2.5}$ **(A)**, NO_2 **(B)**, and O_3 **(C)** concentrations before and during the COVID-19 period derived from land transportation emissions on a global scale.

lockdown period (Gaubert et al., 2021; Keller et al., 2021; Miyazaki et al., 2021), as shown in Figure 5. In addition, it should be noted that the decrease in transportation-related O_3 was significantly higher than the reductions in $PM_{2.5}$ and NO_2, which was in contrast with the trends observed for shipping-related air pollutants (Sun et al., 2024a). In general, the transportation-related NO_X emission reduction was much greater than that of VOCs due to different source apportionments (Lidén et al., 1999; Liu et al., 2016; Shao et al., 2016; Xu et al., 2018; Zhang et al., 2020; Zhao et al., 2019), and thus, the O_3 might increase, especially in VOC-limited regions (Grange et al., 2021; Wang et al., 2023). However, the transportation-related O_3 concentrations displayed decreases in both VOC- and NO_X-limited areas during the COVID-19 period. It was assumed that the deep emission reduction in VOC and NO_X could facilitate the decreases in O_3 concentrations (Liu and Shi, 2021; Sillman, 1999; Xiang et al., 2020).

3.3 Health benefits of transportation-related $PM_{2.5}$, NO_2, and O_3 exposures

Based on Equations 1, 2 from Section 2.3, the all-cause mortalities attributable to $PM_{2.5}$, NO_2, and O_3 levels induced by transportation emissions were estimated. These methods, previously applied for assessing shipping emissions (Contini and Merico, 2021; Tian et al., 2013; Zhang et al., 2021), offer insights into the health impacts of air pollution. In total, transportation-related $PM_{2.5}$ exposure resulted in 243,431 (95% CI: 196,813, 290,048) and 179,884 (95% CI: 149,216, 210,551) deaths globally in 2019 and 2020, respectively. Among the most affected regions, India showed the highest mortality rates, with 55,513 (95% CI: 52,846, 58,179) and 53,191 (95% CI: 51,301, 55,080) cases in early 2019 and 2020, respectively. China followed closely, recording 58,816 (95% CI: 57,633, 59,998) cases in 2019 and 49,709 (95% CI: 48,033, 51,385) in 2020. The slight decline in India's numbers between 2019 and 2020 is attributed to the late imposition of COVID-19 lockdown measures (starting late-March 2020) (Sharma et al., 2020). Meanwhile, China's decrease in both $PM_{2.5}$ levels and related mortalities reflects the earlier implementation of lockdown measures, leading to improved air quality (Chen et al., 2020; He et al., 2020). Europe recorded similar $PM_{2.5}$-related mortalities in early 2019, with 51,993 (95% CI: 35,101, 68,884) deaths, compared to a significant decrease in 2020 with 18,635 (95% CI: 11,631, 25,638) cases. The United States experienced the lowest numbers, with 17,481 (95% CI: 10,555, 24,408) in 2019 and 12,134 (95% CI: 7,233, 17,034) in 2020. The health benefits from the reduction in transportation-related $PM_{2.5}$ emissions were estimated based on the decreased number of cases, as shown in Table 1. The reduction in mortalities amounted to 9,107 (95% CI: 8,613, 9,601) in China, 5,348 (95% CI: 3,322, 7,374) in the United States, 33,358 (95% CI: 23,471, 43,246) in Europe, 2,322 (95% CI: 1,545, 3,098) in India, and 63,547 (95% CI: 47,597, 79,497) globally.

The all-cause mortalities and health benefits associated with transportation-related NO_2 emissions were also calculated. Globally, transportation-related NO_2 exposure resulted in 154,195 (95% CI: 90,311, 218,079) and 101,510 (95% CI: 58,000, 145,020) cases in early 2019 and 2020, respectively. In China, the estimated mortalities were 84,759 (95% CI: 51,886, 117,631) in 2019 and 49,709 (95% CI: 48,033, 51,385) in 2020. Similarly, in India, NO_2-related all-cause mortalities were 54,967 (95% CI: 30,795, 79,140) in 2019 and 40,159 (95% CI: 21,742, 58,576) in 2020 during the February–April period. In Europe, the number of cases attributed to NO_2 exposure from transportation emissions was 16,040 (95% CI: 8,787, 23,293) in 2019, decreasing to 2,628 (95% CI: 1,388, 3,868) in 2020. The United States exhibited the lowest health benefits, with 1,501 (95% CI: 796, 2,207) cases in 2019 and 610 (95% CI: 326, 895) in 2020. Globally, the reduction in NO_2-related mortalities due to decreased transportation emissions was estimated at 52,685 (95%

TABLE 1 Health benefits (95% CI: lower, upper) associated with $PM_{2.5}$, NO_2, and O_3 induced by land transportation emission reduction during the COVID-19 period.

	$PM_{2.5}$	NO_2	O_3	Total
China	9,107 (8,613, 9,601)	23,363 (15,548, 31,178)	25,106 (21,621, 28,591)	57,576 (49,005, 66,147)
The United States	5,348 (3,322, 7,374)	891 (470, 1,312)	21,497 (19,638, 23,357)	27,736 (24,954, 30,518)
Europe	33,358 (23,471, 43,246)	13,412 (7,399, 19,425)	33,422 (30,802, 36,043)	80,193 (68,327, 92,058)
India	2,322 (1,545, 3,098)	14,808 (9,053, 20,564)	29,323 (24,821, 33,824)	46,453 (39,104, 53,801)
World	63,547 (47,597, 79,497)	52,685 (32,310, 73,059)	231,980 (210,373, 253,586)	348,212 (314,502, 381,921)

CI: 32,310, 73,059). Regionally, the health benefits were estimated as follows: China, 23,363 (95% CI: 15,548, 31,178); the United States, 891 (95% CI: 470, 1,312); Europe, 13,412 (95% CI: 7,399, 19,425); and India, 14,808 (95% CI: 9,053, 20,564).

The ambient O_3 concentrations affected by the COVID-19 lockdown were also simulated, and the resulting health benefits from transportation emissions were estimated to be 25,106 (95% CI: 21,621, 28,591) in China, 21,497 (95% CI: 19,638, 23,357) in the United States, 33,422 (95% CI: 30,802, 36,043) in Europe, and 29,323 (95% CI: 24,821, 33,824) in India. During the lockdown period, our simulations indicated a slight increase in O_3 concentration globally, consistent with previous research (Bi et al., 2022; Deroubaix et al., 2021; Keller et al., 2021). Globally, the total O_3-related health benefits were estimated at 231,980 (95% CI: 210,373, 253,586), making it the most significant of the three pollutants examined. Summarizing the health benefits of all three pollutants, the transportation-related benefits were 57,576 (95% CI: 49,005, 66,147) in China, 27,736 (95% CI: 24,954, 30,518) in the United States, 80,193 (95% CI: 68,327, 92,058) in Europe, and 46,453 (95% CI: 39,104, 53,801) in India. Notably, while Europe represents approximately 9.5% of the global population, it accounted for over 24.1% of the health benefits, particularly with 52.5% of the $PM_{2.5}$-related benefits and 25.5% of the NO_2-related benefits. This highlights the substantial health benefits of reduced transportation emissions and emphasizes the severe situation of transportation emissions in Europe (Matthias et al., 2021; Ntziachristos et al., 2016; Rodríguez-Sánchez et al., 2024). Similarly, the United States, representing 4.2% of the global population, contributed 8.0% of the total health benefits.

It is important to acknowledge that the relative risk (RR) values used to estimate health impacts can vary significantly across different regions (Chen and Sun, 2021). As a result, this introduces uncontrolled uncertainties into the simulation process. Future simulations should focus on determining region-specific RR values, particularly in countries with smaller populations, to improve the accuracy of predictions.

4 Conclusions and implications

In this study, the GEOS-Chem model was employed to assess the health impacts associated with the reduction in transportation emissions by removing the corresponding contributions during February–April of both 2019 and 2020, enabling the quantification of the additional effects of the COVID-19 lockdown. Initially, transportation-related emissions were included in the pollutant simulations but were subsequently excluded for a separate simulation. The difference between these simulations was considered the health benefit derived from the reduction in transportation emissions. Therefore, the change in transportation emissions between 2019 and 2020 accounted for the health benefit differences observed between these 2 years. The simulation of selected pollutants in this study demonstrated strong agreement with corresponding observations (R = 0.61 for $PM_{2.5}$, 0.65 for NO_2, and 0.72 for O_3).

According to the simulation, significant spatial variations were observed in transportation-related $PM_{2.5}$, NO_2, and O_3 levels. The estimated $PM_{2.5}$ concentrations followed this order: India > China > Europe > the United States in both 2019 and 2020, a spatial distribution consistent with the findings of Lim et al. (2020). The predicted NO_2 concentrations presented a different pattern between 2019 and 2020. When comparing the influence of excluding transportation emissions, the results showed that the world (36%) > China (26%) > India (21%) > the United States (−23%) > Europe (−57%). This suggests that the COVID-19 lockdown caused a significant decrease in NO_2 levels in China and India, while globally, NO_2 concentrations were suppressed except in Europe and the United States. The lockdowns, which began in early March 2020 in Europe and mid-March in the United States—coinciding with the same period in India—led to varying impacts on NO_2 levels (Berman and Ebisu, 2020; Matthias et al., 2021; Nigam et al., 2021; Sharma et al., 2020). The industrial emissions in China and India contributed to higher NO_2 levels than those in Europe and the United States, where transportation emissions dominated. As a result, the decrease in NO_2 concentrations in China and India was less pronounced compared to the steep declines in Europe and the United States, where transportation was the primary source of NO_2 emissions. Regarding O_3, the reduction in transportation-related emissions caused a larger decrease in O_3 levels compared to $PM_{2.5}$ and NO_2, which contrasts with patterns observed for shipping emissions (Sun et al., 2024a). O_3 levels are generally controlled by photochemical reactions, as explained by the Empirical Kinetic Modeling Approach (EKMA) (Martinez et al., 1983), which suggests that reducing NO_X and VOCs emissions may improve O_3 concentrations. This was further supported by the observed higher O_3 concentrations during the lockdown period compared to pre-lockdown levels (Figure 4). Overall, effective O_3 pollution control requires a comprehensive approach, addressing both NO_X and VOC emissions alongside the local and long-range transport of these pollutants.

The health benefits of reducing $PM_{2.5}$, NO_2, and O_3 emissions due to transportation-related activities were evaluated across key global regions. The all-cause mortalities associated with these pollutants were simulated to be 65,347 (95% CI: 47,597, 79,497) for $PM_{2.5}$, 52,685 (95% CI: 32,310, 73,059) for NO_2, and 231,980 (95% CI: 210,373, 253,586) for O_3. Among the regions studied, Europe saw the greatest health benefits, with estimated reductions in mortalities at 80,193 (95% CI: 68,327, 92,058), followed by China [57,576 (95% CI: 49,005, 66,147)], India [46,453 (95% CI: 39,104, 53,801)], and the United States [27,736 (95% CI: 24,954, 30,518)]. Although previous studies have investigated this by regional or source differences (Cesaroni et al., 2012; Host et al., 2020; Liu et al., 2021; Pappin et al., 2016; Zhang et al., 2021), the transportation emission reduction-related health benefits were derived globally in this study, providing a valuable perspective on the long-term effect of the COVID-19 lockdown.

The findings from this research also hold significant global implications for policy-making. First, the positive health impacts observed from the reduction of transportation emissions demonstrate that limiting vehicle usage can substantially protect populations from pollutant exposure. This underscores the importance of implementing stricter emission standards for fuel-powered vehicles and encouraging the adoption of cleaner, alternative energy vehicles worldwide. As transportation is one of the major sources of pollution globally, future efforts must focus on imposing greater restrictions on emissions in this sector. Moreover, even during the global lockdown in April 2020, when $PM_{2.5}$ and NO_2 concentrations were at their lowest, O_3 levels peaked globally—except in South America, where high cloud cover and frequent rainfall likely contributed to lower ozone concentrations (Cazorla et al., 2021; Gaubert et al., 2021). Of particular concern is the fact that transportation-related ozone exposure accounted for most health benefits across the three selected pollutants, emphasizing the critical role of transportation-emitted precursors (such as VOCs and NO_X) in ozone formation. These precursors should be strictly regulated in future policies.

It is important to acknowledge the limitations to this study. Transportation emissions globally can influence several other factors, such as aerosol optical depth, surface temperature, and the local meteorological transformations that occur in response to the absence of these emissions. Additionally, the health impacts associated with reduced transportation emissions may extend beyond immediate respiratory conditions, potentially affecting crop growth, local photosynthesis, and even the long-term effects of COVID-19 infections. To better estimate health benefits and minimize uncertainties, future studies should incorporate more accurate observations and detailed variable data in modeling efforts. Furthermore, identifying effective strategies for managing secondary pollutants like O_3 is crucial for safeguarding human health worldwide. Furthermore, the health benefits from other specific sources remain uninvestigated (i.e., industrial emissions). As the most important factor in emission reduction, the COVID-19 lockdown plays a significant role in global pollution levels and climate change (Abdullah et al., 2024; Liu et al., 2024; Tautan et al., 2024). More research studies are recommended on the concentration reduction of pollutants to gain a better understanding of regional secondary transformation and global pollution formation.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

YZ: conceptualization, data curation, formal analysis, investigation, methodology, validation, writing–original draft, and writing–review and editing. YC: conceptualization, formal analysis, methodology, validation, and writing–original draft. FZ: conceptualization, formal analysis, validation, and writing–original draft. HF: conceptualization, funding acquisition, resources, supervision, writing–original draft, and writing–review and editing.

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Conflict of interest

Author FZ was employed by Beijing Capital Air Environmental Science & Technology Co., Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declare that no Generative AI was used in the creation of this manuscript.

Publisher's note

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2024.1519984/full#supplementary-material

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