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Meteorology-driven trends in $PM_{2.5}$ concentrations and related health burden over India

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ABSTRACT

As a heavily polluted country, India has made great efforts on mitigating severe $PM_{2.5}$ pollution during last several years. Quantifying meteorological impacts on $PM_{2.5}$ pollution and related health burden is essential to accurately assess pollution control effects and therefore provides a reference for air quality policy in India. This study identifies meteorological influences on $PM_{2.5}$ trends and related mortality during 2014–2021 in five Indian megacities (Chennai, Kolkata, Hyderabad, Mumbai, Delhi). Decreasing trends in $PM_{2.5}$ concentrations are observed in all cities and seasons with the maximum trend of -7.24 μg m^{-3} yr^{-1} in Delhi during winter. Meteorology causes $PM_{2.5}$ decreases in all cities and seasons with meteorology-driven downward trends of $-6.51 \sim -0.36$ μg m^{-3} yr^{-1}. Meteorology dominates $PM_{2.5}$ decreases in Delhi during summer/monsoon and Chennai/Mumbai/Delhi during winter, where meteorology-driven $PM_{2.5}$ trends contribute 65% ~ 105% of observed $PM_{2.5}$ decreases. Better ventilation condition is identified as the primary meteorological factor for $PM_{2.5}$ decrease. Anthropogenic emissions almost play positive roles in improving India's $PM_{2.5}$ air quality, confirming the effectiveness of pollution control measures in India during recent years. Meteorological conditions dominate decreases in $PM_{2.5}$-related deaths in 25% of cities and seasons. The most significant meteorology-driven $PM_{2.5}$-related mortality trend of -127.12 deaths yr^{-1} occurs in Delhi during winter.

1. Introduction

As a developing country with rapid urban expansion and population growth, India is suffering from severe air pollution and therefore becoming a global hotspot for air quality research (Cao et al., 2018; Lu et al., 2018; Pal et al., 2018; M. Gao et al., 2019; Guo et al., 2019; Hammer et al., 2020; Navinya et al., 2020; Lou et al., 2022; Sharma and Mauzerall, 2022; Kumar and Pande, 2023; Sicard et al., 2023). According to a study focused on 46 fast-growing tropical cities, the most significant trends of $+3\%$ $yr^{-1} \sim +8\%$ yr^{-1} in aerosol optical depth were observed in Indian cities for 2005–2018 (Vohra et al., 2022). The winter $PM_{2.5}$ concentrations exceeded daily $PM_{2.5}$ standard (i.e. 60 μg m^{-3}) set by the National Ambient Air Quality Standards (NAAQS) on >90% of days for Delhi and Kolkata during 2013–2016 (Sreekanth et al., 2018).

Exposure to $PM_{2.5}$ has been associated to adverse health effects such as respiratory disease and cardiovascular diseases (Burnett et al., 2018; David et al., 2019; Southerland et al., 2022; Maji et al., 2023). Southerland et al. (2022) reported an estimation of 1.8 million deaths attributable to long-term exposure to ambient $PM_{2.5}$ in 13,160 urban centers for year 2019. For India, premature deaths associated with long-term $PM_{2.5}$ exposure increased at a rate of 3% yr^{-1} during 1998–2015 (Jia et al., 2021). Vohra et al. (2022) reported an estimation of 54.4 and 48.3 thousand $PM_{2.5}$-related premature deaths in 2018 in Kolkata and Mumbai, respectively. Short-term $PM_{2.5}$ exposure can also cause acute health outcomes (Li et al., 2019a; Krishna et al., 2021; Joshi et al., 2022). The daily $PM_{2.5}$-related premature deaths were reported to be 43 for Delhi in January 2015–2018 (Chen et al., 2020). Joshi et al. (2021) indicated a 0.52% increase in non-trauma all-cause mortality for every

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10 μg m^{-3} increase in 6-days cumulative $PM_{2.5}$ exposure during 2013–2017.

The Indian government has made great efforts on monitoring and reducing pollutants to mitigate severe air pollution in last several years (Gulia et al., 2022). Since 2015, the National Air Quality Index (AQI) has been published to assess air quality in India; a nationwide network of ambient air quality monitoring has been built up by the Central Pollution Control Board (CPCB) (CPCB, 2021; Sharma and Mauzerall, 2022). Stricter fuel standards have been executed, stipulating that all new vehicles must use fuel with sulfur content <10 ppm (in line with Bharat Stage VI/Euro VI emission standards) (Maji et al., 2018); electric vehicles and clean fuels have also been vigorously popularized and promoted (MoEFCC, 2020; Gulia et al., 2022). In 2019, India launched the National Clean Air Program (NCAP) aiming to reduce particulate matter pollution level by 20–30% by 2024 (NCAP, 2019; Ganguly et al., 2020). Benefited from air pollution prevention and control policies, $PM_{2.5}$ concentrations in India have experienced considerable decreases during the recent years (X. Yang et al., 2018; MoEFCC, 2020; Singh et al., 2021; Sharma and Mauzerall, 2022).

Changes in $PM_{2.5}$ concentrations are not only influenced by anthropogenic emissions, but also sensitive to meteorological conditions (Chelani, 2013; X. Yang et al., 2018; Dang and Liao, 2019; Zhai et al., 2019; Yin and Zhang, 2020; J. Li et al., 2021; Bose and Roy Chowdhury, 2023). Prevailing westerly winds in winter bring pollution from industrial regions to the National Capital Territory of Delhi, greatly offsetting the positive effect of the "odd-even day" traffic restriction to control $PM_{2.5}$ pollution, which eventually reduce $PM_{2.5}$ concentrations by only 2–3% in most areas (Chowdhury et al., 2017). Precipitation leads to $PM_{2.5}$ removal, with a correlation coefficient of −0.75 between $PM_{2.5}$ and precipitation observed during November 2016–October 2017 in Delhi (Gorai et al., 2018). Mixing layer height, which largely affects the diffusion of air pollutants, is negatively correlated with $PM_{2.5}$ concentrations (Guttikunda and Gurjar, 2012). High relative humidity favors hygroscopic growth of particles, aggravating $PM_{2.5}$ pollution (Kumar et al., 2015).

Quantifying meteorological impacts on $PM_{2.5}$ pollution is essential to accurately assess pollution control effects. To develop appropriate control strategies, it's of great importance to build a better understanding of clear linkages among air quality, meteorological conditions, anthropogenic emissions, and health burden (Hidy and Pennell, 2010). During the past few years, the spatial-temporal characteristics of $PM_{2.5}$ concentrations in Indian cities have been well studied (Sreekanth et al., 2018; Sarkar et al., 2019; Singh et al., 2021; Barudgar et al., 2022). The correlations between $PM_{2.5}$ and meteorological parameters for India have also been reported in more recent studies (Bose and Roy Chowdhury, 2023; Chandu et al., 2023; Chetna et al., 2023). However, recognition and quantification of meteorological influences on $PM_{2.5}$ trends and associated health burden in India remain scarce.

This paper aims to (1) quantitatively assess meteorological influences on $PM_{2.5}$ trends by constructing multiple regression models in conjunction with reanalysis meteorological data; (2) investigate changes in $PM_{2.5}$-related health burden over 2014–2021 and quantify meteorological contribution. The findings of this study hold great significance in accurately evaluating the effectiveness of India's pollution control actions implemented in recent years and therefore provide a scientific reference for air quality policy-making in India.

2. Data and methods

2.1. Study area

As shown in Fig. 1, five megacities in India including Delhi, Mumbai, Kolkata, Chennai, and Hyderabad, where the U.S. Embassy and Consulates in India are located, are chosen for analysis in this study. These cities are located in different regions of India, representing the whole India to some extent. Delhi (28.60°N, 77.19°E), as the capital of India and one of the most densely populated city in the world (Sahu and Kota, 2017), is located in northern India and lies on the Indo-Gangetic Plain (IGP), with deserts in the west, hills in the north and east, and plains in the south (Guttikunda and Gurjar, 2012; Tiwari et al., 2013; Gorai et al.,

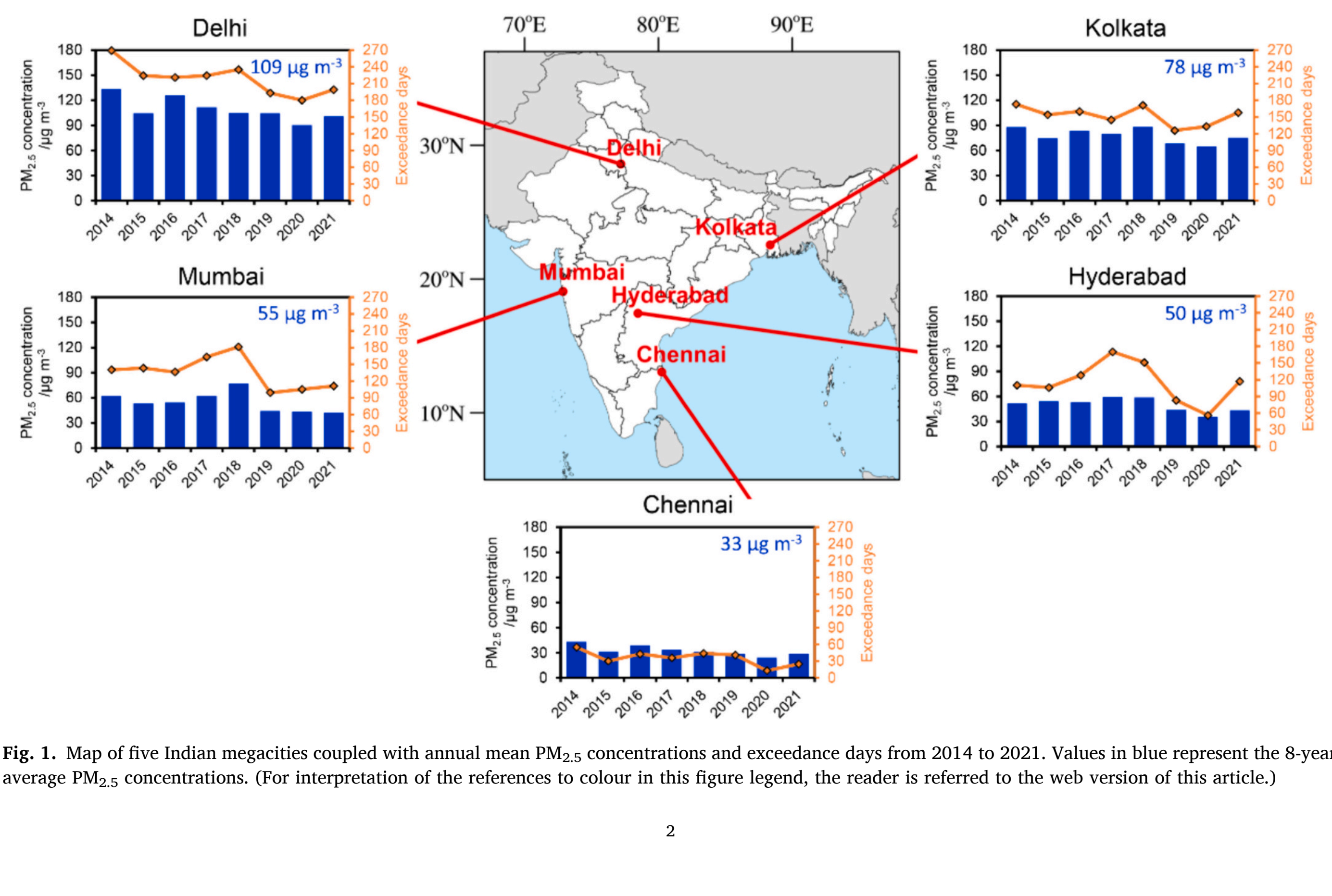

Fig. 1. Map of five Indian megacities coupled with annual mean $PM_{2.5}$ concentrations and exceedance days from 2014 to 2021. Values in blue represent the 8-year average $PM_{2.5}$ concentrations. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2018). Mumbai (19.07°N, 72.87°E), located in western India and east coast of Arabian Sea, is ranked first for the highest exposed population in a vulnerability ranking aimed at estimating $PM_{2.5}$ air quality in Indian cities (Pal et al., 2018). Kolkata (22.55°N, 88.35°E), the capital of the state of West Bengal, is located in northeastern India and northern side of the Bay of Bengal (Dasgupta et al., 2013). Chennai (13.0°N, 80.25°E), located in southern India and the western coast of Bay of Bengal, is the capital of the state of Tamil Nadu and known as "Gateway to South India". Hyderabad (17.44°N, 78.47°E), the capital of the state of Telangana, is located in the middle of the Deccan Plateau (Singh et al., 2021; Nandi and Swain, 2022).

2.2. Data

2.2.1. $PM_{2.5}$ concentration

Hourly $PM_{2.5}$ concentrations during 2014–2021, measured by Beta Attenuation Monitor (BAM-1020) at U.S. Embassy/Consulates in five Indian megacities (Sreekanth et al., 2018), are analyzed in this study. The record prior to November 2016 can be publicly taken from the consulate website (https://in.usembassy.gov/embassy-consulates/new-delhi/air-quality-data/), while the data after November 2016 are available on the AirNow website (https://www.airnow.gov/international/us-embassies-and-consulates/).

The reliability of $PM_{2.5}$ data is challenged by system crashes, parameters exceeding detection limits, and moisture uptake by aerosol particles (Kushwaha et al., 2022). Therefore, the data flagged by quality control as 'Missing, Suspect, Invalid' and negative values are removed (Singh et al., 2021).

The dataset from U.S. Embassy/Consulates covers a long time series with good continuity and has been widely used to assess air quality in India (Sreekanth et al., 2018; X. Yang et al., 2018; Chen et al., 2020; Singh et al., 2021; Barudgar et al., 2022). It has been shown to be in good agreement with other measurements (Mahesh et al., 2019; Singh and Tyagi, 2021; Sharma and Mauzerall, 2022). Although the CPCB has been providing nationwide $PM_{2.5}$ measurements since 2015, we do not choose the CPCB data because of the defect in the continuity and quality for the early time (i.e. before year 2018) (Brauer et al., 2019; Chelani, 2019). Bhardwaj and Pruthi (2019) found that the CPCB $PM_{2.5}$ measurements in Delhi during 2016 were significantly different (14 ± 8 μg m^{-3}) from U.S. Embassy measurements. This study is focused on air quality during 2014–2021, and thus uses $PM_{2.5}$ measurements from U.S. Embassy/Consulates with good continuity and high quality over the eight years even though it covers only five sites.

2.2.2. Meteorological data

Meteorological parameters used in this study are Modern-Era Retrospective Analysis for Research and Applications Version 2 (MERRA-2) reanalysis products with a horizontal resolution of 0.5° × 0.625° (lat × lon) from NASA's Global Modeling and Assimilation Office (http://geoschemdata.wustl.edu/ExtData/GEOS_0.5x0.625_AS/MERRA2/). 26 meteorological parameters during 2014–2021 are selected as meteorological candidates (Table S1) for establishing multiple linear regression (MLR) models. 14 surface-layer meteorological variables at one-hour intervals are observed to be correlated with $PM_{2.5}$ air quality (Trivedi et al., 2014; Sarkar et al., 2019; Chetna et al., 2023); 4 upper-layer meteorological variables at three layers (i.e. 1000 hPa, 850 hPa, 500 hPa) at three-hour intervals can be considered as general indicators of atmospheric stability and large-scale circulation (M. Gao et al., 2019; Yin and Zhang, 2020; J. Li et al., 2021). It is noted that the above-mentioned 26 meteorological candidates are traditional parameters for establishing MLR models to describe air quality-meteorology relationships (Li et al., 2019b; Zhai et al., 2019).

2.2.3. Health-related data

The baseline mortality rate (BMR) data for all ages and both genders are taken from the Global Burden of Disease (GBD) study results tool, which provides an updated estimation of global epidemiological data. We obtain India's BMR data at https://vizhub.healthdata.org/gbd-results/. The official population (Pop) data are obtained from the Registrar General & Census Commissioner of India at https://censusindia.gov.in/census.website/.

2.3. Methods

2.3.1. Establishing multiple linear regression model

Multiple linear regression (MLR) builds a linear function between a response variable and a group of explanatory variables, and thus has been widely used to describe air quality-meteorology relationships (Upadhyay et al., 2018; Bose and Roy Chowdhury, 2023) and further isolate meteorological impacts on air pollutants (Y. Yang et al., 2016; Li et al., 2019b; Zhai et al., 2019; Qin et al., 2021). In this study, we establish MLR models between $PM_{2.5}$ concentration and meteorological parameters during 2014–2021 for each city and each season. MLR model is shown as follows:

$$C_{s,r}(t) = b_{0,s,r} + \Sigma_{i=1}^{k} b_{i,s,r} \times Met_i(t) + \varepsilon \quad (1)$$

where $C_{s,r}(t)$ is daily $PM_{2.5}$ concentration for season s and city r, $Met_i(t)$ is i-th meteorological variable with a total number of k and $b_{i,s,r}$ is corresponding regression coefficient, $b_{0,s,r}$ is the intercept term, and ε is the residual term.

To obtain optimal fitting, we go through a suit of screening processes as follows:

Firstly, we calculate the correlation coefficients between $PM_{2.5}$ concentrations and initial 26 meteorological candidates. Those meteorological parameters that are not statistically significant at the 95% confidence level are removed, and the remainders move to next screening stage.

Secondly, we calculate variance inflation factor (VIF) to measure collinearity between meteorological parameters (Altland, 1999; L. Gao et al., 2021) as follows:

$$VIF = 1 \Big/ \left(1 - R_j^2\right) \quad (2)$$

where R_j^2 is the regression coefficient of determination between the j-th variable and other variables. To minimize multi-collinearity influences, we set the upper limit of 10 for VIF following Kutner et al. (2004). Those meteorological parameters with VIF>10 are abandoned and the remaining candidates go on to next screening stage.

Thirdly, stepwise regression is conducted by adding or abandoning candidates. When Akaike Information Criterion (AIC) statistic (Akaike, 1969) reaches the minimum, the optimal fitting occurs. AIC takes the following form:

$$AIC = N \times ln(SSE/N) + 2 \times (k+1) \quad (3)$$

where SSE is the sum of squared errors $\Sigma(C(t) - P(t))^2$, in which $C(t)$ and $P(t)$ are the observed $PM_{2.5}$ concentration and MLR-fitted $PM_{2.5}$ concentration, respectively; N and k are the total number of $PM_{2.5}$ measurements and meteorological parameters used for MLR construction, respectively. After conducting the above three screening steps, we obtain the optimal fittings.

2.3.2. Quantifying meteorology-driven $PM_{2.5}$ trend

Based on the established $PM_{2.5}$-meteorology relationships, we calculate the meteorology-driven $PM_{2.5}$ trend for each season s and each city r ($TC_{s,r}$) as:

$$TC_{s,r} = \Sigma_{i=1}^{k} b_{i,s,r} \times TMet_i \quad (4)$$

where $TMet_i$ is the trend of i-th meteorological variable used for MLR construction. The $PM_{2.5}$ trend attributed to other factor, mainly referring to the effect of anthropogenic emissions, is the difference between observed $PM_{2.5}$ trend and $TC_{s,r}$. The trends of $PM_{2.5}$ and meteorological variables are derived using Least Square Method (LSM). We also use Mann-Kendall and Theil-Sen (MK-TS) method for trend estimation to test the uncertainty brought by the method, which is displayed in Section 4 and Table 2.

The percentage contribution of each meteorological variable ($Cont_{i,s,r}$) on meteorology-driven $PM_{2.5}$ trend is calculated as:

$$Cont_{i,s,r} = \left(b_{i,s,r} \times TMet_i\right) / TC_{s,r} \quad (5)$$

when it reaches the maximum, the corresponding meteorological variable (with statistically significant trend) is identified as the dominant meteorological factor for $PM_{2.5}$ trend.

2.3.3. Assessing $PM_{2.5}$-related health impacts

This study focuses on changes in $PM_{2.5}$ and related health burden for four seasons, therefore health impact assessment in this study pays attention to premature mortality attributable to short-term $PM_{2.5}$ exposure. Four seasons include winter (December–January-February), summer (March–April-May), monsoon (June–July-August), and post-monsoon (September–October-November), which is a common way to divide seasons for India (Singh et al., 2021; Chandu et al., 2023). The daily premature all-cause mortality (*PreMort*) can be assessed as:

$$PreMort = BMR \times Pop \times (RR - 1)/RR \quad (6)$$

where daily *BMR* data are converted from annual rates taken from GBD2019 for all ages and both genders. Details of *BMR* and *Pop* sources are show in Sections 2.2.3. *RR* is daily relative risk and estimated by a linear exposure-response function (van Donkelaar et al., 2011) as follows:

$$RR = 1 + [\gamma \times (C - C_0) \times 0.1] \quad (7)$$

where the summary risk estimate (γ) from Atkinson et al. (2014) is calculated through a systematic review and meta-analysis of epidemiological studies, taking the value of 1.04% (0.52%–1.56%, 95% confidence interval) corresponding to per 10 μg m^{-3} change in daily mean $PM_{2.5}$ concentrations (C); the threshold concentration (C_0) is 0 μg m^{-3} (Li et al., 2019a; Yuan et al., 2019; Chen et al., 2020; Jat and Gurjar, 2021). Uncertainties involved in this methodology are discussed in Section 4.

2.3.4. Conducting sensitivity experiments

According to the health impact assessment (Eq. (6)), the variations in $PM_{2.5}$-related premature deaths are influenced by BMR, Pop, and concentration (Conc). The Conc variations are further affected by meteorological conditions (Met) and anthropogenic emissions (Emis). We conduct a set of sensitivity experiments, as shown in Table 1, to quantify respective contribution of each factor to variations in $PM_{2.5}$-related mortality during 2014–2021.

Experiment “Exp_CTL” represents that all factors are changed over 2014–2021; “Exp_Conc”/“Exp_Pop”/“Exp_BMR” represents that only Conc/Pop/BMR varies from 2014 to 2021 in order to examine mortality variations due to respective variation alone; “Exp_Met” is designed to assess meteorological influences, core objective of this study, and uses $PM_{2.5}$ concentrations predicted by MLR model and meteorological variables; “Exp_Emis” is the difference between “Exp_Conc” and “Exp_Met”, aiming to examine mortality variations owing to Emis variation alone.

3. Results

3.1. Meteorology-driven trends of $PM_{2.5}$ air quality

Fig. 1 presents yearly variations in annual mean $PM_{2.5}$ concentrations for five Indian megacities, including Delhi, Mumbai, Kolkata, Chennai, and Hyderabad. The $PM_{2.5}$ pollution has been mitigated to varying degrees during the past eight years, with the most significant trend of −4.44 μg m^{-3} yr^{-1} in Delhi. It is noted that the lowest $PM_{2.5}$ level in 2020 reflects the impact of COVID-19 lockdown. As shown in Fig. 1, the most notable feature of $PM_{2.5}$ pollution in India is spatially heterogeneous, with the north more serious than the south which agrees with X. Yang et al. (2018) and Sharma and Mauzerall (2022). Delhi faces high industrial load from power plants in the west and north (Sreekanth et al., 2018; Barudgar et al., 2022) and has a large population with densities 3 to 20 times higher than surrounding cities, causing the severest $PM_{2.5}$ pollution (Kumar et al., 2015; Chowdhury et al., 2017; M. Gao et al., 2018). We also show $PM_{2.5}$ exceedance days with daily $PM_{2.5}$ concentration exceeding 60 μg m^{-3} (i.e. Indian NAAQS for daily $PM_{2.5}$ level). The highest (lowest) exceedance days are observed in Delhi (Chennai), with an average of 218 (36) exceedance days in a year and statistically significant decreasing trends of −9.32 days yr^{-1} (−3.49 days yr^{-1}) at the 90% confidence level.

Seasonal and monthly variations in $PM_{2.5}$ concentrations during 2014–2021 in India are shown in Fig.S1 and Fig.S2. Among the four seasons, the $PM_{2.5}$ concentrations exhibit the maximum values in winter and the minimum values in monsoon, which is consistent with previous studies (Sahu et al., 2020; Singh et al., 2021). For monthly variation, the $PM_{2.5}$ peak and valley mainly occur around December and July every year. The eight-year average $PM_{2.5}$ concentration in Delhi during winter is 190 μg m^{-3} (4.7 times the Indian annual limit of 40 μg m^{-3} set by NAAQS), while the $PM_{2.5}$ concentration during monsoon is 46 μg m^{-3}. Meteorological variations mainly account for the seasonal variations in $PM_{2.5}$ concentrations. During winter, meteorological conditions (e.g. low boundary layer height) inhibit the diffusion of $PM_{2.5}$ (X. Yang et al., 2018; Ojha et al., 2020). In monsoon, however, below-cloud scavenging associated with monsoon is conducive to $PM_{2.5}$ removal (Sreekanth et al., 2018; Sharma and Mauzerall, 2022).

MLR models are established for each city and season to further quantify meteorological contributions to the trends of $PM_{2.5}$ concentrations. Fig. 2 shows variations in observed, meteorology-driven, and emission-driven $PM_{2.5}$ concentrations in five cities and four seasons during 2014–2021. The observed $PM_{2.5}$ concentrations show downward trends in all 20 cities and seasons. In summer and monsoon, the decreasing trends of observed $PM_{2.5}$ concentrations range from −4.98 μg m^{-3} yr^{-1} to −1.26 μg m^{-3} yr^{-1} in five cities, almost statistically significant at the 90% confidence level except for Mumbai during monsoon (Fig. 2(d2)); in post-monsoon, the $PM_{2.5}$ concentrations in

Table 1
Sensitivity experiments for examining $PM_{2.5}$-related mortality variations owing to the variations in each driving factor during 2014–2021.

Driver / Experiment	Conc	Pop	BMR	Purpose
Exp_CTL[a]	2014–2021[a]	2014–2021	2014–2021	Normal condition
Exp_Conc[a]	2014–2021[a]	Fixed at 2014	Fixed at 2014	Examine mortality variation owing to Conc variation alone
Exp_Met[b]	2014–2021[b]	Fixed at 2014	Fixed at 2014	Examine mortality variation owing to Met variation alone
Exp_Pop	Fixed at 2014	2014–2021	Fixed at 2014	Examine mortality variation owing to Pop variation alone
Exp_BMR	Fixed at 2014	Fixed at 2014	2014–2021	Examine mortality variation owing to BMR variation alone
Exp_Emis	The difference between Exp_Conc and Exp_Met			Examine mortality variations owing to Emis variation alone

[a] The observed $PM_{2.5}$ concentrations vary from 2014 to 2021 in Exp_CTL and Exp_Conc experiments.
[b] The MLR-predicted $PM_{2.5}$ concentration vary from 2014 to 2021 in Exp_Met experiment.

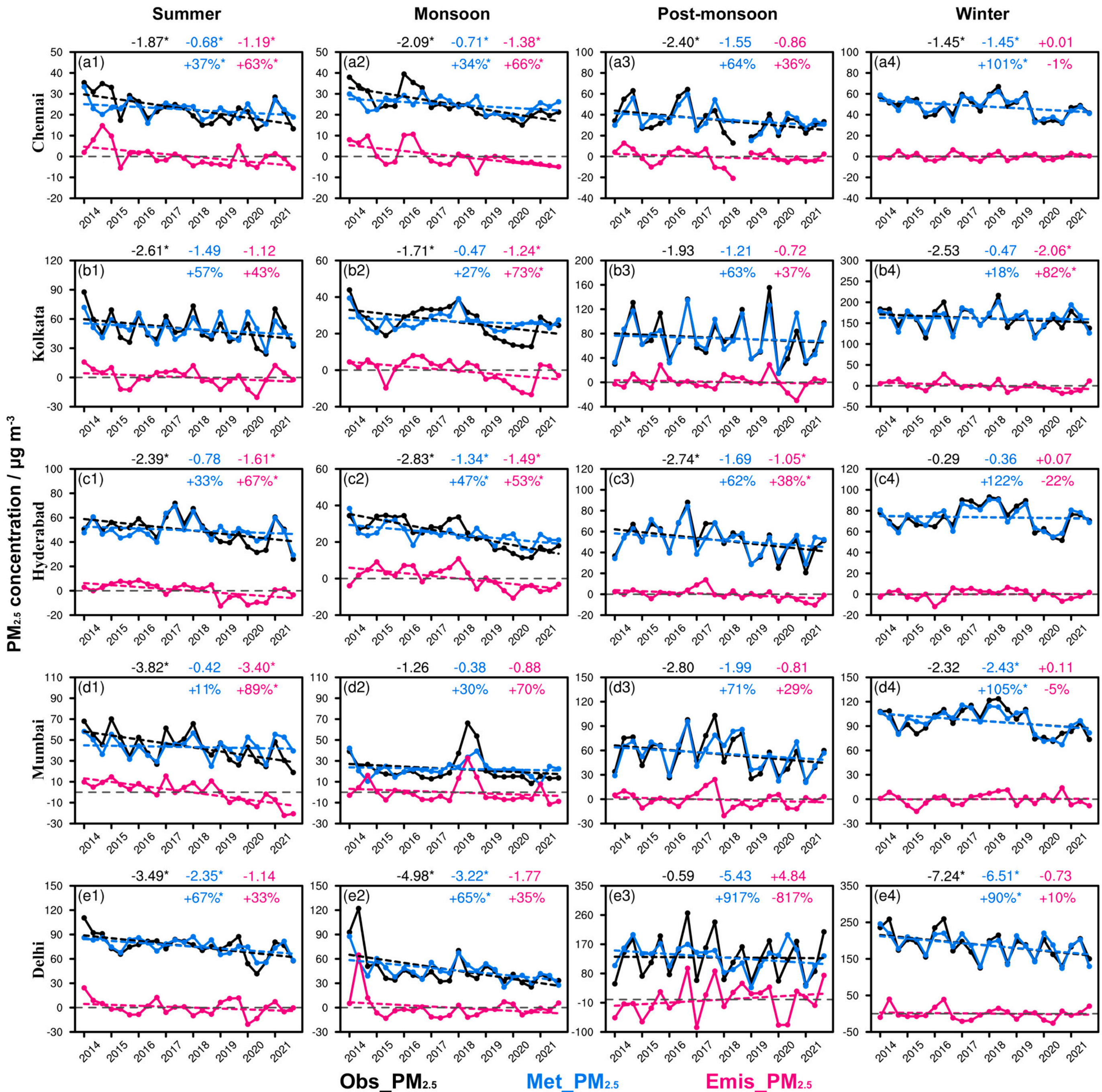

Fig. 2. Variations in observed $PM_{2.5}$ concentrations (Obs_$PM_{2.5}$, shown in black solid lines), meteorology-driven $PM_{2.5}$ concentrations (Met_$PM_{2.5}$, shown in blue solid lines), and emission-driven $PM_{2.5}$ concentrations (Emis_$PM_{2.5}$, shown in red solid lines) during 2014–2021. The calculated 8-year trends (unit: μg m^{-3} yr^{-1}) are shown in dotted lines and values with corresponding colors. Values with an asterisk (*) mean statistically significant trends at the 90% confidence level. The percentage contributions of Met_$PM_{2.5}$ and Emis_$PM_{2.5}$ to Obs_$PM_{2.5}$ are also shown in corresponding colors. Note that Emis_$PM_{2.5}$ is the difference between Obs_$PM_{2.5}$ and Met_$PM_{2.5}$, and thus it has negative values; however it doesn't matter because the trend, rather than the concentration itself, is the focus. Note that the data gap in (a3) indicates missing observations. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Chennai and Hyderabad exhibit statistically significant decreasing trends of −2.40 μg m^{-3} yr^{-1} and -2.74 μg m^{-3} yr^{-1} (Fig. 2(a3) and Fig. 2 (c3)); in winter, statistically significant $PM_{2.5}$ decreases with trends of −1.45 μg m^{-3} yr^{-1} and -7.24 μg m^{-3} yr^{-1} are shown in Chennai and Delhi (Fig. 2(a4) and Fig. 2(e4)). Among all seasonal trends, the maximum decreasing trend of −7.24 μg m^{-3} yr^{-1} appears in Delhi during winter (Fig. 2(e4)).

Anthropogenic emissions almost play positive roles in improving India's $PM_{2.5}$ air quality, confirming the effectiveness of pollution control measures in India during recent years. During summer and monsoon, the emission-driven $PM_{2.5}$ trends are negative in all cities with trends ranging from −3.40 μg m^{-3} yr^{-1} to −0.88 μg m^{-3} yr^{-1}, three-fifths of which are statistically significant. The maximum emission-driven increasing trend of +4.84 μg m^{-3} yr^{-1} appears in Delhi during post-monsoon, mainly contributed by straw burning over the northwest IGP (T. Liu et al., 2018; Ojha et al., 2020; Chetna et al., 2023).

Meteorology causes $PM_{2.5}$ decreases in all 20 cities and seasons with meteorology-driven downward trends of $-6.51 \sim -0.36$ μg m^{-3} yr^{-1}. Here meteorology-driven $PM_{2.5}$ trends that are larger than corresponding emission-driven trends and meanwhile statistically significant are defined as meteorology-dominated $PM_{2.5}$ trends. Meteorological conditions dominate $PM_{2.5}$ decreases in Delhi during summer/monsoon (Fig. 2(e1) and Fig. 2(e2)) and Chennai/Mumbai/Delhi during winter (Fig. 2(a4), Fig. 2(d4), and Fig. 2(e4)). The meteorology-driven $PM_{2.5}$ trends are -2.35 μg m^{-3} yr^{-1}, -3.22 μg m^{-3} yr^{-1}, and $-$ 6.51 μg m^{-3} yr^{-1}, contributing 67%, 65%, and 90% of observed $PM_{2.5}$ decreases for Delhi during summer, monsoon, and winter, respectively. For Chennai and Mumbai during winter, anthropogenic emissions lead to $PM_{2.5}$ increases and therefore meteorology-driven $PM_{2.5}$ trends (-1.45 μg m^{-3} yr^{-1} and -2.43 μg m^{-3} yr^{-1}) contribute >100% (101% and 105%) of observed $PM_{2.5}$ decreases. The meteorology-driven and emission-driven contributions vary in different cities or seasons for reasons such as differences in climatology, topography, and air quality policies. For example, meteorology dominates $PM_{2.5}$ trends in aforementioned five cities and seasons, which can be mainly attributed to better ventilation conditions (Fig. 3); In Chennai/Hyderabad/Mumbai during winter, the emission even causes $PM_{2.5}$ increases, resulting from the lack of strict regulations on traffic emissions and household emissions in winter (Wu et al., 2019; Singh et al., 2021).

We further identify the leading meteorological parameters responsible for $PM_{2.5}$ decreases in above five meteorology-dominated cities/seasons. In Delhi during summer/monsoon (Fig. 3a and Fig. 3b), the dominant meteorological factor is vertical pressure velocity at 1000 hPa (W1000). The weakening of the downdraft with the trend of -0.001 Pa s^{-1} yr^{-1} (summer) and $-$ 0.002 Pa s^{-1} yr^{-1} (monsoon) provides better ventilation condition and favors the upward transport of $PM_{2.5}$, thereby alleviating $PM_{2.5}$ pollution at surface layer (J. Li et al., 2021; Sharma and Mauzerall, 2022). In Chennai during winter (Fig. 3c), 2-m specific humidity (QV2M), regarded as the dominant meteorological factor, exhibits an increasing trend of $+0.12$ g kg^{-1} yr^{-1}. In addition, an upward trend of $+0.07$ mm day^{-1} yr^{-1} in total precipitation (PRECTOT), identified as the second dominant meteorological factor, is also observed during the same time period (it is not shown in the figure). The QV2M and PRECTOT have been reported to be positively correlated with the removal efficiency of aerosol particles (Sarkar et al., 2019; Bose and Roy Chowdhury, 2023; Chetna et al., 2023). Therefore, the increasing QV2M and PRECTOT can lower $PM_{2.5}$ concentrations through enhancing aerosol wet scavenging. In Mumbai during winter (Fig. 3d), 10-m meridional wind (V10M) is the primary meteorological factor. It shows a trend of -0.06 m s^{-1} yr^{-1}, which means stronger north wind, provides better ventilation condition and lowers $PM_{2.5}$ levels (Barudgar et al., 2022). In Delhi during winter (Fig. 3e), 10-m wind speed (WS10), with an upward trend of $+0.05$ m s^{-1} yr^{-1}, is identified as the dominant meteorological factor, which also indicates better ventilation condition and favors the dispersion of $PM_{2.5}$ (Gorai et al., 2018; Ojha et al., 2020; Chandu et al., 2023). In general, better ventilation condition is identified as the primary meteorological factor for $PM_{2.5}$ decrease.

3.2. Variations in $PM_{2.5}$-related health burden and meteorological impacts

India's air pollution has posed a great threat to public health. In 2019, the urban $PM_{2.5}$-attributable mortality rate in India is 1.2 times higher than the global rate (Southerland et al., 2022). We estimate premature deaths attributable to short-term $PM_{2.5}$ exposure in five cities for all seasons. As shown in Fig. 4, among all cities, Delhi faces the greatest $PM_{2.5}$-related health burden owing to severe $PM_{2.5}$ pollution and high population density, with an eight-year average of 4768 (2605–6596, 95% confidence interval) deaths for a whole winter. In China, 46.0 thousand premature deaths in 2019 caused by short-term $PM_{2.5}$ exposure were reported by J. Liu et al. (2021), indicating that the short-term $PM_{2.5}$-related health burden in developing countries such as India and China cannot be neglected (Li et al., 2019a).

The lowest $PM_{2.5}$-related health burden appears in Chennai due to the lowest $PM_{2.5}$ levels, though its population is larger than Kolkata and Hyderabad. The eight-year average premature mortality in Chennai is estimated to be 184 (93–273, 95% confidence interval) deaths for a whole summer, approximately half of that in Kolkata and Hyderabad. Our estimate for Delhi in January 2016 (69 (39–94, 95% confidence interval) deaths for each day) is slightly higher than that in Jat and Gurjar (2021) who reported a daily premature death of 61 (33–91, 95% confidence interval), owing to the discrepancies in BMR values and population size from various databases. From 2014 to 2021, the $PM_{2.5}$-related deaths exhibit decreases in five cities during summer, monsoon, post-monsoon, and Delhi during winter. The maximum decreasing trend (statistically significant) occurs in Delhi during summer (Fig. 4(e1)) and is calculated to be -84.37 deaths yr^{-1}.

As mentioned in Section 2.3.4, the variations in $PM_{2.5}$-related deaths

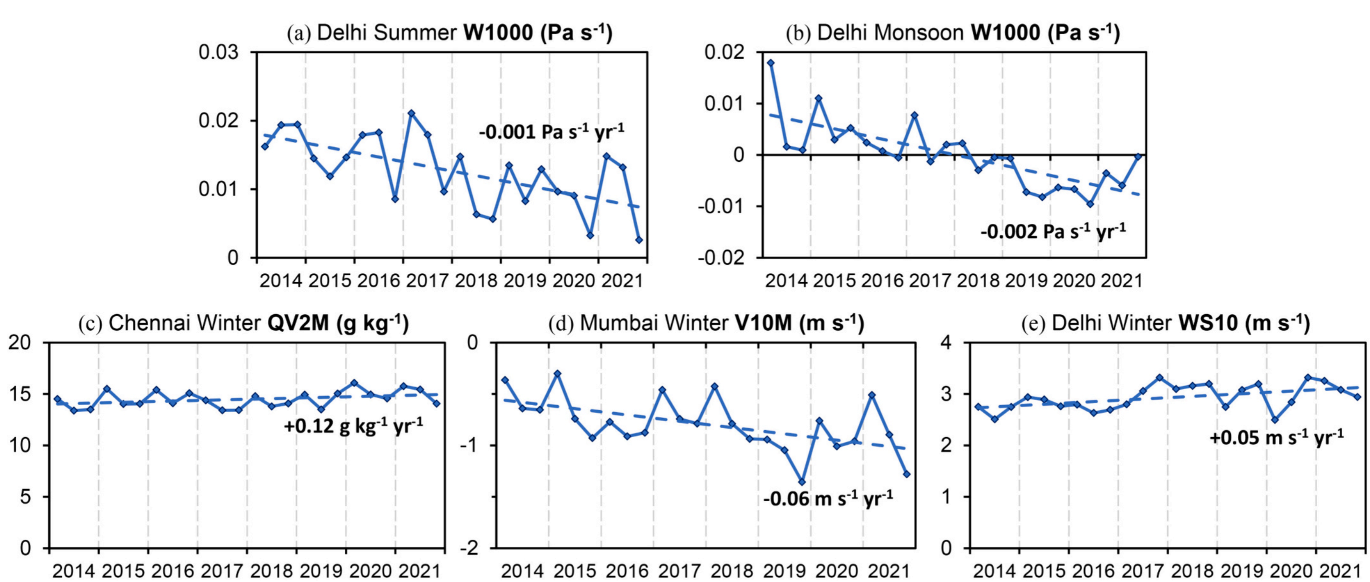

Fig. 3. The dominant meteorological factors responsible for meteorology-dominated $PM_{2.5}$ decreases during 2014–2021. The calculated 8-year trends are shown in dotted lines and values, all statistically significant at the 90% confidence level.

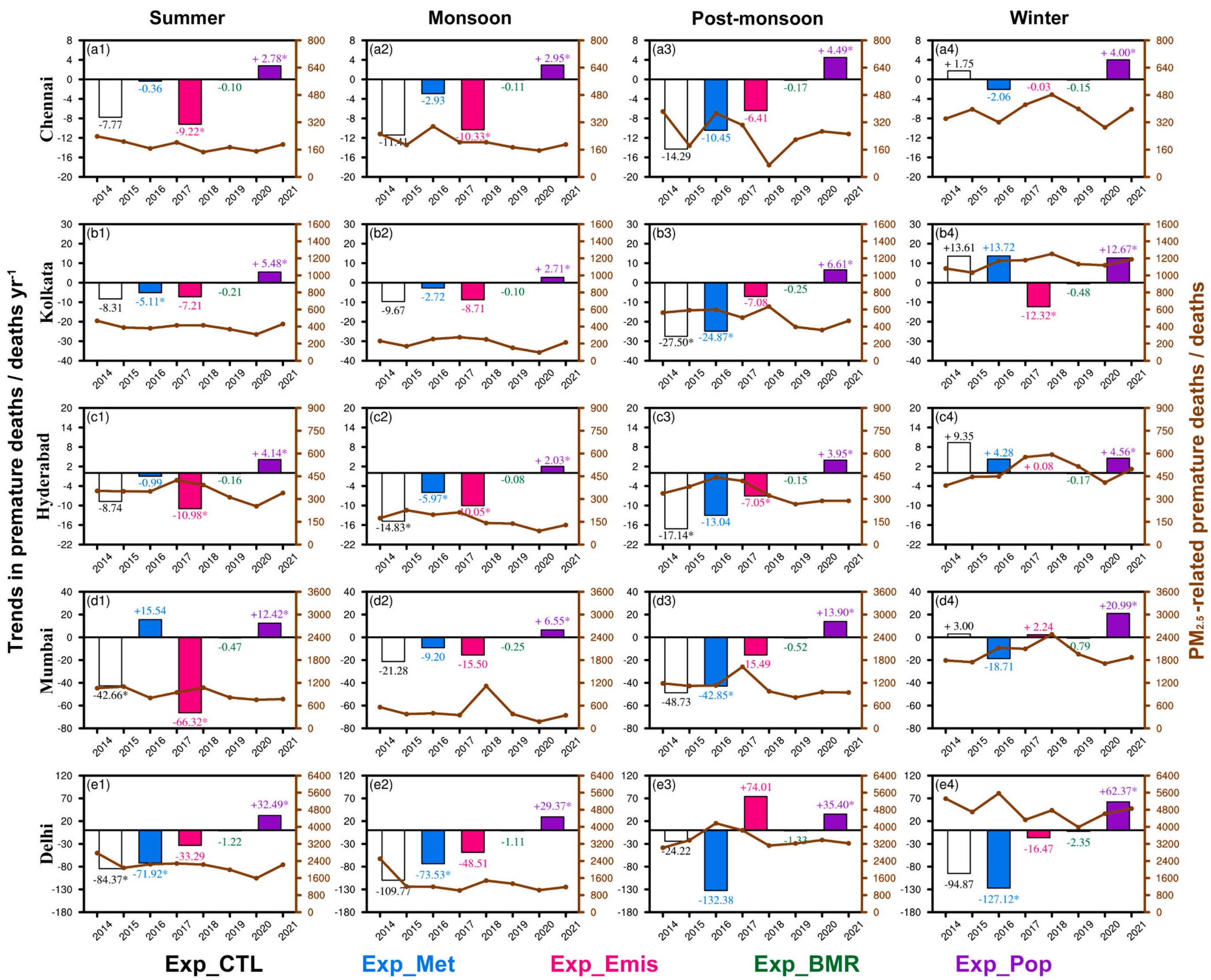

Fig. 4. Premature deaths (brown lines, right axis, unit: deaths) attributable to short-term $PM_{2.5}$ exposure during 2014–2021 and trends in premature deaths (colored bars and values, left axis, unit: deaths yr^{-1}) under five sensitivity experiments conducted in Table 1. Values with an asterisk (*) mean statistically significant trends at the 90% confidence level. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

are influenced by BMR, Pop, Met, and Emis. Bars in Fig. 4 show the trends in $PM_{2.5}$-related deaths owing to the variation in each factor during 2014–2021. The "Exp_CTL" experiment shows that the decreases in $PM_{2.5}$-related deaths are observed for most cities and seasons during 2014–2021. Emission reduction exerts positive impacts on alleviating $PM_{2.5}$-related health burden in almost all cities and seasons except for Delhi during post-monsoon and Hyderabad/Mumbai during winter, with the largest emission-driven decreasing trend of −66.32 deaths yr^{-1} in Mumbai during summer. Despite of advances in medical care, BMR decrease has very limited effects with BMR-driven trends of less than −2.35 deaths yr^{-1}. Population growth exerts negative impacts on mitigating $PM_{2.5}$-related health burden; for some cities and seasons, e.g., Delhi during summer and winter (Fig. 4(e1) and Fig. 4(e4)), the adverse effect of population growth almost offsets the efforts of emission reduction and medical improvement.

Meteorological conditions are favorable for reducing $PM_{2.5}$-related deaths in 85% of cities and seasons. For Delhi during summer/monsoon/winter (Fig. 4(e1), Fig. 4(e2), and Fig. 4(e4)) and Kolkata/Mumbai during post-monsoon (Fig. 4(b3) and Fig. 4(d3)), impacts of meteorological conditions on $PM_{2.5}$-related mortality decreases (statistically significant) are greater than those of other factors. The largest meteorology-driven mortality decrease (statistically significant) occurs in Delhi during winter (Fig. 4(e4)); the meteorology-driven decreasing trend of −127.12 deaths yr^{-1} even exceeds observed trend of −94.87 deaths yr^{-1}.

4. Limitations and uncertainties

There are some aspects in present study that need to be improved in future studies. Besides U.S. Embassy/Consulate data used in this study, a nationwide network of ambient air quality monitoring built by the CPCB has provided $PM_{2.5}$ measurements since 2015, covering >300 cities/towns of India until 2021. However, the comparison between the two databases shows that the CPCB $PM_{2.5}$ measurements are defective in the continuity and quality for the early time, which was also supported by Gorai et al. (2018). Therefore, we choose the $PM_{2.5}$ concentrations observed by U.S. Embassy/Consulate with good continuity and quality during 2014–2021 even though it covers only five sites. Future studies are expected to take full advantage of the CPCB database to examine India's air quality, as the weakness has been overcome gradually since 2018.

Uncertainty may come from trend estimation (Chervenkov and

Slavov, 2019). We compare $PM_{2.5}$ trends with two methods (LSM and MK-TS) to test the uncertainty brought by trend-estimation method. As shown in Table 2, high consistency appears in statistically significant trends while large discrepancy only occurs in statistically insignificant trends. Therefore, subsequent analysis for identification of dominant meteorological factor is conducted in the cities and seasons with statistically significant meteorology-driven $PM_{2.5}$ trends.

Besides traditional statistical methods (e.g., multiple linear regression and Kolmogorov–Zurbenko filter), machine learning methods (e.g., random forest and extreme gradient boosting) and chemistry transport models (e.g., GEOS-Chem model and CMAQ model) can also be used to obtain the effects of emissions and meteorology on $PM_{2.5}$ concentrations. Although a recent study revealed that $PM_{2.5}$ trends showed insignificant differences for both the emission-related and meteorology-related components between these approaches (Zheng et al., 2023), it is recommended to use more models to obtain more accurate assessment in future studies.

Uncertainty also comes from the estimation of $PM_{2.5}$-related health burden. The summary risk estimate (γ) used in this study is mostly based on studies conducted in Europe and the United States (Atkinson et al., 2014; Crippa et al., 2016), where $PM_{2.5}$ levels are lower than those observed in India, giving rise to an uncertainty for health burden estimation. Future studies are expected to use local γ for India to estimate $PM_{2.5}$-related health burden. In addition to the linear exposure-response function used in this study, a logarithmic exposure-response function is also encouraged to provide additional estimate in future studies.

5. Conclusions

This study presents a seasonal analysis of the meteorological influences on $PM_{2.5}$ trends and related health burden in five Indian megacities during 2014–2021. From 2014 to 2021, $PM_{2.5}$ concentrations exhibit downward trends in all cities and seasons, ranging from -7.24 $\mu g\ m^{-3}\ yr^{-1}$ to $-0.29\ \mu g\ m^{-3}\ yr^{-1}$. Meteorology-driven $PM_{2.5}$ downward trends are in the range of $-6.51 \sim -0.36\ \mu g\ m^{-3}\ yr^{-1}$. Variations in meteorological conditions dominate $PM_{2.5}$ decreases in Delhi during summer/monsoon and Chennai/Mumbai/Delhi during winter; the meteorology-driven $PM_{2.5}$ trends contribute 65% ~ 105% of observed $PM_{2.5}$ decreases. Better ventilation condition, identified as the primary meteorological factor, facilitates $PM_{2.5}$ decrease. The premature deaths caused by short-term exposure to $PM_{2.5}$ pollution are further estimated. From 2014 to 2021, meteorological conditions are favorable for reducing $PM_{2.5}$-related deaths in 85% of cities and seasons, and dominate decreases in $PM_{2.5}$-related deaths in 25% of cities and seasons. In Delhi during winter, the meteorology-driven decreasing trend of -127.12 deaths yr^{-1} even exceeds observed trend of -94.87 deaths yr^{-1}.

The $PM_{2.5}$ air quality and related health burden in India have been improved and alleviated a lot since 2014. Anthropogenic emissions exert positive effects on air quality, confirming the effectiveness of pollution control measures implemented in India in recent years. However, meteorological influences can't also be neglected. Our study creatively provides an estimation of meteorology-driven $PM_{2.5}$ trends and related health burden, and shows that meteorology causes $PM_{2.5}$ decreases in all cities and seasons. We also find, quite interestingly, Delhi in winter suffers from the severest $PM_{2.5}$ pollution, along with the maximum meteorology-driven $PM_{2.5}$ downward trend. Future chemical transport models are expected to provide clearer explanation for the considerable meteorological impact in Delhi during winter.

Table 2
Trends calculated with Least Square Method (LSM) and Mann-Kendall and Theil-Sen (MK-TS) method in five cities and four seasons.

City	Season	Obs_$PM_{2.5}$		Met_$PM_{2.5}$		Emis_$PM_{2.5}$	
		LSM	MK-TS	LSM	MK-TS	LSM	MK-TS
Chennai	Summer	**-1.87**	**-2.26**	**-0.68**	-0.63	**-1.19**	**-1.12**
	Monsoon	**-2.09**	**-1.96**	**-0.71**	**-0.67**	**-1.38**	**-1.47**
	Post-monsoon	**-2.40**	-1.82	-1.55	-1.18	-0.86	-1.17
	Winter	**-1.45**	**-1.35**	**-1.45**	-1.39	+0.01	+0.06
Kolkata	Summer	**-2.61**	**-2.65**	-1.49	-1.91	-1.12	-1.22
	Monsoon	**-1.71**	**-1.77**	-0.47	-0.29	**-1.24**	**-1.26**
	Post-monsoon	-1.93	-2.76	-1.21	-2.54	-0.72	-0.25
	Winter	-2.53	**-3.26**	-0.47	-0.84	**-2.06**	**-2.19**
Hyderabad	Summer	**-2.39**	**-2.62**	-0.78	-0.53	**-1.61**	**-1.43**
	Monsoon	**-2.83**	**-2.90**	**-1.34**	**-1.24**	**-1.49**	**-1.61**
	Post-monsoon	**-2.74**	**-2.56**	-1.69	-1.36	**-1.05**	**-1.04**
	Winter	-0.29	-0.23	-0.36	-0.19	+0.07	-0.13
Mumbai	Summer	**-3.82**	**-4.14**	-0.42	-0.61	**-3.40**	**-3.47**
	Monsoon	**-1.26**	**-1.21**	-0.38	+0.13	-0.88	**-1.17**
	Post-monsoon	-2.80	-2.50	-1.99	-1.81	-0.81	-0.62
	Winter	-2.32	-1.91	**-2.43**	-2.14	+0.11	+0.29
Delhi	Summer	**-3.49**	**-3.14**	**-2.35**	**-2.09**	-1.14	-0.76
	Monsoon	**-4.98**	**-2.52**	**-3.22**	**-2.89**	-1.77	+0.17
	Post-monsoon	-0.59	+0.67	-5.43	-4.14	+4.84	+6.53
	Winter	**-7.24**	**-7.38**	**-6.51**	**-5.50**	-0.73	+0.17

Values in bold fonts are statistically significant at the 90% confidence level. Values in red fonts represent trends with large discrepancies calculated by two methods.

CRediT authorship contribution statement

Xueqing Wang: Writing – original draft, Validation, Investigation, Formal analysis. **Jia Zhu:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Ke Li:** Writing – review & editing, Validation, Resources. **Lei Chen:** Writing – review & editing, Funding acquisition, Conceptualization. **Yang Yang:** Validation, Investigation. **Yongqi Zhao:** Validation, Investigation. **Xu Yue:** Validation, Resources. **Yixuan Gu:** Validation, Resources. **Hong Liao:** Resources, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.atmosres.2024.107548.

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