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Impact of acute exposure to ambient $PM_{2.5}$ on non-trauma all-cause mortality in the megacity Delhi

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HIGHLIGHTS

- Novel use of high-resolution (1-km) satellite data to study acute impact of $PM_{2.5}$ exposure in Delhi.
- The impact on all-cause mortality is two-fold higher in winter than in summer.
- Spatially disaggregated exposure of $PM_{2.5}$ exhibits a higher effect on mortality.

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ABSTRACT

Exposure to ambient fine particulate matter ($PM_{2.5}$) is the largest environmental health risk in India. All previous studies in India focused on PM_{10} exposure for acute impact assessment; even the single study examining the $PM_{2.5}$ acute exposure impact used data from a single site. Here we estimated the impact of acute $PM_{2.5}$ exposure on non-trauma all-cause mortality in the megacity Delhi using a quasi-Poisson regression model and satellite-derived high-resolution (1-km) exposure data. Our satellite-$PM_{2.5}$ dataset was calibrated and validated against coincident measurements from ground-based reference-grade monitors. This allowed us to minimize exposure misclassification, which otherwise would have happened due to reliance on limited ground-based monitoring sites with a large spatial gap. The annual average (median) $PM_{2.5}$ exposure (with interquartile range) during this period was 108.5 (63.5–133.6) μg/m^3. We found a 0.52% (95% confidence interval, CI: 0.42–0.62%) increase in non-trauma all-cause mortality for every 10 μg/m^3 increase in 6-days cumulative $PM_{2.5}$ exposure with a relatively higher impact on men (0.57%, 95% CI: 0.46–0.69%) than on women (0.52%, 0.38–0.65%). The impact of $PM_{2.5}$ was almost two-fold higher in winter (0.55%, 0.45–0.66%) per 10 μg/m^3 increase in $PM_{2.5}$ than in summer (0.29%, 0.14–0.45%). The district-level aggregated 6-days cumulative $PM_{2.5}$ exposure had the largest impact on mortality (1.10%, 0.84–1.35%). The impact of acute exposure to $PM_{2.5}$ on all-cause mortality was larger than that of PM_{10} exposure (from previous studies). Our study adds to the global evidence pool, fills the critical gap of evidence of acute $PM_{2.5}$ exposure impact on mortality in India, and most importantly, demonstrates the significance of disaggregated exposure assessment using satellite data to reduce exposure misclassification in health impact studies, particularly in data-poor regions.
Main finding: We estimate a 0.52% increase in all-cause mortality for every 10 μg/m^3 rise in short-term $PM_{2.5}$ exposure with a two-fold higher impact in the winter than in the summer and a higher impact on male (0.57%) than on female (0.52%) in the megacity Delhi.

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1. Introduction

Exposure to ambient fine particulate matter ($PM_{2.5}$) has been identified as the largest environmental health risk globally (Cohen et al., 2017; Pope et al., 2020). Regionally, the South Asian region carries the highest burden of $PM_{2.5}$, with only 6 out of 355 cities meeting the World Health Organization (WHO) annual ambient air quality guideline (AQG) of 10 $\mu g/m^3$ (World Air Quality Report, 2019). Amongst the top 30 most polluted cities in the world in 2019, 21 were located in India, where ambient $PM_{2.5}$ exposure has been identified as one of the leading health risk factors (Dandona et al., 2017). Nearly three-fourths of the population was exposed to $PM_{2.5}$ level exceeding the national ambient air quality standard (NAAQS) of 40 $\mu g/m^3$ in 2017, with the highest exposure observed in megacity Delhi (Balakrishnan et al., 2019).

In the last two decades, several policy measures were implemented in Delhi to curb air pollution. The conversion of the city's public transport from diesel to compressed natural gas (CNG) in 2002–2003 initially improved the air quality (Narain and Krupnik, 2007). However, the benefit could not be sustained due to various factors, including a rapid rise in non-CNG vehicles and emissions from other sources. Later, a graded response action plan (GRAP) was implemented in 2018 to control the high pollution episodes in Delhi. The most recent and vital policy attempt has been in the form of the National Clean Air Program (NCAP) in 2019, which has set a target to reduce $PM_{2.5}$ and PM_{10} concentrations by 20–30% by 2024 relative to 2017. With one year of NCAP, significant progress is seen in terms of an increase in the number of air quality monitoring stations in the region.

However, since the year 2000, the ground-based monitoring sites developed and maintained by the Central Pollution Control Board (CPCB) measured only PM_{10} (particulate matter smaller than 10 μm). Using these data, Cropper et al. (1997) reported a 0.23% increase in mortality with a 10 $\mu g/m^3$ increase in short-term PM_{10} concentration. In the PAPA study, a 0.15% increase in all-cause non-accidental mortality was found for a 10 $\mu g/m^3$ increase in short-term PM_{10} exposure in Delhi (Rajarathnam et al., 2011). A similar study was conducted by Maji et al. (2017) to examine all-cause mortality associated with a suite of pollutants (PM_{10}, NO_2, SO_2, and O_3). A short-term increase in PM_{10} was associated with a higher risk of respiratory and cardiovascular morbidity (Jayaraman and Nidhi, 2008; Maji et al., 2018) in Delhi. Exposure to air pollution in Delhi was also found to contribute to excess cases of respiratory, cardiovascular, total mortality, and chronic obstructive pulmonary disease-related hospital admissions (Kumar and Mishra, 2018; Nagpure et al., 2014) and asthma attacks (Guttikunda and Goel, 2013). The previous three developed their own risk functions whereas, the latter two estimated air pollution attributed health effects based on previously used standardized concentration-response functions. These studies undoubtedly demonstrated the health impacts of air pollution exposure in Delhi. However, all these studies were restricted to the association between PM_{10} and gaseous pollutants with daily mortality counts, and only one study so far has examined the impact of $PM_{2.5}$ in India, but not for the megacity Delhi (Singh et al., 2021).

The primary reason for this gap could be attributed to the sparse ground-based data on $PM_{2.5}$ (Martin et al., 2019). The CPCB monitoring network started measuring $PM_{2.5}$ in Delhi in 2009, but the network expanded only after 2016, limiting the use of a handful of ground-based monitoring sites for a time-series study. Previous studies (e.g., Rajarathnam et al., 2011; Singh et al., 2021) had to rely on a limited number of ground-based observations for assigning exposure, thereby posing a greater uncertainty in exposure misclassification because exposure to $PM_{2.5}$ varies widely within the city (Jain et al., 2017). Balakrishnan et al. (2013) highlighted the role of spatial disaggregation in minimizing exposure misclassification for time-series studies in Indian cities.

To fill this knowledge gap, a need for a longer record of the $PM_{2.5}$ database was recognized, for which satellite-based $PM_{2.5}$ data was generated at 50-km resolution (Dey et al., 2012). Subsequent advancements in satellite algorithm allowed developing $PM_{2.5}$ database at a 1-km resolution at a city scale (Chowdhury et al., 2019), and the data was used to map the $PM_{2.5}$ build-up in Delhi during 2001–2015. The analysis discerned the two major pollution peaks in Delhi – the first during mid-Oct-early Nov and the second during late Dec-early Jan. The first peak was associated with meteorological changes and transport of pollution from upwind states affected by crop residue burning, and the latter affected by meteorology and local emissions. However, no attempt was ever made in utilizing such satellite data for time series analysis on the health effects of $PM_{2.5}$ in Delhi or anywhere else in India. This study addressed this issue by examining the impact of short-term $PM_{2.5}$ exposure on daily non-trauma all-cause mortality in the megacity Delhi between 2013 and 2017.

2. Methods

2.1. Mortality data

The daily mortality data were collected from the Municipal Corporation Headquarters, Civic Centre, New Delhi. The Municipal Corporation of Delhi (MCD) records and compiles zone-wise births and deaths within the jurisdictional boundaries of its three administrative subdivisions, North, East, and South. The area under municipal corporation constitutes approximately 94.2% of the geographical location and accounts for about 75.53% of the total registered deaths in Delhi. (Government of NCT of Delhi, 2020).

The mortality data were received as zone-wise daily individually registered deaths with the deceased's demographic and residential details. Each registered death datum carried details of age, sex, and the latest residential address of the deceased, along with the date and place of death. The deceased's details were exclusively used for research purposes, maintaining strict confidentiality about personal information. Each deceased's residential address was used to extract an identifier zip code for ambient $PM_{2.5}$ exposure assignment at varying spatial scales. The reason to use the residential address and not death address for exposure assignment, unlike past studies (Balakrishnan et al., 2013), was because it was the most consistent information in the death records.

In the raw data received from the MCD, the death events carried the cause of death information, but this was not medically classified according to the international classification system. However, the exclusive cases of accident and suicide were exclusively identifiable. Hence we decided not to use the cause-specific mortality and restrict the analysis to all-cause non-trauma mortality. The raw data was cleaned to exclude deaths attributed to trauma such as accidents, injuries, and suicide. The data of the deceased with residential addresses lying exclusively inside the geographical boundaries of NCT Delhi were used in the analysis. Hereafter, 'all-cause mortality' implies non-trauma all-cause mortality in our results and interpretation.

2.2. Ambient $PM_{2.5}$ exposure

The study used the satellite-based $PM_{2.5}$ exposure that was calibrated against the ground-based measurements in this study. Surface $PM_{2.5}$ concentrations were estimated by converting aerosol optical depth (AOD) from Moderate Resolution Imaging Spectroradiometer (MODIS). MODIS has various algorithms to retrieve AOD at 10-km, 3-km, and 1-km spatial resolutions. In this work, we analyzed the AOD product retrieved using Multiangle Implementation of Atmospheric Correction (MAIAC) algorithm at 1-km resolution (Lyapustin et al., 2018) and converted it to $PM_{2.5}$ using spatially and temporally varying scaling factors (i.e., the ratio of $PM_{2.5}$/AOD) from Modern-Era Retrospective analysis for Research and Applications version 2 (MERRA-2) data (Buchard et al., 2017). The MERRA-2 derived scaling factors were calibrated against that from the ground-based measurements of CPCB sites following Bali et al. (2021). The satellite-derived instantaneous $PM_{2.5}$ (representative of the satellite overpass time 10:00 a.m. to 2:00 p.m.) was converted to 24-hr average $PM_{2.5}$ using a diurnal scaling factor

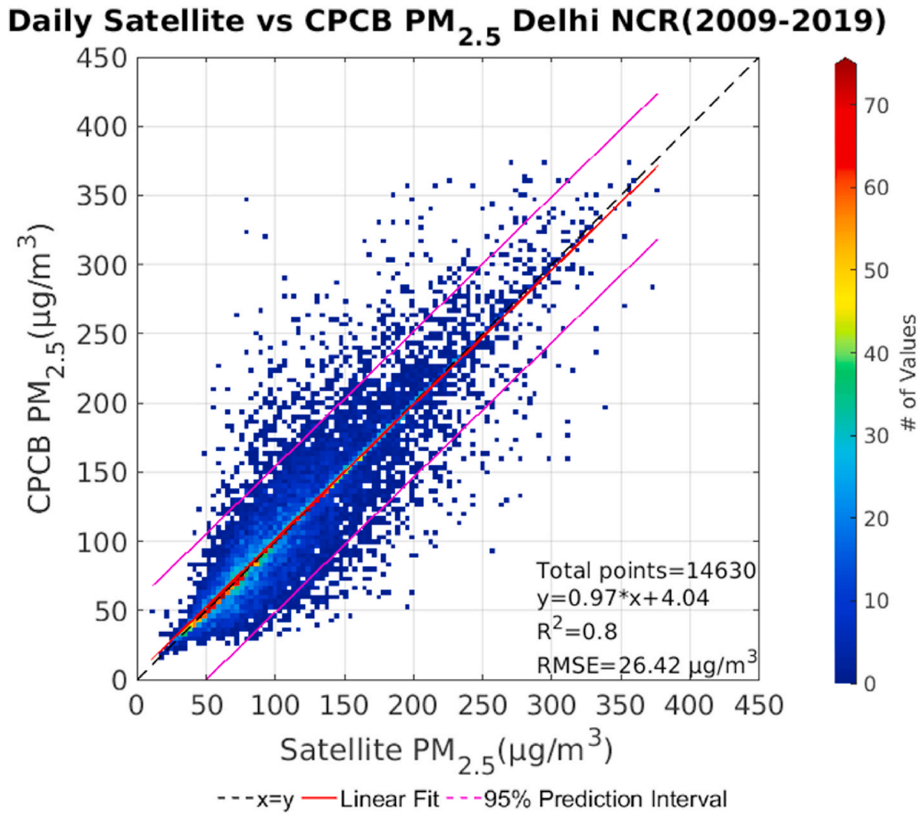

Fig. 1. Regression statistics of 24-hr averaged $PM_{2.5}$ in the NCT Delhi derived from satellite data and CPCB networks over the period 2009–2019.

(i.e., the ratio of 24-hr $PM_{2.5}$/$PM_{2.5}$ during the satellite overpass) from MERRA-2.

The final retrieved 24-hr $PM_{2.5}$ concentration showed a high correlation ($R = 0.89$) and low (26.4 μg/m^3) root mean square error (RMSE) against the data from the CPCB network in Delhi (Fig. 1). The strong correlation and low RMSE for satellite-derived PM $_{2.5}$ over NCT Delhi, our study location, propelled us to use the data further. During our study period, the population-weighted $PM_{2.5}$ exposure ranged from 17 to 583 μg/m^3. More details about the retrieval of $PM_{2.5}$ from satellite data, calibration, and validation are available in Dey et al. (2020). The satellite-derived $PM_{2.5}$ product is accessible from our data portal (www.saans.co.in).

The satellite data was used to carry out exposure assignment to death events at three spatial scales – (1) aggregated over NCT Delhi, (2) disaggregated at the district level in NCT Delhi, and (3) at the zip-codes in NCT Delhi. We used total daily deaths and average daily concentrations of $PM_{2.5}$ over Delhi NCT for the aggregated analysis. In the spatially disaggregated analysis, each death event was identified at two sub-spatial scales, i.e., district and zip-code, using the deceased's residential address and further used for exposure assignment at that particular scale.

For assigning the $PM_{2.5}$ exposure to a particular death event at the zip-code level, we estimated the geographical coordinate of each death event from their respective zip-code using Google Map's API. We then extracted the surface level $PM_{2.5}$ at all grids within 2-km by 2-km area centering the geographical coordinate and assigned its average as a proxy representative of the $PM_{2.5}$ exposure to the respective death event. This process was repeated for all the death events at a 24-hr scale. Similarly, we spatially extracted the $PM_{2.5}$ data for all grid points within the districts of NCT Delhi and assigned that exposure to daily death events in various districts.

2.3. Meteorological data

The daily meteorological data of mean temperature and relative humidity (RH) over NCT Delhi were estimated from the ERA-Interim data assimilation system (Dee et al., 2011). Since this data was not a direct measurement, it was bias-corrected with daily meteorological data of the Indian Meteorological Department (IMD) - Safdarjung Airport Station, New Delhi. The IMD data was segregated month-wise; each month's data were divided into five percentile bins based on ERA-Interim data. In each percentile bin, the median fraction, i.e., IMD station data median divided by Era data median, was calculated to get a weighted correction factor. The weighted correction factor was then used on the coincident Era-Interim data to get the bias-corrected temperature and relative humidity data for NCT Delhi.

2.4. Model specifications

The study used city level daily average $PM_{2.5}$ concentration to estimate the acute effects of ambient $PM_{2.5}$ exposure on daily all-cause non-trauma mortality in the megacity Delhi. The Generalized Additive Model (GAM) or the semi-parametric regression technique is the most commonly used technique to estimate short-term effects of air pollution on health outcomes of interest (Hastie and Tibshirani, 1990; Ruppert et al., 2003). This is a preferred technique as appropriately chosen degrees of freedom not only can remove nonlinear confounding but also resolve multicollinearity issues by correlated weather parameters. A semiparametric quasi-Poisson regression model was chosen to account for overdispersion in a Poisson regression model. The detailed estimation algorithm of the quasi-Poisson model is described in McCullagh and Nelder (1989), and restricted maximum likelihood estimation of semi-parametric generalized linear model details are described in Wood (2011) and Hastie and Tibshirani (1990). The entire quasi-Poisson semiparametric regression algorithm was implemented in R-package 'mgcv' by the 'gam' function. The model was fitted by R version 4.0.3 (R

Table 1
Summary statistics of $PM_{2.5}$, meteorological and non-trauma mortality (counts) during the study period.

Variables	#Days	Mean	SD	Median	IQR	Min	Max
$PM_{2.5}$ (Delhi Average; Unit: μg/m^3)	1232	108.5	68.8	89.9	(63.5133.6)	17.1	583.4
Relative Humidity (%)	1795	63.4	16.2	66.3	(53.6,75.2)	20.2	99.4
Temperature (°C)	1795	25.8	6.9	28.5	(19.6,31.1)	7.9	39.9
Total Mortality	1795	198	34	194	(176,219)	29	319
Mortality: Male	1795	119	22	117	(105,133)	19	200
Female	1795	78	15	77	(68,88)	10	128
Mortality: Age <5y	1795	10	4	10	(8,13)	1	52
Age:5 - 44y	1795	35	8	35	(30,40)	4	66
Age:45-64y	1795	61	12	61	(54,69)	7	108
Age ≥65y	1795	91	21	88	(76,105)	13	167

Core Team, 2019). The core model that was fitted is as follows:

$$\log\{E[(Mortality)_i]\} = \alpha + \beta(PM_{2.5})_t + f(t) + f(temp_t) + f(rh_t), \quad (1)$$

where, $(Mortality)_t$ and $(PM_{2.5})_t$ are the daily mortality and average $PM_{2.5}$ levels in Delhi on a day t. The effects of known confounders, such as time trend (t), temperature (temp), and RH (rh), were modelled through f (.), using penalized cubic smoothing spline (Hastie and Tibshirani, 1990; Ruppert et al., 2003). A generalized cross-validation (GCV) score-based data-driven algorithm was used to determine the degrees of freedom. The above model was compared by 'deviance explained' and precision of regression coefficient (coefficient of variation) for different choices of exposure metrics, such as single-day average exposure to up to 7 days cumulative average exposure. The 6-days cumulative average exposure was found to be the most robust with respect to the above-mentioned criteria and therefore considered as a core exposure metric for the core model in our subsequent analysis.

Further, spatially disaggregated models at district and zip-code levels were also explored using generalized additive fixed as well as mixed-effects model. The fixed-effects model was fitted with a separate intercept for each subdivision in equation (1). But a separate random intercept of Gaussian distribution with zero mean and identical variance for each of the sub-division was included instead of a fixed intercept in equation (1) according to the standard mixed-effects model for cluster data. The mixed model should provide a much stable estimate reducing the number of parameters in the model to be estimated.

2.5. Sensitivity analysis

A detailed sensitivity analysis was carried out with the core model (equation (1)) to assess the variation of effect size over different choices of model parameters such as degrees of freedom and lag exposure. We explored 3–8 degrees of freedom/year for time and 1–5 degrees of freedom/year for the temperature component. The estimates were also compared for 0 to 6-days lag exposure of $PM_{2.5}$ and 0–5 days lag for temperature. We examined the effect modification by season, including $PM_{2.5}$ and season interaction on daily mortality. Two seasons were assumed—one from September through February and the other from March through August. We also estimated the effect size of $PM_{2.5}$ on mortality stratified by age (0–4y, 5–44y, 45–64y, and ≥65y) as well as gender. Estimates were explored at varying spatial scales of $PM_{2.5}$ exposure assignment. The data were analyzed using R statistical software version 4.0.2 (R Core Team, 2019). A 5% type-I error was accepted across all statistical tests during the analysis, and estimates were reported with a 95% confidence level.

3. Results

3.1. Data summary

During the study period (2013–17), the average daily $PM_{2.5}$ concentration ranged from 17 to 583 μg/m^3 (Table 1). The median

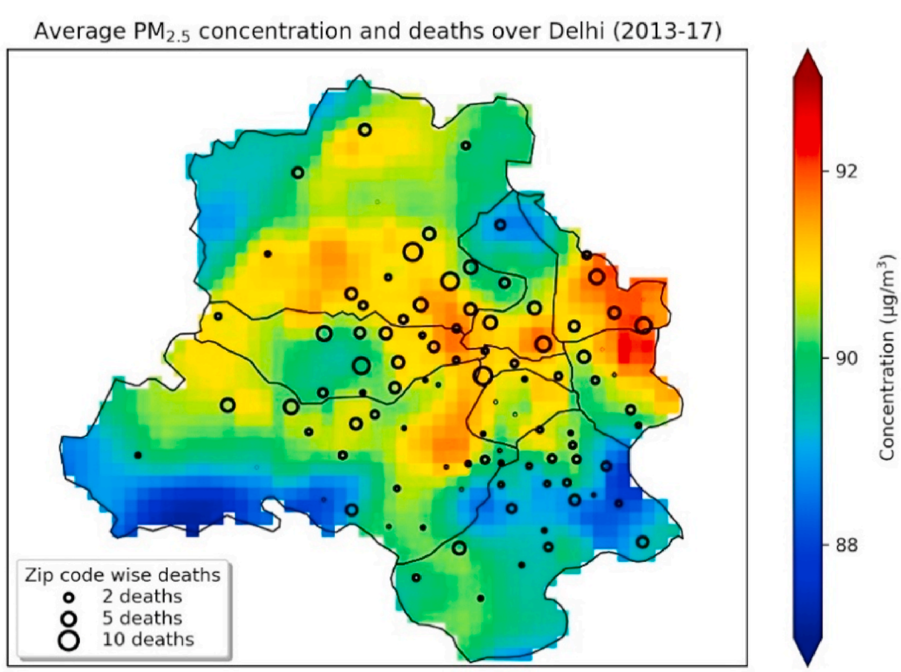

Fig. 2. Spatial plot of five years (2013–17) average PM $_{2.5}$ concentration and mortality count (represented as a circle) at each zip-code over Delhi.

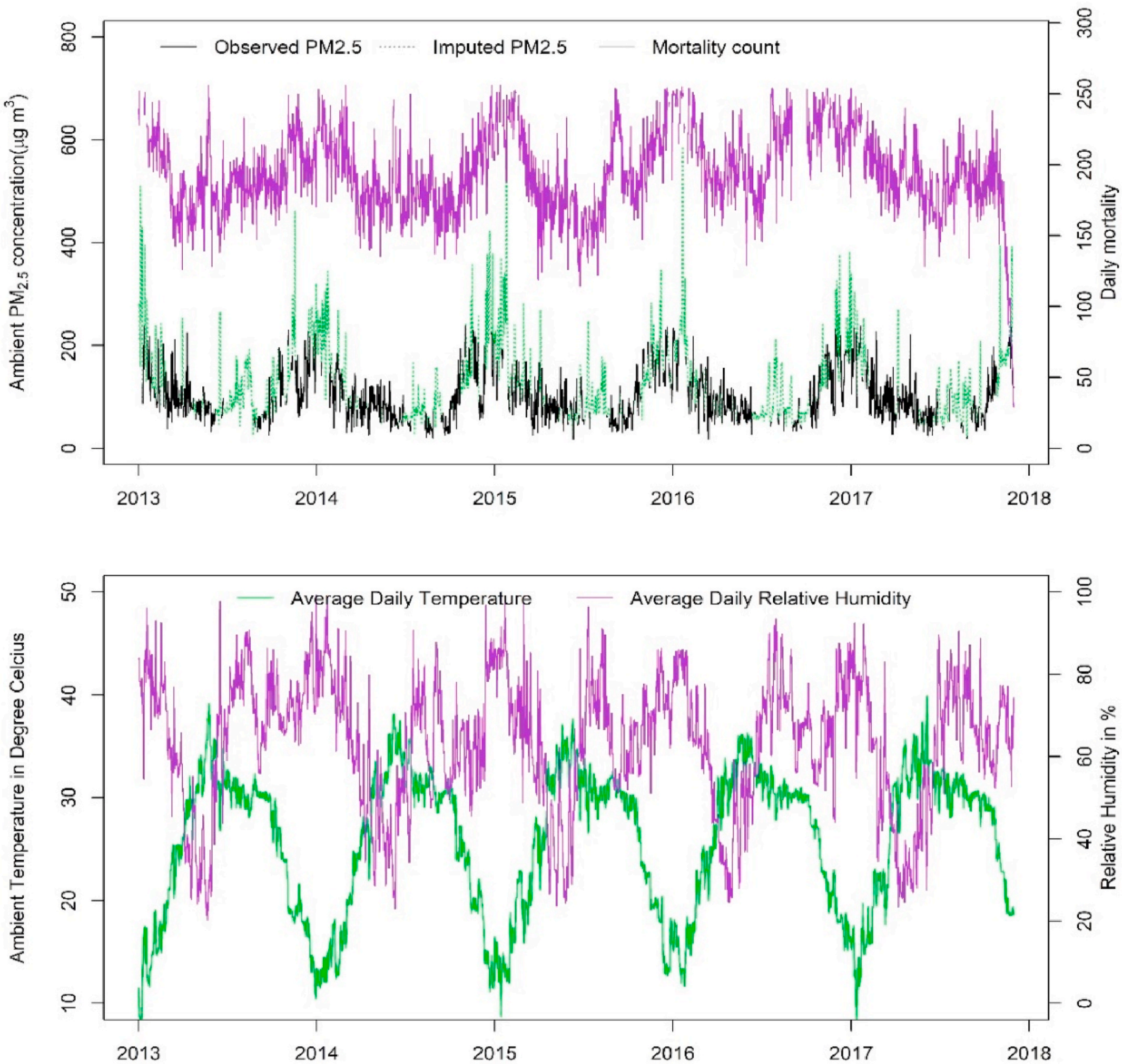

Fig. 3. Time-series plot of (Top) daily $PM_{2.5}$ exposure (satellite-derived and imputed) and daily mortality count between 2013–17 and (Bottom) daily temperature and RH in NCT Delhi between 2013–17.

concentration of 108 μg/m^3 points to high pollution levels, more than 2.5 times the national ambient air quality standard (NAAQS) of 40 μg/m^3. The daily mortality in Delhi NCT ranged from 29 to 319 deaths, with the highest average deaths per day recorded among males (119) and 65 years and above age group (91). The data above the 98th percentile for $PM_{2.5}$ and mortality were both excluded from the study to avoid extreme value effects in estimations. In terms of meteorological conditions, the daily average temperature in Delhi during the study period ranged from 7.9 to 39.9 °C, whereas the relative humidity in the period ranged from 20.2 to 99.4% (Table 1).

3.2. *Impact of short-term $PM_{2.5}$ exposure on mortality*

The spatial gradient of $PM_{2.5}$ compared against the spatial distribution of zip-code wise daily average mortality count over NCT Delhi during the study period are depicted in Fig. 2. The centroid of the city and the north-eastern part showed a good spatial agreement between $PM_{2.5}$ level and daily mortality count. The temporal agreement between the $PM_{2.5}$ and mortality was also observed (Fig. 3). A clear seasonal pattern and inverse association observed between temperature and relative humidity are also visualized in Fig. 3.

The core model was selected out of the best estimates with various exposure metrics ranging from same-day exposure to 6 days lag exposure and cumulative average exposure up to 7 days (Table 2). The core model was selected at 6 days cumulative average exposure on the basis of lowest CV (19%) and highest deviance explained (~61.2%) among all alternate models. The core model estimated 0.52% (95% confidence interval, CI: 0.42–0.62%) increase in mortality at every 10 μg/m^3 increase in $PM_{2.5}$. The GCV based estimated degrees of freedoms used in the core model were 6, 4, and 2 per year for a time, temperature, and relative humidity, respectively.

A detailed sensitivity analysis was performed to check the robustness of the core model. Since the original satellite-derived estimations of $PM_{2.5}$ concentration had some data gaps, we attempted to fill the missing daily average $PM_{2.5}$ time series over Delhi by a model that predicted $PM_{2.5}$ by time trend, temperature, and RH in a semi-parametric structure. The imputed $PM_{2.5}$ series estimated 0.51% (0.40–0.62%) increase in mortality per 10 μg/m^3 increase in $PM_{2.5}$ concentration. Our sensitivity analysis showed an insignificant impact on effect estimates using the satellite-derived and imputed exposure.

Table 2
Mortality effect estimate analysis with alternate choice of exposure metrics *: Core model (df: time ≈6/y; temperature ≈4/y; relative humidity ≈ 2/y).

Exposure Metric	% increase in daily mortality per 10 μg/m^3 increase in $PM_{2.5}$ (95% CI)	p-value	Deviance explained	Coefficient of variation (slope)
Same day	0.33 (0.25–0.40)	<0.001	0.6100	0.22
1-day lag	0.21 (0.13–0.28)	0.005	0.5900	0.35
2-days lag	0.10 (0.03–0.18)	0.16	0.5780	0.71
3-days lag	0.18 (0.11–0.26)	0.013	0.5900	0.40
4-days lag	0.16 (0.08–0.23)	0.034	0.5790	0.47
5-days lag	0.16 (0.08–0.24)	0.029	0.5810	0.45
6-days lag	0.10 (0.02–0.17)	0.173	0.6100	0.73
2-days cumulative average	0.36 (0.2–0.44)	<0.001	0.6050	0.22
3-days cumulative average	0.37 (0.29–0.46)	<0.001	0.6040	0.22
4-days cumulative average	0.46 (0.37–0.55)	<0.001	0.6090	0.19
5-days cumulative average	0.49 (0.39–0.58)	<0.001	0.6110	0.19
*6-days cumulative average	0.52 (0.42–0.62)	<0.001	0.6120	0.19
7-days cumulative average	0.50 (0.40–0.61)	<0.001	0.6100	0.20

Table 3
Sensitivity analysis results on core model using 6 days cumulative average $PM_{2.5}$ exposure.

Model	% increase in daily mortality/10 μg/m^3 increase in $PM_{2.5}$ (95% CI)	*p-Value*
Core model	0.52 (0.42–0.62)	<0.001
$PM_{2.5}$ imputed	0.51 (0.40–0.62)	<0.002
Summer	0.29 (0.14–0.45)	0.05
Winter	0.55 (0.45–0.66)	<0.001
Female	0.52 (0.38–0.65)	0.001
Male	0.57 (0.46–0.69)	<0.001
Age<5y	−0.08 (−0.42–0.26)	0.812
Age: 5-44y	0.52 (0.33–0.71)	0.005
Age: 45-64y	0.36 (0.21–0.51)	0.01
Age≥65y	0.70 (0.57–0.84)	<0.001
Disaggregated at district	**1.10 (0.84–1.35)**	**<0.001**
Disaggregated at zip code	**0.66 (0.51–0.82)**	**<0.001**

With satellite-based estimates at a fine spatial resolution of 1 × 1 km, we had scope to go at varied spatial scales in exposure metric. We leveraged this advantage to check the sensitivity of the core model at the district and pin-code levels. Interestingly, the effect estimate increased significantly with spatially disaggregated exposure metric. A spatially disaggregated exposure metric at district level estimated 1.10% (0.84–1.35%) and at zip code level estimated 0.66% (0.51–0.82%) increase in mortality per 10 μg/m^3 increase in $PM_{2.5}$ concentration, respectively (Table 3).

Along with distributed lag model for exposure metric, as discussed in the core model selection section, we also checked the variation in effects of $PM_{2.5}$ on daily mortality for different single lag days in the temperature. A very less sensitivity of the effect estimates was observed for temperature lags from 0 to 5 days (Fig. 4). The sensitivity of the estimates over choices of different degrees of freedom of time and temperature were also explored. The resulting effect estimate varied from 0.40% (0.30–0.51%) to 0.47% (0.37–0.57%) per 10 μg/m^3 of $PM_{2.5}$ exposure as time degrees of freedom varied from 4 to 8 per year. However, choice of temperature degrees of freedom, 1 to 5 per year, did not show any appreciable change in our effect estimate.

3.3. Effect modification and dose-response curve

An effect modification by age and gender was investigated by stratified analysis. The estimate was relatively higher among men (0.57%, 0.46–0.69%) than women (0.52%, 0.38–0.65%) for every 10 μg/m^3 increase in $PM_{2.5}$ exposure. The age group above 65 years showed a higher effect size (0.70%, 0.57–0.84%) followed by the age group 5–44 years (0.52%, 0.33–0.71%). However, the under 5 years age group did not show any significant effects of $PM_{2.5}$ on daily mortality. The interaction between season and $PM_{2.5}$ exposure was found to be significant (Table 3). The impact of $PM_{2.5}$ exposure was almost two-fold higher in winter months (0.55%, 0.45–0.66%) than in summer (0.29%, 0.14–0.45%).

The potential nonlinear association between daily mortality and $PM_{2.5}$ exposure was investigated by allowing $PM_{2.5}$ in equation (1) to be a penalized cubic spline. The 6-days cumulative average exposure metric exhibited a clear nonlinear association (Fig. 5). The curve is monotonically increasing after 50–60 μg/m^3 average 6-days cumulative exposure. However, the decreasing trend at the beginning is the inclusive absence of sizable data in the lower range of exposure. Though the densest exposure part of the exposure range shows a more or less linear pattern (50–200 μg/m^3), a single-day exposure shows a perfect linear association (Fig. 5).

4. Discussion and conclusions

In this study, we examined the acute impact of $PM_{2.5}$ exposure on all-cause non-trauma mortality in NCT Delhi. To the best of our knowledge, this was the first such attempt in estimating the effect of acute exposure to $PM_{2.5}$ on daily mortality in India using satellite-based exposure data. We report all effect modification and sensitivity tests on the core model at aggregate-city level exposure scale. We still emphasise that the disaggregated exposure estimates are two fold higher than the aggregate city level exposure model. We would like to note here that a stratified analysis at the disaggregated scale was almost impossible because of lower death counts at the district and zip code level. Though an alternative individual-level logistic model could be opted, controlling exposure misclassification at an individual level could be a bigger challenge from the satellite data.

The previous attempt to study acute $PM_{2.5}$ exposure impact on all-cause mortality in Varanasi (1.06%, 0.45–1.66%) was estimated using ground-based data (Singh et al., 2021), assuming that the exposure level (103.6 μg/m^3, 25th-75th percentile ranges: 37.1–145.3 μg/m^3) across the city was uniform and therefore can be represented by a single monitoring site. Our core model estimate in Delhi (0.52%, 0.42–0.62%) was lower than the estimate reported in Varanasi, but district-level disaggregated model estimates almost similar effect of $PM_{2.5}$ exposure on mortality (1.10%, 0.84–1.35%). Earlier, the satellite-based analysis revealed large spatial variability in $PM_{2.5}$ within the city of Varanasi (Jain et al., 2017). This suggests that spatially aggregated analysis over-estimates the impact, most probably due to exposure misclassification, and therefore, a disaggregated analysis is desirable.

Our results with effect estimates for $PM_{2.5}$ exposure came out three-times higher than the previous effect estimates for PM_{10} exposure in Delhi - 0.15% (0.07–0.23%, Rajarathnam et al., 2011), 0.14% (0.02%–0.26%, Maji et al., 2017) and 0.23% (Cropper et al., 1997). The higher effect estimate from $PM_{2.5}$ exposure affirmed greater biological repercussions of finer sub-components of particulate matter pollution in the same population and geographical location. However, we want to mention that we could not control our estimates for other pollutants such as NO_2 and SO_2 due to the unavailability of spatially disaggregated data, and this could enhance our effect estimates.

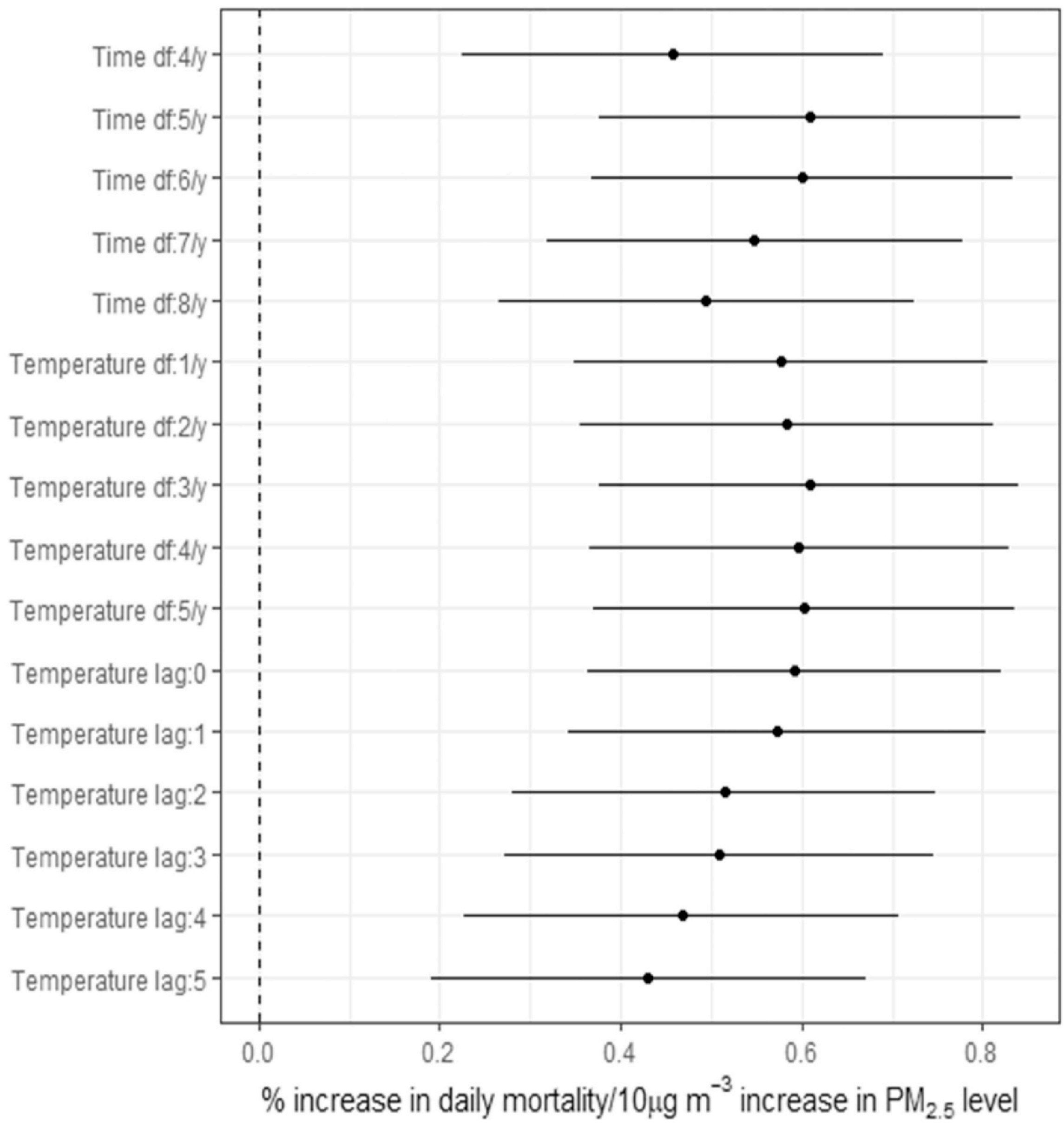

Fig. 4. A comparison of effect estimates from sensitivity analysis with choices of df for time and temperature lag over days.

Our results of 0.52% (0.42–0.62%) increase in all-cause mortality due to a 10 μg/m^3 increase in $PM_{2.5}$ exposure were found to be close with the effect estimates in city-specific time-series studies based in Guangzhou, China (0.55%, 0.24–0.86%), where the average daily $PM_{2.5}$ exposure was 40.5 μg/m^3 (Wu et al., 2018). The estimates in Seoul, South Korea (0.76%, 0.40–1.12%) where the daily exposure varied between 4.2 and 219 μg/m^3 (Bae, 2014), in Beijing, China (0.65%, 0.29–0.80%) where the mean$\pm$1σ exposure was 75 $\pm$ 54 μg/m^3 (Li et al., 2013) and in a meta-analysis with exposure data (varying between 5 and >100 μg/m^3) from 499 cities (0.68%, 0.59–0.77%; Liu et al., 2019) were slightly higher than our estimates for Delhi. However, our study on Delhi gave a higher effect estimate compared to the multicity meta-analysis on mainland China, including Hong Kong and Taiwan (0.36%, 0.26–0.46%), where $PM_{2.5}$ exposure varied in the range 39–177 μg/m^3 (Lu et al., 2015) and East Asia (0.38%, 0.21–0.55%) where $PM_{2.5}$ exposure varied in the range <25 to >60 μg/m^3 (Lee et al., 2015). A similar study in Beijing, China using satellite-based exposure ranging in 9–109 μg/m^3 (Liang et al., 2018), found a linear dose-response curve and a larger effect on lag days smaller than what we found for Delhi. One plausible explanation for these differences could be different exposure ranges and perhaps variation in $PM_{2.5}$ composition across the cities, which needs to be examined in detail.

The effect estimates from exposure to PM_{10} (previous studies) and $PM_{2.5}$ (this study) in the megacity Delhi were smaller than the effect estimates in the developed countries. A recent multicity time-series study in the USA estimated 1.18% (0.93, 1.44%) increase in all-cause mortality with a 10 μg/m^3 increase in 2-day averaged $PM_{2.5}$ concentration with seasonal effect (Dai et al., 2014). Another multi-community study in the USA, accounting for 1.3 million deaths, estimated 0.74% (0.41–1.07%) increase in all-cause mortality with 10 μg/m^3 increase in the previous day's $PM_{2.5}$ (Franklin et al., 2007). In European studies, the effect estimates from $PM_{2.5}$ exposure ranged from 0.8% (0.3–1.2%) in the Netherlands (Janssen et al., 2013) and 0.7% (0.1–1.6%) in a multicity analysis in France (Pascal et al., 2014).

Smaller effect estimates for Delhi where $PM_{2.5}$ exposure is manifold higher than in the developed countries (Apte et al., 2015) are consistent with previous studies demonstrating a stronger association between acute exposure to $PM_{2.5}$ and mortality in locations with lower annual

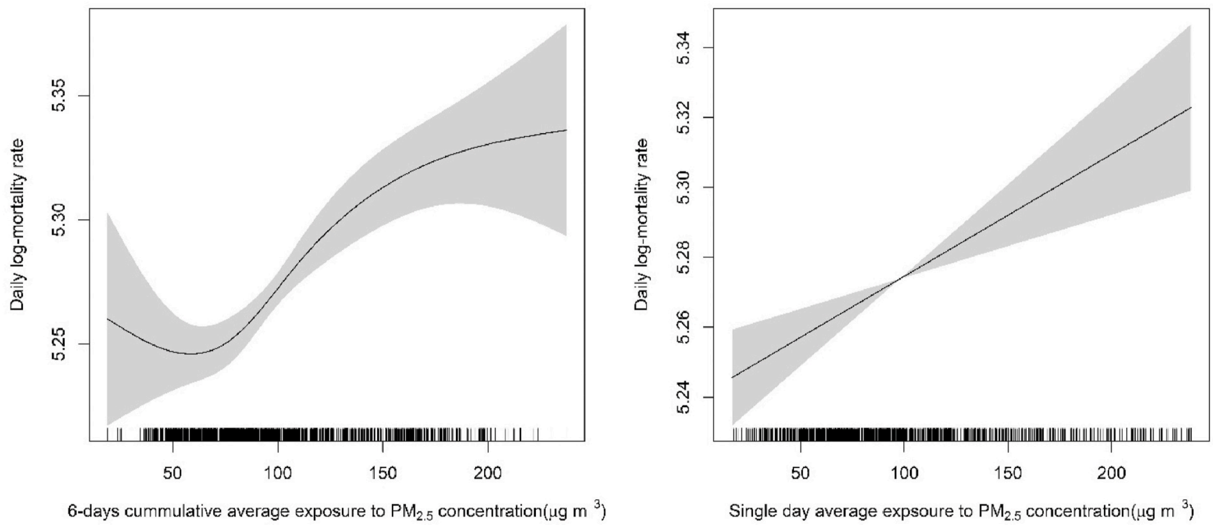

Fig. 5. Dose-response relationship for $PM_{2.5}$ adjusted for other confounders. Right panel dose-response curve based on the same day exposure metric, left panel the same curve estimated for 6 days cumulative average exposure, i.e., core model.

$PM_{2.5}$ concentrations (Liu et al., 2019). One plausible explanation for this could be the differential toxicity in $PM_{2.5}$ (Basagaña et al., 2015; Ostro et al., 2006). In Delhi, a large fraction of $PM_{2.5}$ is resuspended dust (Maji et al., 2017) and organic carbon, which may be of lower toxicity than the particles generated by fossil-fuel burning. Another possible hypothesis could be the variability of effect size over the gradient of exposure. The average daily exposure in Delhi is much higher than in those cities of developed countries. This plausible phenomenon could be explained with supporting evidence from time-series studies with uniform protocol in two cities, Delhi and Chennai in India (Rajaratnam et al., 2011 and Balakrishnan et al., 2013), with two extreme gradients of PM_{10} exposure. The Chennai estimate was almost 2-fold higher than Delhi estimate, with a relatively much lower PM_{10} exposure gradient across the city. This hypothesis needs to be tested with a multicity study in India that the Ministry of Environment, Forest, and Climate Change is currently planning to undertake.

More recently, measurements in Delhi and comparison with similar measurements from the developed countries by Puthussery et al. (2020) showed that particle mass and oxidative potential (a measure of toxicity) are not equivalent. Our results highlight the importance of exploring the impact of $PM_{2.5}$ components on mortality in the future, particularly in developing countries. We plan to address this issue as a follow-up to the present study.

The differential quality of civil registration data between developed and developing countries could also be a factor. The Indian mortality data, in terms of its completeness and representativeness, would not be at par with the robust registration systems of the developed countries. There may be a gender bias in death reporting too. This has, however, not been previously discussed in any other time-series study, and it is difficult to draw any conclusion at this point. The registered deaths under Municipal Corporation jurisdiction included both domiciliary and institutional deaths, and hence not compulsorily medically certified for the cause of death. This rendered the specific causes of death unreliable for any use in our analysis, and we had to restrict our analysis to all-cause mortality. The daily death records also had gaps in the information, such as place of death (institutional vs. non-institutional death), which did not allow us to include it as a proxy indicator of socio-economic condition as an effect modifier in our analysis. Since we focused here on the disaggregated analysis, we could not use a multi-pollutant mix model for our sensitivity analysis due to the lack of spatial data of other pollutants.

Finally, $PM_{2.5}$ exposure increased by more than 200 $\mu g/m^3$ in the dry season relative to the monsoon season in a short period of time (Chowdhury et al., 2019). Our results suggest that interventions during this peak season can result in a substantial health benefit. As various mitigation measures are being implemented across the country under the NCAP, our results can be useful for the policymakers to estimate the potential health benefits in a short-term reduction in $PM_{2.5}$ exposure in Delhi. The study can be replicated in other non-attainment cities and rural regions in India from where health data are made increasingly available, and exposure data are already generated (Dey et al., 2020).

CRediT authorship contribution statement

Pallavi Joshi: Conceptualization, Methodology, Formal analysis, Writing – review & editing, Writing – original draft. **Santu Ghosh:** Methodology, Formal analysis, Writing – review & editing. **Sagnik Dey:** Conceptualization, Methodology, Writing – review & editing, Writing – original draft, Funding acquisition. **Kuldeep Dixit:** Formal analysis. **Rohit Kumar Choudhary:** Formal analysis. **Harshal Ramesh Salve:** Writing – review & editing, Writing – original draft, Resources, Funding acquisition. **Kalpana Balakrishnan:** Writing – review & editing, Writing – original draft.

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.

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