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A Framework for City-Specific Air Quality Health Index: A Comparative Assessment of Delhi and Varanasi, India

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Abstract

Air quality index (AQI) is a crucial tool for communicating the health risks of air quality to the public. However, the current AQI in India does not consider the health impacts of exposure to air pollutants, necessitating the development of air quality health index (AQHI). Here, we proposed a framework for developing city-specific AQHI that better reflects local air quality and associated health risks using air pollution and health data from two polluted and densely populated cities in north India - Delhi and Varanasi (Delhi: 2013–2017; Varanasi: 2009–2016). We also constructed a pooled AQHI by combining data from both cities. Using concentrations of ambient fine particulate matter ($PM_{2.5}$), nitrogen dioxide, and ozone, we applied generalized additive models with a quasi-Poisson link, using daily mortality counts as the outcome, excluding suicide and accidental deaths. A 10 μg/m³ increase in $PM_{2.5}$ was associated with mortality increases of 0.17% (95% CI: 0.01-0.34) in Varanasi, 0.20% (95% CI: 0.1-0.29) in Delhi, and 0.16% (95% CI: 0.08-0.24) in the pooled model. The city-specific AQHI classified 21.8% of days in Delhi as 'Satisfactory' versus 18.2% by the pooled index, while 24.2% of days were 'Poor' compared to 30.1% under the pooled index. In Varanasi, 6.8% of days were 'Good' under the city-specific AQHI, compared to 9.3% by the pooled index, with 15.7% of days classified as 'Poor' versus 19.3% by the pooled index. Our results suggest that a single-pooled AQHI may misrepresent local air quality and associated health risks. Since AQHI values are derived from excess mortality risk estimates, a city-specific AQHI ensures a more accurate reflection of local pollution-related health impacts, supporting targeted public health interventions. We recommend accessibility of health data to enable developing AQHI for non-attainment cities in India and use it to track progress towards cleaner air.

Keywords

Air quality health index (AQHI), AQI, Multi-pollutant model, Mortality.

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1. Introduction

Exposure to ambient air pollution poses a significant hazard to human health, particularly among vulnerable populations such as children under five years of age and the elderly(Fuller *et al* 2022). Air pollution was responsible for 15% of all global fatalities among children under five years of age in 2021(Health Effects Institute. 2024). People in low- and middle-income countries (LMICs) are exposed to 1.3–4 times greater levels of ambient fine particulate matter ($PM_{2.5}$)(Health Effects Institute. 2024) and more than 80% of those living in LMICs are exposed to $PM_{2.5}$ concentrations exceeding the WHO 2021 guideline of 5 µg/m(Rentschler and Leonova 2023). In addition to ambient $PM_{2.5}$, exposure to other air pollutants such as nitrogen dioxide (NO_2), sulphur dioxide (SO_2), carbon monoxide (CO), ozone (O_3), etc. exhibited adverse health effects on human across the ages(World Health Organization 2024). These pollutants often interact, amplifying their health impacts(Mauderly and Samet 2009).

Air Quality Index (AQI) has been proposed to communicate the synergistic health effects of polluted air mixture(USEPA 2012). This method has been questioned since it fails to account for the synergistic health effect attributable to multiple pollutants. To address this, Stieb et al (2008) (Stieb *et al* 2008) proposed an air quality health index (AQHI) that entails adding the extra risks from individual pollutant models. However, this strategy may result in an overestimation of the effects of pollution. Subsequently, Cao *et al* (2021) (Cao *et al* 2021) suggested the cumulative risk index (CRI) to better evaluate the combined effects of various air pollutants. The CRI approach was used to determine the relative risk of mortality caused by simultaneous increases in exposure to various air pollutants. It compares the scenario in which all pollutants rise by one unit to the scenario in which no pollutants increase.

In India, one of the most polluted countries in the world, AQI is calculated as AQI $=Max(I_P)$, where

$$I_P = I_{lo} + \left(\frac{I_{hi} - I_{lo}}{B_{hi} - B_{lo}}\right)(C - B_{lo})$$

In the equation, I_p = Sub-index for pollutant P; C = Observed concentration of pollutant P; B_{hi}, B_{lo} = Breakpoints corresponding to the concentration range containing C; I_{hi}, I_{lo} = AQI values corresponding to these breakpoints(Central Pollution Control Board 2014). In India, AQI calculation requires measurements of either $PM_{2.5}$ or PM_{10} (particles smaller than 10 µm diameter) and at least two other criteria pollutants (NO_2, SO_2, CO, O_3, NH_3, and Pb). Further, overall air quality is assessed qualitatively as 'Good' (AQI<50), 'Satisfactory' (AQI between 51 and 100), 'Moderate' (AQI between 101 and 200), 'Poor' (AQI between 201 and 300), 'Very Poor' (AQI between 301 and 400) and 'Severe' (AQI>400).

However, these AQI thresholds are not supported by any health studies. Gorai *et al* (2017) (Gorai *et al* 2017) proposed an alternative technique to include health in the AQHI, but their model did not use actual health data in its construction and is more complicated than other existing techniques. Health impacts of cumulative exposure to multiple air pollutants depend on many factors such as urban or rural demography, the distribution of pollution sources (that is modulated by weather patterns) relative to the population, meteorological conditions such as temperature, humidity, and planetary boundary layer height and other risk factors. This is reflected in a recent multicity study by de Bont *et al.* (2024)(de Bont *et al* 2024) on the varying effects of short-term $PM_{2.5}$ exposure on daily all-cause mortality across ten Indian cities. Similarly, global studies have shown that the associations of $PM_{2.5}$, NO_2, and O_3 with mortality and other health outcomes differ across cities(Romieu *et al* 2012, Vicedo-Cabrera *et al* 2020, Meng *et al* 2021, Stieb *et al* 2009, Liu *et al* 2019).

This calls for a framework that can address the heterogeneity in these factors yet uniformly represent the health impacts across cities. In this work, we proposed a framework to develop

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city-specific AQHI utilizing air pollution and health data from two cities – Delhi and Varanasi located in the highly polluted Indo-Gangetic Plain (IGP) in north India. Our framework allows policymakers to take action to address air quality issues at the source. We, therefore, proposed a city-specific Air Quality Health Index for Delhi and Varanasi in this study. The AQHI was derived from the exposure-response relationship between multiple air pollutants and daily all-cause mortality, mostly representative of the acute effects of air pollution.

2. Methods

2.1 Mortality Data

We analyzed the daily all-cause non-trauma mortality data for two cities, Delhi and Varanasi. The mortality records in each city were collected and archived by the respective municipal corporations. We used the data from January 1, 2013, to November 30, 2017, for Delhi, and from January 1, 2009, to December 31, 2016, for Varanasi. The data included information on the date and location of death, as well as the deceased's age, sex, and residential address. Although the cause of death was recorded, it was not classified according to the International Classification of Diseases (ICD-10); therefore, we did not conduct a cause-specific mortality analysis. However, the data did identify deaths resulting from suicides and accidents, enabling us to exclude these cases from our calculations and focus exclusively on daily all-cause mortality unrelated to trauma. Previously, these mortality data sets were utilized to understand the impact of acute exposure to air pollution and heat stress in Delhi(Joshi *et al* 2021) and Varanasi(Singh *et al* 2019).

2.2 Air Pollutant Data

The ambient air pollutant data for $PM_{2.5}$, NO_2, and O_3 (24-hour average) were obtained from the Central Pollution Control Board (CPCB), which operates a nationwide network of Continuous Ambient Air Quality Monitoring Stations (CAAQMS) across India. Each station functions in a temperature-controlled environment to ensure measurement accuracy and consistency. The $PM_{2.5}$ data in CPCB sites are collected using Beta Attenuation Monitors (BAMs) and Tapered Element Oscillating Microbalance (TEOM) analysers. While, chemiluminescence analyzers and UV photometric analyzers are used to monitor NO_2, and O_3, respectively. These instruments conform to CPCB's regulatory standards and are regularly calibrated per standard protocols. The real-time air quality data are transmitted to a central server and made publicly accessible through CPCB's online dashboard and the Central Control Room for Air Quality Management dashboard(Central Pollution Control Board 2020). The sites used for exposure estimation were selected based on the maximum number of valid monitoring days during the analysis period to ensure data reliability and representativeness.

2.2.1 Site Selection and Coverage

In Delhi, pollutant concentrations were averaged across four CAAQMS sites: Anand Vihar (a major transit hub adjacent to an interstate bus terminus and high-traffic road network), Delhi Technological University (DTU) (situated within the Delhi Technological University campus, capturing institutional and semi-residential exposure), RK Puram (positioned in a residential colony, surrounded by tree cover), and ITO (located at a heavily trafficked intersection with commercial and government offices nearby). These stations were selected based on data completeness (maximum days with valid data) and spatial diversity, capturing industrial, traffic-heavy, residential, and institutional zones. In Varanasi, only the Ardhali Bazaar station, located in a densely populated commercial and residential area, met the criteria for complete

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multi-pollutant data for the analysis year. Located in a densely populated urban area, the site reflects typical exposure conditions for the city's central population. Figure 1 shows the locations of the selected CAAQMS sites.

2.2.2 Data Validation

The reliability of ground-based CPCB measurements was independently assessed through validation with satellite-derived pollutant estimates in several national studies. Katoch et al. (2023) evaluated $PM_{2.5}$ concentrations by correcting gaps in satellite aerosol optical depth (AOD) data using ground-level CPCB measurements(Katoch *et al* 2023). Singh et al. (2024) developed satellite-based land-use regression models to estimate long-term NO_2 exposure across India, validated using CPCB stations(Singh *et al* 2024). Anand et al. (2025) analyzed ozone trends using CMIP6 models, validating modeled O_3 concentrations against ground-based IMD sites(Anand K A *et al* 2025). Though sourced from a different network, these IMD stations use comparable instruments (e.g., UV photometric analyzers), making them methodologically consistent with CPCB monitors.
These validations support the robustness of ground-based observations for use in exposure assessment, health risk modeling, and integrated indicators such as the Air Quality Health Index (AQHI) adopted in this study.

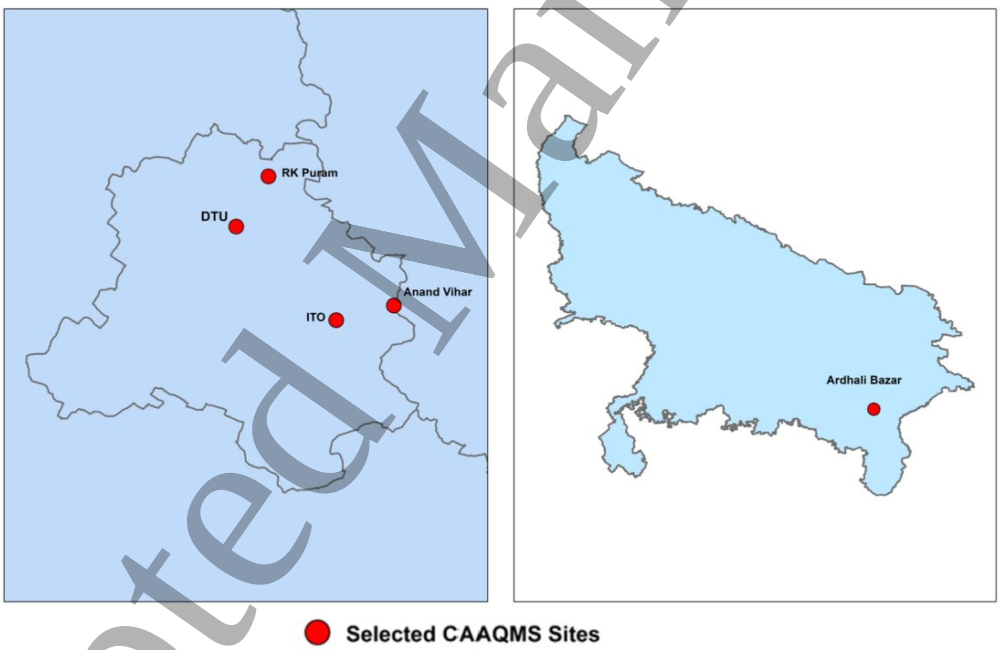

Figure 1. Geographical Locations of Selected CAAQMS Monitoring Sites in Delhi and Varanasi: Delhi stations (Anand Vihar, DTU, RK Puram, and ITO) were used to compute city-wide average pollutant concentrations (left panel). In Varanasi, data were sourced from the Ardhali Bazaar station (right panel).

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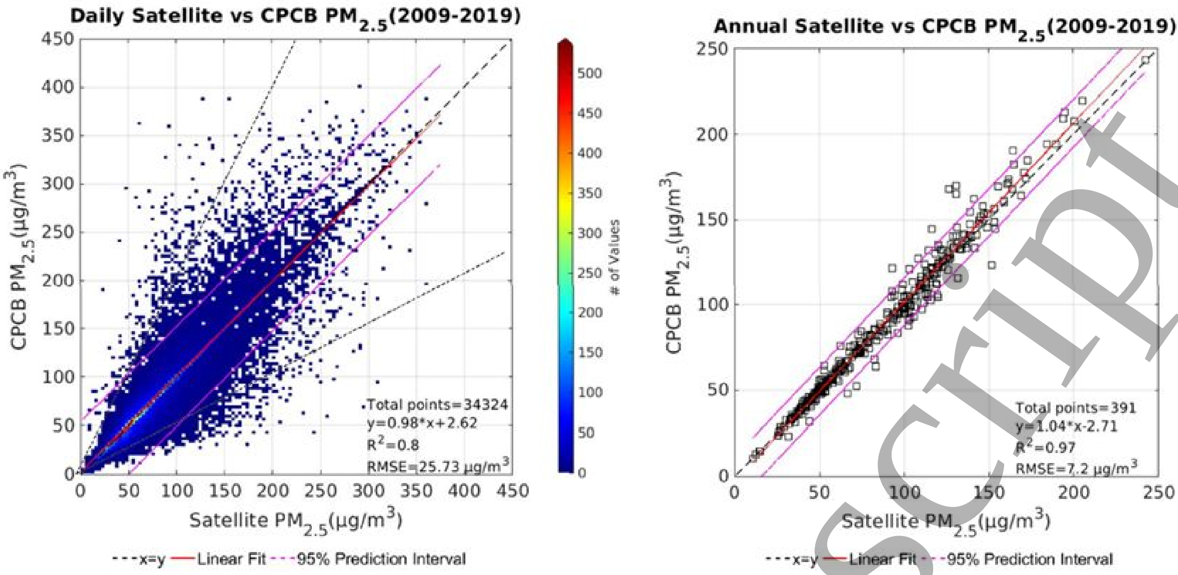

Figure 2. Validation of Ground-Based and Satellite-Derived $PM_{2.5}$ Concentrations Over India: Scatter plot showing the validation of CPCB ground-monitored $PM_{2.5}$ concentrations against satellite-derived $PM_{2.5}$ estimates over selected locations in India. The figure is adapted from 'Dey et al. 2020', which demonstrates strong correlation and highlights the effectiveness of gap-filling methods to improve satellite AOD-based exposure estimates. This figure supports the use of CPCB monitoring data in our study, which has been sufficiently validated against satellite-derived estimates for various pollutants, making it appropriate for exposure and health risk assessment.

Meteorological Data.

The daily meteorological data of mean temperature and relative humidity (RH) for the selected exposure years were obtained from the India Meteorological Department (IMD) via its online data portal (http://dsp.imdpune.gov.in). For Delhi, data were sourced from the Safdarjung Station, while for Varanasi, the Banaras Hindu university station was selected. These stations were chosen based on the availability of the most complete and continuous daily records during the study period, ensuring reliable alignment with the air pollution exposure dataset for each city.

2.3 Statistical method

The data for $PM_{2.5}$, O_3, and NO_2 presented missing values attributed to instrumental error and power issues. These gaps in data were addressed through separate imputation processes for Varanasi and Delhi. Specifically, distinct models were employed to impute missing values for Delhi, accounting for 24% in $PM_{2.5}$, NO_2, and O_3, and Varanasi, addressing 54% in $PM_{2.5}$, 23% in NO_2, and 19% in O_3. The accuracy of these imputations was assessed through leave-one-out cross-validation.

The missing $PM_{2.5}$ was imputed by fitting a generalized additive model (GAM) using PM_{10} as a main predictive variable, adjusted to the time-varying nonlinear meteorological variables (temperature and relative humidity).

$$E\{Log(PM2.5_t)\} = \alpha + \mathrm{PM10} + f_1(\mathrm{RH}_t) + f_2(\mathrm{Tmean}_t) + f_3(\mathrm{Day})$$

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Similarly, another GAM model imputed missing NO_2 using $PM_{2.5}$ as the main predictor variable. This takes advantage of the observed relationship between $PM_{2.5}$ and NO_2, considering common emission sources and shared atmospheric processes. Furthermore, missing O_3 was imputed using a GAM with NO_2 as the main predictor variable, adjusted for time-varying nonlinear meteorological variables. This choice acknowledged the intricate relationship between NO_2 and O_3 formation, which is influenced by varying environmental conditions. Notably, the predicted values were utilized to fill in missing data exclusively when the corresponding predictor variables were accessible.

2.4 Estimating the Associations of Air Pollutants with Mortality

To estimate the direct effects of these three air pollutants on daily mortality, we employed a multiple GAM with a quasi-Poisson link function. To account for seasonal patterns and to adjust the influence of weather-related factors on the relationship between air pollution and mortality, we applied penalized cubic smoothing functions of temperature, relative humidity, and time. The model is described below.

$$Log[E(Y_{it})] = \alpha + \beta_1 PM2.5_{ti} + \beta_2 NO_{2ti} + \beta_2 O3_{ti} + f_1(\mathrm{RH}_{ti}) + f_2(\mathrm{Tmean}_{ti}) + f_3(Day_{ti}) + u_i \quad (1)$$

In this equation, Y represents the daily mortality on day t for the i^{th} city, where i = 1, 2. PM2.5 is the value on the t^{th} day for the i^{th} city. The term u_i denotes a random intercept corresponding to the i^{th} city. The variable t indicates the day of the study, while the functions in questionα is the intercept term. The $f_i(\,)$ are penalized cubic smoothing functions for temperature, relative humidity, and time, which operate using data-driven degrees of freedom. The degrees of freedom are estimated using the generalized cross-validation score and are automatically utilized in the model by the algorithm. Specification of degrees of freedom is not necessary. To assess the robustness of the model to the choice of degrees of freedom, we conducted a sensitivity analysis by varying the degrees of freedom per year for the smooth terms of time, temperature, and relative humidity.

Preliminary models including smooth terms for the pollutants suggested nonlinear associations for NO_2 and O_3 with mortality, based on the shape of the exposure–response curves. Observing these nonlinear patterns in the association between mortality and NO_2 as well as O_3, we conducted a segmented regression analysis to identify breakpoints for both pollutants. This process involved two steps. For NO_2, in the initial phase, mortality was regressed on other pollutants (excluding NO_2), with adjustments made for temperature, relative humidity, and time, as outlined below:

$$Log[E(Y_{it})] = \alpha + \beta_1 PM2.5_{ti} + \beta_2 O3_{ti} + f_1(\mathrm{RH}_{ti}) + f_2(\mathrm{Tmean}_{ti}) + f_3(Day_{ti}) + u_i \quad (2)$$

The residuals from equation (2) were regressed on next step as given below:

$$E\{Res_{Mortality}\} = \alpha + \beta_1 NO2_i + \beta_2 (NO2_i - \psi)_+ \quad (3)$$

Where $\beta_2(NO2_i - \psi)_+ = (NO2_i - \psi) \times \mathrm{I}(NO2_i > \psi)$ and I(.) is the indicator function equal to one when the statement is true, zero otherwise. The breakpoint ψ is estimated using an iterative procedure(Muggeo .V 2008). The above steps were repeated for O_3 to identify the breakpoint of O_3. Once the breakpoints are identified, equation (1) is updated as below:

$$Log\big[E(Y_{it})\big] = \alpha + \beta_1 PM2.5_{ti} + g_\delta(NO_{2ti},\psi) + g_\gamma(O3_{ti},\xi) + f_1(\mathrm{RH}_{ti}) + f_2(\mathrm{Tmean}_{ti}) + f_3(Day_{ti}) + u_i \quad (4)$$

Where $g_\delta(NO_{2ti},\psi) = \beta_1 NO_{2ti} \times \mathrm{I}(NO_{2ti} > \psi) + \beta_2 NO_{2ti} \times \mathrm{I}(NO_{2ti} \leq \psi)$; similar for $g_\gamma(O3_{ti},\xi)$.

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The city-specific estimates for pollutants were derived by incorporating interaction terms for the city with $PM_{2.5}$, NO_2, and O_3 in Equation (4) as below:

$$Log\left[E(Y_{it})\right] = \alpha + \beta_1 PM2.5_{ti} * C_i + g_\delta(NO_{2ti},\psi) * C_i + g_\gamma(O3_{ti},\xi) * C_i + f_1(\mathrm{RH}_{ti}) + f_2(\mathrm{Tmean}_{ti}) + f_3(Day_{ti}) + u_i \quad (5)$$

Where C_i is the indicator for city i.

2.5 Construction of the AQHI

The AQHI was developed by taking the absence of air pollutants as the reference point, and the coefficient indicating the relationship between major air pollutants and health was determined using the exposure-response relationship model. The proposed AQHI is scaled to a 0–100-point scale and is defined as follows:

$$\mathrm{AQHI} = 100 * \mathrm{E_t} / \max_{t\,=\,1\ldots n} \mathrm{E_t} \quad (6)$$

$$\mathrm{E_t} = \left[\frac{\sum_{i=1}^{p} \mathbf{x}_{it}\boldsymbol{\beta_i}}{\alpha}\right] \quad (7)$$

where $\sum_{i=1}^{p} \mathbf{x}_{it}\boldsymbol{\beta_i}$ is the excess mortality (logscale) caused by all pollutants on day t; β is the exposure–response relationship coefficient estimated using the regression model (Eqn 1), that is, the daily increase in mortality caused by a one-unit increase in pollutants; x_{it} is the average concentration of the i^{th} pollutant on day t, α is the average mortality is expressed in log scale. City-specific AQHI and pooled AQHI were calculated using city-specific and pooled coefficients in Equation 6.

The values of developed AQHI mostly vary between 0 and 100. However, AQHI may exceed 100 if E_t for a given day exceeds observed maximum of E_t during the study period. This range was divided into six intervals of equal width to form six categories: Good (0 to 16), Satisfactory (greater than 16 up to 33), Moderate (greater than 33 up to 50), Poor (greater than 50 up to 67), Very Poor (greater than 67 up to 84), and Severe (greater than 84).

3. Results

3.1 Descriptives of Data

The descriptive statistics of the observed pollutant data and daily mortality are given in Table 1. The mean $PM_{2.5}$ concentration was notably high, exceeding the WHO 24hrs standard of 15µg/m^3 by nine times in Delhi and seven times in Varanasi.

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Regarding mortality, Varanasi recorded a total of 64,712 deaths during the period, with a median daily mortality of 22. In Delhi, the total mortality reached 354,963 during the period, with a median daily figure of 194.

Table 1. Descriptive Statistics for $PM_{2.5}$, O_3, NO_2(Unit: μg/m^3) and daily mortality in Varanasi (n=2922; 2009−16) and Delhi (n=1795; 2013-2017).

City	Parameter	n	Mean	SD	Median	Min	Max	IQR	25th Percentile	75th Percentile
Varanasi	$PM_{2.5}$	1321	110.78	83.76	86.92	3.6	398.35	119.92	42.78	162.71
	O_3	2342	22.33	14.52	18.02	0	74.97	19.42	11.23	30.65
	NO_2	2232	20.16	10.18	19.27	0	45.06	15.47	12.11	27.59
	Mortality	2922	22.15	6.08	22	3	78	7	18	25
Delhi	$PM_{2.5}$	1074	141.58	78.73	124.96	1.84	379.58	110.59	81.1	191.69
	O_3	1074	30.9	16.67	26.82	5.19	128.83	18.68	19.45	38.14
	NO_2	1074	69.99	38.01	61.83	0.21	307.84	47.05	44.3	91.36
	Mortality	1795	197.75	34	194	29	319	43	176	219

The distribution of observed pollutant concentrations is shown in Supplementary Figure 1. The time series of daily pollutant concentrations, illustrating temporal patterns and data availability, is presented in Supplementary Figure 2. Supplementary Figure 3 presents the monthly number of daily observations for the pollutants across the four monitoring stations in Delhi. Supplementary Table 1 provides detailed descriptive statistics of the measured pollutant concentrations across the four selected CAAQMS sites in Delhi.

In both Delhi and Varanasi, the highest correlation among pollutants was observed between $PM_{2.5}$ and NO_2 ($r = 0.38$ and $r = 0.61$). All other pollutants exhibited weak correlations ($|r| < 0.1$) (Figure 3).

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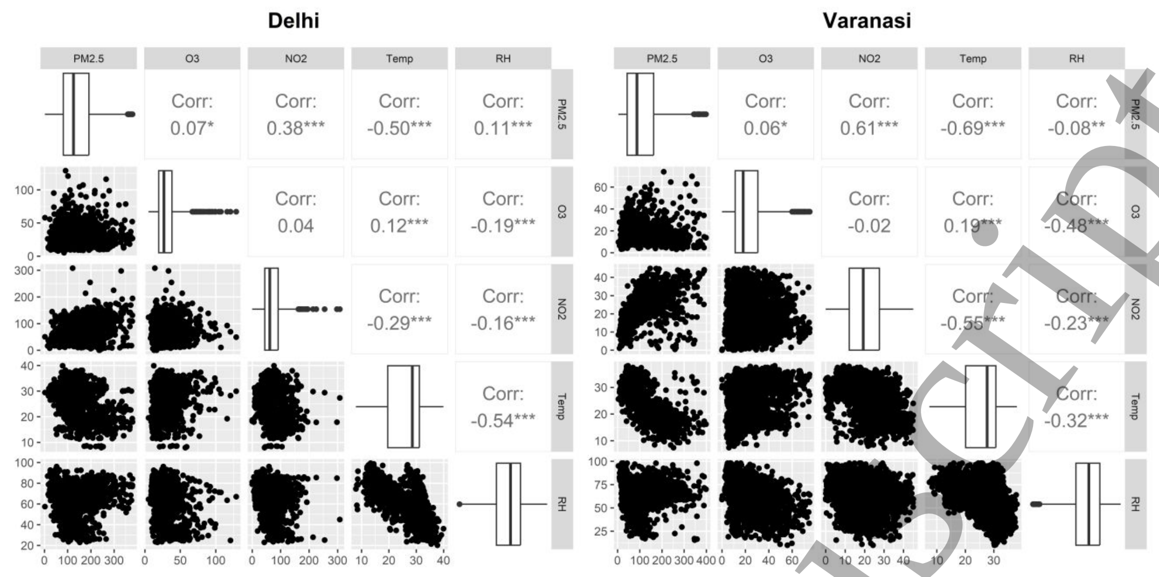

Figure 3: Correlations among air pollutants and meteorological parameters (Temperature and Relative Humidity) in Delhi and Varanasi

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3.2 Missing Value Imputation

The leave-one-out cross-validation demonstrated strong agreement between predicted and actual values. The Pearson correlation coefficients ranged from 0.601 to 0.859 across all pollutants and cities, with values exceeding 0.75 for most cases (Figure 4), underscoring the robust performance of the imputation model.

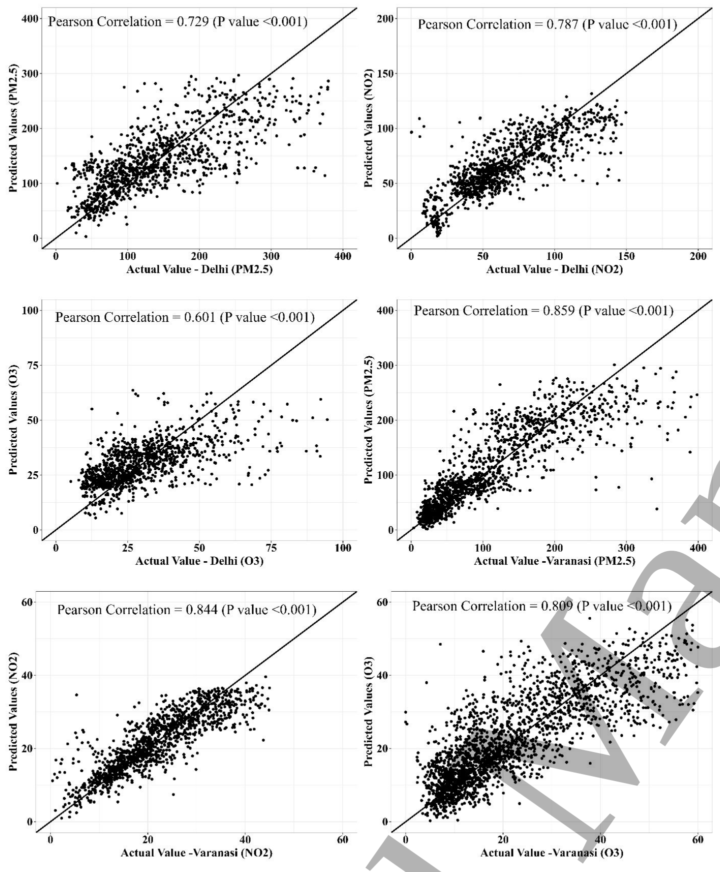

Figure 4: Agreement plot of data imputation

3.3 Effect of Pollutants on Mortality

The breakpoints of NO_2 and O_3 were identified as 65µg/m³ and 52µg/m³ respectively. Table 2 illustrates the impact of pollutants on daily mortality in Varanasi, Delhi and pooled estimates, presented as the percentage increase in mortality for a 10-unit rise in each pollutant.

O_3 levels ≤ 52 µg/m³ showed the highest effect on mortality in both cities. In Varanasi, a 2.73% increase in mortality (95% CI: 1.63–3.83) was observed, while in Delhi, the corresponding increase was 0.94% (95% CI: 0.38–1.51), highlighting city-level differences. The second-highest effect was observed for NO_2 levels > 65 µg/m³ in Varanasi, with a 1.74% increase (95% CI: –0.58 to 4.06), and NO_2 levels ≤ 65 µg/m³ in Delhi, which showed a 0.31% increase (95% CI: –0.07 to 0.69). In the pooled model, the highest effects were observed for O_3 levels ≤ 52 µg/m³ (1.25%, 95% CI: 0.75–1.75) (See Table 2). Sensitivity analyses using the pooled data showed that the estimated effects of $PM_{2.5}$, NO_2, and O_3 on mortality remained consistent across different degrees of freedom per year for time, temperature, and relative humidity (Supplementary Figures S4–S6).

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Table 2: The table reports the estimates of pollutants on daily mortality.

	% increase in mortality for 10-unit increase of pollutant		
Term	**Varanasi**	**Delhi**	**Pooled**
$PM_{2.5}$	0.17(0.01-0.34)	0.2(0.1-0.29)	0.16(0.08-0.24)
O_3: ($O_3 \le 52$)	2.73(1.63-3.83)	0.94(0.38-1.51)	1.25(0.75-1.75)
O_3: ($O_3 > 52$)	1.69(0.41-2.96)	0.05(-0.33-0.44)	0.25(-0.11-0.6)
NO_2: ($NO_2 \le 65$)	1.61(0.32-2.91)	0.31(-0.07-0.69)	0.44(0.08-0.8)
NO_2: ($NO_2 > 65$)	1.74(-0.58-4.06)	0.23(0.01-0.46)	0.29(0.07-0.51)

3.4 City Specific and Pooled AQHI

Based on the effects of pollutants on mortality, proposed city specific and pooled air quality health indices were developed using the equation (2). The formulas for the calculation of AQHI are given below:

$$E_{tDelhi} = \begin{cases} \frac{(0.0002\times PM_{2.5})+(0.00094\times O_3)+(0.0003\times NO_2)}{5.2} & \text{if } O_3 \le 52 \quad NO_2 \le 65 \\ \frac{(0.0002\times PM_{2.5})+(0.00005\times O_3)+(0.0003\times NO_2)}{5.2} & \text{if } O_3 > 52 \quad NO_2 \le 65 \\ \frac{(0.0002\times PM_{2.5})+(0.00094\times O_3)+(0.00023\times NO_2)}{5.2} & \text{if } O_3 \le 52 \quad NO_2 > 65 \\ \frac{(0.0002\times PM_{2.5})+(0.00005\times O_3)+(0.00023\times NO_2)}{5.2} & \text{if } O_3 > 52 \quad NO_2 > 65 \end{cases}$$

$$E_{tVaranasi} = \begin{cases} \frac{(0.00017\times PM_{2.5})+(0.0027\times O_3)+(0.0016\times NO_2)}{3.0} & \text{if } O_3 \le 52 \quad NO_2 \le 65 \\ \frac{(0.00017\times PM_{2.5})+(0.0017\times O_3)+(0.0016\times NO_2)}{3.0} & \text{if } O_3 > 52 \quad NO_2 \le 65 \\ \frac{(0.00017\times PM_{2.5})+(0.0027\times O_3)+(0.0017\times NO_2)}{3.0} & \text{if } O_3 \le 52 \quad NO_2 > 65 \\ \frac{(0.00017\times PM_{2.5})+(0.0017\times O_3)+(0.0017\times NO_2)}{3.0} & \text{if } O_3 > 52 \quad NO_2 > 65 \end{cases}$$

$$E_{tPooled} = \begin{cases} \frac{(0.00016\times PM_{2.5})+(0.00125\times O_3)+(0.00044\times NO_2)}{4.1} & \text{if } O_3 \le 52 \quad NO_2 \le 65 \\ \frac{(0.00016\times PM_{2.5})+(0.00025\times O_3)+(0.00044\times NO_2)}{4.1} & \text{if } O_3 > 52 \quad NO_2 \le 65 \\ \frac{(0.00016\times PM_{2.5})+(0.00125\times O_3)+(0.00029\times NO_2)}{4.1} & \text{if } O_3 \le 52 \quad NO_2 > 65 \\ \frac{(0.00016\times PM_{2.5})+(0.00025\times O_3)+(0.00029\times NO_2)}{4.1} & \text{if } O_3 > 52 \quad NO_2 > 65 \end{cases}$$

$$AQHI_{Delhi} = 100 * E_{tDelhi}/0.032$$
$$AQHI_{Varanasi} = 100 * E_{tVaranasi}/0.116$$
$$AQHI_{Pooled} = 100 * E_{tPooled}/0.044$$

The distributions of the AQHI values for Delhi, Varanasi using city specific (top two panel) and pooled (bottom) AQHI formulas are given in figure 5.

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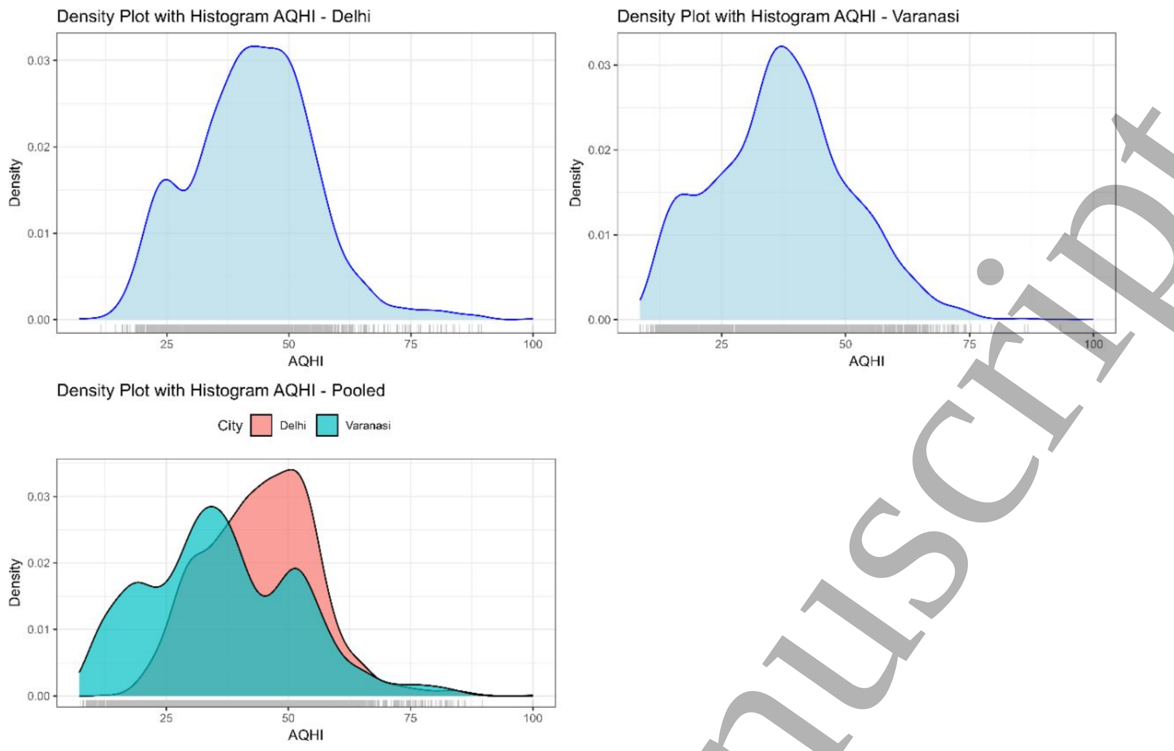

Figure 5: Distribution of AQHI by non-parametric density plot

The AQHI values corresponding to WHO air quality guideline (AQG), WHO interim targets (IT) and National Ambient Air Quality Standards (NAAQS) in India are detailed in Table 3, providing benchmarks for $PM_{2.5}$, O_3, and NO_2 concentrations, as well as the resulting AQHI values for the pooled index, Delhi, and Varanasi. For O_3, the guideline values are provided for an 8-hour average. To estimate the corresponding 24-hour average values, we applied a conversion factor of 1.5, meaning the 8-hour values were divided by 1.5. This approach aligns with methodologies used in previous studies(Anderson and Bell 2010, Bell *et al* 2005, Lange 2018).

Table 3: AQHI corresponding to guideline values

Label	$PM_{2.5}$	O_3	NO_2	AQHI National	AQHI Delhi	AQHI Varanasi
WHO AQG	15	67	25	16	9	45
WHO IT4	25					
WHO IT3	37.5					
WHO IT2	50	80	50	27	18	65
WHO IT1	75	107	120	40	29	116
NAAQS (India)	60	67	80	27	21	76

The AQHI values are categorized into six classes: Good, Satisfactory, Moderate, Poor, Very Poor, and Severe, as delineated in Table 4. Table 5 presents a frequency distribution for AQHI classification for Delhi, and Varanasi using city specific index and pooled index during the study period.

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Table 4: proposed AQHI Classifications

AQHI Health Risk Category	AQHI Values
Good	0-16
Satisfactory	17-33
Moderate	34-50
Poor	51-67
Very Poor	68-84
Severe	>84

Table 5: AQHI classifications by the two Indices based on available data during study period in Delhi and Varanasi

AQHI Classification	Delhi (N = 1,795)		Varanasi (N = 2,922)	
	Delhi Index	Pooled Index	Varanasi Index	Pooled Index
Good	5 (0.3%)	1 (0.1%)	199 (6.8%)	272 (9.3%)
Satisfactory	392 (21.8%)	327 (18.2%)	865 (29.6%)	979 (33.5%)
Moderate	917 (51.1%)	881 (49.1%)	1,351 (46.2%)	1,019 (34.9%)
Poor	434 (24.2%)	541 (30.1%)	458 (15.7%)	565 (19.3%)
Very Poor	40 (2.2%)	38 (2.1%)	45 (1.5%)	81 (2.8%)
Severe	7 (0.4%)	7 (0.4%)	4 (0.1%)	6 (0.2%)

In Delhi, based on the city-specific index, 21.8% of the days were classified as Satisfactory, whereas the pooled index assigned a lower 18.2% of the days to this category. The Moderate category accounted for 51.1% of the days under the city-specific index, slightly decreasing to 49.1% under the pooled index. The Poor category showed a notable difference, with the city-specific index classifying 24.2% of the days as Poor, while the pooled index categorized a higher 30.1% of the days in this range. The Very Poor category remained similar across both indices, with 2.2% of the days classified as Very Poor under the city-specific index and 2.1% under the pooled index. A very small number of days fell under the Severe category, accounting for 0.4% of the study period under both indices.

In Varanasi, the differences between the indices were more pronounced. The Good category accounted for 6.8% of the days under the city-specific index, compared to 9.3% under the pooled index. Similarly, the Satisfactory category was slightly higher under the pooled index (33.5%) than under the city-specific index (29.6%). However, the Moderate category showed a considerable difference, with 46.2% of the days classified as Moderate under the city-specific index, compared to 34.9% under the pooled index. Conversely, the pooled index placed more days in the Poor category (19.3%) compared to the city-specific index (15.7%). The Very Poor category also showed a slight increase from 1.5% (city-specific) to 2.8% (pooled). A very small number of days were in the Severe category, with 0.1% under the city-specific index and 0.2% under the pooled index.

These differences suggest that the pooled index tends to classify air quality in Delhi as Poor more frequently than the city-specific index, while categorizing fewer days as Satisfactory. Similarly, in Varanasi, the pooled index placed more days in higher pollution categories.

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4. Discussion

We developed a novel city-specific multipollutant air quality health index for two cities in India – Delhi and Varanasi. In this study we utilized generalized additive models to estimate the simultaneous effect of three pollutants $PM_{2.5}$, NO_2 and O_3 adjusting for the time varying nonlinear meteorological variables. We defined AQHI by considering the baseline mortality as the reference value. The results underscore the critical need for city-specific AQHIs. Our analysis revealed that applying a uniform pooled index across different cities could significantly misrepresent the health impacts of air pollution. For instance, in Delhi, the city-specific index classified 21.8% of the days as Satisfactory, whereas the pooled index classified only 18.2%. Similarly, the Poor category accounted for 24.2% of the days under the city-specific index but increased to 30.1% under the pooled index. In Varanasi, while the pooled index classified 9.3% of days as Good, the city-specific index showed a lower 6.8%. The Moderate category showed a notable difference, with the city-specific index classifying 46.2% of the days in this category, compared to 34.9% under the pooled index, which instead placed more days in the Poor category (19.3% vs. 15.7% city-specific). This discrepancy reflects the differences in city-specific coefficients, which vary across urban settings. Since AQHI is derived from these coefficients, it should also account for these variations, which is only possible through a city-specific index.

The impact of air pollution on health outcomes, such as mortality, varies significantly across different cities. This variation is influenced by several local factors, including temperature and humidity, which differ from one city to another. For instance, a multicity study by de Bont et al., which covered 10 cities in India, reported varying effects of $PM_{2.5}$ on mortality. In Delhi, the percentage increase in mortality per 10 µg/m³ rise in $PM_{2.5}$ was 0.31 (95% CI: 0.21 to 0.41), while in Shimla, it escalated to 3.45 (95% CI: −3.32 to 10.69)(de Bont *et al* 2024). In Varanasi, the increase was 1.17 (95% CI: 0.49 to 1.86). Our findings in Delhi align closely with these results; however, for Varanasi, our study showed a lower effect, with estimates of 0.20 (95% CI: 0.1-0.29) for Delhi and 0.17 (95% CI: 0.01-0.34) for Varanasi. The discrepancies may stem from our use of multipollutant models, as opposed to the single-pollutant models used in the Bont et al. study.

Similarly, a global study by Liu *et al.,* encompassing 652 cities, demonstrated that the percentage change in all-cause mortality per 10 µg/m³ increase in $PM_{2.5}$ ranged from 0.03 (95% CI: –1.14 to 1.21) to 2.54 (95% CI: 1.28 to 3.83)(Liu *et al* 2019). This variability emphasizes the necessity of addressing differences in effect estimates when developing an AQHI. It is crucial that the AQHI reflects specific local conditions rather than applying a one-size-fits-all approach, particularly in a country as diverse as India, both geographically and climatically. An effective AQHI should be tailored for each locality to accurately communicate the health risks posed by air pollution.

Previously, researchers have developed various versions of the AQHI, many of which are grounded in methodologies proposed by Stieb *et al* and Cairncross (Olstrup *et al* 2019, Adebayo-Ojo *et al* 2023, Gorai *et al* 2017, Chen *et al* 2013, Zeng *et al* 2020, Wai *et al* 2013, Kyrkilis *et al* 2007, Li *et al* 2016, Cao *et al* 2021, Du *et al* 2020). Stieb et al.'s method, which aggregates excess risks from individual pollutant models, can sometimes result in an overestimation of pollutant concentrations. Our study addresses this concern through a multipollutant approach, which is particularly effective given that the correlations among pairs of pollutants are not extremely high(George *et al* n.d.). We have also redefined AQHI normalizing by baseline mortality. This normalization allows for more meaningful comparisons of AQHI across different cities. The methodology we have proposed for calculating AQHI is adaptable and can be modified to incorporate additional pollutants, making it versatile enough to be applied to any urban setting.

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While the city-specific AQHI accounts for differences in pollution levels and meteorological factors, an important source of uncertainty remains unaddressed—the chemical composition and sources of particulate matter. Recent evidence suggests that the cumulative health effects of $PM_{2.5}$ species can exceed those of total $PM_{2.5}$ mass(Chaudhary *et al* 2023). Our current model does not distinguish between pollution sources like traffic emissions, industrial plumes, or biomass burning, which may produce $PM_{2.5}$ of differing chemical profiles and health impacts. Integrating data on $PM_{2.5}$ composition and source attribution could improve the sensitivity and relevance of AQHIs, especially in heterogeneous urban environments. Additionally, due to substantial missingness in pollutant data, imputation was necessary to enable complete time series modeling. While validated through cross-validation, this step introduces a degree of uncertainty. Some effect estimates also show wider confidence intervals, which reflect statistical variability in the pollutant-health associations. The NO_2 data used in this study were obtained from CPCB's ambient air quality monitoring network, which primarily uses chemiluminescence analyzers. While these instruments are known to have a slight positive bias due to interference from other reactive nitrogen species (NO_x), such as nitric acid and peroxyacetyl nitrate(Lamsal *et al* 2008), this bias is not expected to significantly affect the AQHI estimates. Furthermore, the AQHI developed in this study reflects only same-day associations between pollutant exposures and mortality to capture instantaneous risk of mortality ignoring delayed or cumulative health effects. However, one can think of an index of cumulative health effects with a different interpretation. Although the pooled estimate is derived from only two cities, it serves as a comparative tool to underscore the potential for misclassification when a uniform AQHI is applied across multiple cities.

The current AQI in India is based on the sub-index method, which does not account for the cumulative health risks of multiple air pollutants. In contrast, the AQHI integrates the combined effects of pollutants on health, offering a more comprehensive approach to assessing air quality. However, its implementation and refinement depend on strong health data. City-specific AQHIs require city-specific health data, but such data remain limited in India, making it challenging to derive precise local estimates. Implementing the AQHI at regional or national levels requires reliable health data. Collecting comprehensive health outcome data helps in better estimating the relationship between pollution exposure and health effects, making AQHI thresholds more accurate. As more data become available, these thresholds can be updated to improve their reliability.

5. Conclusions

Our research highlights the critical need for a more nuanced approach in measuring air quality impacts on public health. By developing and implementing a city-specific AQHI that takes into account local variations in pollutant interactions and their health implications, we can provide more accurate and actionable information to policymakers and the public. This tailored approach supports targeted interventions aimed at improving air quality and public health outcomes. The flexibility of our AQHI model paves the way for future adaptations and improvements, ensuring that it remains relevant as new data emerge.

Data availability statement

Data will be made available on request to the corresponding author.

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CRediT authorship contribution statement

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Franciosalgeo George: Writing – original draft, Formal analysis, Methodology, Visualization. **Pallavi Joshi:** Formal analysis, Methodology, Visualization, Writing – review and editing. **Sagnik Dey:** Writing – review and editing, Data curation. **R.K. Mall:** Writing – review and editing, Data curation. **Santu Ghosh:** Methodology, Supervision, Writing – review and editing, Data curation.

Conflict interest

SD acknowledges funding from the Clean Air Fund.

All other 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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