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RESEARCH ARTICLE

Beyond household and individual factors: examining the association between ambient air pollution and birth outcomes in India

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Abstract

Low birth weight (LBW) and preterm birth (PTB) are primary factors contributing to morbidity and mortality among children aged under 5, resulting in a range of short- and long-term health consequences worldwide. Among the various risk factors, ambient air pollution poses a significant environmental risk and is a key determinant of child health. The prevalence of LBW and PTB among under 5 children sampled from the NFHS-5, 2019–2021, was combined with monthly $PM_{2.5}$ data (2013–2021) obtained from the Atmospheric Composition Analysis Group at Washington University. Multivariable logistic regression models were used, and a stratified analysis was applied to understand the potential effect modifiers in LBW and PTB. Further, the geographical variation of LBW and PTB spatial autocorrelation (Moran's I) was used. Geographically weighted regression and ordinary least square spatial regression were used to identify the spatial heterogeneity associated with selected variables. The study comprises a total of 208,181 under 5 children. Out of these children, the LBW rate was 17.41%, and the rate of PTB was 12.42%. The in-utero exposure to the mean concentration of $PM_{2.5}$ was 56.01 μg/m^3. The odds of suffering from LBW showed a non-linear shift when $PM_{2.5}$ levels rose from the first octile (<28.02 μg/m^3) to the last octile (>93.84 μg/m^3) (adjusted odds ratio (AOR): 1.06, 95% CI: 1.01–1.12). While comparing the first octile of exposure to $PM_{2.5}$ (>93.84 μg/m^3) to the last octile, there was a 52% more likelihood of having PTB (AOR: 1.52, 95% CI: 1.43–1.61) after accounting for all relevant factors. These findings highlight the urgent need for a thorough strategy to control the air quality in India. Further, to reduce adverse birth outcomes, longitudinal studies and other co-pollutants can consider assessing the possible mechanisms mediating the relationship between maternal exposure and ambient air pollution.

Keywords: Ambient particulate matter; $PM_{2.5}$; maternal exposure; low birth weight; preterm birth; geographical weighted regression; cross-sectional study

Introduction

The substantial morbidity and mortality rates associated with low birth weight (LBW) and preterm birth (PTB) impose a significant burden on health, education, and social services, as well as families (Petrou *et al.*, 2001). To achieve the 2030 Agenda for Sustainable Development Goal (SDG) #3, which is looking towards improving the health and well-being of individuals across all age groups, it is vital to tackle worldwide issues concerning LBW and PTB (Kosciejew, 2020). Both LBW and PTB have been widely used as markers of premature deaths, are associated with morbidity, and have significant implications for both short- and long-term health consequences (Bukowski *et al.*, 2007; Huang *et al.*, 2020). Despite the World Health Organization's (WHO) continued efforts towards reducing the likelihood of adverse birth outcomes in 2020, around 13.4 million infants were born prematurely, and 19.8 million, which accounts for 14.7% of all newborns worldwide, had low birthweight (WHO, 2020; Ohuma *et al.*, 2023). Almost 20 million infants are estimated to have a LBW (WHO, 2019), while about 15 million PTBs are predicted to occur annually (Walani, 2020).

However, premature newborns are considerably more prone to encountering adverse outcomes in comparison to those born at the expected gestational age (Ohuma *et al.*, 2023). LBW is caused by either intrauterine growth restriction or premature birth, or an integration of both factors (Okwaraji *et al.*, 2024). Additionally, Pusdekar *et al.* (2020) stated that gestational age predicts neonatal and childhood mortality risk more accurately than LBW. Further, Marete *et al.* (2020) reported that LBW is more prevalent in low- and middle-income countries (LMICs), particularly in South Asia and sub-Saharan Africa. In contrast, PTB is also prevalent worldwide, accounting for 10.6% of cases, with South Asia bearing about one-third of the burden (Jana, 2023). Based on the findings of the OECD and WHO (2020), India has a greater prevalence of LBW and PTB as compared to the neighbouring countries. The prevalence rate of LBW and PTB in India is 18% and 13%, respectively, whereas Sri Lanka has a prevalence rate of 15.9% for LBW and 7.0% for PTB. In comparison, China has LBW prevalence rate of 6.9% and a PTB prevalence rate of 5.3%, while Nepal has LBW prevalence rate of 12.3% and a PTB prevalence rate of 5.3%.

LBW and PTB are associated with various socio-demographic risk factors, such as birth order, teenage motherhood, maternal weight, anaemic mothers, inadequate visits to antenatal care, and maternal education (Khanal *et al.*, 2014; Bhaskar *et al.*, 2015). Furthermore, the use of tobacco during pregnancy and giving birth by a caesarean section are additional factors that can raise the likelihood of premature birth and having a baby with LBW (Jeena *et al.*, 2020). At the same time, research evidence showcases the detrimental impact of exposure to air pollution during pregnancy resulting in premature birth, LBW, and increased infant mortality (Pereira *et al.*, 2014; Jacobs *et al.*, 2017).

Among the different risk factors, ambient and household air pollution (AAP and HAP) are important environmental threats that considerably impact child health globally. Growing evidence suggests that around 90% of the world's population is vulnerable to the harmful consequences of air pollution, posing a substantial and persistent risk to global health. Furthermore, 99% of the global population resides in regions where the WHO's air quality standards have not been met (WHO, 2019; Shaddick *et al.*, 2020; Murray *et al.*, 2020). Air pollution causes one out of every nine deaths worldwide due to non-accidental diseases such as chronic obstructive pulmonary disease, respiratory infections, ischaemic heart disease, and lung cancer (Burnett *et al.*, 2018; WHO, 2018), resulting in a significant economic burden (Di Renzo *et al.*, 2015). Whereas, out of the 6.7 million premature deaths annually, 4.2 million are caused by ambient air pollution. The majority of premature deaths, accounting for 89%, were in LMICs (Landrigan *et al.*, 2018; WHO, 2019; Murray *et al.*, 2020). According to the Institute of Health Metric Evaluation (IHME), ambient air pollution is currently considered the second most significant risk factor for early mortality in children aged under 5, surpassed only by malnutrition (IHME, 2021). Additionally, research findings indicate that air pollution affects individuals irrespective of geographic location (Burnett *et al.*, 2018; WHO, 2018). However, the severity of health consequences due to air pollution might vary across population groups. This is particularly so for children, elderly, pregnant women, and their unborn offspring (Di Renzo *et al.*, 2015; WHO, 2018). Although the fundamental causes of adverse birth outcomes remain ambiguous, there is increasing evidence from previous research indicating that environmental factors may have a substantial impact on adverse birth outcomes (Li *et al.*, 2017).

Air pollution could contribute to a multifaceted combination of factors leading to increased likelihood of LBW and PTB. The observed effect is caused by several mechanisms, such as inflammation of placenta, poor foetal growth, oxidative stress, and impaired oxygen transport

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throughout the placenta, which can affect early-life child health and lead to growth failure among under 5 children in several ways (Slama *et al.*, 2008; Sinharoy *et al.*,2020; Desouza *et al.*, 2022). The association has been asserted by a time series study conducted in Iran (Sarizadeh *et al.*, 2020), a cohort study conducted in Europe (Pedersen *et al.*, 2013), a cross-sectional study conducted in Africa (Bachwenkizi *et al.*, 2021), as well as studies conducted in India (Balakrishnan *et al.*, 2019; Goyal and Canning, 2021) and China (Liu *et al.*, 2019). Among the various pollutants, prior research has shown that fine particulate matter has greater spatial homogeneity than other contaminants, which makes it a valuable indicator of individual exposure to compare with other pollutants (Sarnat *et al.*, 2005).

As a developing country, India has a considerably greater incidence of morbidity and mortality due to air pollution than other countries (George *et al.*, 2024). Despite the country's progress in reducing air pollution under National Clean Air Programme (NCAP), the long-term challenge of poor air quality has an alarming impact, particularly on child health outcomes (Mondal and Paul, 2020; Chowdhury *et al.*, 2020). In this scenario, air pollution in India is rising due to a lack of sufficient road infrastructure in the face of increasing urbanization, effective transportation management, and spontaneous dispersal of industry (Kaur and Pandey, 2021). Studies suggest that in India, increased levels of $PM_{2.5}$ are primarily attributed to human activities such as industrial processes, commercial biomass burning, road transport, fossil fuel combustion from power generation, the functioning of brick kilns, incineration of waste, and the use of solid cooking fuel in the household (CPCB, 2010; Pant *et al.*, 2015; Gordon *et al.*, 2018). As a result, India's population-weighted annual exposure to $PM_{2.5}$ the predominant pollutant that affects human health is about 90 $\mu g/m^3$, which is substantially higher than the WHO Air Quality Guideline (AQG) level of 5 $\mu g/m^3$ and India's National Ambient Air Quality standards (NAAQS) of 40 $\mu g/m^3$ (WHO, 2024). Whereas, the levels of $PM_{2.5}$ levels in few cities are typically 5–25 times higher than the national average (Roy and Singha, 2021).

However, related to particulate matter air pollution, prior studies have largely discussed indoor air pollution and its toxic effects on respiratory symptoms, asthma, and lung disease among children aged under 5. Furthermore, exposure to air pollution by household solid cooking fuel and its association with child growth failure in India (Mishra and Ratheford, 2007; Balietti and Dutta, 2017; Spears *et al.*, 2019), but no study has estimated and compared the associations between ambient $PM_{2.5}$ with LBW and PTB of different gestation period of individuals (Mothers) and geographical heterogeneity of birth outcomes in India. At the same time, previous studies (Goyal and Canning, 2021; Desouza *et al.*, 2022) assessed the average amount of exposure by computing the mean concentration of $PM_{2.5}$ over the total duration of pregnancy. Due to the high proportion of non-urban population in India, air pollution is not only an urban problem but can also occur in rural areas (Ravishankara *et al.*, 2020). However, exposure to air pollution is expected to result in long-lasting consequences similar to other health disorders across India (Balietti *et al.*, 2022). Therefore, the current research evaluates the association of ambient $PM_{2.5}$ air pollution with the incidence of LBW and PTB among children aged under 5 in India. Additionally, it is crucial to consider the many ways in which household, maternal, child, and environmental level factors contribute to the estimation of the causal link. Hence, to effectively work towards the sustainable development goal of decreasing the incidence of LBW and PTB in children by 2025, it is essential to comprehend and draw well-informed policy conclusions.

Value added of this study

Reducing the burden of childhood morbidity and neonatal mortality, LBW and PTB are significant in promoting healthy lives and well-being for all ages. Beyond the various household, child and maternal level factors, sufficient evidence from ambient particulate matter ($PM_{2.5}$) as environmental factors and its association with adverse birth outcomes, LBW and PTB of different gestation periods of individuals is insufficient in the Indian context.

Using remote sensing and Geographic Information Systems (GIS), this study combines the monthly concentration of $PM_{2.5}$ from different clusters with individual's gestation period from National Family Health Survey (NFHS-5) data sets. Furthermore, the spatial regression analysis in the relationship of LBW and PTB with associated factors highlights that ambient $PM_{2.5}$ is one of the leading risk factors compared with child, maternal, and household level factors for adverse birth outcomes in India.

Materials and methods

Study design

The data evaluated in this study have been derived from the most recent (5th) round of the National Family Health Survey (NFHS) conducted between 2019 and 2021 under the Ministry of Health and Family Welfare (MOHFW). The survey was conducted on a nationwide scale and employed a cross-sectional methodology. The primary goal of the NFHS is to furnish reliable and more accurate data on population and diverse health indicators. The survey was carried out in two phases. The first phase was conducted from June 17th, 2019, to January 30th, 2020, while the second phase was conducted from January 2nd, 2020, to April 30th, 2021. The sample design used in this study involves two stages and is stratified based on rural and urban locales. The selection of main sampling units in rural areas was based on villages, whereas census enumeration blocks were used in urban areas. The probability proportional size method determined the sampling units. Within each cluster, a total of 22 households were selected using a method called systematic sampling. These clusters with geographic location information are recorded as part of the survey process. Whereas, to maintain the respondent's privacy, rural cluster displaced up to 10 km and the urban cluster up to 2 kn. Furthermore, the NFHS-5 (IIPS and ICF 2021) contains a comprehensive account of the techniques, design, collected data, study participants, and other relevant information.

The NFHS-5 is a nationally representative survey that has collected data from 636,699 households. This sample consists of 724,115 women aged 15–49, 1,017,179 males aged 15–54, and 232,920 children. The current study focuses on births that occurred 5 years before the survey. Information regarding children was obtained through the kids recode (KR), while data on household conditions of the respondents was collected using household recode (HR). Observations for children with missing birth weight data (n = 23,654) were excluded from the sample. Hence, the overall sample size comprises 209,266 children. Additionally, observations with missing values (0.54%) for the average total pregnancies $PM_{2.5}$ exposure value (1,135) have been excluded, resulting in a final sample size of 2,08,181 children (refer to Fig. 1).

Outcome variable

The study considers LBW and PTB as outcome variables. According to WHO, preterm newborns as those born before 37 weeks of gestation, while LBW infants are those who weigh less than 2500 grams at birth (Darmstadt *et al.*, 2023). The NFHS-5 collects birth weight data using two methods: relying on the mother's recall of her baby's weight at the time of the survey and using any existing record of the baby's weight (IIPS and IYCF, 2021). Additionally, PTB is determined based on the duration of gestation. Both outcome variables are binary, where '1' indicates that the infants had LBW/PTB, and '0' indicates that the kid did not have LBW/PTB.

Exposure assessment

Due to insufficient ground monitoring stations for air pollution ($PM_{2.5}$) across the Indian subcontinent, researchers relied on high-resolution geographic data acquired from satellites. These data were supplied by the Atmospheric Composition Analysis Group at Washington

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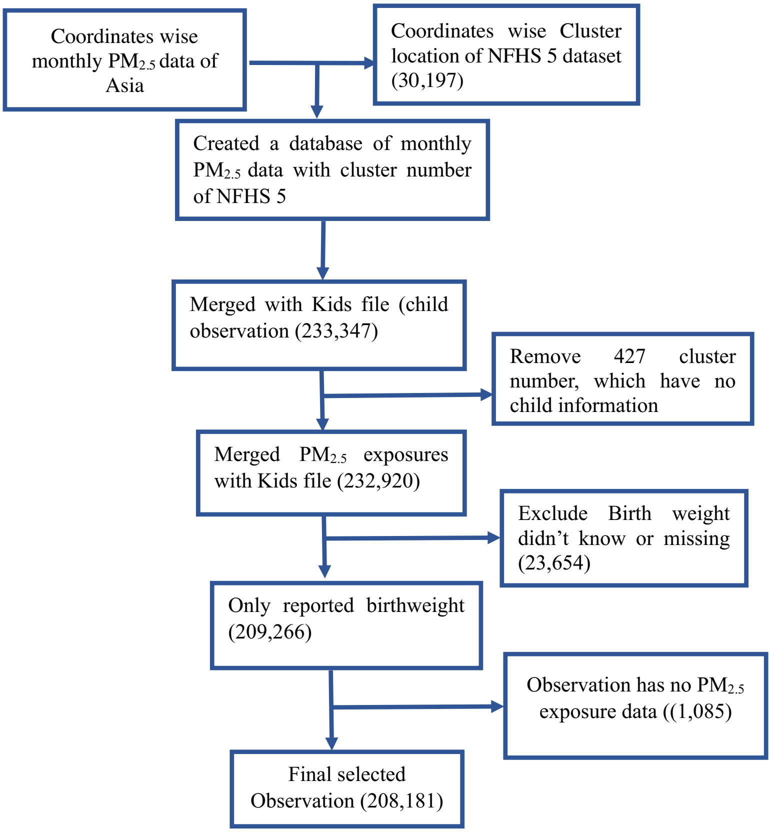

Figure 1. Flow chart of selected variables.

University. The dataset can be accessed by the public through the website https://sites.wustl.edu/acag/datasets/surface-pm2-5/. These data provided the monthly levels of $PM_{2.5}$ are accurately measured at a resolution of $0.01 \times 0.01°$ (about 1 km $\times$ 1 km) by integrating satellite data, ground-based air quality monitoring data, and pollution source modelling. To verify and compare with ground-based surveillance, the prior estimations obtained from satellite data showed less accurate findings as compared to the Indian subcontinent, whereas the most recent version of these satellite-driven data exhibits a strong correlation (0.81) with ground-based monitoring data (Van Donkellar *et al.*, 2016). To evaluate air pollution as a risk factor, the Global Burden of Disease (GBD) study adapted the same methodology (Brauer *et al.*, 2016). $PM_{2.5}$ data and geospatial information taken from the standard DHS dataset for India NFHS-5 2019–21, including geocoded, were integrated to determine the extent of $PM_{2.5}$ pollution in India. Following that, the monthly $PM_{2.5}$ concentrations from each cluster in the dataset were then manually removed, merged with each individual from all clusters, and used as the primary variable for measuring exposure. Taking the advantage of remote sensing and geographic information system, this study revealed substantial variations in $PM_{2.5}$ concentrations among different clusters in India. However, the mean $PM_{2.5}$ exposures were calculated for the actual duration of the respondent's pregnancy, excluding the month of birth and correlated with the reported length of pregnancy using monthly $PM_{2.5}$ data.

Confounding variables and adjustments

This study examines the correlation between the level of $PM_{2.5}$ and the incidence of LBW and PTB, identifying various potential factors that may affect the outcome variables. These

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determinants were present at the individual, maternal, and household levels. The selection of confounders was performed through an extensive review of pertinent literature and theoretical frameworks that demonstrate the association between $PM_{2.5}$ and LBW and PTB in children (Goyal and Canning, 2017; Goyal and Canning, 2021; Desouza *et al.*, 2022). These determinants at the children's level include the sex of the child and birth order. The maternal-level factors include the mother's level of education, teenage motherhood, the underweight status of the mother (BMI <18.5 kg/m^2), mother's age at birth, frequency of visiting antenatal care, and height of mothers. The household-level factors encompass the type of residence, availability of improved drinking water and sanitary facilities, use of unclean cooking fuel, and the wealth quintiles.

Statistical analysis

An analysis of descriptive statistics was conducted to provide insight into the characteristics of the participants in the study. The prevalence of LBW and PTB among children was assessed using a bivariate percentage distribution, considering confounding variables. The Pearson's chi-square statistic was employed to measure the discrepancies between observed and expected frequencies. The sample weight was utilized to calculate the percentage distribution. Multivariate logistic regressions were applied to evaluate the association between $PM_{2.5}$ and the likelihood of experiencing LBW and PTB in children under the age of 5. In this model, $PM_{2.5}$ is evaluated as a continuous exposure and categorized by octiles. However, only categorized $PM_{2.5}$ exposure values were considered in model 1. Model II was used to investigate the contribution of maternal level factors, and model III was combined with all variables. After that, to show the best-fit model log-likelihood, Akaike information criterion (AIC) and Bayesian information criterion (BIC) were used, while lower AIC, BIC, and highest log-likelihood values show the best model. A stratified analysis by sex of the child and place of residence was also used to find out an effect modifier in LBW and PTB. Additionally, to find out the no-linear relationship between exposure level and adverse birth outcomes, a marginal effect analysis with a 95% confidence interval was applied (Rodriguez, 2016; Gudayu, 2022). After running the nonlinear model like multivariate logistic regression, the marginal effect of the exposure variable is an appropriate way to find out how the probability change in the dependent variable occurs with one unit change of exposure variable (Onukwugha *et al.*, 2015; Norton *et al.*, 2019).

The spatial autocorrelation (Global Moran's I) was applied to identify the spatial distribution (clustered, random, or dispersed) of LBW and PTB in India. To measure the spatial autocorrelation, Moran's I value explained through non-random distribution value ranges from −1 to +1 (Anselin, 1995). The value closer to '0' indicates a random pattern, closer to '+1' indicates a cluster pattern, and closer to '−1' explains a dispersed pattern (Chen, 2021). Subsequently, to assess the spatial dependence between LBW and PTB using selected independent variables, ordinary least square (OLS) regression was applied, followed by geographically weighted regression (GWR) analysis. The OLS regression is a global statistical model that estimates the spatial relationship between the explanatory variables and dependent variables along with Koenkar (BP) Statistics, Joint Wald statistics, and Jarque-Bera Statistics, whereas GWR is a local statistic that estimates the different regression of each observation in the entire data set (Noresah and Sanjay, 2020; Tebeje *et al.*, 2024). However, in the model comparison between OLS regression and GWR, the lowest AICs and highest adjusted R^2 were explained as the best-fit model for analysis. All these statistical analyses were conducted using STATA MP version 14.0 and ArcGis 10.8.

Results

Descriptive statistics

Based on the analysis, this study estimated the level of exposure in utero from September 2013 to April 2021. Table 1 displays the outcomes obtained from the analysis utilizing descriptive

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Table 1. Distribution of exposure level and descriptive statistics of study sample by health outcomes in India, NFHS-2021

Descriptive statistics of the study sample			Prevalence's	
Variable	Frequency	Percentage (%)	Low birth weight	Preterm birth
Exposure level of $PM_{2.5}$ μg m^{-3}				
<28.02	25,333	12.17	14.15	12.06
28.02–34.33	26,812	12.88	15.02	10.6
34.33–42.13	27,146	13.04	15.71	10.3
42.13–49.92	26,953	12.95	18.06	12.34
49.92–59.92	26,346	12.66	18.79	13.2
59.92–73.21	25,671	12.33	18	13.38
73.21–93.84	25,206	12.11	20.16	12.7
>93.84	24,714	11.87	19.63	15.02
χ^2			615.44***	388.74***
Sex of the child				
Male	1,08,162	51.96	16.33	12.6
Female	1,00,019	48.04	18.59	12.22
χ^2			184.57***	6.83***
Birth order				
First birth order	82,834	39.79	18.22	12.67
Birth order 2–3	1,01,279	48.65	16.8	12.34
Order 4 and above	24,068	11.56	17.18	11.87
χ^2			64.88***	12.15***
Teenage motherhood				
Birth before 18 years	5,120	2.46	21.17	13.52
Birth between 18 and 19 years	7,025	3.37	19.6	12.8
Birth after 19 years	1,96,036	94.17	17.24	12.37
χ^2			78.00***	6.97**
Maternal BMI <18.5 kg/m^2				
Normal	1,64,998	81.44	16.44	12.28
Underweight	37,610	18.56	21.57	12.89
χ^2			560.84***	10.52***
Mother's level of education				
No education	40,847	19.62	19.64	12.91
Primary	25,816	12.4	19.34	12.2
Secondary	1,10,873	53.26	17.08	12.09
Higher secondary	30,645	14.72	14.02	13.1
χ^2			461.05***	34.44***
Mother's age at birth				
less than 20 years	23,731	11.4	19.89	13.12

(*Continued*)

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Table 1. (*Continued*)

Descriptive statistics of the study sample			Prevalence's	
Variable	Frequency	Percentage (%)	Low birth weight	Preterm birth
20–29 years	1,43,409	68.89	17.41	12.44
30–39 years	38,764	18.62	15.91	11.89
More than 39 years	2,277	1.09	17.13	12.38
χ^2			161.55***	20.73***
Received of antenatal care				
Inadequate visits (<4 times)	87,730	42.14	17.72	13.33
Adequate visits (>4 times)	1,20,451	57.86	17.19	11.75
χ^2			10.23***	116.88***
Mother's use smoke, tobacco				
Yes	12,118	5.82	15.87	8.64
No	1,96,063	94.18	17.51	12.65
χ^2			21.311***	168.63***
Maternal height				
Tall (>150 cm)	1,28,186	63.16	15.86	12.43
Medium (145–150 cm)	51,760	25.5	19.08	12.4
Short (<145 cm)	22,999	11.33	22.17	12.2
χ^2			679.58***	0.94
Drinking water facility				
Unimproved	13,245	6.36	16.68	10.66
Improved	1,94,936	93.64	17.46	12.53
χ^2			5.30**	40.44***
Sanitation facility				
Unimproved	52,014	24.98	19.61	12.44
Improved	1,56,167	75.02	16.68	12.41
χ^2			232.10***	0.03
Using of solid cooking fuel				
Clean fuel	97,466	46.82	16.08	12.82
Unclean fuel	1,10,715	53.18	18.58	12.06
χ^2			224.64***	27
Residence				27.88***
Urban	43,717	21	16.51	12.51
Rural	1,64,464	79	17.65	12.39
χ^2			31.59***	0.44
Wealth quintile				
Poorest	51,109	24.55	19.85	11.55
Poorer	48,430	23.26	18.05	12.58

(*Continued*)

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Table 1. (*Continued*)

Descriptive statistics of the study sample			Prevalence's	
Variable	Frequency	Percentage (%)	Low birth weight	Preterm birth
Middle	41,987	20.17	16.38	12.32
Richer	37,112	17.83	16.03	12.77
Richest	29,543	14.19	15.35	13.37
χ^2			393.17***	64.24***
$PM_{2.5}$ mean exposure of entire pregnancy(μg m^{-3})			56.01	
$PM_{2.5}$ mean exposure of low birth weight (μg m^{-3})			58.94	
$PM_{2.5}$ mean exposure of preterm birth (μg m^{-3})			59.06	
Health outcome (%)				
Low birth weight				
Normal birth weight	1,71,932		82.59	
Less 2500 gm	36,249		17.41	
Preterm birth				
More than 37 week	1,82,335		87.58	
Less than 37 week	25,846		12.42	

***Significant at: $P \le 0.001$, **Significant at: $P \le 0.01$, * Significant at: $P < 0.05$.

statistics. The mean birth weight of the study sample is 2812.50 grams. The prevalence of LBW is 17.24% (36,249 cases), and PTB is 12.42% (25,846 cases). The mean exposure to $PM_{2.5}$ during pregnancy is 56.01 μg/m^{-3}, the mean exposure with LBW is 58.94 μg/m^{-3}, and the mean exposure with PTB is 59.06 μg/m^3, all of which are 12 times higher than the WHO recommended level of 5 μg/m^3. The exposure level is divided into octiles with corresponding child proportions in Table 1, with each octile representing 12.5% of the sample as a whole. The reference group consists of children exposed to $PM_{2.5}$ levels in the lowest octile, which is below 28.02 m^{-3}. The results exhibit that there are different levels of risk for children, and those living with higher levels of $PM_{2.5}$ exposures are more likely to be LBW and PTB. The correlation between in utero $PM_{2.5}$ and LBW and PTB is represented in Table 2.

Out of 208,181 children under the age of 5, 51.69% were males and 48.31% were females. Further, the sample was divided based on their area of residence. Around 79% of the total sample lived in rural areas, whereas 21% resided in urban areas. In addition, 93.64% of children resided in households with access to improved drinking water sources, and 7% of children lived in households that relied on unimproved sources of drinking water, such as surface water, as their main water source. It was observed that approximately a quarter of children resided in families lacking improved sanitation facilities (24.98%). Only 57.86% of women were taken to adequate ANC facilities. On the other hand, mothers age at birth less than 20 years was 11.4%. Further, 19.62% of mothers had no education, while only 12.4% had completed primary education. Moreover, around 18.56% of mothers had a body weight below normal BMI, while over 5% were teenage mothers, and based on birth records, 39.79% were experiencing their first childbirth.

The data shown in Table 1 indicate that over 17% of children below the age of five in India have encountered a case of LBW, with 12% of these infants experiencing PTB in India. This table also explains the distribution of the prevalence of child health outcome episodes and the corresponding x^2 tests. The occurrence of LBW and PTB was substantially associated with exposure to $PM_{2.5}$. However, LBW was particularly common among children as the level of $PM_{2.5}$

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increased. The prevalence of LBW and PTB declined with enhanced levels of maternal education and household affluence. The proportion of LBW and PTB was higher among infants of teenage mothers. Additionally, the cases of LBW were more in the case of female infants, whereas PTB was more prevalent among male infants. Among children with a known birth order, approximately 18.22% of those who were the firstborn had a LBW, and 12.67% were born preterm.

Multivariate regression analysis of predictor variables associated with LBW and PTB

Table 2 presents a concise overview of the outcomes of a multivariate logistic regression analysis, which demonstrates the relationship between $PM_{2.5}$ exposures and the occurrence of LBW and PTB in children aged under 5. In model 1, which does not include adjusting for any confounders, the relationship between $PM_{2.5,}$ LBW, and PTB remained significant. At the last model III was the best-fitted model after accounting for all the factors upon controlling for variables such as $PM_{2.5}$ exposure level, sex of child, birth order, teenage motherhood, BMI of mother, mothers age at birth, visit of ANC, mother's height, educational status of mother, type of residence, cooking fuel, type of sanitation, and drinking water facility and household wealth quintile, a notable and favourable correlation is observed between $PM_{2.5}$ exposure and health outcomes.

Moreover, model I reflects that exposure levels up to 42.13 μg/m^{-3} have a less significant impact on the chance of LBW and PTB compared to the reference group. After accounting for different factors in model III, the odds ratio for LBW increased from 1.01 (CI: 0.96–1.06) with a concentration of 42.13–49.92 μg/m^{-3} to 1.04 (CI: 0.99–1.10) with a concentration of 49.92–59.92 m^{-3} in the fifth octile, and further increased to 1.06 (CI: 1.01–1.12) with a concentration of 93.84 μg/m^{-3} in the last octile. However, the findings indicated a lack of consistency in the dimension of LBW, which explains the existence of non-linear relationship between the variables. On the other hand, there was a consistent association between exposure to $PM_{2.5}$ at a level of 42.13 μg/m^{-3} and an increased risk of PTB. Children in the fourth octile of exposure, with a range of 42.13–49.92 m^{-3}, have a relative risk of PTB of 1.27, with a CI of 1.20–1.36. The risk of PTB increases steadily from the first to the fifth octile, with a risk ratio of 1.39 (95% CI: 1.31–1.48). The highest risk of PTB is observed in the last octile, with a risk ratio of 1.52 (95% CI: 1.43–1.61).

Stratified analysis

Additionally, to find out the potential effect modifiers that vary LBW and PTB across different subgroups, the association between maternal exposure to $PM_{2.5}$ and LBW and PTB are presented in Tables S1 and S2. For LBW, stratified by sex of the child, a more significant association was observed among male children compared to female children. Similarly, stratified by place of residence more significant was found in rural areas. On the contrary, for PTB stratified by sex of the child, strong associations were observed among female children and the following subgroups: mothers had the highest education level and rural areas. Besides that, stratified by place of residence, higher exposure to $PM_{2.5}$ and mothers' level of education in rural had a significant association.

Marginal effect analysis

Tables S3 and S4 show the marginal effect of LBW and PTB of maternal exposure to $PM_{2.5}$ by octile format. Overall, the results show that increasing the level of exposure to $PM_{2.5}$ increases the likelihood of LBW and PTB, although no linearity exists. For LBW, Table S3 represents that after the third octile, it increased up to the fifth octile and then decreased in the sixth octile. After that, from the sixth octile, it increased continuously (Figs 2 and 3). Whereas, for PTB, it has been observed that after the second octile, the risk of PTB becomes more acute as the exposure to $PM_{2.5}$ level increases.

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Table 2. Multivariate regression results showing the association between $PM_{2.5}$ with LBW and PTB among under-5 children (n = 208,181), NFHS-2021

	Model I		Model II		Model III	
Determinants	Low birth weight	Preterm birth	Low birth weight	Preterm birth	Low birth weight	Preterm birth
In utero $PM_{2.5}$ exposure level	Crude OR	Crude OR	AOR	AOR	AOR	AOR
<28.02 ®						
28.02–34.33	0.97 (0.92–1.02)	0.96 (0.90–1.02)			0.93** (0.88–0.98)	0.94 (0.88–1.01)
34.33–42.13	0.98 (0.93–1.04)	1.04 (0.97–1.11)			0.91*** (0.87–0.96)	1.03 (0.97–1.10)
42.13–49.92	1.11*** (1.05–1.17)	1.27*** (1.19–1.35)			1.00 (0.96–1.06)	1.27*** (1.20–1.36)
49.92–59.92	1.16*** (1.10–1.22)	1.41*** (1.33–1.50)			1.04 (0.99–1.10)	1.39*** (1.31–1.48)
59.92–73.21	1.07* (1.01–1.12)	1.37*** (1.30–1.46)			0.96 (0.91–1.01)	1.34*** (1.26–1.43)
73.21–93.84	1.22*** (1.16–1.28)	1.33*** (1.25–1.41)			1.10*** (1.05–1.16)	1.29*** (1.21–1.37)
>93.84	1.17*** (1.12–1.23)	1.58*** (1.43–1.67)			1.06** (1.01–1.12)	1.52*** (1.43–1.61)
Sex of child						
Male ®						
Female					1.19***	0.97* (0.94–0.99)
Birth Order						
First birth order ®						
Birth order 2–3					0.87***	0.98 (0.95–1.01)
Birth order 4 and above					0.84***	0.96 (0.91–1.01)
Teenage motherhood						
Birth before 18 years ®						
Birth between 18 and 19 years			0.87*** (0.80–0.95)	1.00 (0.90–1.10)	0.88**	0.99 (0.89–1.09)
Birth after 19 years			0.90 (0.84–0.98)	0.98 (0.90–1.08)	0.93*	0.97 (0.88–1.06)
Maternal BMI <18.5 kg/m^2						
Normal ®						

(*Continued*)

Table 2. (*Continued*)

Determinants	Model I		Model II		Model III	
	Low birth weight	Preterm birth	Low birth weight	Preterm birth	Low birth weight	Preterm birth
In utero $PM_{2.5}$ exposure level	Crude OR	Crude OR	AOR	AOR	AOR	AOR
Underweight			1.29*** (1.26–1.33)	1.07*** (1.04–1.11)	1.28***	1.08*** (1.04–1.12)
Mother's level of education						
No education ®						
Primary			1.03 (0.99–1.07)	0.90*** (0.86–0.95)	1.05*	0.91*** (0.87–0.96)
Secondary			0.92*** (0.89–0.95)	0.87*** (0.84–0.91)	0.945**	0.89*** (0.86–0.93)
Higher secondary			0.75*** (0.72 0.78)	0.934** (0.90–0.98)	0.77***	0.94* (0.89–0.99)
Mother's age at birth						
Less than 20 years ®						
20–29 years			0.91*** (0.87–0.95)	0.92** (0.87–0.97)	0.96 (0.91–1.01)	0.92 (0.87–0.97)
30–39 years			0.87*** (0.83–0.92)	0.89*** (0.84–0.95)	0.97 (0.91–1.02)	0.92* (0.86–0.98)
More than 39 years			0.88*** (0.77–1.00)	1.04 (0.90–1.20)	0.97 (0.85–1.12)	1.09 (0.94–1.27)
Received of antenatal care						
Inadequate visits (<4 times) ®						
Adequate visits (>4 times)			0.98 (0.96–1.01)	0.85*** (0.83–0.87)	0.98 (0.96–1.00)	0.89*** (0.87–0.92)
Mother's use smoke, tobacco						
No ®						
Yes			1.06 (0.99–1.13)	0.87*** (0.80–0.94)	1.06 (1.00–1.13)	0.92* (0.85–1.00)
Maternal height						
Tall (>150 cm) ®						
Medium (145–150 cm)			1.24*** (1.20–1.27)	1.04* (1.01–1.07)	1.22*** (1.19–1.25)	1.02* (1.00–1.07)
Short (<145 cm)			1.51*** (1.46–1.56)	1.01 (0.97–1.05)	1.47*** (1.42–1.52)	1.00 (0.96–1.04)
Drinking water facility						
Unimproved ®						

(*Continued*)

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Table 2. (*Continued*)

Determinants	Model I		Model II		Model III	
	Low birth weight	Preterm birth	Low birth weight	Preterm birth	Low birth weight	Preterm birth
In utero $PM_{2.5}$ exposure level	Crude OR	Crude OR	AOR	AOR	AOR	AOR
Improved					0.98 (0.93–1.04)	1.07* (0.93–1.04)
Sanitation facility						
Unimproved ®						
Improved					0.98 (0.95–1.00)	0.98 (0.95–1.00)
Using of solid cooking fuel						
Clean fuel ®						
Unclean fuel					1.02 (0.99–1.05)	0.92*** (0.89–0.95)
Residence						
Urban ®						
Rural					0.93*** (0.90–0.96)	1.12*** (1.09–1.17)
Wealth quintile						
Poorest ®						
Poorer					0.98 (0.94–1.01)	1.08*** (1.04–1.13)
Middle					0.90*** (0.86–0.94)	1.04 (0.99–1.09)
Richer					0.92*** (0.88–0.96)	1.09** (1.03–1.15)
Richest					0.86*** (0.82–0.91)	1.12*** (1.06–1.20)
Test for model fit						
AIC	190917.8	152504.4	189537.6	152839.2	189042.4	152309.3
BIC	190999.5	152586.2	189680.7	152982.3	189369.4	152636.3
Log likelihood	−95450.89	−76244.2	−94754.8	−76405.59	−94489.21	−76122.65

Note: AIC: Akaike information criterion, BIC: Bayesian information criterion, AOR: adjusted odds ratio, ®: Reference category, * Significant at: $P < 0.05$; **Significant at: $P \leq 0.01$, ***Significant at: $P \leq 0.001$.

Spatial autocorrelation and OLS regression analysis

To understand the spatial pattern of LBW and PTB in India, spatial autocorrelation results were reported in Figs. 4 and 5. It illustrates that the Moran's Index value for LBW is 0.37 and PTB 0.16, representing the clustering pattern in India. Based on selected explanatory variables related to LBW and PTB, the OLS regression results are significant and explain about 16.7% (adjusted R2 = 0.167) of LBW and 13.7% (adjusted R2 = 0.137) of PTB spatial variation persisting, with non-existence of multicollinearity between predictors variables and birth outcomes (Tables S5 and S8).

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Additionally, Table S6 revealed that joint F statistics and Joint Wald statistics are significant (<0.01), which shows that the association between predictors variables and LBW is free from non-stationary, and residuals are normally distributed, whereas Table S9 explains that in the case of PTB, all four statistics, Jarque-Bera, Joint F, Joint Wald, and Koenkar statistics, are significant (<0.01), which explains that residuals are not normally distributed due to non-stationary among the data. However, compared between LBW and PTB among the five selected variables, only district-level average of $PM_{2.5}$ in the entire pregnancy received antenatal care less than 4 is statistically significant in both cases, and child from the poorest quintile is significantly associated with PTB. Therefore, the GWR model was considered for further analysis to give more strength and appropriate estimates in the analysis.

GWR regression analysis

After analysing the OLS regression, GWR modelling was performed to find out the spatial variation of predictor variables for LBW and PTB in India. Compared with the OLS model in GWR, the adjusted R2 value was increased from 0.17 to 0.37, with the AIC value decreased from 4317.1 to 4127.74 in LBW; this shows that the GWR model enhanced by 20% and the difference of AIC was 189.36 (Table 3). In contrast, for PTB, GWR R2 value increased from 0.14 to 0.24, whereas the AIC value decreased from 4876.18 to 4794.94 (Table 3). Overall, Table 3 revealed that the GWR model was improved than OLS regression both for LBW and PTB.

Additionally, the GWR model illustrates that the predictor variables were strongly and negatively associated with LBW and PTB. In the case of LBW, Fig. 6(a)–(f) explains that as the gestational average of $PM_{2.5}$ increased, the proportion of LBW increased in northeast India and parts of Jammu and Kashmir. Related to inadequate visits of ANC, GWR coefficient was strong in Jammu and Kashmir as well as Punjab and Himachal Pradesh. Furthermore, regarding the poorest wealth quintile, the GWR coefficient was strong in parts of Tamil Nadu and Kerala. For mothers who had no education, the GWR coefficient was moderately concentrated in the central and middle part of India, and adverse birth outcomes from rural areas were strongly found in northeast India and followed by the eastern part of India, whereas, the predicted LBW areas were mostly concentrated in districts of Uttar Pradesh and Madhya Pradesh.

On the contrary, Fig. 7(a)–(f) shows the results of spatial variations of GWR coefficient of five predictor variables. The proportion of PTB with a gestational avg. of $PM_{2.5}$ was more concentrated in districts of West Bengal, Odisha, Bihar, and Jharkhand. The proportion of mothers who had visited less ANC care the GWR coefficient was strongly found in Assam, Arunachal Pradesh, and parts of Tripura. Similarly, the strong GWR coefficient for having the poorest wealth quintile

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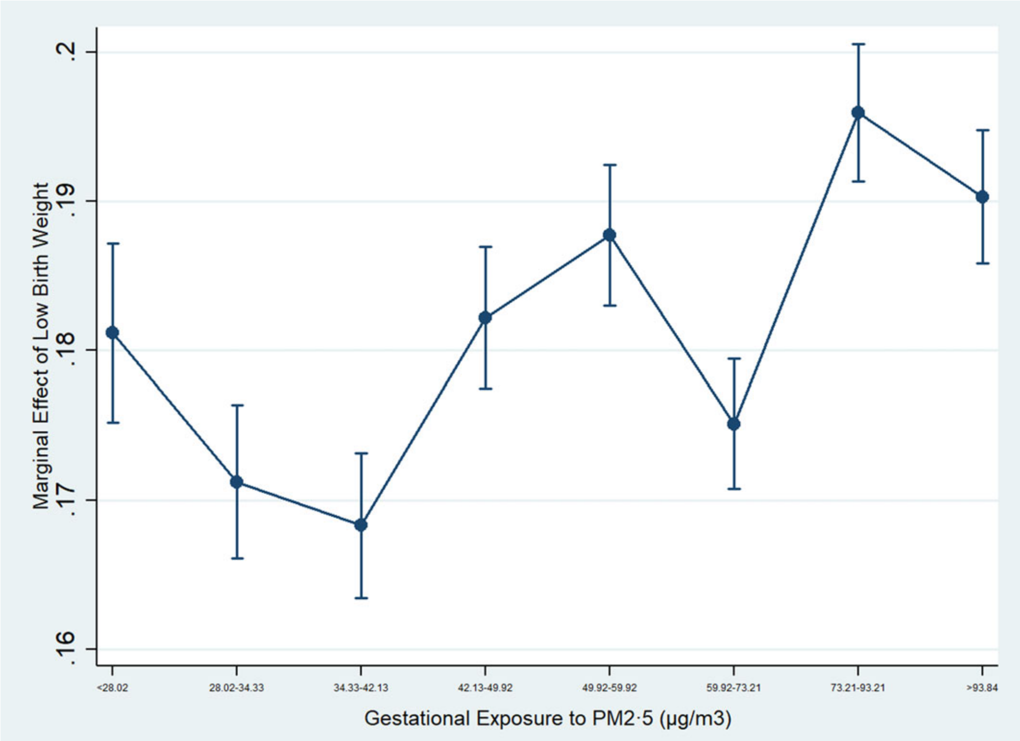

Figure 2. Marginal effect analysis of low birth weight by octile of gestational exposure to $PM_{2.5}$.

with PTB was observed particularly in districts of Kerala and Tamil Nadu. Besides, for mothers who had no education with PTB, a moderate positive association was identified in most of the southern and eastern parts of Indian districts. In the same way regarding the GWR coefficient of being a PTB child from a rural residence, a strong and positive association was found in most parts of Gujrat, Kerala, and Ladakh. However, adjusted with five selected variables, Fig. 7 shows that the potential concentration of PTB is significantly dispersed.

Discussion

Over the years, there has been a steady increase in the level of particulate matter air pollution globally. Between 1998 and 2021, there was a significant increase of 67.7% in the annual level of particulate matter air pollution, resulting in a decrease in average life expectancy by 2.3 years (CPCB, 2022). Over the last 10 years, India's $PM_{2.5}$ levels have increased significantly by more than 1μg/m^3 per year (Dey *et al.*, 2020). However, India's average $PM_{2.5}$ levels increased by 15% between 1998 and 2019 (Srivastava *et al.*, 2020). On an average, Delhi had the highest $PM_{2.5}$ concentrations, but the number of cities in Uttar Pradesh with high $PM_{2.5}$ levels was the most. From this study, it was observed that the air quality was consistently deteriorating and getting worse, reaching an average of 56.01 μg/m^{-3} in 2021.

Additionally, India was responsible for 59.1% of the worldwide rise in air pollution from 2013 to 2021 (Slater *et al.*, 2022). Against this backdrop, a substantial quantity of cross-sectional research has examined the association between $PM_{2.5}$ and maternal exposure. Several suggested pathways by which $PM_{2.5}$ could cause PTB and LBW. Evidence suggests that pregnant women exposed to particulate matter air pollution may be at increased risk of PTB due to acute

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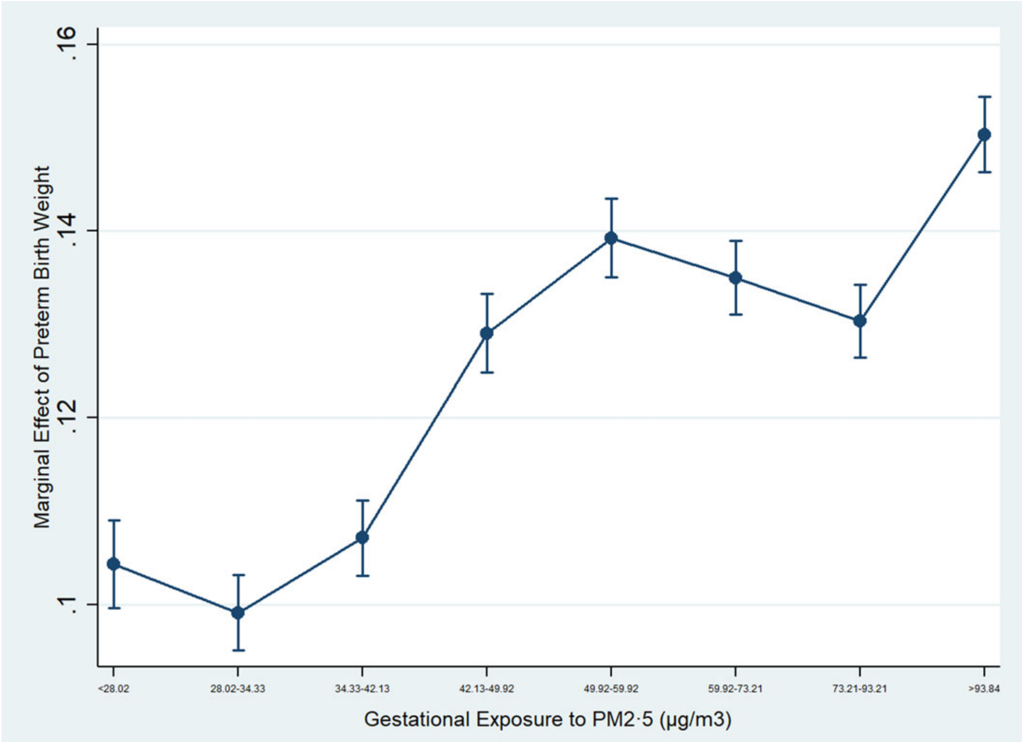

Figure 3. Marginal effect analysis of preterm birth by octile of gestational exposure to $PM_{2.5}$.

inflammation in the lungs and other organs (Liu *et al.*, 2003). Furthermore, with a similar mechanism, a recent study evaluated whether certain maternal health conditions and pregnancy difficulties can influence the link between air pollution and poor birth outcomes (Laurent *et al.*, 2014).

The results demonstrated that there are direct and significant relationship between $PM_{2.5}$ exposures and LBW and PTB. Although maternal exposure to particulate matter air pollution is prevalent in India, only a few epidemiological studies have evaluated the outcome as an LBW and PTB independently (Goyal and Canning, 2021; Dimitrova *et al.*, 2022; Jana, 2023), while none of these studies have considered both the outcomes in the same study. After accounting for several confounding variables, the present study reveals a significant association between LBW and PTB, as well as an increased risk of these conditions among under 5 children in India. It shows that there is a lower chance of PTB exposed to $PM_{2.5}$ levels up to 40μg/m^3. Beyond that point, it rises sharply to >93.84 μg/m^3 (OR 1.58, CI: 1.48–1.67). But when it comes to LBW, it is uneven from the first octile to the last octile. Similar to the previous study, the results of this study validate that overall, increasing the pollution level has higher odds of LBW and PTB, followed by 'National Ambient Air Quality Standards' (NAAQS), which has set a threshold value of 40 μg/m^3 for $PM_{2.5}$ in India (Adhikary *et al.*, 2024). Whereas, a meta-analysis of polling estimates indicated that there was an 11% increased likelihood of LBW (AOR 1.11, CI: 1.07–1.16), and a 12% chance of an early delivery (AOR 1.12, CI: 1.06–1.19) for every 10 μg/m^3 rise in ambient $PM_{2.5}$ levels (Ghosh *et al.*, 2021).

Referring to the potential effect modifiers, the odds ratio for LBW and PTB are increased compared with the multivariate regression model. Earlier studies showed that the likelihood of LBW among female children (OR 1.19, CI: 1.17–1.22) is 19% more acute compared to males

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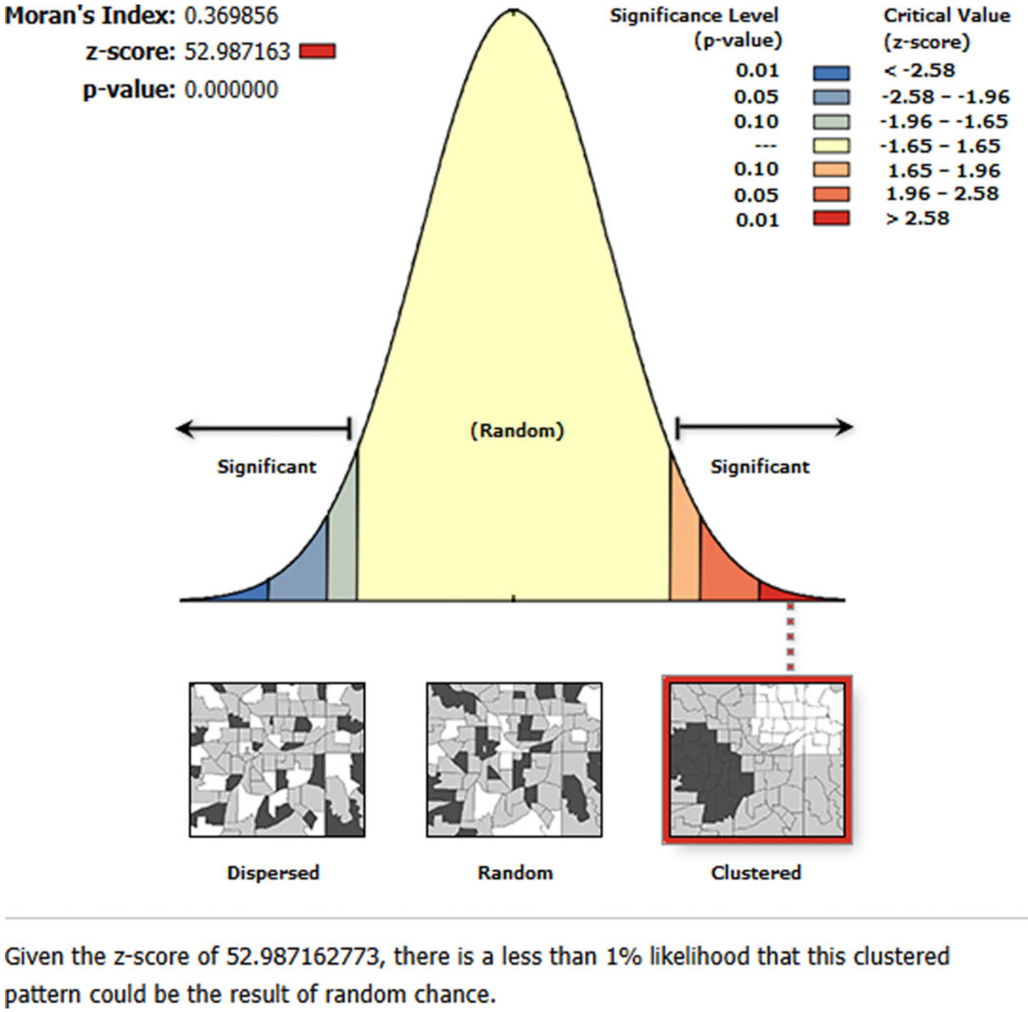

Figure 4. Spatial autocorrelation of low birth weight among under-5 children in India, NFHS-5.

(Bachwenkizi *et al.*, 2022) As a result, LBW female children are at high risk to get disease in their later life as compared to male counterparts (Zimmermann *et al.*, 2015). Furthermore, compared to the first birth order child, increasing the birth order of children reduces the chances of LBW. Likewise, adjusting with other factors the study showed that increasing the mother's level of education reduces the risk of LBW. On the contrary, by lowering the mother's BMI, they were at more risk for delivering LBW infants.

The present study found that inadequate visits to ANC care increase the likelihood of being PTB children compared with LBW children. Alignign with previous studies, it influences adverse birth outcomes, including PTB (Alexander and Kotelchuck, 1996). Therefore, to reduce the burden of PTB and LBW, increasing awareness of the ANC programme is one of the best public health strategies (Pervin *et al.*, 2020). The study also highlights that mothers who were in short stature were more likely to be associated with LBW and PTB. However, it remains unclear, whether tall stature reduces the risk of adverse birth outcomes or whether short stature has more risk of either LBW and PTB (Chan and Lao, 2009; Han *et al.*, 2012).

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Table 3. Model comparison between Ordinary least square regression and geographically weighted regression in India, NFHS-2021

Model comparison	Low birth weight		Preterm birth weight	
	OLS	GWR	OLS	GWR
AIC	4317.1	4127.74	4873.18	4794.9
Adjusted R-squared	0.17	0.37	0.14	0.24

Note: AIC: Akaike information criterion, OLS: ordinary least square, GWR: geographically weighted regression.

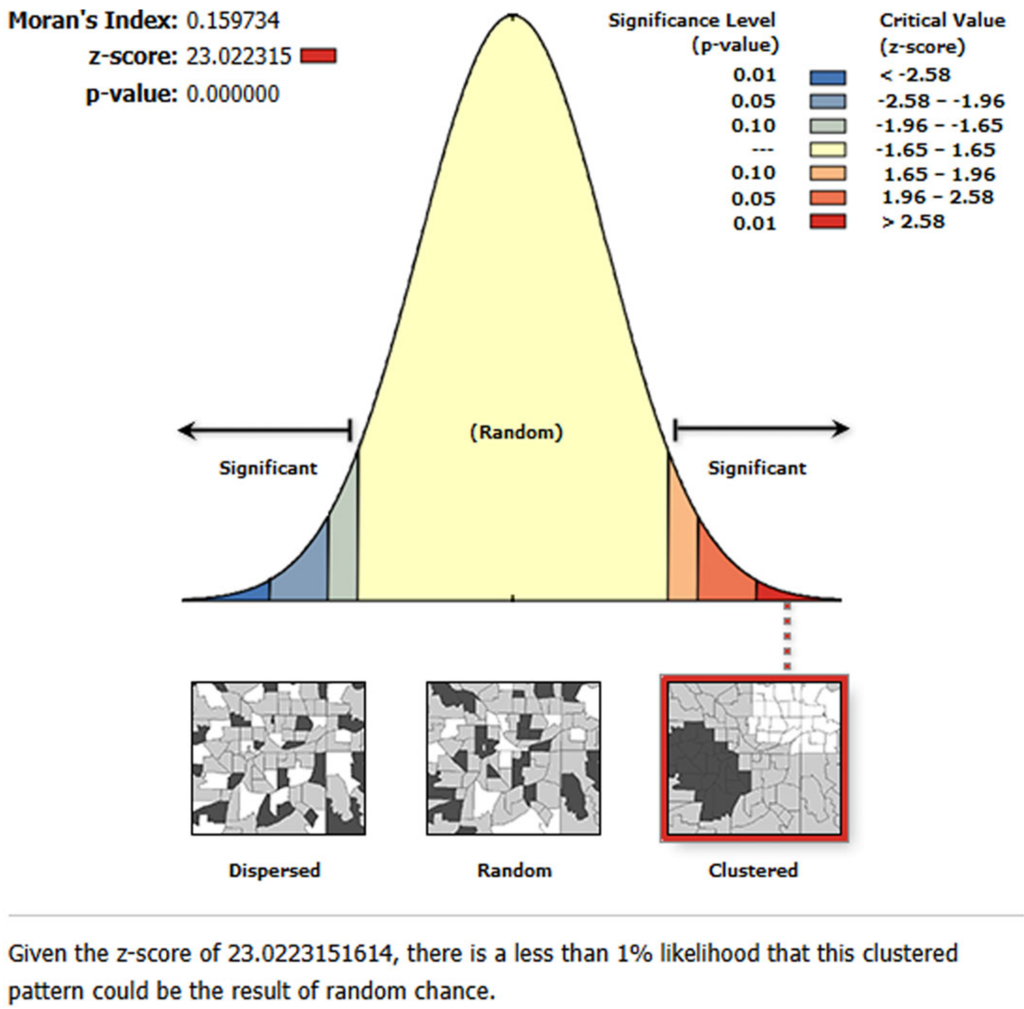

Figure 5. Spatial autocorrelation of preterm birth among under-5 children in India, NFHS-5.

Similar to cohort research conducted on 1285 pregnant women in Tamil Nadu, India, which reported that there was a 10 µg/m^3 increase in gestation period $PM_{2.5}$ after adjusting for the child's sex, the mother's age, her BMI, her history of LBW children, the birth order, and the season of conception. This study further reported a significant drop in birth weight by 4 gm odds ratio (CI: 1.08–6.76) decrease in birth weight and a 2% increase in the prevalence of LBW (OR 1.02, CI:

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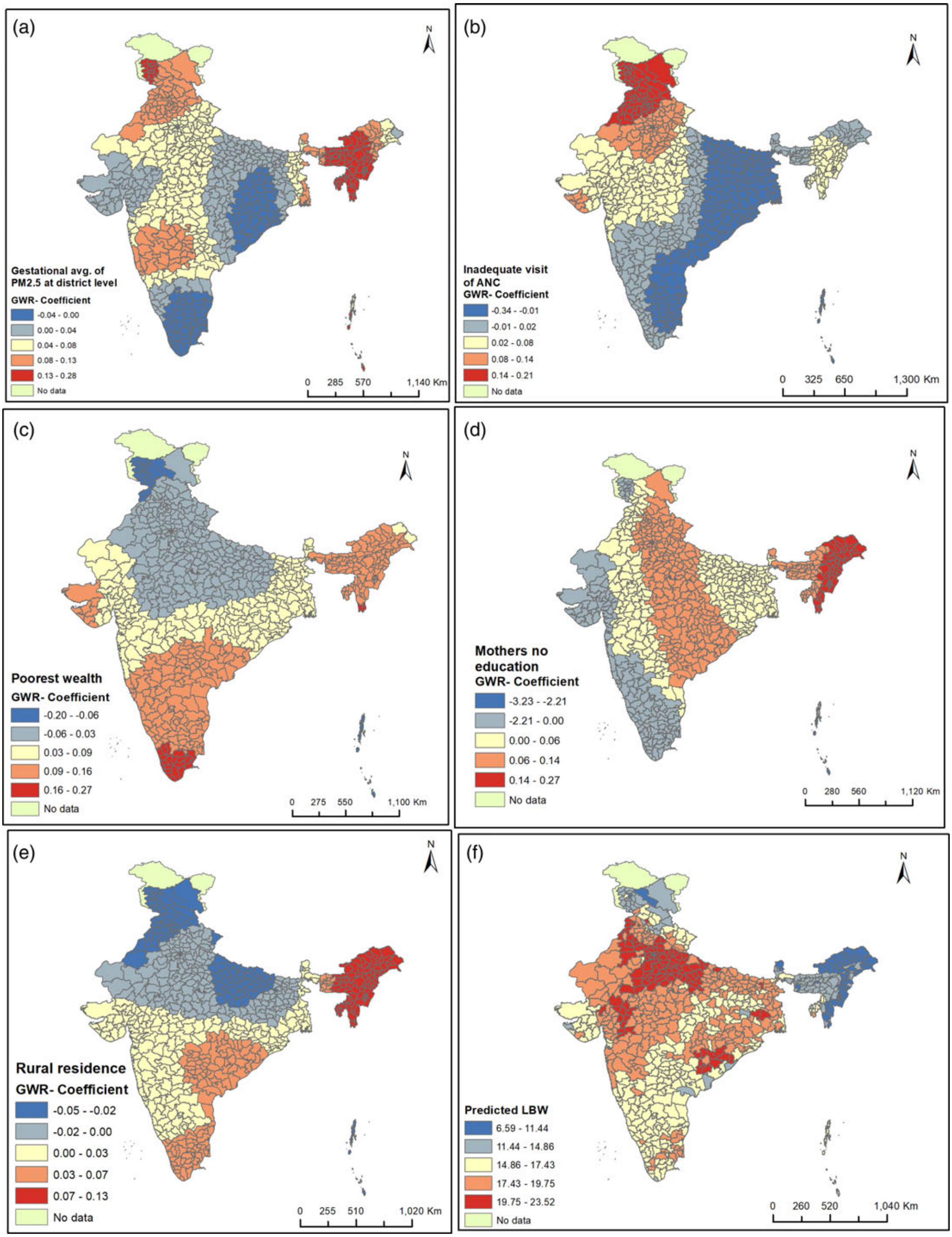

Figure 6. GWR coefficient of (a) district level ag. of $PM_{2.5}$, (b) visit of antenatal care, (c) poorest wealth quintile, (d) mothers with no education, (e) rural residence for LBW, and (f) predicted LBW in India.

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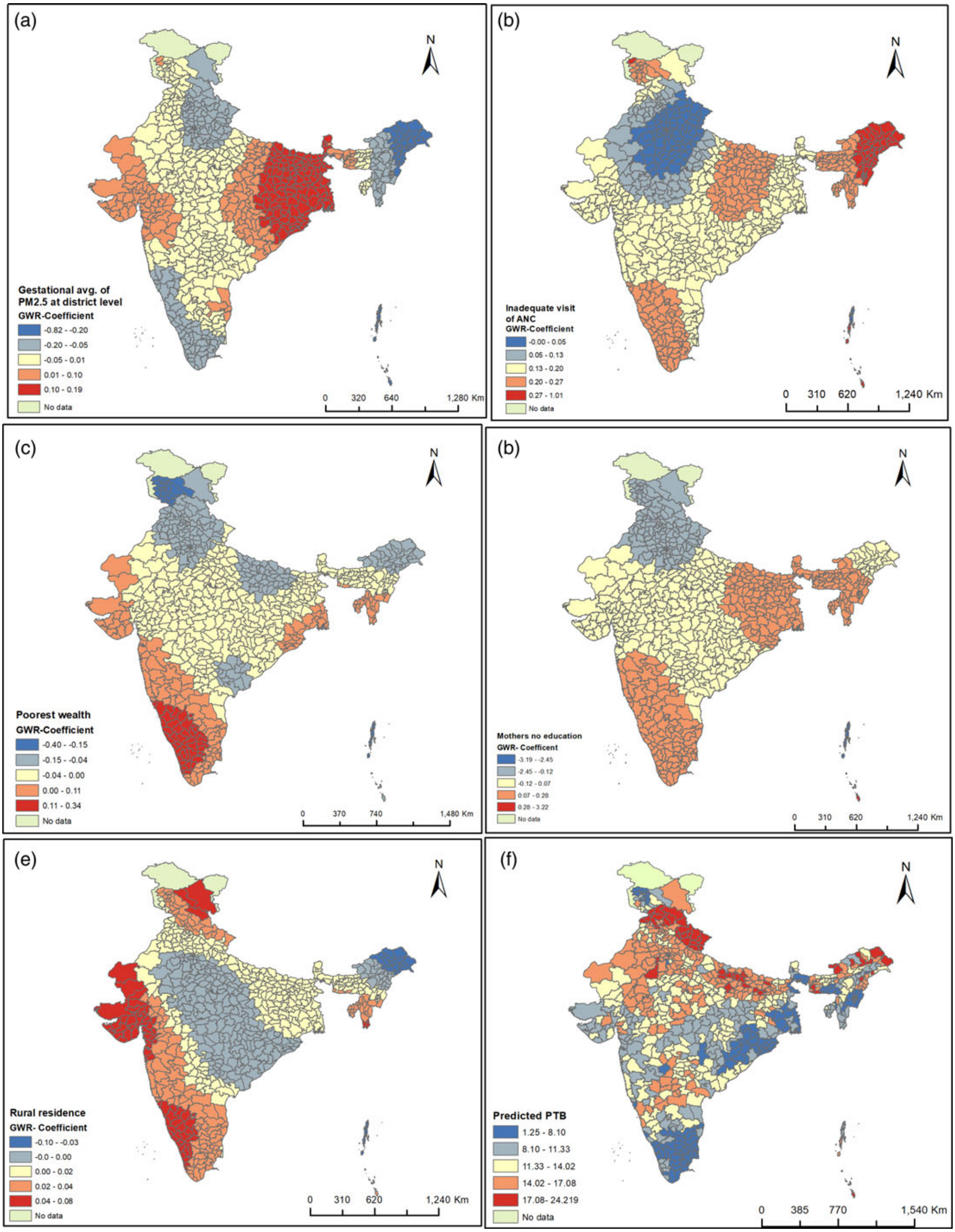

Figure 7. GWR coefficient of (a) district level ag. of $PM_{2.5}$, (b) visit of antenatal care, (c) poorest wealth quintile, (d) mothers with no education, (e) rural residence for PTB, and (f) predicted PTB in India.

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1.005–1.041) (Balakrishnan *et al.*, 2018). Consistent with previous research, the findings suggest that other factors, such as teenage motherhood, drinking water facilities, and forms of sanitation, were not statistically significant among LBW infants (Nazari *et al.*, 1995; Borkowski and Mielniczuk, 2008). Earlier research, whereas advanced mothers age at birth (>35 years) is associated with LBW, PTB, and stillbirths (Fall *et al.*, 2015), the present study stated an uneven significant relationship between maternal exposure to $PM_{2.5}$ adjusted with other variables.

Based on earlier studies, related to PTB findings, the study suggests that mothers' exposure to $PM_{2.5}$ can increase the chances of premature birth (Bachwenkizi *et al.*, 2022; He *et al.*, 2022). It seems that the growth and development of the placenta are adversely affected by the exposure of pregnant mothers to $PM_{2.5}$ during the gestation period (Lee *et al.*, 2011; Van den Hooven *et al.*, 2012). Results show that compared to male counterparts, female children are at low risk of PTB. Similar to prior studies, multivariate analysis confirmed that male foetal is an independent risk factor for PTB (Peelen *et al.*, 2016).

Women with higher educational levels have lower chances of giving PTB in comparison to women with lower educational levels. At the same time, it has been observed that the increased risk of having PTB is higher in women with low BMI. Prior literature explained that infants of teenagers are at high risk of poor infant outcomes (Carter *et al.*, 2007). More specifically, the results of this study determined that increasing the mother's age at the time of birth reduces the risk of PTB.

Studies suggest that children living in rural areas had a 13% higher chance of experiencing PTB compared to those living in urban areas. Research revealed that households utilizing unclean cooking fuel (OR 0.92, CI: 0.89–0.95) are less likely to experience PTB. Against this backdrop, despite urban regions having better access to improved water sources, increased urbanization, and industrialization in major cities, where pollution emissions from transportation and manufacturers are more pronounced, the diverse socio-economic differences between rural and urban areas can lead to these inequalities.

The study revealed that, based on spatial dependency with predictor variables, the variation of LBW and PTB is significant. Similar to previous studies, spatial autocorrelation of LBW confirms the spatial heterogeneity in India (Banerjee *et al.*, 2020). Overall, it was depicted that different explanatory variables of LBW and PTB (district level ag. of PM2.5, visit of antenatal care, poorest wealth quintile, no education of mother, and rural residence) play a significant role in the entire India. This indicates that existing variability of LBW and PTB across India could be due to unequal availability and affordability of healthcare services, cultural practices, socio-economic disparities, geographical barriers, and lack of awareness among mothers in the time of their gestation period. Furthermore, the earlier studies predicted R2 map depicts that associated with exposure to $PM_{2.5}$ the potential area of LBW and PTB is also concentrated in places where the exposure level of $PM_{2.5}$ is higher (Jat and Gurjar, 2021; Jana *et al.*,2024).

However, the present study estimated the analysis based on octile categorization and individual's different gestation periods. Therefore, the disparities between these findings and this analysis are attributable to the differences in the study design and methodology (Goyal and Canning, 2021). However, not all studies have found a consistent relationship between LBW, PTB, and maternal exposure to $PM_{2.5}$. Multiple studies (Bonzini *et al.*, 2010; Ghering *et al.*, 2011; Fleischer *et al.*, 2014; Jacobs *et al.*, 2017) have found no statistically significant relationship. Aligning with prior studies, several factors could contribute to the unpredictable findings in different studies on the association between $PM_{2.5}$ exposure and maternal outcomes (Ho *et al.*, 2023). The utilization of suitable models and exposure assessment approaches is of utmost importance (Fleischer *et al.*, 2014; Xiao *et al.*, 2018). Furthermore, when particulate matter was chosen as a risk factor, various geographical areas with unique co-pollutants (PM_{10}, $PM_{2.5}$, NO_2, and O_3) have exhibited varied results, particularly in LMICs with higher levels of air pollution (Bchwenkizi *et al.*, 2021). Therefore, more extensive research is required to elucidate these conflicting results, and mechanistic investigations are necessary to substantiate the present findings, particularly in LMICs that face significant air pollution levels (Bchwenkizi *et al.*, 2021).

Strengths and limitations of the study

The study comprehensively evaluates the association of $PM_{2.5}$ with LBW and PTB in India. It is the first of its kind to involve spatially connecting the NFHS-5 reported data with monthly $PM_{2.5}$ data to estimate the individual-level in-utero exposures in different gestation periods after controlling several confounding variables in India. Additionally, as ground monitoring stations were insufficient, satellite-derived $PM_{2.5}$ data were employed to provide spatial coverage of India. This allows us to determine the way $PM_{2.5}$ is connected with LBW and PTB at the individual level. Moreover, the calculation of $PM_{2.5}$ exposures depends on each individual's gestation period, depending on the information provided in the NFHS-5 regarding the duration of their pregnancy. According to earlier research, the average gestation time for all mothers was predicted to be 9 months (Goyal and Canning, 2021; Goyal and Canning, 2017). Therefore, our method for estimating exposure is more refined than earlier studies.

Despite the uniqueness and strengths of this study, it has certain limitations. The existing exposure model was limited to considering $PM_{2.5}$ as a pollutant, was unable to account for other types of pollutants, and did not adjust the spatial noise of DHS location with $PM_{2.5}$ data. Further data on the duration of pregnancy and birth weight were obtained using report cards and the mothers' recalling basis, although, in NFHS datasets, there was no other available method to verify the accuracy of reported data. It might, therefore, be subject to recall information bias. Moreover, the trimester-wise exposure model was not applicable since the gestation time of each mother differed. On the other hand, average exposures from conception to the date of birth were the only ones that could be utilised for the actual duration of pregnancy. At last, individual's information with a missing value of $PM_{2.5}$ indicates that this research has a measurement error.

Conclusion

The purpose of this study was to estimate the relationship between ambient $PM_{2.5}$ and maternal exposure. The study's findings indicate that children aged under 5 had a significantly higher likelihood of experiencing LBW and PTB when exposed to higher levels of fine particulate matter ($PM_{2.5}$) during pregnancy. These findings demonstrate the crucial significance of prenatal and early-life exposure to air pollution for a child's overall growth and health. This study will contribute to significant policy reforms pertaining to the reduction of air pollution in India. The findings of the study will encourage the extension of ground-based air monitoring throughout the nation. Additional research is required to verify these results by examining various pollutants or contaminants. Furthermore, conducting longitudinal studies to investigate the potential mechanism mediating the association between ambient air pollution and maternal exposure will add clarity to understanding the relationship among the above-mentioned constructs.

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