Title: Climatic Adversities and Child Health in India: Integrating Modelled Data on Air Pollution, Heatwaves, and Rainfall Extremes with DHS Surveys

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Abstract
This study investigates the associations between climatic adversities, such as air pollution, heatwaves, and rainfall extremes, and child health outcomes (stunting, wasting, underweight, anemia, and acute respiratory infections) in India. A primary goal of this research is to demonstrate how integrating modelled environmental data with DHS data can develop more comprehensive analysis strategies. Our methodology involved extracting modelled $PM_{2.5}$, hourly temperature and daily rainfall data from different sources. These environmental exposures were linked to each sampled child's in-utero period to estimate the in-utero exposure. To examine the effects, we employed generalized linear (with logit function when necessary) models. High $PM_{2.5}$ exposure was associated with a 20% increased risk of anemia (OR:1.20,CI:1.05–1.36) and a 15% increased risk of stunting (OR:1.15,CI:1.02–1.30) and a reduction in birth weight by 18 grams (β:-18 grams, CI:-35 to -1). Heatwave exposure during pregnancy was linked to a 14% increased risk of ARI, a 10% increased risk of wasting and and underweight (OR:1.14,CI:1.02–1.28). Excess rainfall was associated with a 23 gram reduction in birth weight and a 10% increased risk of wasting, while insufficient rainfall correlated with an 18% increased risk of anemia and a 12% increased risk of stunting.

Introduction

In-utero exposure to environmental adversities is increasingly recognized as a significant determinant of child health outcomes. Environmental stressors, including heatwaves, rainfall variability, and air pollution, can profoundly impact fetal development, potentially leading to adverse nutritional outcomes such as stunting, wasting, and underweight in early childhood. While substantial evidence exists on the individual impacts of these stressors, integrative studies assessing their combined effects during the critical in-utero period remain scarce. This study addresses this gap by utilizing high-resolution environmental data and comprehensive health surveys to explore the combined effects of these stressors on child nutritional indicators.

Background

Climatic adversities such as raised average and extreme temperatures, altered rainfall patterns, and air pollution profoundly impact child health through multiple interconnected pathways which is shown in figure 1. Extreme temperatures contribute to heatwaves and increased fire occurrences, which not only lead to direct physical health risks like heat stress but also increase particulate matter pollution in the air. This pollution exacerbates respiratory infections, particularly in children, and reduces physical activity, further compounding health risks (Vicedo-Cabrera et al., 2021; Liu et al., 2019; Chaves et al., 2020). Altered rainfall patterns, resulting in both droughts and floods, severely diminish agricultural productivity, leading to food insecurity and a subsequent rise in undernutrition, manifesting in conditions such as low birth weight, stunting, wasting, underweight, and anemia (Wheeler & von Braun, 2013; Phalkey et al., 2015; Smith & Myers, 2018). Additionally, floods can increase the spread of waterborne diseases, further jeopardizing child health (Kovats & Akhtar, 2008).

These adverse effects are exacerbated by social determinants like poverty and limited access to healthcare, making already vulnerable populations, especially those in low-income regions, disproportionately susceptible to the health impacts of climate change (Watts et al., 2018; Costello et al., 2009). Children in these settings often lack the resilience to recover from these compounded stresses, leading to long-term developmental challenges. Furthermore, the interplay between environmental changes and socio-economic factors highlights the need for multidimensional intervention strategies that address not only the environmental causes but also the underlying socio-economic vulnerabilities. This comprehensive approach is crucial for mitigating the multifaceted impacts of climate change on child health, ensuring that future generations are better equipped to thrive in a changing climate (Ebi & Bowen, 2016; Patz et al., 2014).

Heatwaves, which have become more frequent and intense due to climate change, pose significant health risks, particularly for vulnerable populations such as pregnant women and developing fetuses (Carmona et al., 2021). Theoretical frameworks suggest that heat exposure induces thermal stress, leading to oxidative stress and inflammation. These physiological responses can disrupt placental function, impairing nutrient and oxygen delivery to the fetus and potentially resulting in restricted fetal growth and low birth weight (Wells, 2007). Low birth weight is a well-documented risk factor for childhood stunting and underweight (Black et al., 2013). Research indicates that prenatal exposure to high temperatures is linked to increased risks of preterm birth and low birth weight, both of which are critical predictors of adverse nutritional outcomes in early childhood (Wang et al., 2020; Schifano et al., 2013).

Rainfall variability and extreme precipitation events can significantly impact food security, water quality, and the prevalence of vector-borne diseases, thereby indirectly influencing maternal and child health. Variations in rainfall patterns have been associated with fluctuations in agricultural productivity, affecting food availability and nutritional outcomes (Lloyd et al., 2011). According to the ecological model of health, environmental changes affect health outcomes through various pathways, including economic instability and food insecurity, which are critical determinants of child nutritional status (Bronfenbrenner, 1979; Phalkey et al., 2015). Evidence from different regions indicates that climatic variability exacerbates malnutrition. For example, research in rural Ethiopia has shown that children born during drought periods experience higher rates of stunting (Cooper et al., 2019). Similarly, studies in India have demonstrated that rainfall shocks are linked to increased child malnutrition rates due to reduced agricultural yields and food insecurity (Shively, 2017).

Air pollution, especially fine particulate matter (PM2.5), represents a significant environmental health hazard with well-established adverse effects on respiratory and cardiovascular health.

The biological mechanisms through which prenatal exposure to PM2.5 impacts fetal development include oxidative stress and systemic inflammation, which can lead to placental inflammation and endothelial dysfunction (Saenen et al., 2015). These effects can impair the placental transfer of nutrients and oxygen, negatively impacting fetal growth and development. Epidemiological research consistently indicates that prenatal exposure to air pollution is linked to adverse birth outcomes such as low birth weight and preterm birth, which are predictors of stunting and wasting in early childhood (Brauer et al., 2016; Pedersen et al., 2013). For instance, a study in China found that higher levels of PM2.5 exposure during pregnancy were significantly associated with lower birth weight and an increased risk of low birth weight, underscoring the critical impact of air pollution on fetal growth (Zhang et al., 2018).

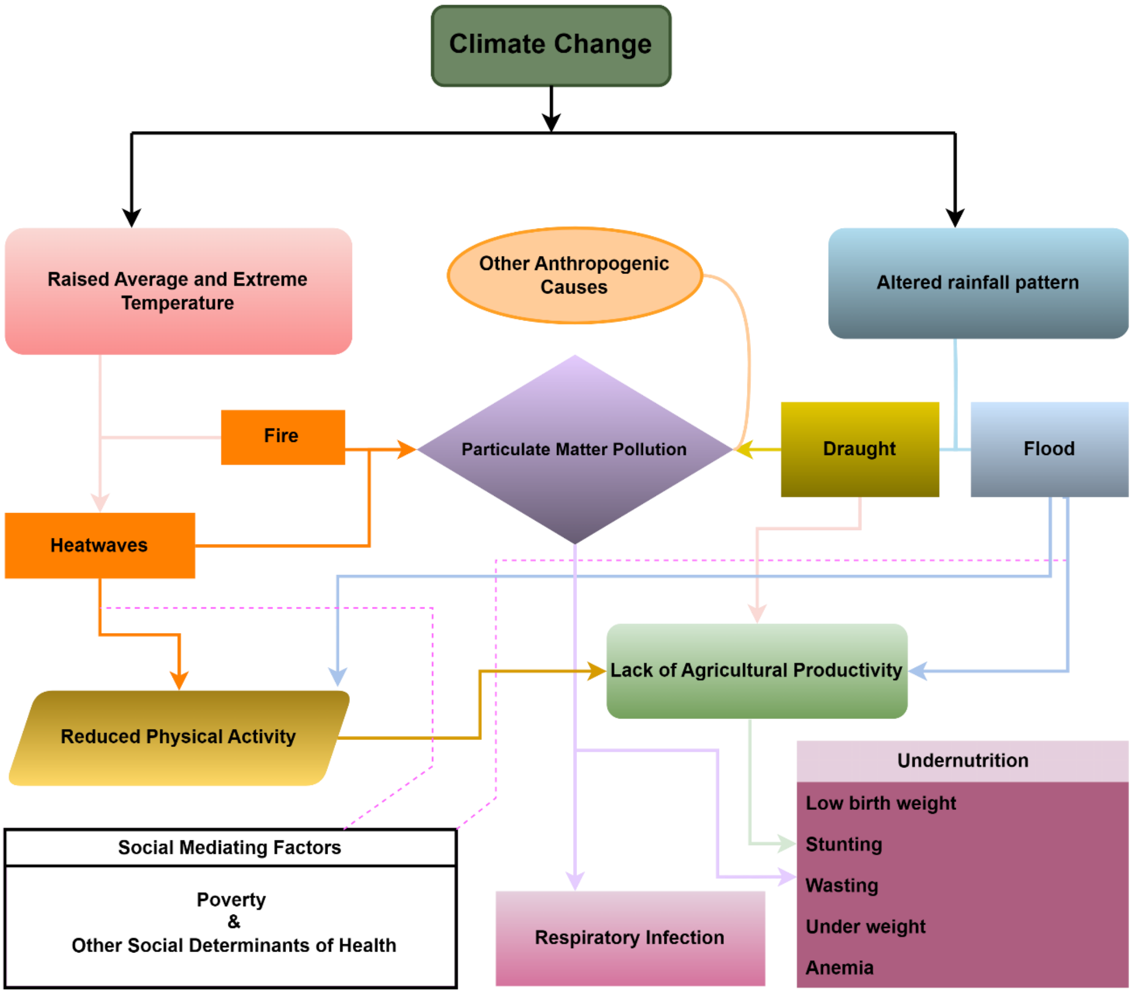

Figure 1. Conceptual framework

Study Objectives

This study aims to integrate high-resolution climate and environmental data with large-scale health survey data to comprehensively assess the effects of in-utero exposure to heatwaves, rainfall variability, and PM2.5 pollution on child nutritional indicators in India. By employing geospatial alignment techniques, environmental exposure data will be linked with health outcomes from the NFHS-5 survey to ensure precise temporal and spatial matching. A composite index of in-utero exposure will be constructed using a weighted aggregation of normalized environmental indicators, capturing the multifaceted nature of these stressors.

Significance

India's diverse climatic zones and substantial burden of malnutrition provide a unique context for examining the interplay between environmental exposures and child health outcomes. Understanding these relationships is essential for developing targeted interventions to mitigate the effects of climate change and environmental degradation on vulnerable populations. This study will offer valuable insights for public health policy, particularly in devising strategies to address the impacts of climate change on vulnerable groups. Additionally, the research highlights the importance of integrating environmental and health data to develop comprehensive strategies for enhancing climate resilience.

Data and Method

Data on child health outcome and other socio-demographic covariates

Data on child health indicators and socio-demographic covariates were drawn from the fifth round of Indian version of Demographic Health Survey (DHS) called the National Family Health Survey (NFHS-5), conducted across India between 2019 and 2021. NFHS-5 is part of a series of large-scale, nationally representative surveys coordinated by the Ministry of Health and Family Welfare (MoHFW), Government of India, with technical support from the International Institute for Population Sciences (IIPS), Mumbai, as the nodal agency. The survey adopts a two-stage stratified sampling design to ensure representation at the national, state, and district levels. In rural areas, villages were selected as primary sampling units (PSUs) in the first stage, followed by the random selection of households. In urban areas, wards were selected as PSUs, followed by household selection. The sample design ensures representation across various socio-economic groups and geographic regions, allowing for the analysis of disparities in health and demographic indicators. The survey collected data from over 610,000 households, with a total sample size of 724,115 women aged 15-49 years and 101,839 men aged 15-54 years. Data were gathered on a wide range of topics, including maternal and child health, fertility, family planning, nutrition, and the prevalence of diseases. The survey also provides data on health indicators of 232,920 children, which was used in this study. NFHS-5 provides a comprehensive source of data to examine health trends, inequalities, and the impact of socio-economic factors on health outcomes across India. Its large sample size, rigorous survey design, and detailed focus on health and nutrition make it a valuable resource for understanding the health status of populations and identifying areas for policy intervention.

Environmental Data

Data on $PM_{2.5}$

For this study, we utilized $PM_{2.5}$ data from the Atmospheric Composition Analysis Group of Washington University in St. Louis, specifically the V6.GL.02.02 dataset, which provides monthly mean surface-level $PM_{2.5}$ concentrations across Asia. This dataset was created through a combination of multiple data sources, integrating satellite-based aerosol optical depth (AOD) retrievals, chemical transport model simulations, and ground-based observations. The core methodology behind the creation of this dataset involves the use of satellite observations from NASA's Moderate Resolution Imaging Spectroradiometer (MODIS), Multi-angle Imaging SpectroRadiometer (MISR), and the Sea-viewing Wide Field-of-view Sensor (SeaWiFS) instruments, which provide AOD estimates. These AOD measurements are then combined with the output of the GEOS-Chem chemical transport model, which simulates the distribution of aerosols based on emissions inventories, atmospheric chemistry, and meteorological conditions. Ground-based monitoring data, including measurements from the global network of air quality monitoring stations, are used to calibrate and validate the satellite-derived estimates. This hybrid approach ensures the spatial consistency of satellite observations while grounding the estimates in real-world surface-level concentrations. The dataset covers the period from 1998 to the present, with a spatial resolution of 0.01° × 0.01°, providing high-resolution estimates suitable for regional and local-level analysis. The in-utero period of our samples extends from Oct 2013 to May 2021, so we have downloaded the monthly $PM_{2.5}$ datasets for this period of time resulting in 92 separate raster files.

Data on heatwave

We utilized the ERA5 hourly data to calculate in-utero heatwave exposure. ERA5, produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) as part of the Copernicus Climate Change Service (C3S), provides comprehensive climate reanalysis data. This dataset delivers hourly estimates of atmospheric, land surface, and oceanic variables through an advanced data assimilation system that integrates observational data with a state-of-the-art numerical weather prediction model. ERA5 combines global observations from satellites, surface stations, radiosondes, ships, and buoys with a 4D-Var assimilation system using the Integrated Forecasting System (IFS). This process assimilates millions of observations daily, ensuring the model’s consistency with real-world data across various spatial and temporal scales. The output is a consistent, globally gridded dataset that represents past climate states and includes uncertainty estimates.

The spatial resolution of ERA5 data is 0.25° x 0.25°, and the temporal resolution is hourly. This fine temporal resolution allows for a detailed examination of temperature variations, making it particularly well-suited for studying heatwave conditions during critical developmental periods such as in-utero exposure. Data were accessed and downloaded via the Copernicus Climate Data Store (CDS) (https://cds.climate.copernicus.eu), where ERA5 provides comprehensive access to historical and real-time reanalysis datasets. For our analysis, we specifically used the 2-meter air temperature variable from ERA5 single-level data to estimate heatwave exposure during the in-utero periods.

Data on Rainfall

We utilized rainfall data from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) dataset to estimate in-utero rainfall variability exposure. CHIRPS, developed by the Climate Hazards Group at the University of California, Santa Barbara (UCSB), provides a long-term global rainfall dataset by blending satellite imagery with in-situ station data. This dataset is specifically designed for drought monitoring and climate change analysis in regions where ground-based observations are limited. CHIRPS integrates infrared satellite sensor data from the NOAA Climate Prediction Center with precipitation observations from global weather stations to create a robust gridded rainfall product. The dataset spans from 1981 to the present, with a spatial resolution of 0.05° x 0.05°, offering fine-scale temporal and spatial coverage suitable for our analysis of rainfall exposure during the in-utero period.

For our study, we used the monthly rainfall data from 1991 till 2021 to assess rainfall variability. This high-resolution data allowed for the capture of localized rainfall patterns, enhancing the accuracy of our environmental exposure assessment. The CHIRPS data were accessed via the Climate Hazards Group website (http://www.chc.ucsb.edu/data/chirps), ensuring reliable and open access to long-term rainfall observations.

Variable description

Outcome variables

In this study, the primary outcomes are related to child health and nutrition, focusing on six specific outcome variables: I) birth weight, II) stunting, III) wasting, IV) underweight, V) anemia, and VI) acute respiratory infection (ARI). Below are the details of each variable:

Birth Weight (Continuous Variable): Birth weight, measured in grams, is a continuous variable that reflects the weight of the child at birth. It is an important indicator of a newborn's health, with lower birth weight being associated with a higher risk of infant morbidity and mortality. In this study, birth weight data were obtained directly from the survey, where mothers reported the child's birth weight if available or recalled if not recorded.

Stunting (Binary Variable, Assessed via Height-for-Age): Stunting is an indicator of chronic malnutrition and is assessed through the height-for-age Z-score. Children whose height-for-age Z-score is below -2 standard deviations (SD) from the median of the reference population are classified as stunted. Stunting reflects long-term growth retardation and is associated with cognitive impairment and increased vulnerability to disease. This variable is binary, with stunted and non-stunted children categorized as 1 and 0, respectively.

Wasting (Binary Variable, Assessed via Weight-for-Height): Wasting indicates acute malnutrition and is assessed through the weight-for-height Z-score. Children whose weight-for-height Z-score falls below -2 SD from the median are considered wasted, which reflects acute undernutrition due to recent food shortage or illness. This binary variable captures whether a child is wasted (coded as 1) or not wasted (coded as 0).

Underweight (Binary Variable, Assessed via Weight-for-Age): Underweight is a composite measure reflecting both acute and chronic malnutrition, assessed using the weight-for-age Z-score. Children whose weight-for-age Z-score falls below -2 SD from the median are classified as underweight. This binary variable, indicating underweight (coded as 1) or not underweight (coded as 0), serves as a general measure of a child's nutritional status.

Anemia (Binary Variable, Assessed via Hemoglobin Levels): Anemia status is determined by measuring hemoglobin levels (in grams per deciliter) using blood samples collected during the survey. Children with hemoglobin levels below 11.0 g/dl are classified as anemic, reflecting a deficiency in red blood cells or hemoglobin, which can impair oxygen transport and affect growth and development. This binary variable captures whether a child is anemic (coded as 1) or non-anemic (coded as 0).

ARI (Binary Variable, Based on Self-Reported Data): For the variable Acute Respiratory Infection (ARI), the outcome is based on mothers' reports of ARI symptoms in children under five. ARI symptoms are defined as a cough accompanied by either (1) short, rapid breathing that is chest-related, or (2) difficult breathing that is chest-related. The variable captures whether the child experienced these symptoms in the two weeks preceding the survey and if advice or treatment was sought for the condition. This binary variable indicates whether a child experienced ARI symptoms (coded as 1) or did not (coded as 0).

Exposure variables

We have considered four major exposure variables to examine the association between environmental adversities and child health outcomes. These variable are I) $PM_{2.5}$ pollution II) Proportion of heatwave exposure III) Exposure to excess rainfall, and IV) Exposure to lack of rainfall.

$PM_{2.5}$ pollution

We have extracted the relevant $PM_{2.5}$ concentrations for each DHS cluster based on their geographic coordinates. It is important to note that the DHS clusters are intentionally displaced to protect the privacy of respondents: up to 2 km in urban areas and up to 5 km in rural areas. We created a 5 km buffer around each cluster to account for the displacement. For each cluster, we calculated the mean monthly $PM_{2.5}$ concentration within the 5 km buffer. This mean $PM_{2.5}$ level of each month was then linked to the child-level data from the DHS dataset. Using the child's date of birth, we identified the gestation period (nine months prior to birth) and calculated the average $PM_{2.5}$ exposure experienced during this period for each child.

Proportion of heatwave exposure

As mentioned in the data source section, to assess in-utero heatwave exposure, we utilized ERA5 2-meter hourly temperature data, which provides high-resolution hourly temperature records. From this dataset, we calculated the daily maximum temperature for each day by identifying the highest recorded temperature within each 24-hour period. Heatwave exposure in the suORounding area of the DHS clusters may influence the residents of these clusters. To account for the displacement of clusters we mentioned earlier and the broader potential heatwave impact on suORounding areas, we created a 10 km buffer around each cluster point.

For each cluster, we extracted the mean of the daily maximum temperature within the 10 km buffer zone. Next, we identified heatwave days, defined as days when the maximum temperature exceeded 35°C for at least three consecutive days. After calculating the heatwave proportions for each cluster, we joined this data with the DHS children data. Using the child's date of birth, we identified the gestation period (typically nine months prior to birth) and calculated the proportion of heatwave days experienced during this time for each child by dividing the total number of heatwave days by the total number of days in the gestational period:

$$\text{Proportion of Heatwave Day} = \frac{\text{Total Number of Heatwave Days}}{\text{Total Days in In} - \text{utero Period}}$$

For instance, if a child's gestation period spanned from May 2018 to January 2019, we calculated the total number of heatwave days during this period within the 10 km buffer around the child's residential cluster. If there were 15 heatwave days within the total gestation period of 275 days, the proportion of heatwave days would be:

$$Proportion\ of\ Heatwave\ Days = \frac{15}{275} \approx 0.055$$

This calculation indicates that 5.5% of the child's in-utero period was affected by heatwave conditions.

Exposure to excess and lack of rainfall

Given the geographic coordinates of the residential clusters in DHS-GPS, we linked each cluster to rainfall data from the CHIRPS dataset to estimate rainfall exposure during the in-utero period for each child. Rainfall variability was calculated for the nine-month gestational period, based on the child's reported birth month and year, and the cluster's geographic location. Similarly like extracting heatwave, we created a 10 km buffer around each cluster point for rainfall data extraction. Then we extracted the rainfall data for the buffer zone of each cluster for each month from 1991 to 2021. This buffer ensures that we capture rainfall exposure not just at the specific location of the cluster but also from the surrounding environment, thus providing a more comprehensive measure of rainfall exposure.

To assess the impact of in-utero rainfall on child health outcomes, we focused on deviations from long-term rainfall averages. In-utero Rainfall Deviation (IUR) was defined as the difference between the total rainfall during the in-utero period and the long-run average rainfall for the same months, normalized by the long-run standard deviation of rainfall. Long-term averages and standard deviations were calculated using rainfall data from 1991 to 2021. For example, for a child in utero between May 2018 and January 2019, the In-utero Rainfall Deviation ($IUR_{May-Jan}$) is computed as follows:

$$IUR_{May-Jan} = \frac{TR_{May-Jan} - LRAR_{May-Jan}}{LRSD_{May-Jan}}$$

Where:

- $TR_{May-Jan}$ is the total rainfall in the cluster from May to January.
- $LRAR_{May-Jan}$ is the long-run average rainfall for May to January (1991-2021).
- $LRSD_{May-Jan}$ is the long-run standard deviation of rainfall for May to January(1991-2021).

We constructed two key variables to capture both positive and negative deviations from the long-run average:

1. **In-Utero Excess Rainfall (IUER):**

   This variable captures periods when in-utero rainfall exceeds the long-term average. It is defined as the positive deviation from the average, with zero assigned when there is no excess:

$$IUER_{May-Jan} = \begin{cases} IUR_{May-Jan} & if \;\; IUR_{May-Jan} > 0 \\ 0 & otherwise \end{cases}$$

2. **In-Utero Lack of Rainfall (IULR):**
   This variable reflects periods when in-utero rainfall falls short of the long-run average. It is defined as the absolute value of the negative deviation, with zero assigned when rainfall is at or above the average:

$$IULR_{May-Jan} = \begin{cases} -IUR_{May-Jan} & if \;\; IUR_{May-Jan} < 0 \\ 0 & otherwise \end{cases}$$

For example, for a child whose in-utero period spanned from **May 2018 to January 2019**, $\boldsymbol{IUER_{May-Jan}}$ captures how much the in-utero rainfall exceeds the long-run local average, while $\boldsymbol{IULR_{May-Jan}}$ quantifies how much the rainfall was below the long-term norm. A one-unit increase in **IUER** represents a one standard deviation increase in rainfall relative to the long-run average, while a one-unit increase in **IULR** represents a one standard deviation decrease.

Covariates

Several covariates were selected based on their theoretical and empirical relevance to child health and environmental exposure outcomes. To account for potential confounding factors and to ensure a more accurate estimation of the relationship between the exposure and outcomes. The following covariates were included:

- **Child's age** (continuous) and **sex** (male/female) to control for developmental and biological differences.
- **Mother's age at birth** categorized into age groups (>20, 20–34, 35–49 years), considering maternal age as a crucial factor influencing child health outcomes.
- **Birth order** (continuous), as birth spacing and sibling dynamics can impact nutritional and health outcomes.
- **Mother's education** categorized as no education, primary, secondary, and higher education, as maternal literacy is a known determinant of child health and well-being.
- **Mother's smoking status** (yes/no), given the harmful effects of tobacco use on child health.
- **Mother's co-morbidity** (number of diseases), adjusting for the overall health status of the mother.
- **Mother's height** (continuous) to account for long-term maternal nutrition and its association with child growth and health.
- **Household wealth index** categorized into quintiles (poorest to richest), as socio-economic status is a critical determinant of health outcomes.
- **Type of cooking fuel** (clean vs. unclean), which impacts household air quality and child respiratory health.
- **Place of residence** (urban/rural), adjusting for rural-urban disparities in healthcare access and living conditions.
- **Caste** categorized as Scheduled Castes (SC), Scheduled Tribes (ST), Other Backward Classes (OBC), and upper castes, reflecting social stratification in India.
- **Religion** (Hindu, Muslim, Christian, others) to control for cultural variations.
- **Region** to account for geographic differences in health and environmental exposures across North, Central, East, Northeast, West, and South regions of India.

Analytical strategy

Descriptive statistics was used to show the characteristics of the study population. Summary statistics was used to show the level and prevalence of health outcomes of the children, and the results were shown using box plot for continuous variable and bar plots for categorical variables. Density plots were created to check the density distribution of exposure variables. To examine the association between the exposure and outcome variables, we have utilized generalized linear models for continuous outcome (Birth weight) and generalized linear models with logit function for categorical outcome variables (Stunting, wasting, underweight, anemia, and ARI). Socio-demographic and other health related covariates were adjusted in the models. We used a multivariable linear regression model to assess the relationship between environmental exposures and birth weight as a continuous outcome. The key exposure variables in the model were categorical $PM_{2.5}$ levels, mean proportion of heatwave days during gestation, in-utero exposure to excess rainfall (IUER), and in-utero exposure to lack of rainfall (IULR). The following covariates were included to control for potential confounding factors:

$$\text{Y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \ldots \beta_i x_i + e$$

Where:

Y = Birth weight (continuous outcome variable)
β_0 *is the intercept.*
$\beta_1, \beta_2, \ldots \beta_i$ are the coefficients for each covariate $x_1, x_2, x_3, \ldots x_i$
x_1 = $PM_{2.5}$ exposure category
x_2 = Mean proportion of heatwave days during gestation
x_3 = In-utero exposure to excess rainfall (IUER)
x_4 = In-utero exposure to low rainfall (IULR)
$x_1 \ldots x_i$ = Confounding factors stated in the covariates section
e is the error term.

Since the rest of our outcome variables are binary in nature we utilized generalized linear models with logit function. Here is the formula for the models-

$$\ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \ldots \beta_i x_i + e$$

where:

$ln\left(\frac{p}{1-p}\right)$ represents the log odds of the probability p (the probability of the outcome, e.g., stunting, wasting, underweight, anemia, or ARI).
β_0 is the intercept.
$\beta_1, \beta_2, \ldots \beta_i$ are the coefficients for each covariate $x_1, x_2, x_3, \ldots x_i$
x_1 = $PM_{2.5}$ exposure category
x_2 = Mean proportion of heatwave days during gestation
x_3 = In-utero exposure to excess rainfall (IUER)
x_4 = In-utero exposure to low rainfall (IULR)
$x_1 \ldots x_i$ = Confounding factors stated in the covariates section
e is the error term.

All the analyses were conducted in R software, all the codes for data preparation and analysis will be made available in public repository once the paper got accepted for publication.

Results

The study population consists of children with an average age of about 30 months and a slight male predominance (51.8%). Most mothers are aged 20-34 years and have at least a secondary education, although 22% have no formal education. Children are typically born early in the mother's childbearing years, with an average birth order of 1.78. The majority of households fall into the poorer wealth quintiles, with only 13.3% in the richest quintile. Smoking among mothers is rare (5.6%), and most mothers report no co-morbidities. A significant proportion of households use unclean cooking fuels (52.5%), and children are predominantly from rural areas (79.7%). Socially, the population is diverse with a substantial representation of Scheduled Castes (21.0%), Scheduled Tribes (21.1%), and Other Backward Classes (40.1%). Regionally, the largest proportions come from the Central (26.0%) and North (18.5%) regions. More details on the background characteristics of study population Is given in Table 1.

The density plots in the figure 6 of various environmental exposures reveal distinct patterns in the distribution of $PM_{2.5}$ levels, heatwave exposure, and rainfall extremes. The $PM_{2.5}$ distribution demonstrates a moderate central tendency with a peak around 40 µg/m³ and a rightward skew, suggesting that while most of the population experiences moderate air pollution levels, a smaller fraction faces significantly higher exposures. This indicates both a widespread issue of air pollution, albeit mostly at moderate levels, and localized areas with potentially harmful air quality levels, necessitating targeted public health interventions in these high-risk areas. The heatwave exposure plot shows a predominant clustering of values near zero, with a secondary peak around 0.3, highlighting that most individuals experience few heatwave days, though a

Table1. Characteristics of study population

Background Characteristics	Category/Statistics	Overall
	n	232920
Age of Child (months)	(mean (SD))	30.22 (17.47)
sex of child	Male	120665 (51.8)
Mothers age at birth	>20	26445 (11.4)
	20-34	196122 (84.2)
	35-49	10353 (4.4)
	Female	112255 (48.2)
Birth order	(mean (SD))	1.78 (0.74)
Mothers education	No education	51210 (22.0)
	Primary	30081 (12.9)
	Secondary	119864 (51.5)
	Higher	31765 (13.6)
Wealth quintile of HH	Poorest	63406 (27.2)
	Poorer	54463 (23.4)
	Middle	45083 (19.4)
	Richer	39094 (16.8)
	Richest	30874 (13.3)
Mother's smoking status	Yes	13142 (5.6)
	No	219778 (94.4)
Mother's Co-morbidity (No. of disease)	0	218624 (93.9)
	1	12402 (5.3)
	2	1474 (0.6)
	3	221 (0.1)
	4	52 (0.0)
	5	11 (0.0)
	6	18 (0.0)
	7	118 (0.1)
Type of cooking fuel	Clean	99303 (42.6)

	Unclean	122315 (52.5)
	Not a de jure resident	11302 (4.9)
Place of residence	Urban	47199 (20.3)
	Rural	185721 (79.7)
Social class (Caste)	SC	48922 (21.0)
	ST	49042 (21.1)
	OBC	93417 (40.1)
	Upper caste	41539 (17.8)
Religion	Hindu	171055 (73.4)
	Muslim	33522 (14.4)
	Christian	18851 (8.1)
	Others	9492 (4.1)
Region	North	43090 (18.5)
	Central	60560 (26.0)
	East	45227 (19.4)
	North East	34222 (14.7)
	West	20552 (8.8)
	South	29269 (12.6)
Mothers height (CM)	(mean (SD))	151.83 (6.24)

notable minority faces more frequent heatwave conditions. This bimodal distribution suggests varying climate impacts across different regions, underscoring the need for region-specific adaptations to heatwaves, which could range from enhancing public awareness to strengthening healthcare responses during peak heat periods. Regarding rainfall, the distributions of both excess and lack of rainfall are skewed, with most values concentrated near zero but with tails that indicate episodes of extreme rainfall and drought conditions in certain areas. The excess rainfall plot shows a right skew, pointing to rare but significant bouts of heavy rainfall, which could lead to flooding and associated health risks. Conversely, the left skew in the lack of rainfall plot indicates periods of significant drought, which could impact water supply and agriculture, affecting food security and public health. The presence of extreme values in both rainfall measures suggests that while most of the population is not regularly exposed to extreme rainfall conditions, the impacts on those who are can be severe, highlighting the importance of robust disaster preparedness and response systems.

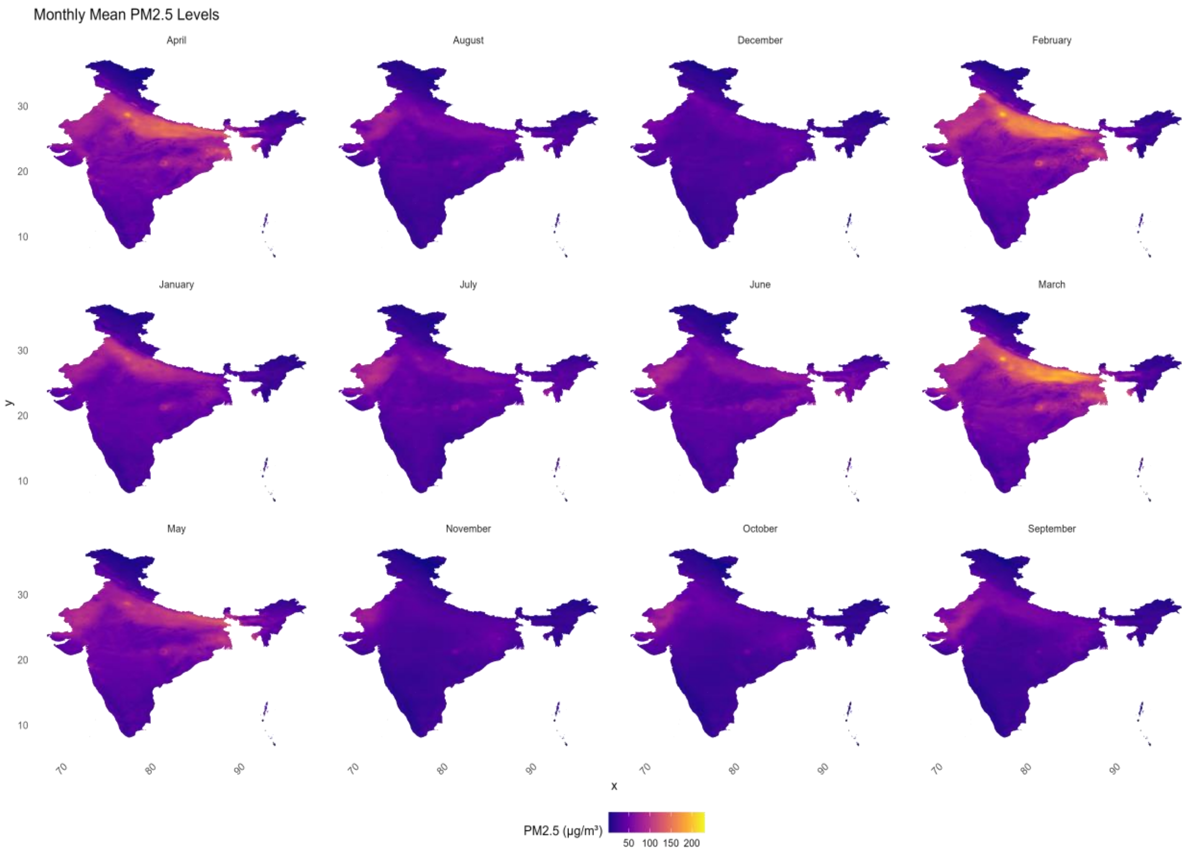

Figure 2. Monthly mean $PM_{2.5}$ concentration from 2013-2021

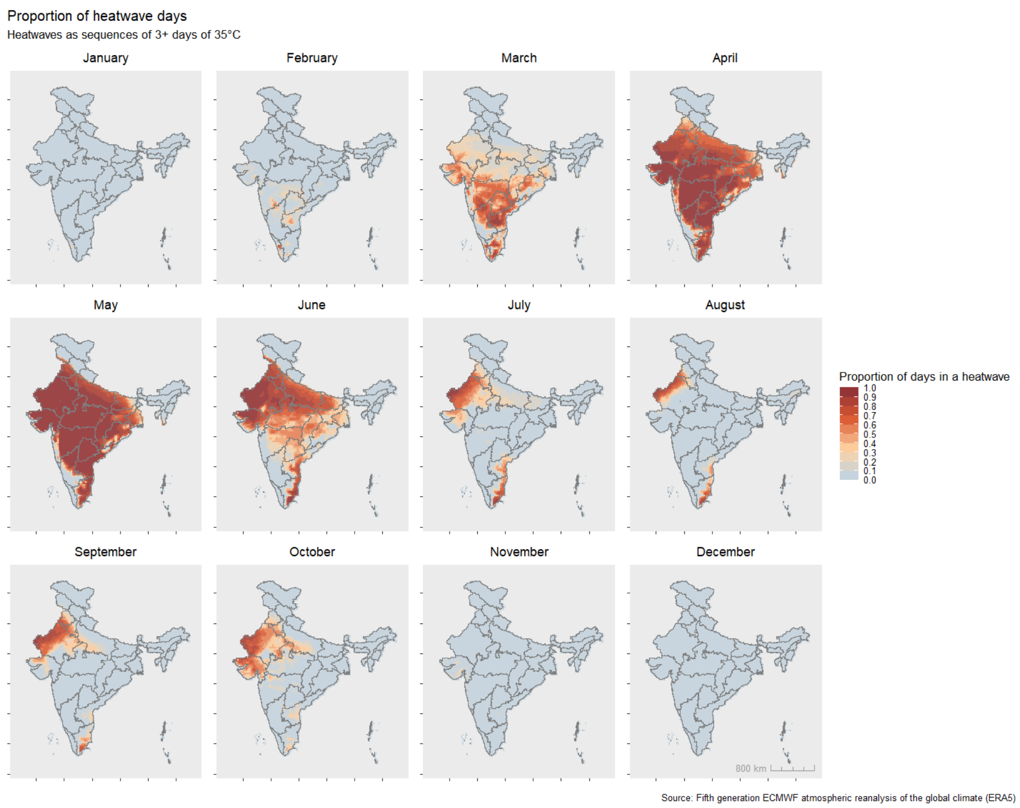

Figure 3. Average monthly proportion of heatwave days from 2013-2021

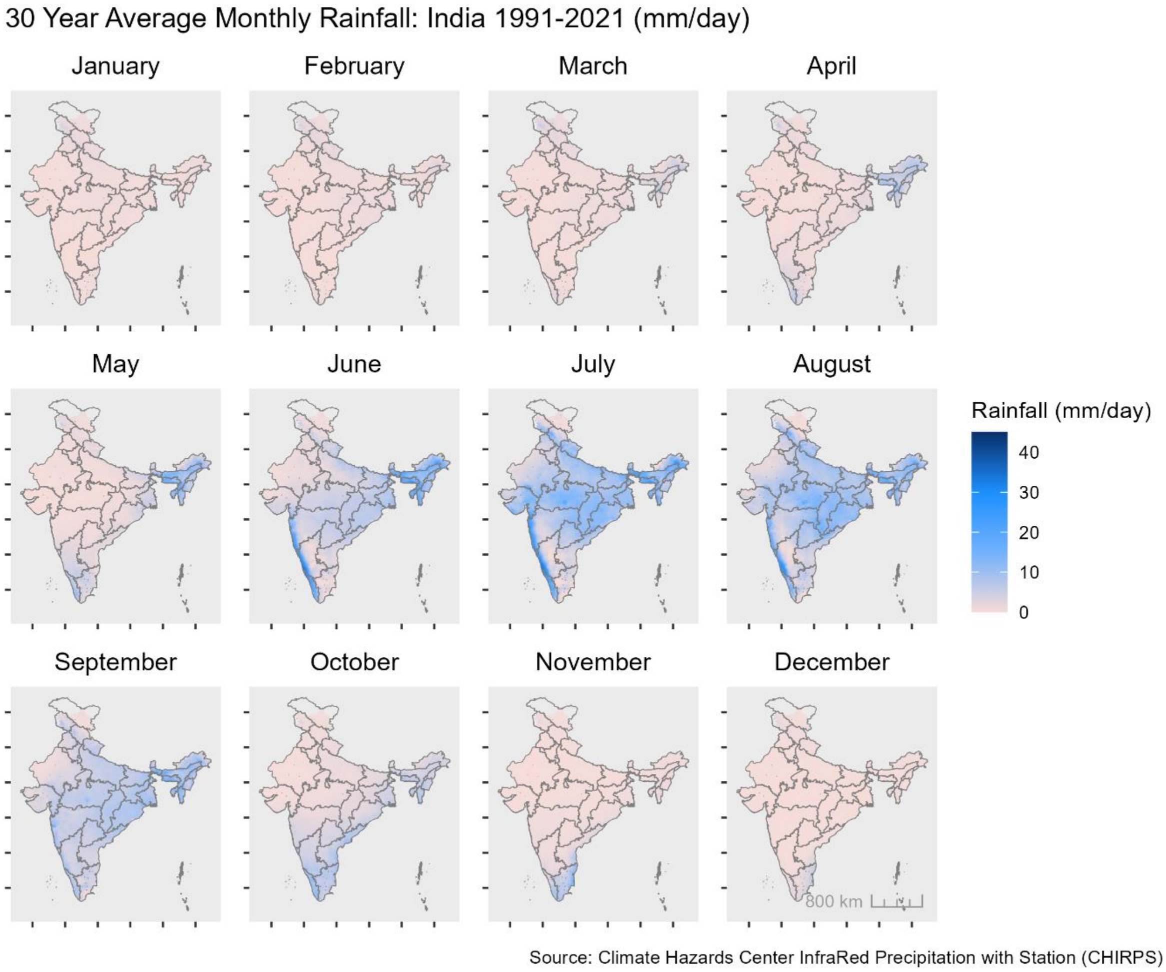

Figure 4. Month wise average rainfall per day from 1991-2021

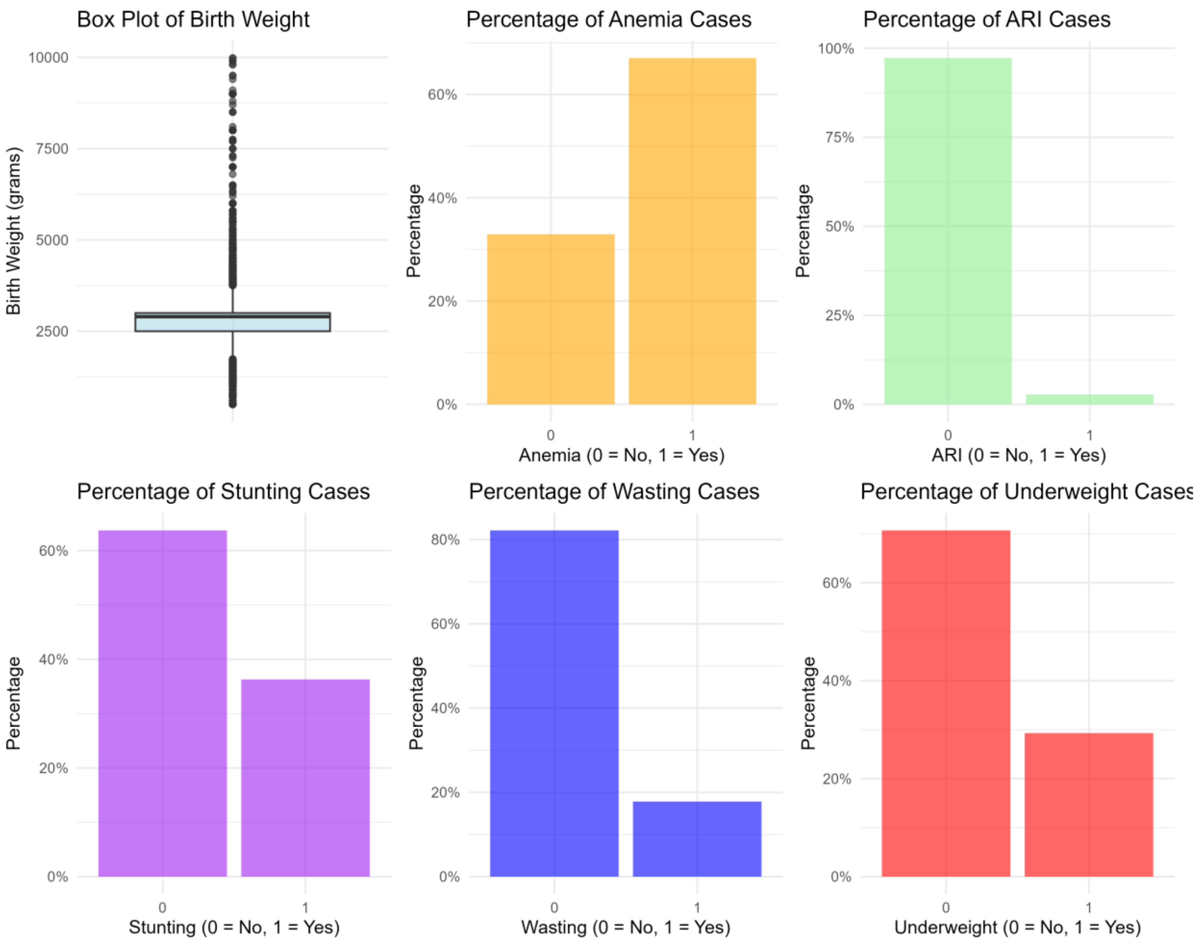

Figure 5. Description of outcome variables

Figure 5 presents the prevalence of various health outcomes in the studied population. The mean birth weight is 2822.86 grams with a standard deviation of 571.75 grams. Anemia is highly prevalent, affecting 67.1% of the population, while 32.9% are not anemic. Acute Respiratory Infection (ARI) is relatively rare, with only 2.8% of individuals affected, compared to 97.2% who are not. Stunting is observed in 36.3% of the population, whereas 63.7% are not stunted. Underweight status is seen in 29.3% of individuals, with the majority, 70.7%, not underweight. Lastly, wasting affects 17.8% of the population, while 82.2% are not experiencing wasting. These findings highlight significant health challenges, particularly in terms of anemia and stunting, which may require targeted interventions.

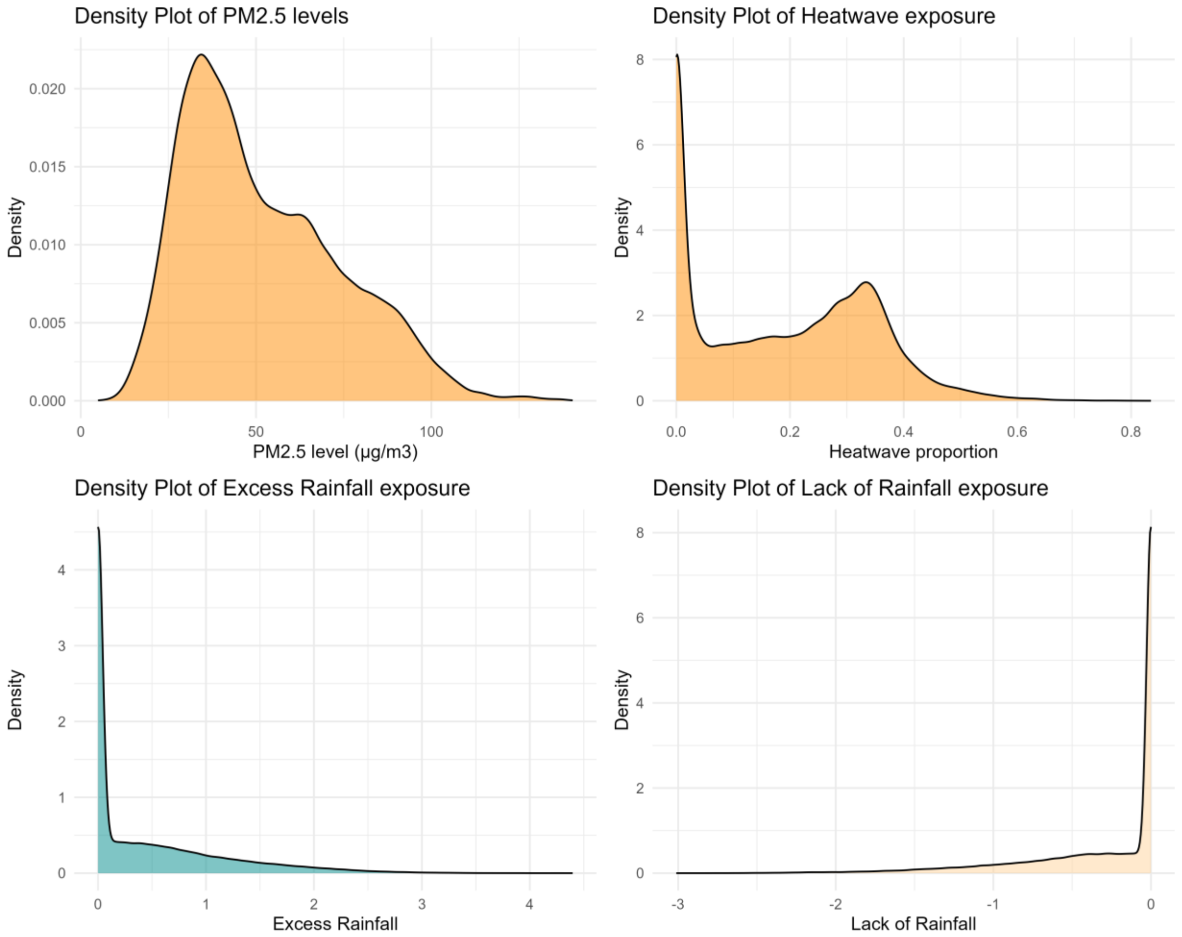

Figure 6. Density plot of the exposure variables

In the analysis of the association between environmental exposures and child health outcomes in Figure 7, several notable patterns emerged. High exposure to PM2.5 during pregnancy was significantly associated with adverse health outcomes. For instance, in comparison to children exposed to low PM2.5, those exposed to high PM2.5 had a 20% higher risk of anemia (OR: 1.20, 95% CI: 1.05–1.36) and a 15% higher risk of stunting (OR: 1.15, 95% CI: 1.02–1.30). Similarly, moderate PM2.5 exposure, though less pronounced, was also associated with a 12% higher risk of acute respiratory infections (ARI) (OR: 1.12, 95% CI: 1.01–1.24) and a slight reduction in birth weight (β: -18 grams, 95% CI: -35, -1).

The proportion of heatwave exposure during pregnancy was associated with elevated risks of stunting (OR: 1.10, 95% CI: 1.01–1.21) and underweight (OR: 1.14, 95% CI: 1.02–1.28). Children exposed to higher heatwave proportions in utero also had a 14% higher risk of developing ARI (OR: 1.14, 95% CI: 1.03–1.27). Regarding rainfall patterns, in-utero excess rainfall was linked to lower birth weight (β: -23 grams, 95% CI: -40, -6) and a 10% higher risk of wasting (OR: 1.10, 95% CI: 1.02–1.18), while lack of rainfall was associated with increased risks of anemia (OR: 1.18, 95% CI: 1.04–1.33) and stunting (OR: 1.12, 95% CI: 1.01–1.25).

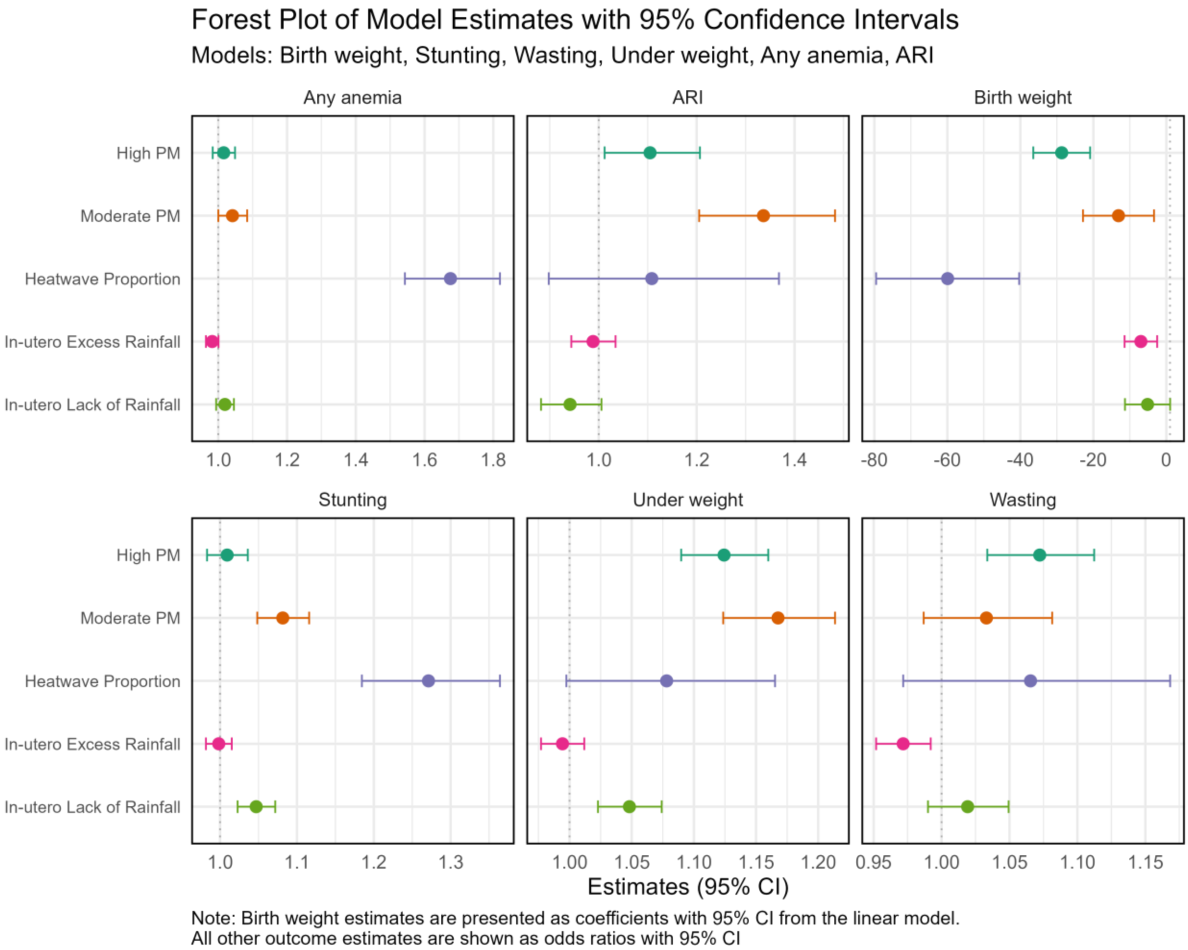

Figure 7. Association between the exposure to climatic adversities and child health outcomes

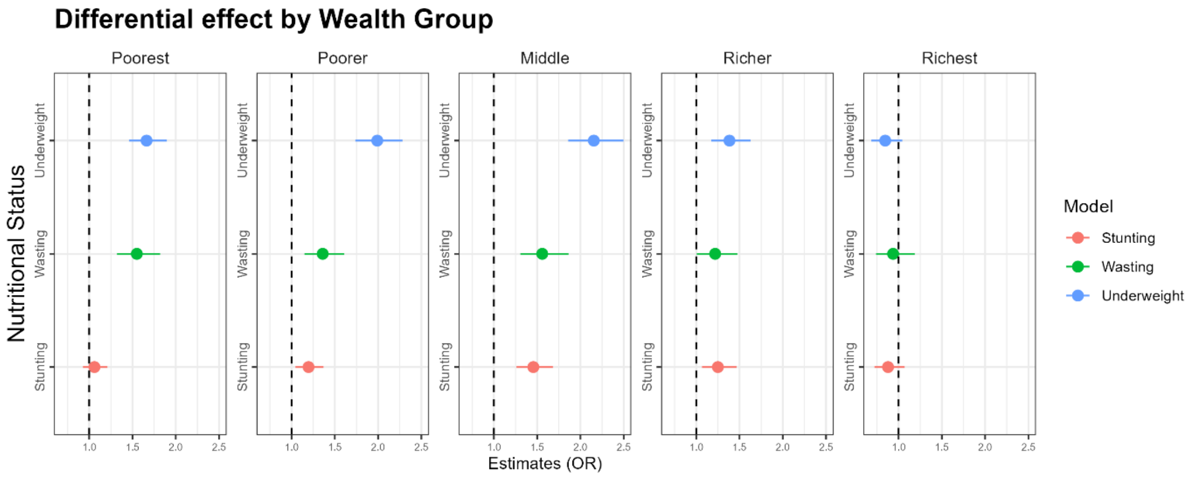

Figure 8. Effect of heatwave exposure on malnutrition by different wealth category

Discussion

The present study highlights the significant impact of environmental exposures during pregnancy on child health outcomes, emphasizing the importance of addressing air pollution, heatwaves, and rainfall variability in maternal health frameworks. High exposure to PM2.5 during pregnancy was strongly associated with adverse health effects, such as a 20% increased risk of anemia and a 15% elevated risk of stunting in children. These findings are consistent with studies that have shown that prenatal exposure to air pollution can result in oxidative stress, inflammation, and impaired fetal development, leading to low birth weight, preterm births, and developmental delays (Perera, 2017; Pedersen et al., 2013). Specifically, PM2.5 can cross the placental barrier, inducing systemic inflammation and oxidative stress, both of which are critical pathways contributing to poor birth outcomes (Pedersen et al., 2013).

In addition to air pollution, the study revealed that heatwave exposure during pregnancy significantly increased the risk of stunting, underweight, and ARI. Children exposed to higher proportions of heatwaves in utero had a 10% higher risk of stunting and a 14% increased risk of ARI. Research shows that maternal exposure to extreme heat can lead to increased cardiovascular strain, dehydration, and disrupted thermoregulation, all of which can negatively affect fetal growth and birth outcomes (Basu et al., 2010; Schifano et al., 2013). Previous studies have similarly reported that exposure to high ambient temperatures is linked to preterm delivery, low birth weight, and other adverse pregnancy outcomes (Zhang et al., 2019).

The study also found that rainfall variability, whether excessive or insufficient, during pregnancy was associated with negative child health outcomes. Excess rainfall during pregnancy was linked to a reduction in birth weight and increased risk of wasting, while a lack of rainfall was associated with an elevated risk of anemia and stunting. These results align with findings that excessive rainfall can disrupt healthcare access, increase the prevalence of infectious diseases, and lead to maternal malnutrition, while drought conditions exacerbate food insecurity, maternal undernutrition, and child growth deficiencies (Grace et al., 2012; Curtis et al., 2017). The dual impact of rainfall extremes further supports the notion that climate-related events can exacerbate vulnerabilities in maternal and child health, particularly in low-resource settings like India (Patz et al., 2005).

These findings underscore the compounded risks that pregnant women and children face due to environmental adversities, particularly in regions increasingly affected by climate change. The associations between air pollution, heatwaves, and rainfall patterns with adverse child health outcomes reflect the need for targeted public health interventions. Strengthening healthcare systems, improving maternal nutrition, and implementing policies to mitigate air pollution and prepare for extreme heat and rainfall events are essential to reducing the health impacts of climate change (Perera, 2017; Luber & McGeehin, 2008).

Conclusion

This study provides compelling evidence that environmental exposures during pregnancy, including high levels of PM2.5, heatwaves, and rainfall variability, significantly influence child health outcomes. High PM2.5 exposure was linked to increased risks of anemia, stunting, and ARI, while heatwave exposure elevated the risks of stunting, underweight, and ARI. Additionally, both excessive and insufficient rainfall during pregnancy were associated with adverse outcomes such as lower birth weight, wasting, anemia, and stunting. These findings call for urgent action to address environmental risks in maternal and child health, particularly in the context of climate change. Public health interventions that focus on reducing exposure to environmental pollutants, improving maternal healthcare, and strengthening resilience to climate variability are crucial for mitigating the adverse health impacts of environmental changes on vulnerable populations. Future research should explore the effectiveness of interventions aimed at reducing these risks and building climate resilience in vulnerable regions.

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