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Environmental determinants of anaemia and its spatial association with Mosquito-Borne disease vulnerability: a case of Eastern and North-Eastern India

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Abstract

Background Understanding anaemia prevalence in the context of environmental exposure calls for in-depth research. This study delves into the clustering and determinants of anaemia, focusing on environmental factors and their association with mosquito-borne disease vulnerability in Eastern and North-Eastern India.

Methods Using the National Family Health Survey (NFHS-5, 2019–21), Bivariate and Binary logistic regression analyses were used to determine the effect of environmental, health and demographic factors on anaemia separately for females and males, followed by spatial clustering of anaemia and its association with mosquito-borne disease vulnerability.

Results The study reveals that anaemia was more likely to occur in females and males living in areas characterised by lower altitudes, higher mean annual temperatures, higher annual rainfall, more frequent drought episodes, and denser vegetation. Factors such as more number of children, being underweight, age 15–24, lower levels of education, being Hindu, tribal status, and belonging to the poorest wealth categories were also risk factors for anaemia. Furthermore, riverine areas of humid subtropical regions had a higher clustering of anaemia hotspots among females and males and were positively associated with areas of high mosquito-borne disease vulnerability in the study region.

Conclusion The study underscores the significant role of environmental determinants in shaping anaemia risk in Eastern and North-Eastern India, calling for integrated, environment-informed public health interventions.

Keywords Anaemia, Environment, Mosquito-Borne disease, Analytical hierarchy process, Eastern and North-Eastern India

1 Background

Environmental factors pose a significant threat to nutritional deficiencies. Anaemia as a nutritional indicator is critical in achieving SDG-2 (Zero Hunger) [1]. Women and children face unforeseen negative consequences of anaemia, such as impaired cognitive development, low work productivity, and maternal and perinatal mortality [2]. The prevalence of anaemia is more severe in developing nations with poor socio-economic conditions, such as countries in South Asia and Western and Central Sub-Saharan Africa [3]. Poor health owing to anaemia has a marked effect on the economy. Research estimates the economic cost of anaemia among children aged 6 to 59 months is 24,001 million USD in productivity losses and 1.3% of GDP in India [4, 5]. India ranks fifth in anaemia severity among all the countries, as per the WHO Global Anaemia Estimates 2021 [6]. The Government of India has made commendable efforts in anaemia reduction policies like the National Nutritional Prophylaxis Programme of 1970, making India the first developing country to initiate a government-aided programme towards anaemia reduction targeting young children and women of the reproductive age group, to the recent Anaemia Mukt Bharat of 2018 [7–9]. However, at the national level, as per the latest round of NFHS, the anaemia prevalence for women of the reproductive age group increased from 53.1% (2015-16) to 57% (2019-20) [10]. This draws attention to the policy approach in such a huge country as India, which requires a diverse, aspiring approach, considering the disentanglement of the complex aetiology of anaemia. Most research on anaemia has primarily considered socio-economic and health determinants, like age, educational attainment, residence, wealth index, pregnancy status, etc., which can primarily affect anaemia [11–16]. Alongside socio-economic and health factors, primary environmental factors can also significantly affect anaemia, particularly in Eastern and North-Eastern regions, experiencing monsoon dominated humid sub-tropical climates, owing to infection spread by vectors.

The fact that the physical environment is an essential determinant of health has gained global scientific recognition. According to study estimates of the global disease burden, environmental risk factors were responsible for 22% of global disability-adjusted life years (DALYs) and 23% of global deaths in 2012 [17]. Developing countries endure the burden of diseases such as infection, vector-borne disease, diarrhoea, malnutrition, respiratory diseases and a growing share of non-communicable diseases attributed to environmental risk factors, while the relevance in developed countries is relatively less [18]. Environmental factors here can be categorised into general external/macro-level and specific external/micro-level factors [19]. There are ample studies on the association between micro-level environmental factors and anaemia, including factors such as air pollution, water quality, heavy metal contamination, etc [20–24]. However, the macro-level factors, which are more dormant overall, are still an under-researched arena. Although studies reveal macro-level environmental factors such as climate, vegetation and meteorological hazards such as drought and flood are directly and indirectly related to agricultural failure, alteration of micronutrients in crops and food security issues [25–27], alteration in drinking water quality, and increased occurrence of vector-borne disease [28] and parasitic infections [29], exacerbating the severity of anaemia. However, there is a dire need to dissect the depth of the complex relationship between macro-level environmental factors and anaemia.

Regionally, Eastern and North-Eastern states such as Bihar, Tripura, Jharkhand, Assam, and West Bengal were deficient in Key Performance Index scores of the programme called Anaemia Mukt Bharat, placing them near the bottom. In contrast, North-Eastern states like Manipur, Mizoram, Nagaland, Sikkim, Meghalaya and Arunachal Pradesh performed well [30]. Likewise, the explanation for the disparity in anaemia prevalence among Eastern and North-Eastern states of India can have additive aspects alongside socio-demographic and health-related factors. The link between infection and anaemia is well established. Infection can result in reduced intestinal absorption, nutrient loss in the gut due to increased secretion, internal diversion for infection-related metabolic responses, and elevated basal metabolic rate, accelerating nutrient loss [31]. According to the National Center for Vector Borne Disease Control (NCVBDC), the East and North-Eastern States are highly prone to vector-borne diseases such as malaria, dengue, chikungunya, etc., which can contribute to anaemia [32]. Declassifying these diseases, India has been witnessing rapid progress in decreasing malaria cases, but Eastern India still witnesses a high burden of malaria. The WHO High Burden High Impact (HBHI) initiative (2019) has been focused on three eastern Indian states: West Bengal, Odisha, and Jharkhand, alongside Madhya Pradesh in Central India, for action against malaria [33]. An estimated 33 million clinically evident dengue cases occur annually in India, and the spread has progressed rapidly from urban to rural [34]. As per the reported estimates of dengue cases by NVBDCP 2023, West Bengal and Bihar rank 2nd and 3rd with 10.61% and 6.99% share of total dengue cases; Odisha, Assam and Jharkhand were the other states having a high share of dengue burden respectively [35].

Changing environment and climatic conditions can further impact the expansion and relocation of mosquito vectors in spreading diseases through multiple pathways [36]. The challenge lies in determining mosquito-borne disease in changing environmental and climatic conditions, as environmental conditions are not static [37]. The currently available research on anaemia primarily focuses on children and females of reproductive age group, while research on male counterparts is limited. It is to be noted that a lower prevalence of anaemia among men compared to women is linked to inequality in nutrition, blood loss due to menstrual bleeding, multiple pregnancies, and so on [38]. However, a similar prevalence pattern is observed in India, i.e., states with high female anaemia prevalence also correlate with high male anaemia prevalence, although of lesser intensity among males is observed with general exception in some states as shown in (Fig. 1); this made us revisit the role of macro-level environmental factors in explaining anaemia among males and females in Eastern and North-Eastern India.

Considering the abovementioned problems and findings from past available literature, the study aims to determine the clustering of anaemia hotspots among males and females in Eastern and North-Eastern India. It explores determinants of anaemia among males and females aged 15–49 attributed to Environmental, Health, and Demographic factors. Further, the study explores the spatial correlation between mosquito-borne disease vulnerability and anaemia.

2 Materials and methods

2.1 Description of the study area

The study area covers Eastern and North-Eastern India as shown in (Fig. 2), comprising states such as Bihar, Jharkhand, Odisha, and West Bengal in the east, characterised by

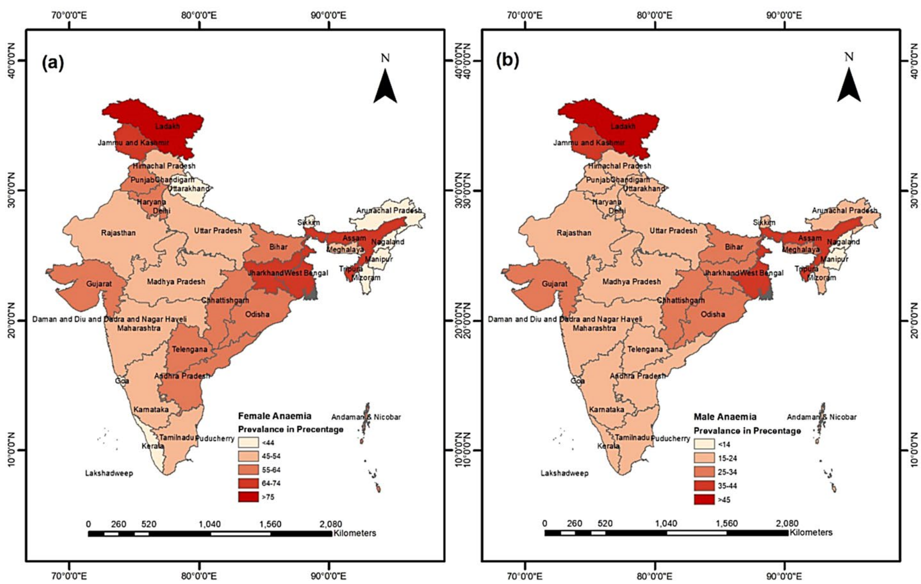

Fig. 1 State/UT wise prevalence of anaemia among **a** females, and **b** males in India (NFHS-5) 2019-21

fertile plains, river basins, and a mix of plateau and coastal plains, and the North-Eastern region of India consists of eight states including Assam, Manipur, Meghalaya, Mizoram, Nagaland, Tripura, Arunachal Pradesh, and Sikkim characterised by hilly and mountainous terrain, and dense forests [39].

The climate across these regions varies significantly. Eastern India typically experiences a humid subtropical climate with hot summers and distinct rainy seasons, while the North-East receives some of the highest rainfall levels in the country and has a humid subtropical to temperate climate, depending on altitude [40]. As per to Census of India 2011 the, Eastern and North-Eastern India also reflects vast difference in population, with Eastern India having some of the highest population states in India, such as Bihar and West Bengal, ranking third and fourth in total population with 10.8% and 7.54% of India's population whereas the North-East represents only 3.7% of total population of India [41]. However, despite these differences, Eastern and North-Eastern India still house 35.9% of the Scheduled Tribe population [41].

2.2 Data source and study population

The Demographic and Health Studies (DHS) or National Family and Health Survey (NFHS) is a nationally representative survey conducted by the Ministry of Health and Family Welfare (Government of India), with the International Institute for Population Sciences (IIPS), Mumbai, as the Nodal Agency. The samples are selected using a stratified multi-stage cluster sampling method to ensure nationally representative estimates. There are currently five rounds of survey covering comprehensive data on various indicators such as household population and housing characteristics, fertility, family planning, maternal and child health, selected morbidity issues, HIV/AIDS, domestic violence etc [10]. Likewise, the study used NFHS-5 (2019-21) data, inclusive of the Eastern and North-Eastern States of Bihar, West Bengal, Jharkhand, Odisha, Assam, Tripura, Meghalaya, Arunachal Pradesh, Manipur, Mizoram, Nagaland, and Sikkim (Eastern and North-Eastern states of India).

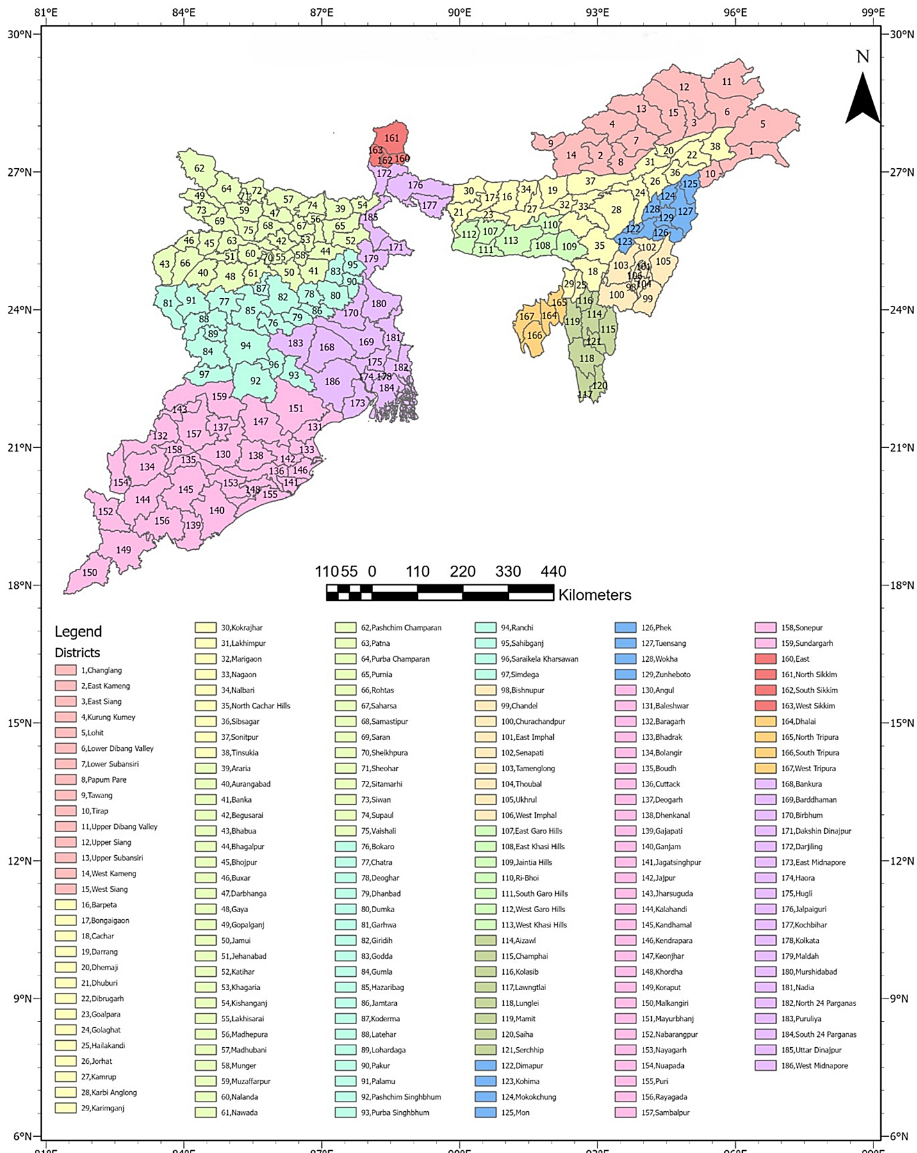

Fig. 2 District level map of Eastern and North-Eastern India depicting study area coverage and administrative boundaries

The study population included all women and men of the reproductive age group 15–49, who were tested for haemoglobin levels, excluding the missing values. The sample included 214,231 females and 25,953 males. DHS provides data on geographical covariates and cluster geo-coordinates wherein the rural clusters are displaced to 5 km, and urban clusters are displaced to 2 km to maintain confidentiality. However, assuming that within the displaced distance, the geographical factors such as cluster altitude, annual rainfall, mean annual temperature, drought episodes, and enhanced vegetation index are unlikely to vary greatly, the geographical covariates were merged into the individual files for further analysis.

The data used to generate the mosquito-borne disease vulnerability map included several geospatial data, such as Digital Elevation Model (DEM) [42], Normalized Differential Vegetation Index (NDVI) [43], Land Use Land Cover (LULC) [44], Annual Rainfall

[45], Mean Annual Temperature [45], Population Density [46], Proportion Poor [10], and Wetness Index. These geospatial data are stratified to DHS years and are essential predictors of mosquito-borne disease, the data source for which has been highlighted in (Table 1).

2.3 Outcome variable

The dependent or outcome variable anaemia status was recoded as a dummy variable (0 non-anaemic and 1 anaemic) where anaemic females included non-pregnant women whose haemoglobin count was less than 12.0 g per decilitre (g/dl) and pregnant women whose count was less than 11.0 (g/dl) against non-anaemic having higher haemoglobin cut off values. Additionally, males whose haemoglobin count was less than 13.0 g per decilitre (g/dl) were considered anaemic against non-anaemic with a haemoglobin count higher than 13.0 g per decilitre (g/dl) [47].

2.4 Predictor variable

The predictor or independent variables included environmental, demographic, and health variables such as altitude, mean annual temperature, annual rainfall, drought episodes, enhanced vegetation index, children ever born, body-mass index, type of diet consumption, source of water, toilet facility, age, educational level, religion, caste, type of residence and wealth index.

The environmental determinants in health studies are limited in identifying standard cutoffs for environmental parameters. Given the limitations, the categorisation and the demarcation of the threshold for ecological parameters were carefully marked based on indicators of agroecological zonation, as anaemia is an important indicator of nutritional levels. Altitudinal differences are an essential predictor of landforms and resultant vegetation typologies. As such, the categories of altitude were categorised as 0 to 100 m, 100 to 500 m, 500 to 1000 m and above 1000 m as a single category [48]. The mean annual temperature was distinctly selected to divide the humid subtropical part of India from the mountain climatic category, with 20 °C as the standard cutoff based on the Koppen climatic classification [49, 50]. Furthermore, studies also highlight that all-cause mortality increases when the temperature increases greater than the threshold of 20 °C, marking it as an important threshold limit in health studies [51]. Similarly, according to the Indian Meteorological Department (IMD) reports 2021, the annual rainfall in Eastern and North Eastern India was recorded to be 1236.4 mm with significant variation among the states with Himalayan high altitudes ranging from 2,000 to 3,000 mm due to the

Table 1 Geospatial data input and sources for assessment of Mosquito-Borne disease vulnerability in Eastern and North-Eastern India

Geospatial variables	Indicators	Data source
Digital Elevation Model (DEM)	Altitude (meters)	United States Geological Survey
Topographic Wetness Index (TWI)	Soil Moisture Saturation (%)	Derived from DEM
Normalized Differential Vegetation Index (NDVI)	Greenness Vegetative cover	Moderate Resolution Imaging Spectroradiometer (MODIS)
Land Use Land Cover (LULC)	Land Use Characteristics	Copernicus Global Land Service
Annual Rainfall	Precipitation in (mm)	Indian Meteorological Department (IMD)
Annual Mean Temperature	Temperature in (°C)	Indian Meteorological Department (IMD)
Population Density	Population per 1 km	World Pop
Proportion Poor	Percentage of Population below poor wealth quintile	NFHS- 5

orographic nature of monsoon which impacts the agricultural productivity, and vegetation as such annual rainfall was categorised into less than 1500 mm, 1500 to 2000 mm and more than 2000 mm as the upper limit category [52–54]. Drought Episodes is a spatially classified index of long-term drought frequency, it ranges from 0 to 10 levels, with higher values indicating more frequent and severe historical drought experience and has been classified into less than 2, 2-5, and greater than 5. Furthermore, the Enhanced Vegetation Index (EVI) as an indicator of vegetation health ranges between +1 to -1, where positive values represent healthy vegetation and negative values represent bare soil. Studies highlight that EVI value 0.2 is the lower bound threshold of healthy vegetation below which, as it approaches negative values the vegetative health is considered as sparse or bare ground, as such, we categorised EVI into three groups less than 0.20, 0.20–0.30, and more than 0.30 [55, 56].

2.5 Statistical analysis

To address the complex survey design, including sampling weights, clustering, and stratification, we used svyset function, to ensure that statistical analysis appropriately accounts for the survey structure, producing accurate and representative results. Univariate analysis was used to describe the distribution of the sample by background characteristics, a detailed description of which is given in (Table S1 in the Supplementary Material), and chi-square test was used to examine the association between anaemia prevalence across distinct covariates in bivariate analysis.

Binary logistic regression was assembled into two distinct models, model 1 for environmental factors and model 2 for environmental factors adjusted with health and demographic factors, for both females and males separately. The model explanation follows:

$$\text{Logit (Y)} = \text{natural log (odds)} = \ln\left(\frac{p}{1-p}\right) = \beta_{0} + \beta_{1}x_1 + \ldots + \beta_{k}x_k$$

where p is the probability of outcome of interest, $\beta 0$ is the intercept and $\beta_{1}, \beta_{2}, \ldots, \beta_{k}$ regression coefficients for predictor $x_1, x_2, \ldots, x_k$. The outcomes were presented as odds ratio (OR) with 95% confidence interval (CI). Furthermore, multicollinearity diagnostics were conducted before the binary logistic regression analysis using Variance Inflation Factor (VIF) separately for females and males, as highlighted in (Table S2 in the Supplementary Material). The output of VIF, with a mean VIF value of 1.44 for females and 1.41 for males, showed low multicollinearity among the predictor variables. Furthermore, none of the variables included in the model exceeded the commonly accepted VIF threshold of 10 [57]. Additionally, to check for the model efficiency and improvement after adjusting for socio-demographic predictors, Log Likelihood, Pseudo R^2, Akaike information criterion (AIC), and Bayesian information criterion (BIC) have been checked and reported respectively for each model.

2.6 Geospatial analysis

Getis-Ord Gi* statistics for detecting prominent hotspots/coldspots of a particular attribute variable is the function of attribute values and distance of points/polygons, developed by Getis and Ord to identify spatial patterns [58]. Prior to Getis-Ord Gi* statistics, the incremental spatial autocorrelation revealed spatial clustering among females was most pronounced at a distance of 35 km, while for males, the strongest clustering occurred at 45 km. The output distance thresholds were used as fixed distance bands to define spatial neighbourhood structure, followed by spatial autocorrelation of anaemia among both females and males in Eastern and North-Eastern India, details of which are highlighted in (Figs. S1 and S2 in the Supplementary Material). Lastly, to determine anaemia hot/cold spots at the cluster level among females and males in Eastern and North-Eastern India, the Getis-Ord Gi* statistics (Standardized Z-score) were implemented and classified following a standard z-distribution cutoff, which can be explained as follows:

$$Z\left(G_i^*\right) = \frac{\left(\Sigma_{j=1}^{n} w_{ij} x_j - \bar{X}\,\Sigma_{j=1}^{n} w_{ij}\right)}{\sqrt[S]{\frac{\left[n\,\Sigma_{j=1}^{n} w_{ij}^2 - \left(\Sigma_{j=1}^{n} W_{ij}\right)^2\right]}{n-1}}}$$

where, G_i^* is the statistics function of spatial dependency of incident i over all n events; w_{ij} represents weight value distance between geographical points i and j; and x_j represents the magnitude/values of the variables under study (anaemia for males and females) at point j.

The Analytic Hierarchy Process (AHP), introduced by Satty is a general theory of measurement and a widely used method in multi-criteria decision-making, planning and resource allocation, including suitability or vulnerability analysis [59]. The mosquito-borne diseases subjected to Anopheles and Aedes mosquitoes, such as malaria, dengue and chikungunya, are subjected to environmental factors that require suitable environmental conditions for breeding and spread of infection; as such, to map their vulnerability to the lowest scale, the application of geospatial techniques has been reliable and emerging in recent times. Studies have focused on mosquito-borne disease vulnerability maps based on environmental and socio-economic factors, notably in Kolkata and Northern South America [60, 61]. Using a similar conceptuality, the mosquito-borne disease vulnerability map for Eastern and North-Eastern India was attempted using the Analytic Hierarchy Process. Firstly, key environmental and socio-demographic indicators associated with vector ecology were selected through review of previous studies on mosquito-borne disease vulnerability in similar ecological setups, as shown in (Fig. S3 in the Supplementary Material) [60, 62, 63]. Key domain-specific experts in public health, environmental health and climate science were consulted to independently rate the relative importance of variables using Saaty's scale. The weights for each factor were generated through a pairwise comparison matrix based on the mean of ratings; relative weights were assigned to the individual variable, details of which are highlighted in (Table S3 in the Supplementary Material). The measure of consistency was assessed using the Consistency Ratio (CR), which can be expressed as:

$$CR = \frac{CI}{RI}$$

where, $Consistency\ Index\ (CI) = \frac{\lambda\ max - n}{n - I}$, here $\lambda\ max$ is the maximum eigenvalue of the comparison matrix, and n is the dimension of the comparison matrix, and RI is the random consistency index corresponding to n. A consistency ratio of less than or equal to 0.1 or 10% is acceptable; the CR value of 2.40% marks the parameter weights in identifying mosquito-borne disease vulnerability in Eastern and North-Eastern India.

The individual variables were re-classified and ranked according to weights as highlighted in the Supplementary Material (Table S4); individual re-classified layers were then multiplied by their standard weight and then overlayed to others for providing mosquito-borne disease vulnerability in Eastern and North-Eastern India. The weighted overlay method can be expressed as

$$s = \frac{\Sigma\, w_i s_{ij}}{\Sigma\, w_i}$$

wherein, s is the spatial unit value in the output raster; w_i is the weight of i^{th} variable; and $s_{ij}$is the i^{th} risk value of j^{th} variable.

Random points were generated, and raster values were extracted from two subset geospatial variables of mosquito-borne disease vulnerability and anaemia clusters for both males and females. The spatial association was then assessed by Bivariate Local Moran's-I, expressed as follows:

$$I_B = \frac{\Sigma_{\,i}\,(\Sigma_{\,j} w_{ij}\,(d)\, x_i \times\, y_j)}{\Sigma_{\,i} x_i^2}$$

where $x_i \times\, y_j$ is the cross product of the first variable (mosquito-borne disease vulnerability) at location *i* and the second variable (anaemia clusters) at each neighbouring location j, and $w_{ij}\,(d)$ represents the weighted value of the neighbourhood between geographical points i and j at distance d.

3 Results

3.1 Distribution of anaemia by selected characteristics

Anaemia in females and males based on selected characteristics as illustrated in (Table 2) shows that environmental factors such as low altitude ranging from 0 to 100 m, mean annual temperature above 20 °C, annual rainfall between 1500 and 2000 mm, and experience of frequent drought episodes in the past (index greater than 5) recorded higher anaemia levels in both females and males. The increase in enhanced vegetation index indicates higher levels of anaemia among females, with the highest anaemia among those residing in areas where the index ranged above 0.30. Females with one or two children were found to be more anaemic compared to women with no children; the other characteristics, such as Body Mass Index and WASH practices, were also crucial. Those identified females and males who were underweight and used unimproved water sources and unimproved toilet facilities had a higher share of anaemia in Eastern and North-Eastern India. Considering demographic variables, such as age, anaemia was found to be more prevalent among females than males across all age groups, with the highest prevalence among females aged 15–24. Contrary to this, the age group 35–49 was most prone to anaemia in males. The prevalence of anaemia was highest in the Schedule Caste among females (69.04%), and males belonging to the Schedule Tribe (36.22%) were more anaemic than other caste groups. Belonging to the Hindu religion, being illiterate, belonging to the poorest wealth quintile and living in a rural setup had a higher share of anaemia prevalence in Eastern and North-Eastern India.

Table 2 Prevalence of anaemia among females and males according to selected characteristics in Eastern and North-Eastern India (NFHS-5) 2019-21

Background characteristics	Females		Males	
	Frequency	Percentage	Frequency	Percentage
Altitude in meters	**8800*** **		**476.77**	
0-100	79,740	66.84	6121	33.15
100–500	21,860	66.8	941	33.7
500–1000	3798	53.83	120	19.47
> 1000	970	40.93	70	16.84
Annual mean temperature in °C	**8700*** **		**409.38*** **	
< 20	898	35.09	80	15.93
> 20	1,05,471	66.38	7171	32.92
Annual rainfall in mm	**858.12*** **		**38.68*** **	
< 1500	15,993	63.49	1,085	27.7
1500–2000	69,601	66.39	4,311	33.58
> 2000	20,775	66.11	1,854	33.53
Drought Episodes	**3900*** **		**175.80*** **	
< 2	4003	61.33	340	29.99
3–5	42,041	64.98	2966	31.57
> 5	60,325	66.87	3945	33.56
Enhanced vegetation index	**197.52*** **		**8.17***	
< 0.20	1207	61.36	79	34.51
0.20–0.30	13,608	64.33	983	31.26
> 0.30	91,554	66.19	6190	32.72
Children ever born	**202.64*** **		**-**	
0	29,562	64.06	-	-
1–2	43,426	67.32	-	-
> 2	33,380	65.72	-	-
BMI	**2000*** **		**301.25*** **	
Normal	64,871	65.84	4677	32.04
Underweight	23,363	70.14	1612	40.18
Overweight/obese	18,135	61.25	962	26.17
Type of diet consumption	**139.94*** **		**1.6794**	
Vegetarian	6816	65.69	229	30.06
Non-Vegetarian	99,552	65.9	7022	32.62
Source of Water	**0.0493**		**1.1364**	
Improved	97,187	65.78	6896	32.41
Unimproved	9181	66.99	355	35.19
Toilet facility	**1600*** **		**101.32*** **	
Improved	71,672	65.06	5080	31.13
Unimproved/no facility/open defecation	34,696	67.66	2171	36.37
Age	**137.39*** **		**41.34*** **	
15–24	38,050	66.28	2427	31.7
25–34	31,421	65.11	1906	29.59
35–49	36,897	66.15	2917	35.64
Education level	**962.21*** **		**181.03*** **	
No education	29,777	67.39	1301	40.62
Primary	14,348	66.63	1180	32.82
Secondary	53,244	65.78	4007	32.32
Higher	9000	60.91	763	24.71
Religion	**8,400*** **		**337.65*** **	
Hindu	88,817	67.04	5887	33.29
Muslim	13,112	62.33	1123	31.46
Christian	2904	53.02	186	23.07
Others	1535	62.95	55	24.44

Table 2 (continued)

Background characteristics	Females		Males	
	Frequency	Percentage	Frequency	Percentage
Caste	**3700*** **		**72.10*** **	
Others	23,771	65.05	1516	30.85
Schedule caste	28,379	69.04	2086	34.97
Schedule tribe	15,042	67.37	998	36.22
OBC	39,176	63.74	2651	30.64
Type of iesidence	**489.18*** **		**97.94*** **	
Urban	22,468	63.63	1447	27.09
Rural	83,900	66.52	5804	34.25
Wealth index	**1600*** **		**252.67*** **	
Poorest	40,637	68.84	2993	37.98
Poorer	28,502	65.66	1959	31.79
Middle	18,734	63.75	1214	30.37
Richer	12,272	62.91	708	25.39
Richest	6224	61.55	377	25.89

Values in bold indicate chi-square values with significance level $p < 0.001$***, $p < 0.01$** and $p < 0.5$*

3.2 Determinants of anaemia in Eastern and North-Eastern India

The binary logistic regression (Table 3) delves into the determinants of anaemia by taking two models for males and females each, wherein Model 1 shows the unadjusted odds ratios of environmental variables, and Model 2 shows the environmental variables adjusted for potential confounding variables attributed to demographic and health characteristics in Eastern and North-Eastern India. The addition of socio-demographic factors to environmental factors significantly improved model fit statistics for females in the adjusted model (Model 2), compared to the unadjusted model (Model 1), with a higher log-likelihood (− 124063.22), improved proportion of variance explanatory power (Pseudo $R^2 = 0.0577$), and lower AIC (248194.44) and BIC (248540.38). Similarly, for males, the adjusted model (Model 2) improved significantly after adjusting for socio-demographic factors compared to the unadjusted model (Model 1), with higher log-likelihood (− 13177.86), improved Pseudo R^2 (0.0433), and reduced AIC (26423.71) and BIC (26697.76).

In Eastern and North-Eastern India, the environmental variables demonstrated a significant association with anaemia prevalence. The moderate to high-altitude residents were associated with lower odds of anaemia compared to the low-altitude residents residing below 100 m, possibly due to physiological adaptations or better nutritional environments. Similarly, females and males in hotter regions with annual mean temperature more than 20 °C were 65% and 41% more likely to be anaemic compared to those in cooler areas having annual mean temperature less than 20 °C females [AOR 1.65; 95% (1.59–1.72)] and males [AOR 1.41; 95% (1.24–1.62)].

Annual rainfall as a predictor has slight differential effects by gender. The likelihood of anaemia was 7% higher in females residing in regions having annual rainfall ranging between 1500 and 2000 mm [AOR 1.07; 95% (1.04–1.10)] compared to females residing in regions receiving annual rainfall less than 1500 mm. However, males residing in regions receiving annual rainfall of more than 2000 mm faced a 14% higher risk of anaemia [AOR 1.14; 95% (1.02–1.27)] than those residing in regions receiving annual rainfall of less than 1500 mm. Higher temperature and rainfall could be associated with higher

Table 3 Output of binary logistic model explaining anaemia among females and males according to selected characteristics in Eastern and North-Eastern India (NFHS-5) 2019-21

Anaemia		Female		Male	
Variables	Sub-category	Model 1	Model 2	Model 1	Model 2
		Odds ratio	Odds ratio	Odds ratio	Odds ratio
Altitude in meters	< 100	Reference	Reference	Reference	Reference
	100–500	0.77 [0.75–0.79]***	0.81 [0.79–0.83]***	0.82 [0.77–0.88]***	0.84 [0.78–0.91]***
	500–1000	0.51 [0.49–0.52]***	0.60 [0.58–0.62]***	0.59 [0.53–0.65]***	0.62 [0.55–0.69]***
	> 1000	0.46 [0.45–0.48]***	0.60 [0.58–0.63]***	0.47 [0.42–0.54]***	0.54 [0.46–0.62]***
Annual mean temperature in °C	< 20	Reference	Reference	Reference	Reference
	> 20	1.86 [1.79–1.93]***	1.65 [1.59–1.72]***	1.51 [1.33–1.71]***	1.41 [1.24–1.62]***
Annual rainfall in mm	< 1500	Reference	Reference	Reference	Reference
	1500–2000	1.08 [1.05–1.11]***	1.07 [1.04–1.10]***	1.12 [1.02–1.23]*	1.05 [0.95–1.15]
	> 2000	0.95 [0.92–0.97]***	1.06 [1.03–1.10]***	1.17 [1.06–1.29]**	1.14 [1.02–1.27]*
Drought episodes	< 2	Reference	Reference	Reference	Reference
	3–5	1.21 [1.18–1.24]***	1.12 [1.09–1.15]***	1.17 [1.07–1.28]***	1.14 [1.04–1.26]**
	> 5	1.47 [1.43–1.51]***	1.40 [1.35–1.44]***	1.38 [1.26–1.52]***	1.32 [1.20–1.46]***
Enhanced vegetation index	< 0.20	Reference	Reference	Reference	Reference
	0.20–0.30	1.55 [1.42–1.70]***	1.14 [0.98–1.33]	1.45 [1.11–1.93]*	1.41 [0.88–2.26]
	> 0.30	1.60 [1.47–1.74]***	1.12 [0.96–1.30]	1.46 [1.11–1.93]**	1.28 [0.81–2.04]
Children ever born	0	-	Reference	-	-
	1–2	-	1.18 [1.15–1.21]***	-	-
	> 2	-	1.13 [1.09–1.17]***	-	-
BMI	Normal	-	Reference	-	Reference
	Underweight	-	1.26 [1.23–1.29]***	-	1.42 [1.31–1.54]***
	Overweight/Obese	-	0.81 [0.79–0.83]***	-	0.73 [0.67–0.80]***
Type of diet consumption	Vegetarian	-	Reference	-	Reference
	Non-Vegetarian	-	1.00 [0.96–1.05]	-	0.98 [0.80–1.19]
Source of water	Improved	-	Reference	-	Reference
	Unimproved	-	1.00 [0.97–1.03]	-	1.02 [0.93–1.12]
Toilet facility	Improved	-	Reference	-	Reference
	Unimproved/No facility/Open defecation	-	1.00 [0.97–1.02]	-	0.94 [0.87–1.01]
Age	15–24	-	Reference	-	Reference
	25–34	-	0.90 [0.87–0.92]***	-	0.90 [0.83–0.98]**
	> 35	-	0.90 [0.88–0.93]***	-	1.10 [1.02–1.18]*
Education level	No education	-	Reference	-	Reference
	Primary	-	0.98 [0.94–1.01]	-	0.87 [0.78–0.97]*
	Secondary	-	0.94 [0.84–0.96]***	-	0.80 [0.73–0.87]***
	Higher	-	0.87 [0.84–0.91]***	-	0.69 [0.61–0.79]***

Table 3 (continued)

Anaemia		Female		Male	
Variables	**Sub-category**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
		Odds ratio	**Odds ratio**	**Odds ratio**	**Odds ratio**
Religion	Hindu	-	Reference	-	Reference
	Muslim	-	0.76 [0.73–0.79]***	-	0.87 [0.77–0.99]*
	Christian	-	0.58 [0.56–0.60]***	-	0.64 [0.57–0.72]***
	Others	-	0.76 [0.73–0.80]***	-	0.86 [0.74-1.00]*
Caste	Others	-	Reference	-	Reference
	Schedule Caste	-	1.01 [0.98–1.05]	-	1.10 [0.98–1.23]
	Schedule Tribe	-	1.08 [1.04–1.12]***	-	1.40 [1.25–1.58]***
	OBC	-	0.94 [0.91–0.97]***	-	1.03 [0.93–1.14]
Type of residence	Urban	-	Reference	-	Reference
	Rural	-	1.06 [1.03–1.09]***	-	1.19 [1.09–1.30]***
Wealth index	Poorest	-	Reference	-	Reference
	Poorer	-	0.88 [0.86–0.91]***	-	0.84 [0.78–0.91]***
	middle	-	0.86 [0.83–0.88]***	-	0.85 [0.77–0.93]***
	Richer	-	0.82 [0.79–0.85]***	-	0.80 [0.71–0.90]***
	Richest	-	0.82 [0.77–0.86]***	-	0.79 [0.66–0.95]**
Log Likelihood		-137826.49	-124063.22	-14872.00	-13177.86
Pseudo R^2		0.0437	0.0577	0.0238	0.0433
AIC		275674.99	248194.44	29766.003	26423.71
BIC		275787.92	248540.38	29855.674	26697.76

Significance level $p < 0.001$***, $p < 0.01$** and $p < 0.5$*

nutritional demands and associated co-morbidities through infectious disease, which are significantly associated with anaemia.

The probability of being anaemic increased with an increase in the occurrence of drought episodes in the past; Females and males residing in regions experiencing high occurrence of drought episodes in the past (index more than 5) had a higher probability of being anaemic; this corresponds to both females 40% higher risk [AOR 1.40; 95% (1.35–1.44)] and males 32% higher risk [AOR 1.32; 95% (1.20–1.46)] compared to females and males residing in regions experiencing low occurrence of drought episodes in the past (index less than 2). Drought, as an important driver of agricultural productivity, could possibly lead to nutritional deficiency and increases the risk of anaemia. Enhanced Vegetation Index (EVI) was found to be sensitive to adjustment; the output result in model 1 for EVI highlighted those females and males residing in the periphery of moderately low to moderate vegetation had higher odds of anaemia compared to residents residing in low vegetation periphery. However, with the adjustment of environmental variables with other demographic and health-related variables, the AOR results were found to be insignificant for both females and males in Eastern and North-Eastern India.

The other controlling demographic and health variables, such as females and males of age 15–24, belonging to the Hindu religion, having no education, tribal status, rural residence, lower wealth index, higher number of children for females and low body mass index, were found to be significant predictors of anaemia in Eastern and North-Eastern India. Overall, these findings highlight the critical association between environmental factors and anaemia.

3.3 Spatial clustering of anaemia in Eastern and North-Eastern India

The output of spatial autocorrelation of anaemia clusters in the Eastern and North-Eastern regions of India, as shown in (Fig. 3), with Moran's I values of 0.47 and 0.18, signified significant autocorrelation and a clustering pattern of anaemia among females and males, respectively.

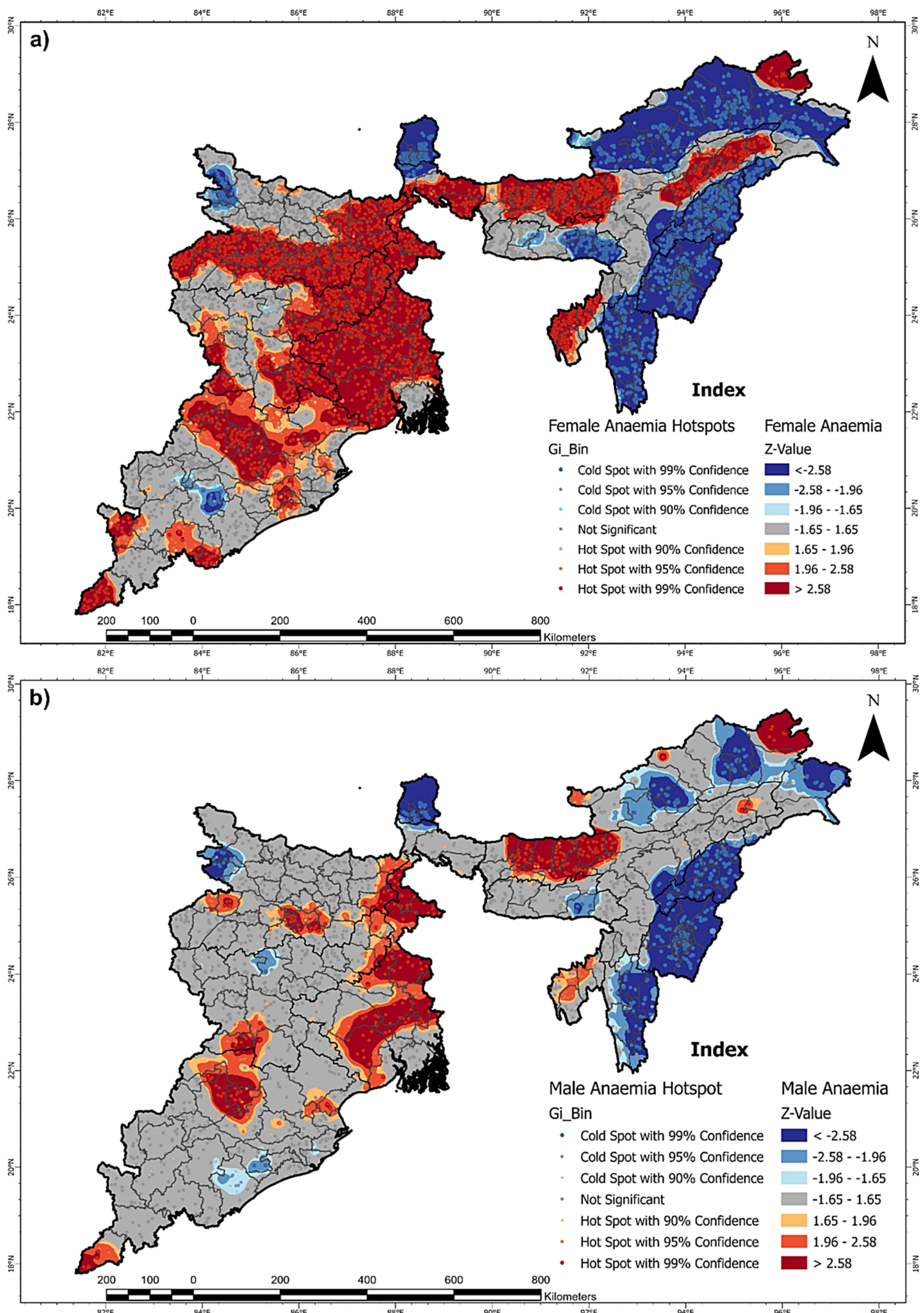

Fig. 3 Spatial Distribution/ Clustering of Anaemia among **a** females and **b** males in Eastern and North-Eastern India (NFHS-5) 2019-21

The clustering of anaemia hotspots (i.e. high prevalence clustering) was significantly concentrated in the floodplain regions of Gangetic, Brahmaputra and Mahanadi belts, with pockets over Tripura, the southern tip of Odisha and North-Eastern Arunachal Pradesh. The concentration was particularly over districts such as Dakshin Dinajpur, Paschim Medinipur, Purba Barddhaman, Murshidabad, Hugli, Koch Bihar, Maldah, and Nadia in West Bengal; Udalguri, and Golaghat in Assam; Jamui, Bhojpur and Bhagalpur in Bihar; Pakur and Jaamtara in Jharkhand; and Anugul in Odisha. Similarly, the clustering of coldspots was found to be in the Eastern Himalayan belt, extending from the hilly regions of Sikkim to the North-Eastern states of Arunachal Pradesh, Nagaland, Manipur, and Mizoram in both females and males. The output result of spatial clustering of anaemia hotspots in females and males had a similar pattern, with a higher concentration of clustering in females and a lower concentration among males.

3.4 Mosquito-Borne disease vulnerability and its Spatial association with anaemia clusters

The final output of Mosquito-Borne Disease vulnerability generated through the analytical hierarchy process (AHP) as highlighted in (Fig. 4), represents a similar trend of high vulnerability over the floodplain regions of Gangetic, Brahmaputra, and Mahanadi belt covering Bihar, West Bengal, Assam, parts of Odisha and Jharkhand, with pockets over Tripura, the southern tip of Odisha and western Meghalaya. On the other hand, the very low vulnerability was concentrated in the Eastern Himalayan belt, extending from the hilly regions of Sikkim to the North-Eastern states of Arunachal Pradesh, Nagaland, Manipur, and Mizoram along with parts of Meghalaya Jharkhand and southern Odisha.

The output of a bivariate Local Indicator of Spatial Association (LISA) map (Fig. 5) with Moran's I values of 0.42 and 0.31 indicated a significant positive spatial association between mosquito-borne disease and anaemia among females and males in Eastern and North-Eastern India. The spatial association between high mosquito-borne disease vulnerability zones and high anaemia among females and males over the flood plain zones, signified by red high-high clusters, can be perceived as fitting to the environmental conditions such as wet, warm and humid climatic conditions alongside lower altitudes. In

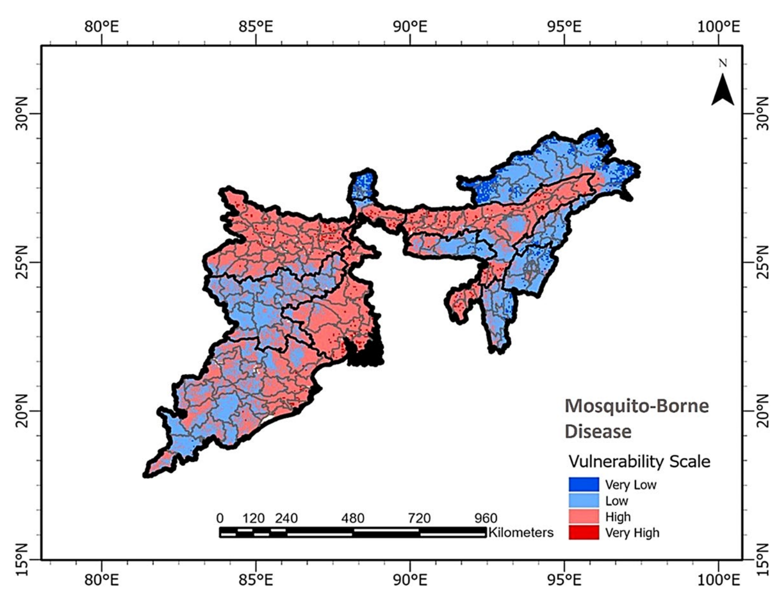

Fig. 4 AHP generated Mosquito-Borne disease vulnerability map of Eastern and North-Eastern India

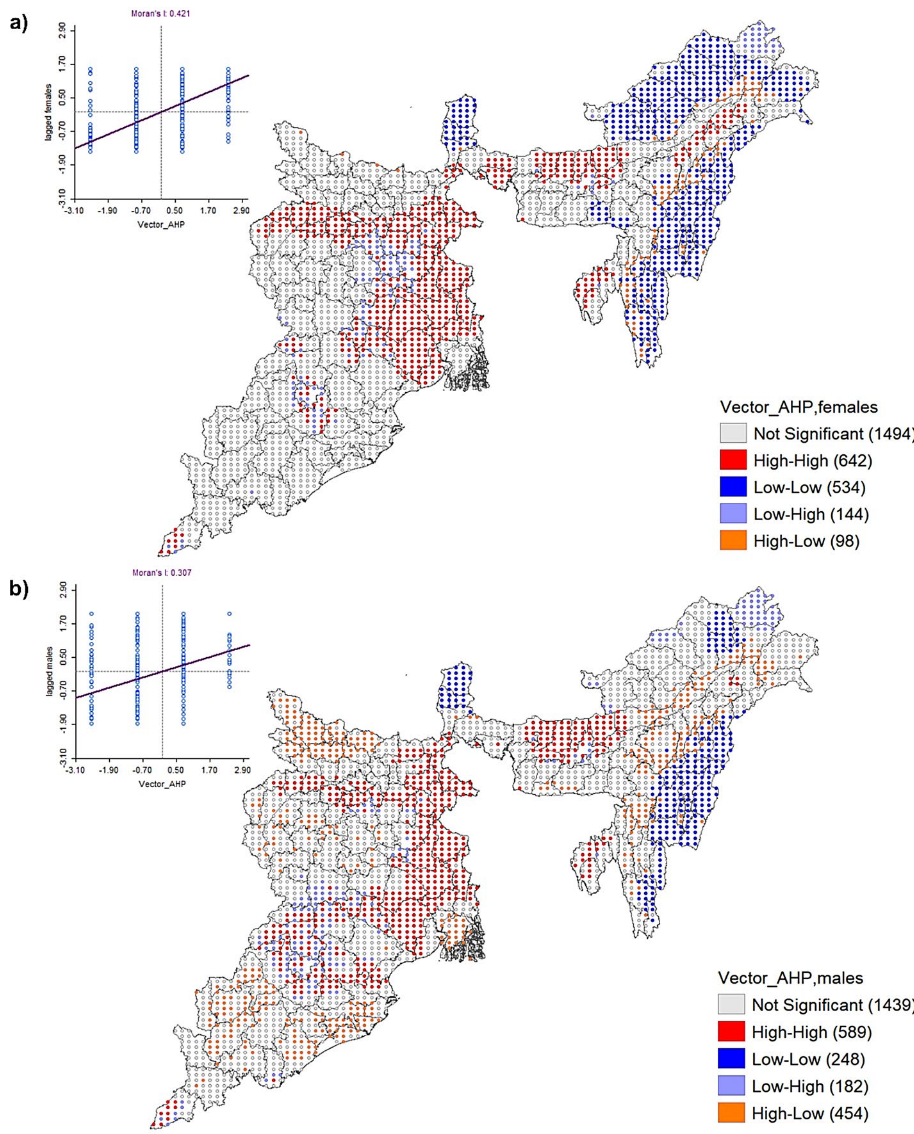

Fig. 5 Bivariate LISA map showing the spatial correlation between Mosquito-Borne Disease Vulnerability and Anaemia among **a** females and **b** males in Eastern and North-Eastern India

contrast, the low mosquito-borne disease vulnerability zones and low anaemia among females and males, signified by blue low-low clusters, were concentrated over the Eastern Himalayan region of North-East India. The conditions mentioned above render the mosquito vectors' thriving capacity exposed to the population, causing diseases like malaria, dengue, and chikungunya, which have ample clinical studies showing evidence of a close association with anaemia.

4 Discussion

The study on anaemia among males and females over the Eastern and North-Eastern regions highlights significant findings that can be summed up broadly on determinants and clustering of anaemia and its spatial association with mosquito-borne diseases.

The study highlighted that clustering of hotspots of anaemia among females and males was mainly concentrated in flood plains of Bihar, West Bengal, Odisha, Assam and parts of Tripura covering districts such as Dakshin Dinajpur, Paschim Medinipur, Purba Barddhaman, Murshidabad, Hugli, Koch Bihar, Maldah, and Nadia in West Bengal; Udalguri, and Golaghat in Assam; Jamui, Bhojpur and Bhagalpur in Bihar; Pakur and Jamtara in Jharkhand; and Anugul in Odisha and cold spots was primarily concentrated over the Eastern Himalayas of Sikkim, Arunachal Pradesh, Mizoram, Manipur and Nagaland. Our study is the first to present anaemia clustering dropping down from district to cluster level for Eastern and North-Eastern India using the latest round of NFHS surveys. Similarly, the study shows near similar spatial patterns and anaemia clustering in a nationally represented study using NFHS-5 at the district level for females and males in Eastern and North-Eastern India. Studies that explored district-level anaemia prevalence [14, 24, 64] And some regional studies support our finding of the prevalence of anaemia [16, 65]. However, our study is more detailed and highlights the micro-level spatial clustering of disease.

In addition, low residential altitude as an environmental factor was found to be an essential predictor associated with higher anaemia prevalence; the odds of anaemia decreased as residential elevation increased in Eastern and North-Eastern India. Low altitude anaemia prevalence can be associated with numerous factors, predominantly socio-cultural factors, alongside environment, which can be associated to high anaemia prevalence. Studies in India highlight that increased pollutants, such as increased ambient PM2.5 exposure, result in anaemia among women of the reproductive age group, with a prominent effect over regions of coal units spread over the Gangetic Plains [66, 67]. Hypoxia also contributes to low levels of anaemia at higher altitudes, a condition of physiological adaptation to low parcel pressure oxygen at high altitudes in the form of increased concentration of haemoglobin [68]. Several studies mention this phenomenon in different samples of high-altitude residents, particularly in Andean and Tibetan populations [69–71].

Furthermore, high mean annual temperature and high annual rainfall as climatic factors were found to be an essential risk factor associated with anaemia prevalence compared to regions with mean annual temperatures less than 20 °C and rainfall less than 1500 mm. The association between high temperature and childhood anaemia is limited, but studies have documented that a 1 °C increase in mean annual temperature was associated with a 13.8% increase in anaemia and further projected increase of anaemia by 7,597 per 100,000 person-years in 2090 among children of 26 Sub-Saharan Africa under high emission climatic scenario, three times more than low emission scenario [72]. The evidence on annual rainfall directly associated with anaemia was not available as such, but studies report that an increase in rainfall was linked with the maternal outcome of anaemia [73]; alongside, a study on riverine regions of Brazil highlights mean haemoglobin and haematocrit levels among children and adolescents to be higher in the dry season, wherein the anaemia prevalence was reported to be 4% in the dry season against 12% in the rainy season [74].

On the other hand, compared to regions experiencing lower drought episodes in the past, the regions with index of more than 5 drought episodes, as meteorological hazards were found to be associated with higher anaemia prevalence among both females and males in Eastern and North-Eastern India. Studies highlight the increase in the frequency and intensity of droughts in the Indian sub-continent, with high impacts on the agricultural belt of Maharashtra and the Indo-Gangetic Plains, hampering food security issues and socio-economic vulnerability [75]. Studies and reviews in drought-affected communities in South-Central Ethiopia and Africa also linked the nutritional outcome of anaemia as an effect of drought exacerbated by socio-economic factors and malaria [76, 77].

The environmental determinants, except altitude, do not directly contribute to anaemia; instead, calamities such as floods and droughts compound agricultural failure and food security issues, alongside changing climatic conditions, affecting heat-related disease, waterborne disease and infection, are linked with higher prevalence of anaemia. The environmental characteristics associated with anaemia mentioned above are typical to humid subtropical regions favourable for breeding and infection through mosquito-borne diseases, particularly malaria and dengue [78]. Considering these findings, the environmental and socio-economic characteristics-based vulnerability map of mosquito-borne disease was generated. The output results found a significant spatial association of mosquito-borne disease vulnerability with anaemia. Anaemia due to malaria and dengue can be attributed to high loss of (RBC) red blood cells due to rupturing of RBCs by the malaria virus and cytopenia, and gastrointestinal bleeding in dengue [79–82]. The finding remains constant, with studies reporting that districts with more than 23.6% anaemia prevalence had higher odds of being malaria endemic districts, with similar high annual parasitic index and anaemia patterns among males in Eastern and North-Eastern India [83].

The findings on socio-demographic determinants of anaemia highlighted that females and males aged 15–24, belonging to the Hindu religion, having no education, tribal status, rural residence, and lower wealth index are linked with a higher risk of having anaemia in India. Studies with similar findings at the national and sub-national levels in India can be found [11–16]. These factors also correspond to socio-cultural practices, norms, and attitudes alongside inequality and marginality, directly associated with nutritional status. The study also focuses on health factors, where a higher number of children ever born was found to be a risk factor for anaemia; similar findings can be traced in studies at the national level, the reason being multiple gestations resulting in higher iron demand and blood loss during complications [12, 84, 85]. The underweight category in BMI was associated with a higher anaemia burden; such an association has been established in India and several other countries as well, but the explanation for it remains bounded by low nutritional intake, failure of nutritional absorption, physiological disadvantage and so on [13, 14, 86–88].

4.1 Limitations

The study incorporates environmental factors into all individual categories, assuming environmental factors are constant for all individuals within clusters. Although DHS purposively does it to maintain respondents' privacy, the level of displacement in urban and rural areas is minimal. However, individual data on environmental factors would suffice for the study to measure environmental determinants of health more significantly.

Data on selected important vector-borne diseases are administered by the National Centre for Vector Borne Disease Control (Ministry of Health and Family Welfare, Government of India), such as malaria, dengue, chikungunya, etc. The majority of diseases are reported at the state level. The micro-level geospatial data on mosquito-borne disease vulnerability was generated using geospatial modelling through available environmental and socio-economic data. As far as our knowledge goes, this is the first of its kind to visualise the clustering of anaemia with mosquito-bornedisease vulnerability. The real-time micro-level data on prevalence and fatality would suffice for more accurate output.

5 Conclusion

The study highlights a strong association between anaemia and environmental factors, particularly high mean annual temperatures, high annual rainfall, and recurrent drought episodes among females and males in Eastern and North-Eastern India. The findings call for a shift beyond socio-economic and health service determinants to a more comprehensive framework that integrates environmental factors in addressing anaemia.

The findings on spatial clustering of anaemia and its spatial association with mosquito-borne disease vulnerability underscore the need for a coordinated public health approach targeting females and males in the floodplain regions of Eastern and North-Eastern India. At the early detection level, a coordinated synergy between the existing Integrated Disease Surveillance Programme (IDSP) and the National Centre for Vector-Borne Disease Control is essential. This approach would help in regulating routine Web-GIS-based surveillance and biomarker tracking of syndromic symptoms for early detection and further research on disease outbreaks.

At the prevention and response level, integrated vector control, environmental management, and community education should be inculcated in anaemia reduction strategies. This could be achieved by deploying community health workers to raise environmental-risk awareness and promote vector prevention, alongside iron and folic acid supplementation and nutritional education. Furthermore, more detailed research should build on these findings by incorporating longitudinal data on environmental exposures to better understand causal pathways between environmental exposures and anaemia.

Supplementary Information

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Supplementary Material 1

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Author contributions

Lobsang Tshering Bhutia: Conceptualization, Data Processing & Analysis, Visualization; Writing– drafting manuscript. Aparajita Chattopadhyay: Conceptualization; Validation; Writing– review & editing.Listed authors read and approved the final manuscript.

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Data availability

The datasets used in the current study are freely available online on the official website of the Demographic Health Survey Program: https://www.dhsprogram.com. Alongside, spatial data have been retrieved from multiple publicly available sources listed as follows: Digital Elevation Model (DEM) retrieved from https://www.usgs.gov; Normalized Difference Vegetation Index (NDVI) retrieved from https://lpdaac.usgs.gov/; Land Use Land Cover (LULC) retrieved from https://doi.org/10.5281/zenodo.3518038; Climatic gridded data Rainfall and Temperature retrieved from https://www.imdpune.gov.in/; Population Density retrieved from https://www.worldpop.org/. However, the datasets used can be made available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate
The study incorporates the use of a publicly available dataset at https://www.dhsprogram.com and no personally identifiable information has been disclosed by any means. Therefore, no ethical approval is required for this study. The study also does not involve any clinical intervention as such clinical trial registration and clinical trial registration number are not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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