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Spatio-temporal pattern and associate meteorological factors of airborne diseases in Bangladesh using geospatial mapping and spatial regression model

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Abstract

Background and Aims: Airborne diseases due to climate change pose significant public health challenges in Bangladesh. Little was known about the spatio-temporal pattern of airborne diseases at the district level in the country. Therefore, this study aimed to investigate the spatio-temporal pattern and associated meteorological factors of airborne diseases in Bangladesh using exploratory analysis and spatial regression models.

Methods: This study used district-level reported cases of airborne diseases (meningococcal, measles, mumps, influenza, tuberculosis, and encephalitis) and meteorological data (temperature, relative humidity, wind speed, and precipitation) from 2017 to 2020. Geospatial mapping and spatial error regression models were utilized to analyze the data.

Results: From 2017 to 2020, a total of 315 meningococcal, 5159 measles, 1341 mumps, 346 influenza, 4664 tuberculosis, and 229 encephalitis cases were reported in Bangladesh. Among airborne diseases, measles demonstrated the highest prevalence, featuring a higher incidence rate in the coastal Bangladeshi districts of Lakshmipur, Patuakhali, and Cox's Bazar, as well as in Maulvibazar and Bandarban districts from 2017 to 2020. In contrast, tuberculosis (TB) emerged as the second most prevalent disease, with a higher incidence rate observed in districts such as Khagrachhari, Rajshahi, Tangail, Bogra, and Sherpur. The spatial error regression model revealed that among climate variables, mean ($\beta = 9.56$, standard error [SE]: 3.48) and maximum temperature ($\beta = 1.19$, SE: 0.40) were significant risk factors for airborne diseases in Bangladesh. Maximum temperature positively influenced measles ($\beta = 2.74$, SE: 1.39), whereas mean temperature positively influenced both meningococcal ($\beta = 5.57$, SE: 2.50) and mumps ($\beta = 11.99$, SE: 3.13) diseases.

Conclusion: The findings from the study provide insights for planning early warning, prevention, and control strategies to combat airborne diseases in Bangladesh and

Arman Hossain Chowdhury and Md. Siddikur Rahman contributed equally to this study as joint first authors.

similar endemic countries. Preventive measures and enhanced monitoring should be taken in some high-risk districts for airborne diseases in the country.

KEYWORDS
climate change, measles, meningococcal, mumps, spatial regression

1 | INTRODUCTION

Airborne diseases not only cause worldwide epidemics and pandemics but also cause death and disability.[1] During the last several decades, numerous significant airborne disease outbreaks have been witnessed globally, such as measles, mumps, avian flu, severe acute respiratory syndrome (SARS), Middle East respiratory syndrome (MERS), and the current coronavirus disease 2019 (COVID-19).[2,3] Among these, measles is a major global cause of mortality in children, accounting for 140,000 fatalities in 2018 and 1.4 billion people worldwide have tuberculosis disease.[4]

In Bangladesh, airborne diseases represent a significant public health threat.[5] Among the airborne diseases, tuberculosis (TB) is the most prevalent disease, with an estimated incidence rate of 221 per 100,000 cases yearly in Bangladesh, with a death rate of 24 per 100,000 individuals.[6,7] Regarding TB risk, Bangladesh is ranked seventh out of 30 nations.[8] Measles is also another most prevalent airborne disease, with estimated deaths of 9,021 people in Bangladesh in 2020 (1.26% of all fatalities).[9] It has already been investigated that meteorological factors such as temperature, relative humidity, and precipitation impact the transmission of airborne diseases.[10–12] According to previous studies, temperature, relative humidity, rain, and wind speed are the climatic risk factors that can significantly affect tuberculosis.[13,14] Higher humidity was negatively connected with meningitis and encephalitis but positively associated with malaria and diarrhea. Low rainfall was accompanied by higher encephalitis and meningitis rates.[15] People's risks of developing airborne diseases increase by 5.7% for every 1°C temperature increase and by 1.5% for every 1% increase in humidity.[16] In addition, the high population density,[17] and weak healthcare infrastructure make Bangladesh susceptible to airborne diseases.[5] Acknowledging the significant impact of climatic factors on airborne illnesses is crucial, particularly concerning how particulate matter spreads in the atmosphere.[18–20] Therefore, understanding the effects of climatic factors becomes essential for the early prevention and management of airborne infections.

Several previous studies used several methods to investigate the relationship between meteorological factors and different airborne diseases, including time series analysis,[21] SEIAR model,[22] Poisson regression model,[23] lag nonlinear model,[24] structural equation modeling (SEM)[25] and boosted regression tree model.[26] However, these studies investigated the relationship as a whole and did not capture the spatial characteristics of the diseases. On the other hand, few studies were conducted in Bangladesh to investigate the relationship between meteorological factors and airborne diseases.[15,27] Moreover, no studies in Bangladesh investigated the spatio-temporal pattern and relationship between meteorological factors and airborne diseases. A spatial analysis of airborne diseases is required to determine which areas of Bangladesh are most susceptible to the transmission of airborne diseases and what meteorological factors contribute most to the spread of these diseases. Therefore, this study used geospatial mapping and spatial error regression models to examine the spatiotemporal pattern and connection between climatic parameters and airborne diseases in Bangladesh. The study findings will assist policymakers and government officials in identifying the areas where resources are most needed to combat airborne diseases. Additionally, our study outcomes will provide the opportunity for early warning, preventative, and control measures to mitigate airborne diseases and infections linked to them.

2 | MATERIALS AND METHODS

2.1 | Study location

Bangladesh is a South Asian nation with latitudes ranging from 20°34′ to 26°38′ north and longitudes ranging from 88°01′ to 92°41′ east. Its greatest extent is approximately 440 km in the east-west direction and 760 km in the north-northwest-southeast direction. The total area is 147,570 square kilometers, divided into 64 districts under eight divisions investigated in this study (Figure 1).[28] Bangladesh experiences seasonal solid changes in rainfall, hot temperatures, and high humidity due to its subtropical to tropical monsoon weather. The average annual temperature in Bangladesh has historically been approximately 26°C, with seasonal variations between 15°C and 34°C.[29,30] High temperatures might contribute to the development of airborne diseases, rendering the north and north-western regions of the country particularly susceptible to them. It is also important to remember that the lengthening of summers, warming winters, and abnormally erratic monsoons can all impact the occurrence and spread of these illnesses.[16]

2.2 | Data source

Our study compiled a data set of six airborne diseases (meningococcal, measles, mumps, influenza, tuberculosis, and encephalitis) and seven meteorological factors (maximum temperature [°C], minimum temperature [°C], mean temperature [°C], relative humidity [%], maximum wind

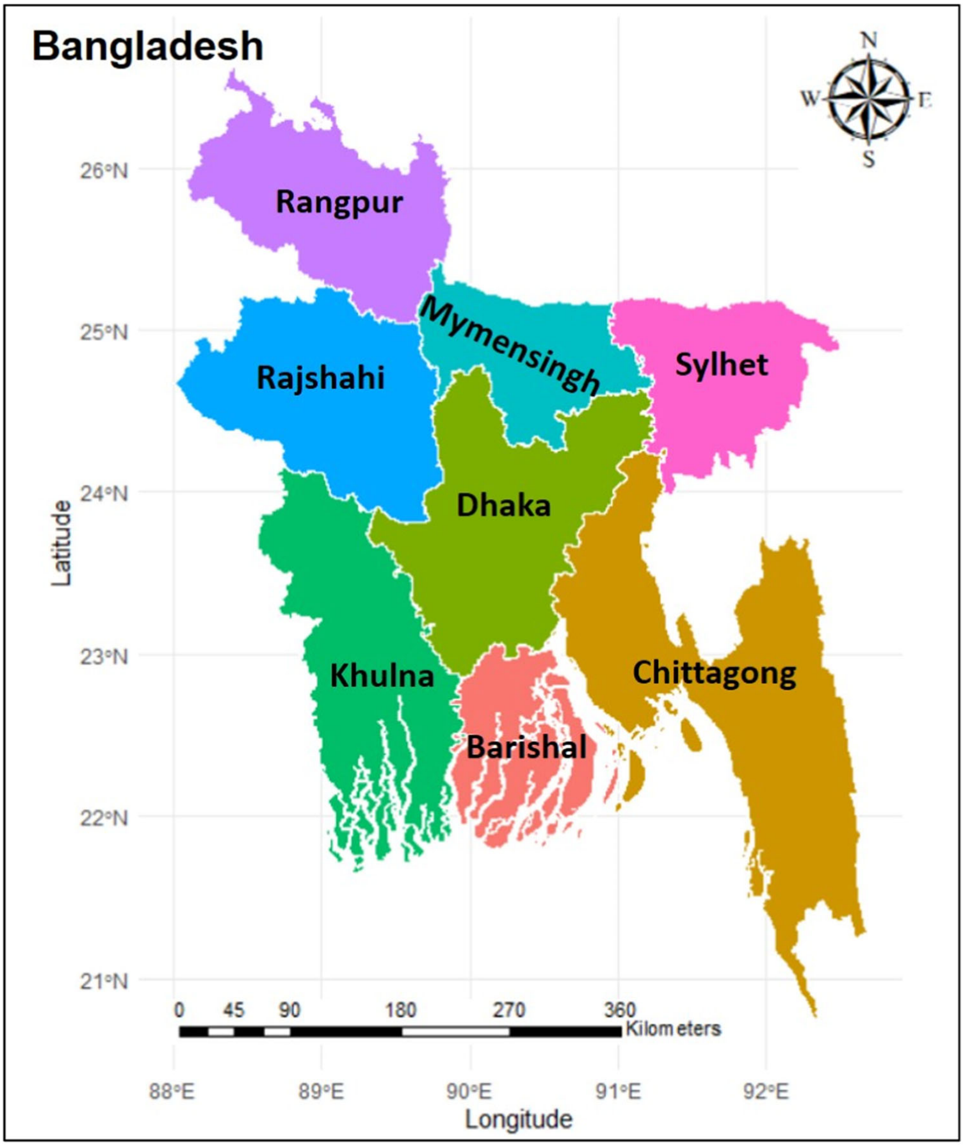

FIGURE 1 The study area encompasses eight divisions located in Bangladesh.

speed [m/s], minimum wind speed [m/s], and precipitation [mm]) between 2017 and 2020. The meteorological data were collected based on hourly weather measurements from the NASA Langley Research Center (LaRC) website.[31] The district-wise population data for computing incidence rates were collected from the population and housing census (PHC-2011).[32] The airborne disease cases were collected from Bangladesh Environment Statistics 2020, Strengthening Environment, Climate Change and Disaster Statistics (ECDS) Project. This project was carried out by the Department of Statistics and Information, Bangladesh Bureau of Statistics.[33] The detailed description of the data is presented in Table 1.

2.3 | Spatial regression

The ordinary least-squares (OLS) estimator of the linear regression model fails to attain BLUE (best linear unbiased estimator) when there is geographic dependency.[34] Anselin developed the spatial regression technique to produce a more accurate estimate of spatial dependency, which is mathematically expressed as follows:

$$y = \rho W_y + X\beta + \varepsilon, \quad \varepsilon \sim N(0, \sigma^2 I), \tag{1}$$

where y represents the dependent variable ($n \times 1$ matrix), X represents the independent variable ($n \times k$ matrix), W_y represents the spatial weight matrix ($n \times n$), ρ denotes the spatial lag parameter, β is the slope of the regression ($k \times 1$), and ε represents the random error. By including a spatial variable (W_y) in the spatial lag model in Equation (1), we were able to adjust the geographical dependency while still taking endogenous issues into account.[35]

On the other hand, in the situation of geographical dependency of the error term in the OLS model, the spatial error model was implemented using the spatial error term (W_ε), which is mathematically defined as

$$y = X\beta + \varepsilon, \quad \varepsilon = \lambda W_\varepsilon + \mu, \tag{2}$$

TABLE 1 Description of all input predictors and response variables.

Type	Codes	Description
Spatial-temporal	Year	Year
	Districts	District names
	Latitude	Latitude values
	Longitude	Longitude values
Climate	x1	MERRA-2 temperature at 2 m (C)
	x2	MERRA-2 relative humidity at 2 m (%)
	x3	MERRA-2 temperature at 2 m maximum (C)
	x4	MERRA-2 temperature at 2 m minimum (C)
	x5	MERRA-2 precipitation corrected (mm)
	x6	MERRA-2 wind speed at 50 m maximum (m/s)
	x7	MERRA-2 wind speed at 50 m minimum (m/s)
Airborne diseases	y1	Meningococcal infection
	y2	Measles infection
	y3	Mumps
	y4	Influenza due to identified avian influenza virus
	y5	Tuberculosis
	y6	Encephalitis
Total airborne diseases	y7	The sum of six airborne disease cases

where y represents the dependent variable ($n \times 1$ matrix), X represents the independent variable ($n \times k$ matrix), W_ε represents the spatial weight matrix ($n \times n$), λ denotes the spatial error parameter, β is the slope of the regression ($k \times 1$), and μ represents the matrix of random error.[36] The standard method of moments was used to estimate the spatial error model.

2.4 | Statistical analyses

After preprocessing the data, we performed Pearson bivariate product–moment correlation analysis to see the correlation between airborne diseases and climate factors. We then employed the spatial error regression model to examine the effect of climate factors on airborne diseases (Figure 2). All statistical analyses were conducted using Microsoft Excel (Version 2013)[37] and RStudio (Version 4.3.1).[38] Missing value imputation and data transformation were performed in MS Excel. The spatial error regression model was built using the "sp," "spData," "spdep," and "spatialreg" packages of RStudio. The "ggplot 2," "maps" and "sf" packages were used to create maps. The correlation plot was created using the "corrplot" package.

3 | RESULTS

We included six airborne diseases in our study, the most prevalent of which was measles. The most significant measles cases were recorded in 2019 (Supporting Information S1: Table S7), while the fewest were in 2018. In Bangladesh, tuberculosis is the second most prevalent disease, with many cases recorded in 2020 and a small number of cases recorded in 2017. On the other hand, the lowest number of mumps cases was recorded in 2018, and the highest number was recorded in 2019 (Figure 3).

The mean number of meningococcal cases varied less across the years, ranging from 0.47 to 1.84, with the highest mean of 1.84 cases

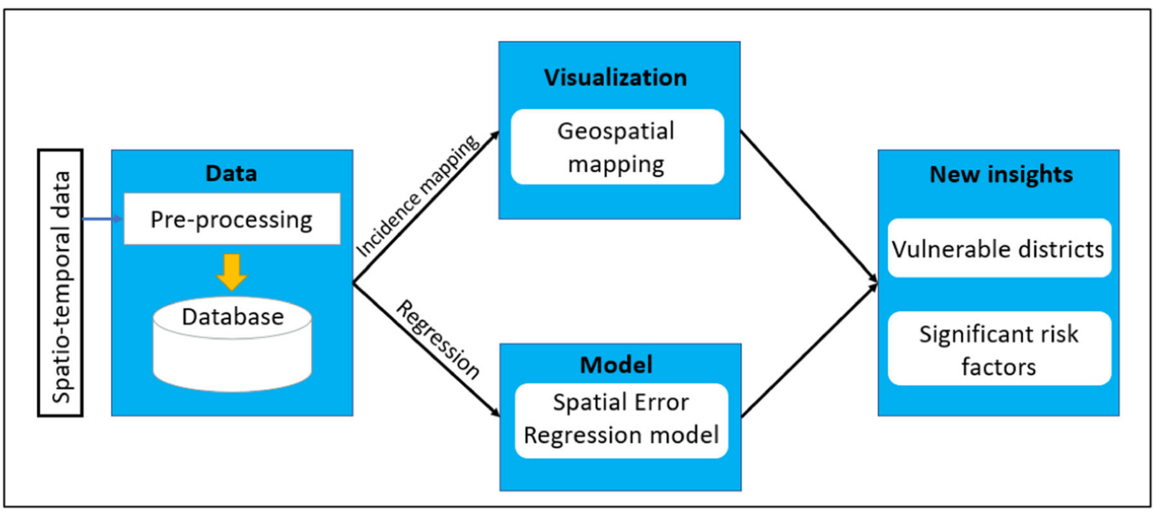

FIGURE 2 Proposed study design overview with key components.

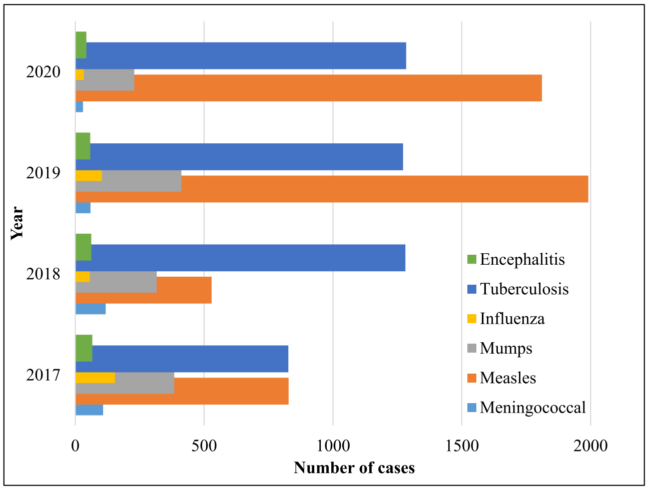

FIGURE 3 Different airborne disease cases in Bangladesh from 2017 to 2020.

TABLE 2 Descriptive statistics for different airborne diseases in Bangladesh from 2017 to 2020.

Diseases	Year	Min	Median	Max	Mean ± SD
Meningococcal	2017	0	0	38	1.68 ± 5.13
	2018	0	0	38	1.84 ± 4.99
	2019	0	0	7	0.92 ± 1.59
	2020	0	0	3	0.47 ± 0.80
Measles	2017	0	2	169	12.94 ± 32.23
	2018	0	3	92	8.26 ± 14.32
	2019	0	9	353	31.10 ± 59.55
	2020	0	5.50	334	28.30 ± 56.73
Mumps	2017	0	4	39	6 ± 7.63
	2018	0	3	34	4.93 ± 6.47
	2019	0	5	29	6.43 ± 5.38
	2020	0	2	23	3.58 ± 4.37
Influenza	2017	0	0.50	37	2.40 ± 6.47
	2018	0	0	16	0.87 ± 2.56
	2019	0	0	68	1.60 ± 8.54
	2020	0	0	15	0.51 ± 1.92
Tuberculosis	2017	0	8	98	12.92 ± 17.52
	2018	0	10.5	185	20.02 ± 32.95
	2019	0	9	205	19.88 ± 31.82
	2020	0	8	413	20.06 ± 53.75
Encephalitis	2017	0	0	12	1.03 ± 2.72
	2018	0	0	17	0.96 ± 2.86
	2019	0	0	36	0.90 ± 4.65
	2020	0	0	26	0.67 ± 3.33

Abbreviations: Max, maximum; Min, minimum; SD, standard deviation.

recorded in 2018 (Table 2). The mean number of measles cases ranges from 8.26 to 31.10, with the highest mean number of 31.10 cases recorded in 2019. Similarly, the mean number of mumps cases varied from 3.58 to 6, with the highest mean number of six cases in 2017. More details about the summary statistics of the diseases are presented in Table 2.

During the study period between 2017 and 2020, yearly mean maximum and minimum temperatures varied from 36.35°C to 39.42°C and 6.66°C to 7.93°C, respectively (Table 3). The mean relative humidity ranged from 75.83% to 79.74%, with the highest humidity of 79.74% recorded in 2020. The mean annual precipitation across the country was 4470.64, 2931.04, 3542.35, and 3386.29 mm in 2017, 2018, 2019, and 2020, respectively (Table 3).

As depicted in Figure 4, an extensive investigation of airborne diseases from 2017 to 2020 reveals significant trends and variances in their frequency across various districts of Bangladesh. Among airborne diseases, measles exhibited the highest prevalence with a higher incidence rate in the coastal districts of Lakshmipur, Patuakhali, and Cox's Bazar, as well as in the Maulvibazar and Bandarban districts from 2017 to 2020 (Supporting Information S1: Table S2). Conversely, TB is the second most prevalent disease, showing a higher incidence rate in the Khagrachhari, Rajshahi, Tangail, Bogra, and Sherpur districts (Supporting Information S1: Table S5). Meningococcal disease demonstrated a higher prevalence in the Jhenaidah district in southwest Bangladesh during the same period (Supporting Information S1: Table S1), in comparison to Narayanganj, Feni, Panchagarh, Pirojpur, Sylhet, Dhaka, and Barisal districts. Mumps disease exhibited a higher prevalence with a greater incidence rate in Magura, Patuakhali, Rangamati, Kushtia, and Meherpur districts (Supporting Information S1: Table S3). Faridpur and Rajbari districts of the Dhaka division emerged as hotspots for influenza with a high incidence rate (Supporting Information S1: Table S4), while districts such as Lalmonirhat, Sherpur, Narayanganj, and Sylhet reported no incidences. Encephalitis demonstrated a higher incidence rate in the Bogra, Kishoreganj, Patuakhali, Lakshmipur, and Faridpur districts (Supporting Information S1: Table S6), with no reported incidences in Dhaka, Barisal, Jhalokathi, and Bandarban districts from 2017 to 2020 (Figure 4) (Supporting Information S1: Figure S1).

The correlation analysis revealed significant associations between mean temperature and meningococcal cases.[23] Additionally, relative humidity and minimum and maximum temperatures exhibited significant associations with measles cases, while mumps positively correlated with mean temperature. However, no direct associations were found between influenza, tuberculosis, and encephalitis diseases with the examined climate factors (Supporting Information S1: Table S8). Although no significant relationships were found between those airborne illnesses and meteorological data, the investigation did discover positive associations between minimum and mean temperatures and the overall number of airborne disease cases (Figure 5).

TABLE 3 Descriptive statistics of monthly climate factors in Bangladesh from 2017 to 2020.

Factors	Year	Min	Median	Max	Mean ± SD
Mean temperature	2017	24.68	25.33	26.39	25.31 ± 0.41
	2018	23.29	25.03	26.04	24.97 ± 0.44
	2019	23.92	25.65	26.25	25.52 ± 0.44
	2020	23.57	25.01	26.09	24.90 ± 0.42
Maximum temperature	2017	31.63	36.10	41.71	36.57 ± 2.93
	2018	30.83	35.86	41.40	36.35 ± 1.81
	2019	31.18	39.74	44.53	39.82 ± 2.96
	2020	31.70	37.94	41.22	37.71 ± 1.88
Minimum temperature	2017	4.02	6.55	17.34	6.99 ± 2.07
	2018	4.45	6.26	15.63	6.66 ± 1.81
	2019	4.17	7.90	17.12	7.86 ± 2.28
	2020	5.89	7.63	15.95	7.93 ± 1.70
Relative humidity	2017	69.88	79.88	84.69	78.98 ± 3.49
	2018	67.12	83.12	83.12	76.91 ± 3.62
	2019	67.38	76.35	81.12	75.83 ± 3.21
	2020	73.69	79.75	83.88	79.74 ± 1.94
Precipitation	2017	1492.48	4419.14	9792.77	4470.64 ± 1899.32
	2018	1102.15	2549.71	8121.09	2931.04 ± 1437.53
	2019	1244.53	3071.78	9502.73	3542.35 ± 1659.56
	2020	1629.49	3058.59	7467.19	3386.29 ± 1190.56
Maximum wind speed	2017	10.63	15.10	20.66	15.14 ± 2.39
	2018	6.68	12.43	15.80	12.31 ± 1.47
	2019	8.84	14.90	18.19	14.54 ± 1.88
	2020	7.64	19.55	25.07	18.80 ± 4.22
Minimum wind speed	2017	0.01	0.05	0.12	0.05 ± 0.03
	2018	0.01	0.05	0.16	0.05 ± 0.03
	2019	0.01	0.05	0.12	0.05 ± 0.03
	2020	0.01	0.03	0.11	0.04 ± 0.03

Abbreviations: Max, maximum; Min, minimum; SD, standard deviation.

The aforementioned significant climate factors were then used as covariates in the spatial error regression model. In Model 1, targeting the meningococcal disease, the spatial distribution of the residual term exhibited a statistically significant positive relationship. The prevalence of meningococcal disease showed a positive association with mean temperature and a negative association with maximum temperature. In Model 2, targeting the measles disease, the spatial distribution of the residual term was observed to exhibit a statistically significant negative relationship. The prevalence of measles disease positively correlated with relative humidity and maximum and minimum temperature. In Model 3, targeting the mumps disease, the spatial distribution of the residual term was observed to exhibit a statistically significant positive relationship. The prevalence of mumps was positively associated with the mean temperature. In Model 4, targeting the overall airborne disease, the spatial distribution of the residual term was observed to exhibit a statistically significant positive relationship. The mean and maximum temperatures were positively associated with airborne diseases (Table 4).

4 | DISCUSSION

Airborne diseases impose a substantial health burden at the district level in Bangladesh. However, this study revealed that among the six airborne diseases, measles was the most prevalent, exhibiting a higher incidence rate in the Lakshmipur, Patuakhali, Cox's Bazar,

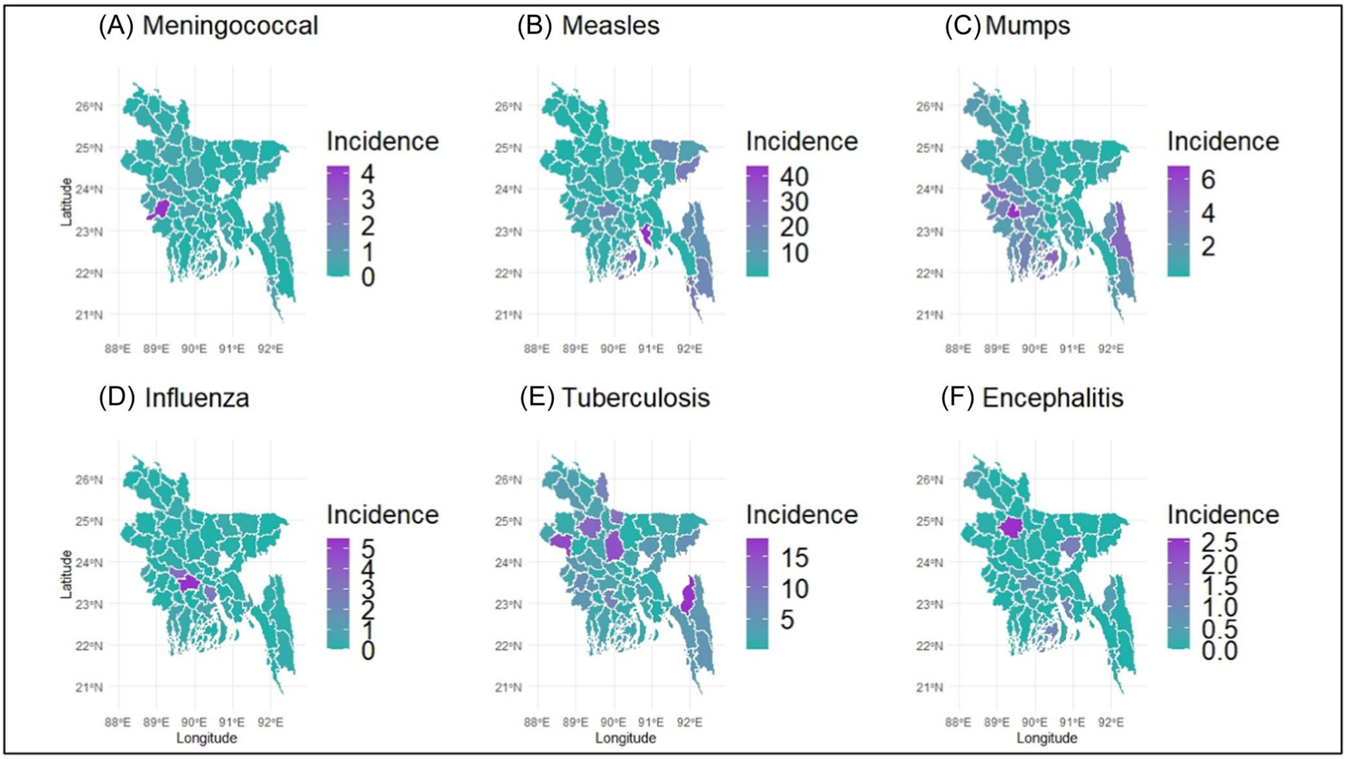

FIGURE 4 Spatial distribution of airborne diseases incidence rate per 100,000 population in Bangladesh from 2017 to 2020. (A) Meningococcal. (B) Measles. (C) Mumps. (D) Influenza. (E) Tuberculosis. (F) Encephalitis.

Maulvibazar, and Bandarban districts during the 2017–2020 period in Bangladesh. Conversely, TB emerged as the second most prevalent disease, with a higher incidence rate observed in the Khagrachhari, Rajshahi, Tangail, Bogra, and Sherpur districts during the same period. This study also identified the significant meteorological factors that influence airborne diseases. Notably, the findings align with some earlier studies while differing from others, highlighting the intricate link between climate factors and disease transmission. For instance, mean temperature positively impacted meningococcal disease, and maximum temperature negatively influenced meningococcal disease cases, which aligns with a previous study conducted in Chaoyang City, China.[25] However, a prior study in Auckland, New Zealand, revealed that cool temperatures and high humidity can increase the incidence of meningococcal disease.[23] This study also found that measles was positively associated with relative humidity and minimum and maximum temperature. However, some previous studies conducted in China claimed that hot and cold temperatures decrease the risk of measles.[24,39] We also found that mean temperature was positively associated with the mumps disease, which aligns with a previous study conducted in Jining City, China.[26] Our study found no association of meteorological factors with influenza, tuberculosis, and encephalitis diseases. However, some previous studies examined that temperature and relative humidity impacted the spread of the influenza virus.[10,11] Some previous studies also found that temperature, relative humidity, precipitation, and wind speed were associated with tuberculosis disease.[13,14] An earlier study conducted in Bangladesh also found that encephalitis disease is positively associated with increased temperature.[15] However, we found that the overall airborne diseases were positively associated with mean and maximum temperature. The intricacies of these findings might be attributed to the diverse characteristics of airborne diseases and the interactions among several factors.

This study examined the relationship between meteorological factors and airborne diseases. Meteorological factors might impact human health, particularly concerning infectious diseases such as airborne.[40–42] The majority of infectious illnesses must have three components to spread: (i) a disease-causing agent (or pathogen), (ii) an infecting host (or vector), and (iii) a spreading environment.[43] Some diseases require intermediary organisms or hosts for the completion of their lifecycles or get transmitted by vectors. To survive, procreation, dispersion, and spreading of disease-causing agents, vectors, and hosts depend on favorable meteorological and atmospheric conditions. As a result, changes in meteorological factors may impact airborne diseases by influencing their disease-causing agents.[43,44] Furthermore, the patterns of meteorological factors can significantly affect how particulate matter disperses and accumulates in the atmosphere, subsequently impacting the spread of airborne infections.[18–20] A thorough understanding of these nuanced relationships between climatic conditions and the incidence of airborne illnesses is essential for developing more effective preventative and control tactics.

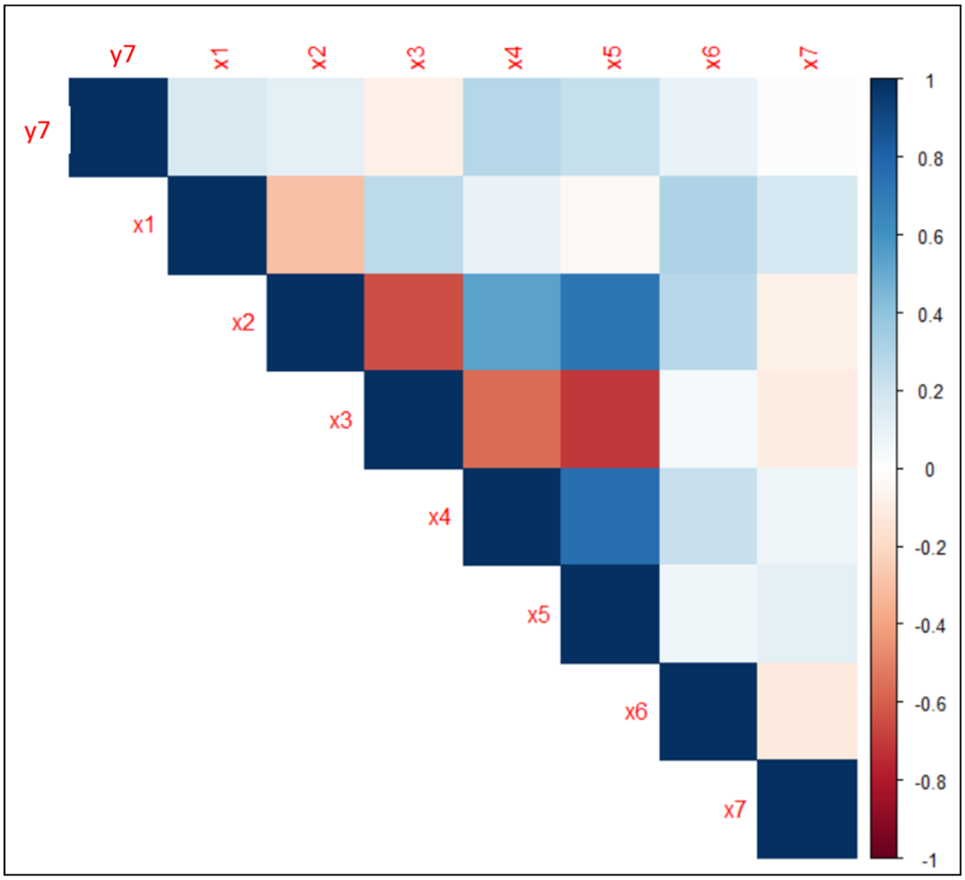

FIGURE 5 Pearson product–moment correlation between airborne disease total and climate variables.

TABLE 4 Estimated parameters of significant climate factors of spatial error model for different airborne diseases.

	Meningococcal Model 1		Measles Model 2		Mumps Model 3		Overall Model 4	
Factors	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Maximum temperature	−1.57*	0.68	2.74*	1.39	–	–	1.19*	0.40
Minimum temperature	–	–	2.86*	0.48	–	–	–	–
Mean temperature	5.57*	2.50	–	–	11.99*	3.13	9.56*	3.48
Relative humidity		–	3.54*	1.78	–	–	–	–
Spatial error parameter (λ)	0.31*	0.06	−3.85*	0.37	0.22*	0.06	0.44*	0.08

Abbreviations: Coef., coefficient; SE, standard error.

*Significance at 5% level.

The spatio-temporal pattern of airborne infections and their relationship to climatic factors provide important insights into disease dynamics. The observed heterogeneity in the effect of climatic conditions on various diseases highlights the intricacy of these interactions, implying a region-specific effect likely linked to local climate subtleties. This emphasizes the need to explain meteorological factor-related relationships within the context of each research area's unique climatic circumstances. We believe that the findings of our study have significant implications for public health in Bangladesh. It emphasizes the need for a targeted and district-level disease mitigation and control strategy. Additionally, our findings will provide insights for planning early warning, prevention, and control strategies to combat airborne diseases and infections in Bangladesh.

5 | LIMITATION

The study's results indicate that specific climatic parameters are associated with the spread of airborne illnesses; however, not all of these factors were determined to be statistically significant. This limitation arises from a lack of disease data, as only 4 years of yearly data were included in the study. In addition, the absence of variables such as air pressure, air quality, population density, human mobility, and sex ratio—known to influence airborne diseases—represents another limitation. Another drawback of our study is the lack of precise socioeconomic data, which might provide significant insights into the intricate interplay between socioeconomic variables and the frequency of airborne illnesses. This gap highlights the need to include socioeconomic factors in future studies to improve understanding of these complex linkages.

6 | RECOMMENDATION

The results of this study contribute to the expanding body of knowledge on the complex relationships between climatic conditions and airborne illnesses. However, future studies should adopt a comprehensive and multidimensional strategy with sufficient data, integrating multiple scientific disciplines to untangle the intricacies of climate-disease linkages. This approach aims to improve public health initiatives and enhance our understanding.

7 | CONCLUSION

This study investigated measles, the most common illness in Bangladesh, and discovered a high prevalence rate in coastal districts. Among climatic variables, mean and maximum temperatures appeared as significant risk factors for airborne diseases in Bangladesh. While these findings are consistent with previous research, they differ from others, emphasizing the complex relationship between climatic conditions and disease transmission. This underscores the need for more study and discussion, supported by proper data, to investigate how climatic elements reflect a specific geographical range when addressing district airborne illnesses. The findings of this study have the potential to spark integrated local development and district administration activities in Bangladesh to battle airborne infections successfully.

AUTHOR CONTRIBUTIONS

Arman Hossain Chowdhury: Conceptualization; investigation; writing—original draft; methodology; visualization; writing—review and editing; software; formal analysis; data curation; supervision; resources. **Md. Siddikur Rahman**: Conceptualization; investigation; funding acquisition; writing—original draft; writing—review and editing; visualization; validation; methodology; software; formal analysis; project administration; resources; supervision; data curation.

ACKNOWLEDGMENTS

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

All necessary data and source codes are available at https://github.com/siddikur2022/airborne-disease-study-in-Bangladesh.

TRANSPARENCY STATEMENT

The lead author Md. Siddikur Rahman affirms that this manuscript is an honest, accurate, and transparent account of the study being reported; that no important aspects of the study have been omitted; and that any discrepancies from the study as planned (and, if relevant, registered) have been explained.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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