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Research article

Association of climate factors with dengue incidence in Bangladesh, Dhaka City: A count regression approach

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ABSTRACT

Background: In Bangladesh, particularly in Dhaka city, dengue fever is a major factor in serious sickness and hospitalization. The weather influences the temporal and geographical spread of the vector-borne disease dengue in Dhaka. As a result, rainfall and ambient temperature are considered macro factors influencing dengue since they have a direct impact on Aedes aegypti population density, which changes seasonally dependent on these critical variables. This study aimed to clarify the relationship between climatic variables and the incidence of dengue disease.
Methods: A total of 2253 dengue and climate data were used for this study. Maximum and minimum temperature (°C), humidity (grams of water vapor per kilogram of air g.kg^{-1}), rainfall (mm), sunshine hour (in (average) hours per day), and wind speed (knots (kt)) in Dhaka were considered as the independent variables for this study which trigger the dengue incidence in Dhaka city, Bangladesh. Missing values were imputed using multiple imputation techniques. Descriptive and correlation analyses were performed for each variable and stationary tests were observed using Dicky Fuller test. However, initially, the Poisson model, zero-inflated regression model, and negative binomial model were fitted for this problem. Finally, the negative binomial model is considered the final model for this study based on minimum AIC values.
Results: The mean of maximum and minimum temperature, wind speed, sunshine hour, and rainfall showed some fluctuations over the years. However, a mean number of dengue cases reported a higher incidence in recent years. Maximum and minimum temperature, humidity, and wind speed were positively correlated with dengue cases. However, rainfall and sunshine hours were negatively associated with dengue cases. The findings showed that factors such as maximum temperature, minimum temperature, humidity, and windspeed are crucial in the transmission cycles of dengue disease. On the other hand, dengue cases decreased with higher levels of rainfall.

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Conclusion: The findings of this study will be helpful for policymakers to develop a climate-based warning system in Bangladesh.

1. Introduction

Aedes aegypti mosquitoes, which carry the Zika Chikungunya virus, are also responsible for the transmission of Dengue, a mosquito-borne viral disease. The Flaviviridae family is thought to be the origin of the dengue virus [1,2]. DENV-1, DENV-2, DENV-3, and DENV-4 are four different strains of the virus that cause dengue fever [3]. The risk of contracting more severe illnesses including Dengue Hemorrhagic Fever (DHF) and Dengue Shock Syndrome (DSS) is significant among individuals who have been re-infected with another serotype [4]. Three-quarters of dengue cases worldwide are found in Southeast Asian and Western Pacific nations because of the favorable weather conditions for mosquito population expansion in those regions [5]. Dengue fever can seriously decrease life expectancy because of the likelihood of producing severe symptoms after secondary exposure to various dengue serotypes [6]. Consequently, it is crucial to comprehend the effects of climate on the spread of dengue in these areas, since this can function as an early warning system and permit the implementation of prevention strategies before outbreaks evolve [7].

However, the first known dengue fever pandemic in Bangladesh occurred during the 2000 monsoon, where it resulted in 5521 officially recorded cases and 93 fatalities [8]. In Dhaka, DENV-1 and DENV-2 have been increasingly prevalent this decade [9]. Dhaka was the most endemic metropolitan location in the country from 2000 to 2009, accounting for 91% of all recorded dengue cases [10]. Dengue is spreading to further metropolitan cities in Bangladesh. Numerous studies have been undertaken to determine the climatic variation and distribution of dengue cases in the city of Dhaka [11]. In 2019, a study found that Serotype DENV-3 is correlated with a high frequency of acute dengue cases [12]. Between 2000 and 2010, the estimated yearly frequency of dengue incidence dropped. However, since that period, Bangladesh has seen a sharp spike in the occurrence of annual dengue cases [7]. The largest outbreak the nation has ever seen occurred recently in 2019, while the second-largest incidence occurred just a year earlier in 2018 [7]. It is still entirely uncertain whether or how climate variability may have caused this unprecedented increase in outbreaks in 2018 and 2019 [13].

Multiple studies have demonstrated a substantial and continuous correlation between the climate of an area and the frequency of dengue incidence [14]. Some believed the climate would likely have a minor but substantial effect, while others dismissed any meaningful role [15]. Various models have been created to anticipate a potential dengue outbreak by correlating cases of dengue with climate data [1,16]. Lai [17] concluded that the threat of dengue infection is positively correlated with high temperatures. Rainfall, as well as sunshine, were also discovered to be negatively linked with the transmission of dengue disease in this study. Rainfall, temperature, humidity, and wind speed, according to Sulekan [2], are climate variables that have a substantial impact on dengue occurrence. The study also concluded that low humidity, low rainfall, and low wind speed promote Aedes survivability, adding to dengue transmission.

Dengue, then called "Dacca fever," was first reported in the 1960s in Bangladesh. Dengue has become endemic in Bangladesh due to the spread of the Aedes aegypti mosquitoes and urbanization. Since 2010, there has been an increase in dengue cases that has been correlated with regional precipitation patterns (May to September) and higher ambient temperatures. Because of superfluous rainfall, waterlogging, flooding, increase in temperature, and unexpected alterations in the country's conventional seasons, Bangladesh's climate patterns are growing more suitable for the propagation of dengue as well as other vector-borne illnesses, including malaria and chikungunya [18].

Numerous studies were conducted to assess the prevalence of dengue in Bangladesh utilizing previous climatic data; however, the underlying causes of the disease's rising burden after 2010 are still unknown [19]. Temperature and precipitation are identified as significant contributors to dengue incidence [11]. Previous research similarly presumed that the impacts of climate factors are independent of the time of the year. However, climate variables can also have time-dependent consequences as numerous studies have shown that the impact of precipitation on dengue occurrence can fluctuate year-round [20]. Using data from or near subtropical regions, the most recent research has shown that the prevalence of dengue, as well as the abundance of mosquitoes, can be altered by meteorological conditions up to five months before the beginning of the season [21,22]. During the rainy season, Nazmul observed a rise in dengue infections beginning in June, reaching its apex in August, and then decreasing to near zero during the post-monsoon period [23]. On the other hand, the pre-seasonal climate for an early warning system of dengue incidence is determined in the literature [7]. The study found that minimum temperatures showed a strong correlation with dengue incidence from January to March, but closer to the beginning of the dengue season, from April to June, there was a negative correlation. Ekasari, in their study between 2011 and 2015, found the highest number of dengue incidences in April 2014 and the lowest in October 2012, which associates with the wet and dry seasons of the country [24]. Finally, the surge in the Aedes population is connected with an increase in temperature, relative humidity, and precipitation during the monsoon season, which is followed by an increase in the prevalence of dengue [25].

Several Bangladeshi urban centers are experiencing a dengue outbreak. Numerous research has been done to look at the climatic variability and distribution of dengue incidence in Dhaka, while other cities in Bangladesh received less attention [19,26]. Although several researchers have aimed to determine dengue prevalence in Bangladesh utilizing meteorological data, the majority of this research focused on data gathered before 2010, and some only tried to evaluate the seasonal data [11,27]. Also, most of the studies tried to portray the association of temperature, humidity, rainfall, and wind speed but not the sunshine hour. For this study, we considered all five factors – temperature, humidity, rainfall, sunshine hour, and wind speed and tried to understand how these affect the incidence of dengue transmission in Dhaka, Bangladesh.

Because the association between the vectors and the climate is as significant as the relationship between the vector and humans, climate variability studies can help us understand and forecast the periodicity of epidemics. Epidemiological studies have increasingly pursued climate-based statistical and mathematical systems that might elucidate the cycles of dengue occurrence [28]. It is primarily used to assist public health administrators in identifying dengue incidence prediction models with a high degree of accuracy [29]. We collected the dengue data from the Directorate General of Health Services (DGHS) and the temperature, humidity, rainfall, sunshine hour, and wind speed data (2013–2020) from the Bangladesh Meteorological Department (BMD. The reliability of our data sources and the effectiveness of our statistical methods strengthens the objectives of this study.

2. Methods

2.1. Data

All data on Dengue (2013–2020) in Dhaka city was gathered from the Directorate General of Health Services (DGHS) in Bangladesh [30]. Maximum and minimum temperature, humidity, rainfall, sunshine hour, and wind speed data (2013–2020) in Dhaka city were collected from Bangladesh Meteorological Department (BMD) [31]. Daily basis data were collected for each year and month (January to December).

2.2. Outcome variable

Daily basis dengue data (total dengue cases that occurred in a day) in Dhaka was considered as an outcome variable for this analysis.

2.3. Independent variable

Maximum and minimum temperature (°C), humidity (grams of water vapor per kilogram of air $g.kg^{-1}$), rainfall (mm), sunshine hour (in (average) hours per day), and wind speed (knots (kt)) in Dhaka were considered as the independent variables for this study.

2.4. Multiple imputation procedure

A total of 2253 dengue and climate data were used for this study. We found around 22% missing values in our data sets and we used multiple imputation techniques using the classification and regression trees method to impute the missing values [32]. The multiple imputation method imputes the missing values multiple times by using an appropriate model [33]. The aim of multiple imputation is to consider the uncertainty that the imputed values are the sample draws for the missing values instead of the actual values. A number of m copies of the data set are found by substituting each missing values by a set of $m > 2$ imputed values that are simulated from an apropos imputation model. Each imputed data set is then considered as a complete data set and analyzed using the standard method. The results from the m imputed data sets are then combined using Rubin's formula [34]. In our study, we used R packages **mice** with 5 number of multiple imputations ($m = 5$), 50 number of iterations ($maxit = 50$), and also used set. seed = 500 for getting the fixed finalized data sets [35].

2.5. Classification and regression trees

CART, unlike logistic and linear regression, does not create a prediction equation. Instead, data is partitioned along the predictor axes into subsets with homogenous dependent variable values—a process represented by a decision tree that may be used to create predictions based on new observations [36].

2.6. Statistical analysis

Firstly, descriptive statistics were performed to see the basic characteristics of each variable (mean, sd, min, max) for each year. Secondly, Pearson correlation analysis was performed among outcomes and all predictor variables to see whether there is any correlation between them. Since our main goal is to test whether there is an association between climate factors and dengue cases regardless of time frame, we used a stationary test using R packages **tseries** for Augmented Dickey-Fuller Test. We found the time series process is stationary and considered this problem as a cross-sectional instead of a time series analysis.

Since our outcome is count data, we used the Poisson regression model at first. After that, we checked for zero inflation and overdispersion using the R function check_zeroinflation (supplementary material CLimateDengue.R code file) and R packages AER, respectively. We fitted the Poisson regression model (Model-1), the Negative binomial regression model in case of overdispersion (Model 2), and the zero-inflated Poisson regression model in case of zero inflation (Model-3) using R packages MASS and pscl. Moreover, the goodness of fit of these models was checked using Akaike information criterion (AIC) values. Finally, a final model was selected based on the minimum AIC values, and the multicollinearity of this model also was investigated using R car packages and the vif function.

3. Results

3.1. Descriptive statistics

A total of 2253 dengue and climate data was used for this study from 2013 to 2020. We observed around 600 missing values and imputed them by using multiple imputation techniques. After imputation, the total number of observations is 2853. The descriptive statistics such as the total number of observations, mean, standard deviation, and minimum and maximum of both dengue cases and climate factors showed in supplementary materials for each year separately in descriptive.smcl file. The mean maximum temperature was highest in 2016 and it shows ups and down trends over the periods. The minimum temperature means was decreasing after 2015 and it also showed an increasing trend after 2019. The mean of rainfall reported ups and down patterns over the periods. The maximum mean of humidity was observed in 2019 and this showed some fluctuations over the time interval. The mean of the sunshine hour showed the reverse of humidity, and it showed the highest point in 2016. Wind speed also reported some fluctuations with the maximum point in 2018. The mean number of dengue cases showed slightly increasing trends from 2013 to 2018, after that, it reported a rapid increase trend in 2019 (Fig. 1).

3.2. Correlation analysis

Maximum and minimum temperature, humidity, and wind speed were positively correlated with dengue cases. However, rainfall

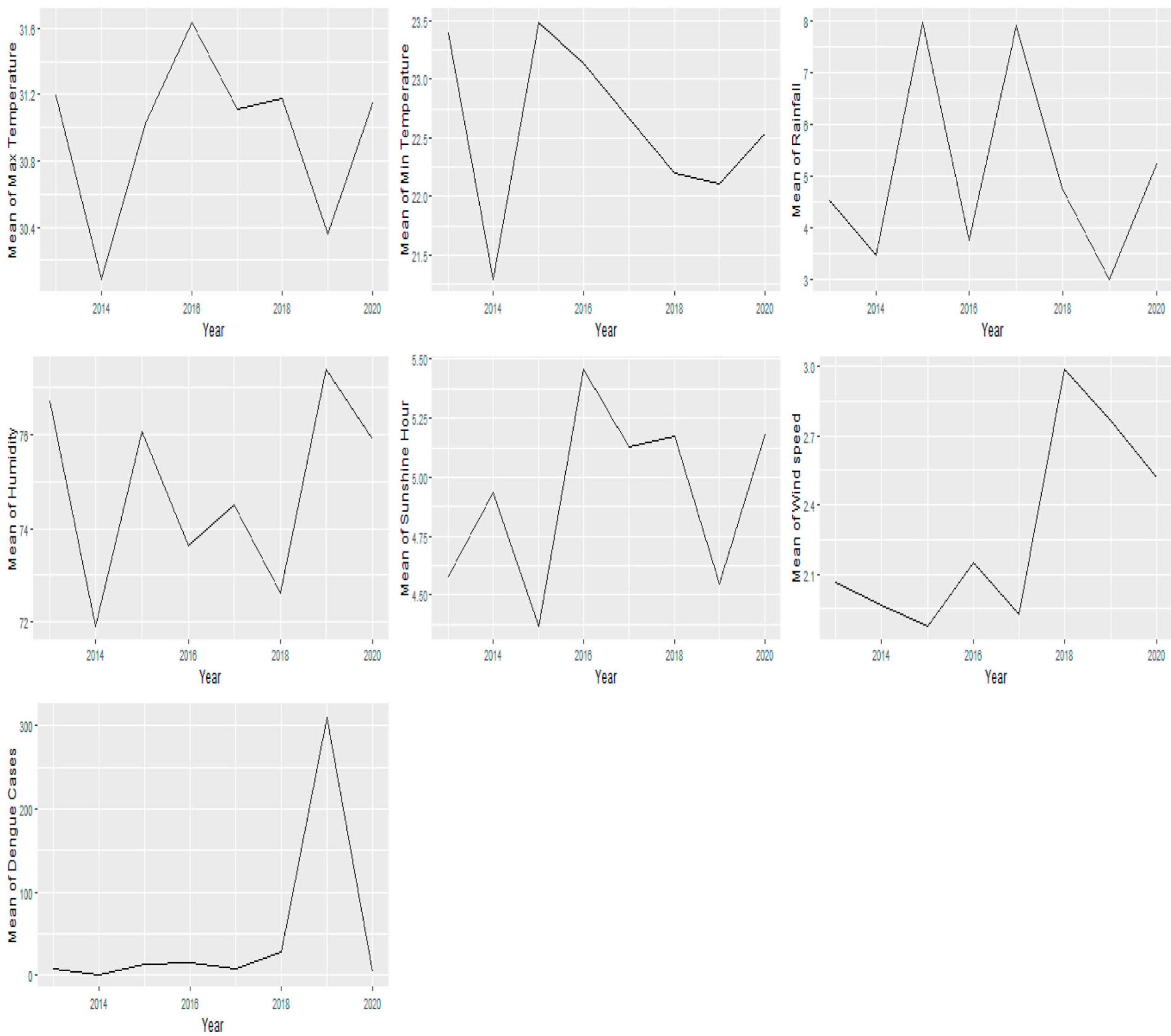

Fig. 1. Mean of dengue cases and climate factors from 2013 to 2020.

and sunshine hours were negatively associated with dengue cases (Table 1). Since all climate factors showed a correlation with dengue cases, we considered all climate variables as predictor variables for the outcome of dengue cases.

3.3. Time series stationary test

We have conducted a stationary test and found the time series process is stationary with Dickey-Fuller = −5.7446, Lag order = 14 and p-value = 0.01. That is why we decided to conduct data analysis by ignoring the time point and considering it as cross-sectional data.

3.4. Fitting count data model (Poisson model)

Since our outcome was count data, we fitted the Poisson model. The results of the Poisson regression model were given below:

Table 2 presents the coefficient estimate, exponential form of estimate as Exp (estimate), 95% confidence interval, test statistics (z-value), and p-value for different climatic predictor variables. From the p-value, we can interpret that, maximum and minimum temperature, rainfall, humidity, sunshine hour, and wind speed were significantly associated with dengue cases. On one hand, the mean number of dengue cases increased with a higher level of maximum temperature (1.13), humidity (1.03), wind speed (1.25), and minimum temperature (1.07). On the other hand, the mean number of dengue cases decreased with a higher level of sunshine hours (0.97) and rainfall (0.98) (Table 2).

In our outcome variable (total number of dengue cases daily), many zero values exist. So, we expect to get zero inflation and overdispersion problems in our data and we test further whether the model was zero-inflated or overdispersion.

3.5. Zero inflation and overdispersion test

We used the checkzero_inflation function in R to test whether the data is zero-inflated or not. However, we found observed zeroes = 472, predicted zeroes = 6, ratio = 0.01, and the Model is underfitting zeros (probable zero-inflation). Furthermore, we also test overdispersion and found z-value = 6.1461, p-value < 0.001, and alpha = 212.7411 which indicates overdispersion in the data sets.

Since we observed both zero inflation and overdispersion in the data sets, we decided to fit the zero-inflated Poisson regression model and the negative binomial regression model.

3.6. Compare three models using AIC values

We run the three models including model-1 (Poisson regression model), model-2 (zero-inflated model), and model-3 (negative binomial regression model). After that, we calculated the AIC values for these three models and found minimum AIC values for model-3, and considered this model as a final regression model for this study (Table 3).

Although our final model was a negative binomial regression model, we explained the results of Model-2 (zero-inflated Poisson regression model) for comparison with other regression model results.

Table 4 shows the output of the zero-inflated Poisson regression model. This table showed the exp (estimate), standard error (SE), Z value, and P value, respectively. The probability of dengue cases occurring in Dhaka was 0.526 when there was the maximum temperature (significant) increased. Moreover, the chances of dengue cases occurring in Dhaka were 49.2%, 48.5%, 52.2%, and 46.2% with Humidity, sunshine hour, wind speed, and minimum temperature, respectively (Table 4(b)).

The mean number of dengue cases will increase 1.13 times if the maximum temperature increases by 1 °C (C). Similarly, the average dengue cases will increase 1.03, 1.25, and 1.07 times if the humidity, wind speed, and minimum temperature increase by 1 unit. Contrasting to this manner, the dengue incidence will decrease with the increasing rate of rainfall and sunshine hours, which decreased by 2% and 3% with per unit increases (Table 4(a)).

3.7. Final model results and interpretation

After the final screening, we selected the negative binomial regression model as a final model and run this model. We also checked multicollinearity and didn't find any collinearity problem in our model (see VIF tables in supplementary files). Table 5 presents the negative binomial regression model results. The mean number of dengue cases increases with a higher level of maximum temperature,

Table 1
Correlation analysis with dengue cases and climate factors.

	Maximum temperature	Minimum temperature	Rainfall	Humidity	Sunshine hour	Wind Speed	Dengue Cases
Maximum temperature	1.000	0.807	0.110	−0.053	0.376	0.162	0.121
Minimum temperature	0.807	1.000	0.254	0.390	−0.080	0.174	0.163
Rainfall	0.110	0.254	1.000	0.273	−0.217	0.069	−0.014
Humidity	−0.053	0.390	0.273	1.000	−0.701	0.025	0.103
Sunshine hour	0.376	−0.080	−0.217	−0.701	1.000	0.067	−0.038
Wind Speed	0.162	0.174	0.069	0.025	0.067	1.000	0.123
Dengue Cases	0.121	0.163	−0.014	0.103	−0.038	0.123	1.000

Table 2
Poisson regression model results of the association between dengue cases and climate variables.

Coefficient	Estimate	Exp (Estimate)	95% CI	Z value	P value
(Intercept)	−4.60	0.01	(0.01, 0.01)	−51.89	0.00
Maximum Temperature	0.12	1.13	(1.12, 1.14)	37.02	0.00
Rainfall	−0.02	0.98	(0.98, 0.98)	−51.81	0.00
Humidity	0.03	1.03	(1.03, 1.03)	36.00	0.00
Sunshine hour	−0.03	0.97	(0.97, 0.98)	−12.25	0.00
Wind Speed	0.23	1.25	(1.25, 1.26)	88.34	0.00
Minimum Temperature	0.07	1.07	(1.07, 1.08)	29.37	0.00

Table 3
Three model comparisons by AIC values.

Model	AIC
Poisson regression model (Model-1)	198939.1
Zero-inflated Poisson regression model (Model-2)	229165.3
Negative binomial regression model (Model-3)	16353.62

Table 4
Zero-inflated regression model results (a) Poisson with logit link (b) binomial with a logit link.

(a)

	Estimate	Exp (Estimate)	SE	Z value	P value
(Intercept)	−3.42	0.01	0.0766	−44.57	<0.001
Maximum Temperature	0.10	1.13	0.002	35.93	<0.001
Rainfall	−0.02	0.98	0.0003	−62.55	<0.001
Humidity	0.02	1.03	0.0006	36.53	<0.001
Sunshine hour	−0.04	0.97	0.001	−19.11	<0.001
Wind Speed	0.23	1.25	0.002	106.35	<0.001
Minimum Temperature	0.07	1.07	0.002	33.38	<0.001

(b)

Coefficient	Estimate	Exp (Estimate)	SE	Z value	P value	Probability of dengue cases occurred ($e^x/(1+ e^x)$)
(Intercept)	0.28	1.33	0.75	0.381	0.70	
Maximum Temperature	0.11	1.11	0.032	3.460	0.00054	0.526
Rainfall	−0.01	0.99	0.004	−1.393	0.16351	0.497
Humidity	−0.03	0.97	0.006	−4.012	<0.001	0.492
Sunshine hour	−0.06	0.94	0.027	−2.102	0.03558	0.485
Wind Speed	0.09	1.09	0.039	2.322	0.02024	0.522
Minimum Temperature	−0.14	0.86	0.025	−5.667	<0.001	0.462

SE = standard error.

humidity, wind speed, and minimum temperature. On the contrary, average dengue cases decreased with a higher level of rainfall. However, we didn't find any association between dengue cases and sunshine hour. Average dengue cases will increase by 1.097 and 1.089 times if the maximum temperature and minimum temperature increase by 1 °C, respectively. Moreover, dengue incidence will increase on average by 1.257 and 1.050 times if wind speed and humidity are expanded by 1 unit. However, dengue incidence decreased by 2% with the high level of rainfall.

Table 5
Negative binomial regression model results of the association between dengue and climate factors.

Coefficient	Estimate	Exp (Estimate)	95% CI	Z value	P value
(Intercept)	−5.86	0.003	(0.001, 0.010)	−8.919	0.000
Maximum Temperature	0.09	1.097	(1.040, 1.157)	3.431	0.001
Rainfall	−0.02	0.980	(0.975, 0.986)	−6.861	0.000
Humidity	0.05	1.050	(1.037, 1.062)	8.157	0.000
Sunshine hour	0.00	1.004	(0.962, 1.048)	0.188	0.851
Wind Speed	0.23	1.257	(1.183, 1.335)	7.434	0.000
Minimum Temperature	0.09	1.089	(1.046, 1.134)	4.127	0.000

CI = confidence interval.

4. Discussion

The development, transmission, and growth of dengue incidence are depended on climate. Dengue is a vector-borne disease, and its spread is greatly dependent on the density and availability of its vector. Many studies found that ecological and climate factors influence the seasonal incidence of the dengue virus [37,38]. In subtropical and tropical climate regions, climate change dramatically threatens global health due to the expansion of dengue fever. Since 2010, in Bangladesh, the total number of dengue cases has been increasing; in 2018, the number of confirmed dengue cases was more than 10,000 [30,39].

This study shows the climate sensitivity of dengue fever outbreaks in Bangladesh. It has been identified that dengue incidence is correlated with climate factors; however, the relationship between dengue fever and climatic patterns is not well understood [40]. It happens for the complexity of the life cycle of the vector and the host because the life cycle of the Aedes aegypti vector is climate sensitive.

As a part of tropical Asia, the climate of Bangladesh is mainly divided into two monsoons (wet and dry monsoons). This study developed a model to estimate the impact of various climate factors on dengue incidence, typically occurring during Bangladesh's monsoon season. Previous studies had been conducted in South and Southeast Asian countries to investigate the effects of climate change on dengue fever spreading [23,41–45] in which dengue fever has become a severe health burden. These studies found that temperature, rainfall, and humidity are the commonly used climate factors influencing dengue outbreaks. These studies also showed an overall effect of certain climate factors throughout the years. In this research, we find the impact of climate variables on dengue incidence. It would help reduce any impending severe incidence of dengue in Bangladesh, allowing sufficient time for preparedness.

This study suggests that some climate factors might affect the number of dengue cases. From this research, it was found that maximum and minimum temperatures are positively correlated with dengue cases. An increase in global temperature may increase the number of vector-borne disease cases [46]. Minimum temperatures from January to March were positively correlated with dengue cases; however, a negative correlation was seen from April to June, closer to the start of dengue season. It may happen due to a critical dependency between the dengue vector and climate change, such as the seasonal transformation from winter to summer with increasing temperatures [47]. A study argued that 21.3–34 °C temperature is optimal for expanding Aedes aegypti vectors [48]. Our study found a significant positive correlation between relative humidity and dengue cases. Dengue cases were reported more during monsoon months when relative humidity was higher because the higher humidity during the rainy season facilitates the growth and survival of infected mosquitoes for the successful propagation of the virus [49–51].

Wind speed was also positively correlated with dengue cases. A similar result was also found in a study [52]. Rainfall was found as negatively related to dengue cases. Several studies have also found a similar pattern of a negative association between rainfall and dengue cases [20–22]. Rainfall was found to have a negative relationship with dengue cases in winter, whereas a positive relationship was found in summers such as April and June. Rainfall is considered to have both beneficial and harmful impacts on mosquito growth. Rainfall can supply standing water for mosquito breeding, and imprudent rainfall can damage potential mosquitoes [53].

Additionally, the sunshine hour was significantly negatively correlated with dengue cases. A previous study also found a negative association between sunshine hour and dengue incidence [54]. A small duration of sunshine is preferable for dengue transmission because mosquitoes are more active in dark environments and increase the frequency of mosquito bites [54]. Another study in Bangladesh also found that climatic factors (monthly humidity, rainfall, and minimum and maximum temperature) significantly predict dengue incidence [23].

4.1. Limitation

Though this study has many implications, it has some limitations too. This study aims to find the impact of climate parameters on dengue incidences in Bangladesh. But there were many missing or incomplete data in the dataset, which indicates that the data is poor record-keeping and reporting system. It may happen because of a flawed monitoring system or a lack of awareness among the reporting authorities. This lack of data or the poor record system of population data is a crucial gap. The actual estimate might be affected by under or over-reporting bias because the dengue data includes confirmed and suspected cases.

5. Conclusion

This study aims to find the relationship between climate factors and dengue incidence in Dhaka, Bangladesh. Maximum temperature, minimum temperature, humidity, and wind speed positively impact dengue incidence, while rainfall and sunshine hours have a significantly negative effect. This research observed a potential alert system by modeling dengue outbreaks using climate variables, which is required to improve Bangladesh's public health and disease control systems. The findings of this study will be helpful for policymakers to develop a climate-based warning system in Bangladesh. Therefore, future attempts to build a model to predict the total number of dengue cases, including immunological, and entomological data, demographical factors, and climatic factors, and also for community-based observation to develop more practical dengue prevention strategy in Bangladesh at the time of dengue pandemic.

Ethical statement

The authors did not personally collect data for this study. Dengue and Meteorological data were extracted from the IEDCR (Institute of Epidemiology, Disease Control, and Research) and Bangladesh Meteorological Data (BMD). Concepts from participants and ethical clearances were handled by the IEDCR and BMD.

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Data availability

The authors did not personally collect data for this study. Dengue and Meteorological data were extracted from the IEDCR (Institute of Epidemiology, Disease Control, and Research) and Bangladesh Meteorological Data (BMD).

Code availability

Data and Code are available upon request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2023.e16053.

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