Waliullah et al. BMC Public Health (2025) 25:318
https://doi.org/10.1186/s12889-024-20920-z

BMC Public Health

RESEARCH

Open Access

Unveiling the future: Wavelet- ARIMAX analysis of climate and diarrhea dynamics in Bangladesh's Urban centers

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Abstract

Background Diarrheal infections continue to be a major public health concern in Bangladesh, especially in urban areas where population density and environmental variables increase dissemination risks. Identifying the intricate connections between weather variables and diarrhea epidemics is critical for developing effective public health remedies.

Methods We deploy the novel approach of Wavelet-Autoregressive Integrated Moving Average with Exogenous Variable (WARIMAX) and the traditional Autoregressive Integrated Moving Average with Exogenous Variable (ARIMAX) technique to forecast the incidence of diarrhea by analyzing the influence of climate factors.

Results Higher temperatures are associated with greater diarrheal occurrences, demonstrating the vulnerability of diarrheal epidemics to weather fluctuations. The Wavelet-ARIMAX method, which uses wavelet analysis within the ARIMAX structure, is better at forecasting performance and model fit than the standard ARIMAX model. Based on climatic variables, Wavelet-ARIMAX can accurately predict diarrheal occurrence, as indicated by the mean absolute error (MAE), root mean squared error (RMSE), and root mean squared logarithmic error (RMSLE). The outcomes highlight the necessity of employing advanced time-series modeling tools such as Wavelet-ARIMAX to better understand and anticipate climate-health interactions. Wavelet-ARIMAX uses wavelet analysis to identify time-varying patterns in climate-disease interactions, providing useful insights for public health initiatives.

Conclusions The results of this research have implications for climate-adaptive health planning, emphasizing the need for focused actions to reduce the impact of climate change on diarrheal illness burdens in towns and cities.

Keywords Diarrhea, Climate factors, ARIMAX model, Wavelet-ARIMAX model, Climate-health interactions

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Introduction

Diarrhea is a major cause of disease and death, especially in underdeveloped nations where it is the leading cause of child mortality. In 2015, diarrhea caused an estimated 688 million illnesses and 499,000 deaths in children under five years of age [1]. Diarrhea is generally a mild illness that can be easily controlled. While diarrhea normally disappears within a week, extended symptoms (over seven days) could signify a serious underlying condition. For persons with reduced immune systems, such as young children, elders, and those with weakened immunity, diarrhea can bring a greater risk. Furthermore, it can be caused by several factors, including bacterial infections such as E. coli or persistent problems such as lactose intolerance [2, 3]. In neonates and young children, recurrent diarrhea can be an indication of illnesses, such as HIV or cryptosporidiosis [4]. In cities such as Dhaka, Chattogram, Rajshahi, and Khulna in Bangladesh, diarrhea rates are greatly affected by climate change. Researchers have identified scientific evidence for the connection between climatic conditions and infectious diseases [5, 6]. Another study had demonstrated that climatic variables greatly affect seasonal diarrhea in susceptible groups, particularly in children under 5 years of age [7–9]. There are several reasons why it is vital to understand the association between climatic conditions and diarrhea. First, climatic conditions may alter the survival and transit of pathogenic microorganisms that might cause diarrhea. A greater understanding of the association between climate and diarrhea may enable us to forecast epidemics of this illness, which can help healthcare systems and physicians be better prepared. Second, climate is one of the primary variables for the availability of water, and changes in the environment can lead to contamination of water sources. A greater understanding of how climate change may affect diarrhea may help to limit the dissemination of waterborne infections. Finally, the occurrence of diarrhea is a crucial indicator of the safety of drinking water and water used in food production. Epidemiological studies exploring the climate and diarrhea should increase our understanding of the relevance of water contaminated with infectious organisms in the transmission of this disease [10]. Research has demonstrated a strong correlation between weather patterns and epidemics. Factors include strong rains, humidity, floods, ocean temperatures, and El Niño-Southern Oscillation (ENSO), all of which influence disease spread [11]. For instance, climate change is closely associated with cholera outbreaks, and the relationship between ENSO and cholera in Dhaka has changed over time [12]. However, the actual impact of climate change on cholera in big cities, such as Dhaka, varies, and the specific ways in which they spread inside these cities are still being studied [13]. Climate change does not affect only cholera. Researchers have explored its impact on various health conditions. For example, a study in Bangladesh related climatic conditions to the spread of COVID-19 [14]. Another study revealed a correlation between variations in the Indian Ocean Dipole and cholera outbreaks in Bangladesh, indicating how climate and disease are tightly related [15]. In Bangladesh, concerns about the health repercussions of climate change have led to a focus on finding methods to prevent these effects [16] [17]. suggested that the health challenges experienced by climate-displaced persons living in urban slums indicate disparities in vulnerability to health issues between migrants and non-migrants in regions such as Khulna and Bangladesh. Understanding the association between climate and diarrhea in urban Bangladesh is vital for its prevention and treatment. In Bangladesh, unusual weather and topography make it simple for diseases such as rotavirus, Shigella, cholera, and E. coli to spread [18]. Research suggests that climate is a key factor in the spread of cholera in large cities, such as Dhaka and Bangladesh [19]. Therefore, it is crucial to use chance-based models to predict cholera outbreaks. In addition, climate change has a negative impact on impoverished people in Bangladesh's cities, making them more likely to suffer from its effects [20]. The autoregressive integrated moving average (ARIMA) model is frequently used as a classic method for diarrhea incidence prediction. However, it has several downsides at the same time [21, 22]. In particular, some researchers applied the ARIMA model in the early warning systems of diarrhea and achieved a poor fit [21]. Several studies have demonstrated that climatic parameters are connected with diarrhea and can be used to forecast its incidence [8, 23] [24]. created a multivariable ARIMA (ARIMAX) model considering temperature and rainfall and only achieved high short-term forecast accuracy. This may be because the ARIMAX models assume linear relationships between the independent and dependent variables. However, meteorological parameters have been demonstrated to be nonlinearly linked to the pandemic of infectious diarrhea [23, 25].

It is crucial to answer the following question: what is the relationship between climate and the number of diarrhea cases in Bangladesh? Meanwhile, a critical analysis of the data required for forecast models and significant public health initiatives is required to reduce the negative effects of climate change on human health. Unlike previous studies that only utilized VAR, ARIMA, ARMA, ARIMAX, and linear regression, they did not use this new approach such WARIMAX, in Bangladesh and other nations. Previous models performed well but sometimes they not forecast the actual fluctuations accurately. WARIMAX has added dimensions because it can incorporate information from the time and frequency domains, which ordinary ARIMAX models cannot.

This two-pronged strategy increases the model's performance in finding difficult multiple climatic and illness patterns, resulting in higher forecasting capabilities and comprehension that would have been overlooked by the simplistic approach. Therefore, we attempted to identify the primary climate variables linked to disease outbreaks and to assess the forecast efficacy of the WARIMAX model in accurately analyzing disease trends related to these climatic extremes. In this study, we used a wavelet decomposition approach to capture nonstationary time-series data. Subsequently, we implemented the unique WARIMAX model, which significantly improved the performance and accurately forecasted the future, outperforming the previous traditional models. Furthermore, this study will improve the understanding of urban health climate influences and encourage sound public health policies while establishing an innovative perspective on the methodology in the field of epidemiology, thus boosting the prognostic model through Wavelet-ARIMAX for climatic diarrhea dynamics. Climate change has varying implications for health depending on the population.

Literature review

Dhaka-based research has examined the relationship between hospital visits for diarrhea other than cholera and climate variability. The findings indicate that there is a positive relationship between high and low rainfall levels, elevated ambient temperatures, and escalation in episodes of diarrhea. Individuals with a lower quality of education and unclean toilet usage exhibited more severe diarrhea [26]. Climate change has been recognized as a substantial determinant of human health through multiple avenues, one of which is the limited availability of potable water. Climate change is widely recognized to have significant effects on freshwater supplies in southwestern Bangladesh, resulting in many health concerns, including diarrhea, dysentery, and skin ailments [27]. This research highlights the importance of health adaptation techniques and the adoption of locally accessible adaptive practices to address the impacts of climate change on water shortages and public health [27]. The occurrence of 'climate refugees' individuals who have been displaced as a result of climate change has been a subject of research in Dhaka, Bangladesh. Climate refugees exhibit a greater prevalence of diarrhea and asthma than individuals who are not refugees affected by climate change, resulting in a notable increase in the number of disability-adjusted life years (DALYs). Research indicates that the health of children who are climate refugees is negatively affected by their exposure to household environmental factors, specifically water and indoor air quality [28].

An initial cross-sectional survey conducted in Bangladesh indicated that climate change has the potential to affect health, particularly in vulnerable populations where climate-sensitive diseases, such as malaria, dengue, infantile diarrhea, and pneumonia, are prevalent. The findings of this study indicate that the implementation of community-based adaptation methods for health may have positive effects in mitigating the health impacts associated with climate change [29].

Comparative studies conducted in Gambia and Bangladesh have emphasized the effects of climatic conditions on the prevalence of diarrheal sickness. The occurrence of diarrhea in both countries is associated with seasonal fluctuations, reaching its highest point during the rainy season. Additionally, research highlights the significance of personal cleanliness, breastfeeding, and weaning behaviors as non-seasonal variables that impact the occurrence of diarrheal illnesses [30].

An investigation using multi-site time regression was conducted to determine the immediate impact of climate variability on hospitalizations related to childhood diarrhea in six administrative divisions of Bangladesh. The research revealed that a 1 °C increase in the maximum temperature resulted in a 4.6% increase in hospitalizations for diarrhea. However, it is essential to note that the association between temperature and diarrhea hospitalizations differed between the different divisions [31]. The occurrence of significant floods in Bangladesh in 2007 resulted in a notable change in the prevalence of prominent diarrheal infections. Among hospitalized patients, Vibrio cholerae O1 (33%), rotavirus (12%), and enterotoxigenic Escherichia coli (12%) are the most prevalent [32]. A separate investigation concentrated on the rural region of Matlab, Bangladesh, between 2000 and 2006. The study revealed a substantial correlation between extreme weather occurrences (such as the frequency of hot days and days with intense rainfall) and an increase in pediatric diarrheal disease. The research emphasized that the prevalence of diarrhea was significantly influenced by both the intensity and frequency of these harsh weather events [33]. A study conducted in Dhaka, Bangladesh, examined the transmission of the dengue virus, incorporating both mean temperature and daily temperature changes. The study revealed that a high average temperature with minimal variation led to an increase in the incidence of dengue one month later. This suggests that the intricate connections between climate and disease incidence may also apply to diarrheal disorders [34]. Multiple studies have confirmed a direct relationship between the surrounding temperature and the occurrence of Escherichia coli, which causes diarrhea. One study found an 8% increase in the occurrence of this type of bacteria for every 1 °C increase in the average monthly temperature [35]. The observed link exhibits consistency across several climate zones in China, as evidenced by a positive correlation between temperature and all instances of infectious diarrhea [36]. In a study conducted in China, an M-shaped curve link between temperature and the incidence of category C notifiable infectious diarrhea was observed. The study also indicated that the relationship between temperature and diarrhea incidence was more potent at higher temperatures [37]. A study conducted in Taiwan found a strong correlation between maximum temperature and extreme rainfall days and diarrhea-associated morbidity, notably among children and older individuals [8].

The incidence of diarrhea among young children in rural Tamil Nadu, India, has been linked to high temperatures and heavy rainfall [38]. A time-series investigation conducted in Guangzhou, a city located in southern China, revealed a positive correlation between low mean temperature, relative humidity, and precipitation and an elevated susceptibility to infectious diarrhea [39]. A study conducted in Jiangsu Province, China, found a correlation between meteorological parameters, including mean temperature, relative humidity, temperature range, rainfall, and morbidity, in children aged 0–5 years. For individuals over 20 years of age, there is a U-shaped relationship between mean temperature, rainfall, and disease risk [40]. The literature supports the concentration-dilution hypothesis, which suggests that the occurrence of diarrhea can be increased by rainfall after dry periods owing to the flushing of pathogens into surface water. Conversely, rainfall after wet periods can dilute pathogen concentrations. The occurrence of diarrhea was higher when heavy rainfall occurred after the dry intervals. However, the opposite pattern was observed when heavy rainfall occurred after wet periods [41]. The occurrence of diarrhea was higher in the urban areas of Esmeraldas Province, Ecuador, when there were significant rainfall events followed by dry antecedent circumstances [42]. Furthermore, research conducted in Surabaya, Indonesia, revealed that extremely low and high temperatures, together with low relative humidity and high precipitation, were linked to heightened risks of diarrhea. The intensity of these relationships varies across different regions [43].

After an in-depth analysis of the previous research paper, we found that researchers carried out their study in Bangladesh; they did not conduct a study in a particular field such as epidemiology using WARIMAX. They also performed a time analysis using a linear regression model; however, they were not made any future forecast. Additionally, researchers conducted in other nations did not adopt the Wavelet-Arimax model and instead employed alternative methods for future forecasting, such as VAR, ARIMA, ARMA, ARIMAX, and linear regression. These models are applicable to stationary data sometimes they perform with non-stationary data, but it needs some transformation or differencing. Most cases, they are unable to forecast actual variations with non-stationary data. Also, the fact that earlier models did well, but they occasionally failed to precisely forecast the real fluctuations. For this reason, we use the Wavelet-Arimax approach to capture non-stationary data and accurately forecast the future, and we analyze four significant places: Dhaka, Khulna, Chattogram, and Rajshahi of Bangladesh. Bangladesh was our study location of choice because the country's health is precarious. To observe the effects of climatic variables on viral (diarrhea) diseases, this study could be expanded to other countries.

Method and materials

Study area

The study area focuses divisions in Bangladesh, namely Dhaka, Chattogram, Rajshahi and Khulna due to variation in climatic conditions, population density. Dhaka is the capital of Bangladesh. Another study location is Chattogram division. Chattogram is one of the largest cities in the country, and it is the Port City of Bangladesh, the next study locations are Khulna and Rajshahi, which are the second and 3rd largest among eight divisions in Bangladesh (see Fig. 1).

Data source

Our study collected data for different divisions for two types of data: meteorological and virological (diarrhea). From the Directorate of General Health in Bangladesh[1] (DGHs), we collected this diarrhea dataset. There are 704 daily entries for each division consists of daily recorded data of diarrheal cases, spanning January 31, 2022, through December 12, 2023. Due to limitations on the data availability we only have 704 entries. Data on temperatures (maximum and minimum), humidity, and rainfall between January 31, 2022 and December 12, 2023 are acquired from NASA's Power[2] and the Bangladesh Meteorological Department[3].

Data preprocessing

There were few missing values in diarrhea cases. We address these missing values via linear interpolation methods. Linear interpolation is a regularly used method in numerous domains for guessing values between two known data points. In the context of time series data, linear interpolation acts as a basic yet efficient technique for filling in missing values or providing a smoother representation of the data. In the domain of geo-statistics, linear interpolation has been compared with other approaches like quantile kriging, showing its role as a linear estimator for interpolating variables of interest to unknown locations [44].

[1] https://dghs.gov.bd/.

[2] https://power.larc.nasa.gov/data-access-viewer/.

[3] https://www.bmd.gov.bd/.

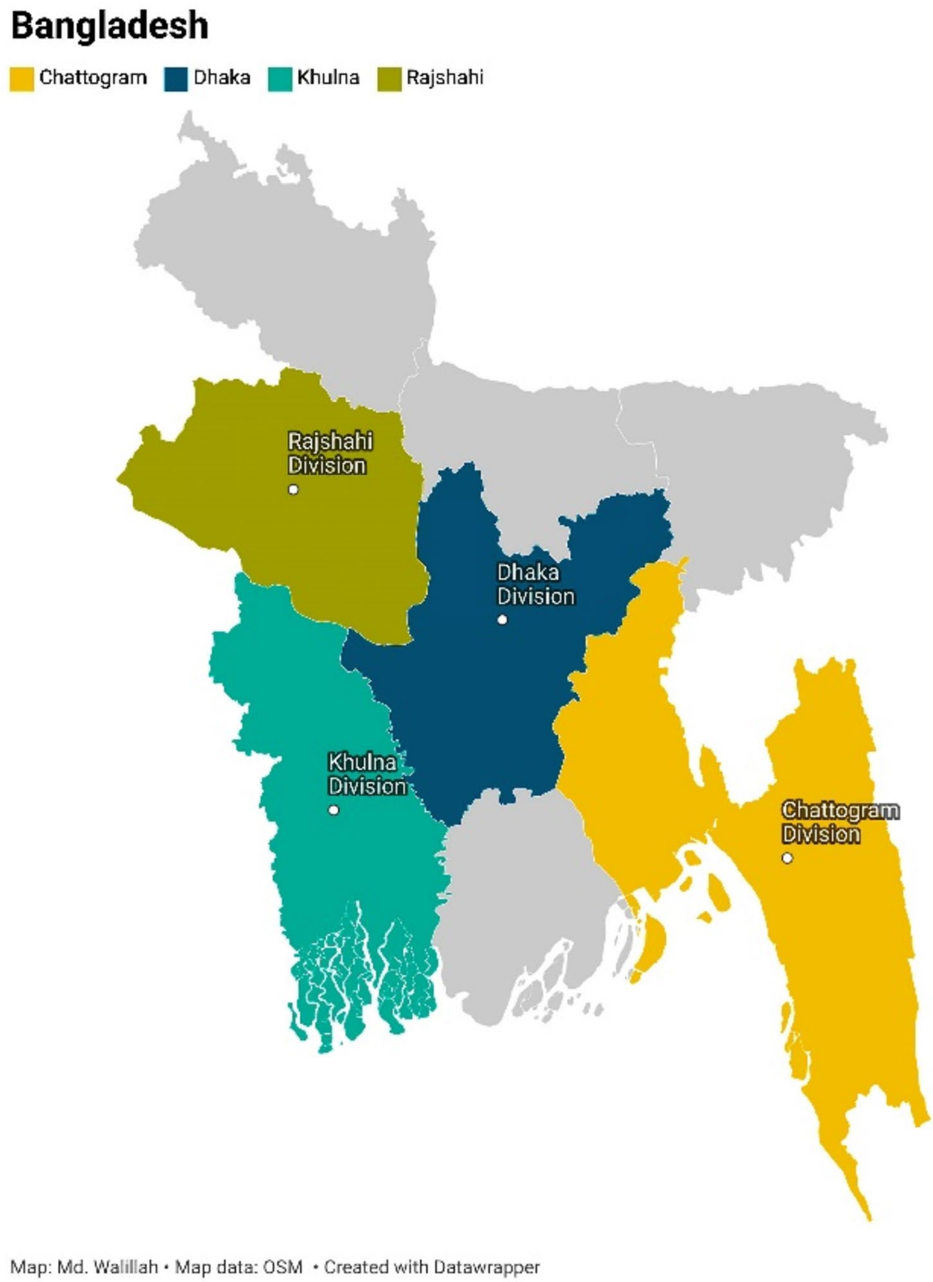

Fig. 1 Map of Bangladesh

The formula of Linear Interpolation is:

$$y = y_1 + \frac{(x - x_1)(y_2 - y_1)}{(x_2 - x_1)}$$

In this formula, we have the following terms: x_1 and y_1 are the first coordinates, x_2 and y_2 are the second coordinates, x is the place where we execute the interpolation, y is the interpolated value.

Stationarity test

Time series data frequently show seasonality; however, some may not. When dealing with non-stationary data, accurate forecasting becomes difficult and requires a check for stationarity. In this work, we employed the ADF test to evaluate the stationarity of a time series and establish the confidence level for further analysis and forecasting. The ADF test is referred to as a "unit root test," which is the right way for determining time series stationarity. Furthermore, in the context of the Augmented Dickey-Fuller (ADF) test, the null hypothesis (H_0) argues for the presence of a unit root in the time series, implying non-stationarity. The alternative hypothesis (H_1) claims that the time series is stationary.

Wavelet transformation

Wavelet transform is a mathematical tool that decomposes a signal into different frequency components, allowing for a multi-resolution study of the data. Wavelet has advantages in modeling seasonal and nonlinear climate variations, which are some of the deficiencies in traditional models, such as ARIMA and SARIMA. Incorporating wavelets into the model allows for the decomposition of climate data and representation of different frequency components, which enables the modeling of irregular climate changes such as fluctuations in monsoon seasons quite accurately. There are various types of wavelet functions are employed in wavelet transformations, such as the Haar wavelet, the Daubechies wavelet, coifflets, symlets, the biorthogonal wavelet, and the discrete Meyer wavelet [45]. In this study, we use Daubechies wavelet functions with level 4, due to the best compromise between localization and smoothness. These wavelets serve a significant role in the decomposition process, enabling the extraction of both short-term fluctuations and long-term trends in the data. Wavelet transforms have been intensively explored for their applications in several domains, including signal processing, picture compression, and feature extraction [46]. The numerous types of wavelets employed in wavelet transformations give versatility in analyzing and extracting information from signals, making the wavelet transform an important approach in current data analysis and processing. Wavelets effortlessly handle stationary or non-stationary time series data and deliver better outcomes for future forecasting. For this reason, we apply wavelet decomposition to extract the high- and low-frequency signals. There are two types of wavelet transformation, namely continuous wavelet transformation (CWT) and discrete wavelet transformation (DWT). Wavelets are defined by the wavelet function $\psi\ (t)$ (mother wavelet) and scaling function ϕ(t) (father wavelet) in the time domain. Wavelets are normalized, finite, short-duration, zero mean functions.

$$\int_{-\infty}^{\infty} \psi\ (t)\, dt = 0$$

The wavelet function, typically represented as $\psi\ (t)$, acts as the “Mother wavelet” from which “Child wavelets” are formed by dilation and translation operations. These Child wavelets are then used to evaluate the input signal and produce wavelet coefficients, which offer information about the signal’s frequency content at multiple scales and places. The wavelets created by scaling and translating the mother wavelet are known as “children” wavelets. They are indicated as $\psi\ _{k,s}\,(t)$, where k indicates the translation factor, and s represents the scaling factor. These parameters control how the Wavelet is positioned and scaled relative to the original (mother) wavelet.

Mathematically, given a mother wavelet $\psi\ (t)$, the offspring Wavelet is defined as $\psi\ _{k,s}\,(t)$.

$$\psi\ _{k,s}\,(t) = \frac{1}{\sqrt{|a|}}\psi\ \left(\frac{t-b}{a}\right) dt$$

Wavelet Transform W_f of a function $f\,(t)$ is computed by taking the inner product of $f\,(t)$ with the translated and dilated versions of the mother wavelet.

$$W_f(a,b) = \int_{-\infty}^{\infty} f\,(t)\,.\frac{1}{\sqrt{|a|}}\psi\ ^*\left(\frac{t-b}{a}\right) dt$$

This equation is known as the continuous wavelet transformation (CWT) general form. Where a is the scaling parameter, b is the shift or translation parameter, and $\psi\ ^*$ is the complex conjugate function.

ARIMAX model

The ARIMA model is a frequently-used technique in time series analysis and forecasting. ARIMA stands for Autoregressive Integrated Moving Average. It is a mathematical model that helps capture trends and patterns in time-series data, making it valuable for forecasting future values. By incorporating autoregressive, moving average, and differencing components, the ARIMA model provides a flexible framework for studying and forecasting time series data. Moreover, ARIMA does not account for exogenous variables, which may alter the time series data. In contrast, ARIMAX combines these external aspects into its forecasting process to generate more accurate and comprehensive forecasts. By including important exogenous variables into the model, ARIMAX enables greater accuracy in forecasting future values of time series data while also allowing for a better understanding of their interaction with exogenous elements. Additionally, it can aid in spotting probable outliers within the dataset for increased forecasting precision. Our dataset comprises these external parameters for forecasting the occurrence of diarrhea sickness. We selected the ARIMAX model due to this rationale and the inclusion of exogenous factors in our dataset. And, we used autoarima algorithm for selection the best lags for training our model, which identifies optimal lag structures based on model performance and AIC criteria. Therefore, we advocate adopting the ARIMAX model instead of the usual ARIMA model for our investigation.

The Autoregressive (AR) model is stated as following Eq. (1):

$$Y_t = \alpha + \gamma_1 Y_{t-1} + \gamma_2 Y_{t-2} + \ldots + \gamma_p Y_{t-p} + ?_t,\ p > 0 \quad (1)$$

Here $p = 1,2,3, \ldots \ldots$

The Moving Average (MA) model is written as following Eq. (2):

$$Y_t = \alpha + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \ldots + \theta_q e_{t-q} + ?_t,\ q > 0 \quad (2)$$

Here $q = 1,2,3, \ldots$.

Exogenous Term as follows Eq. (3):

$$Y_t = \alpha + \beta_1 X_{1,t} + \beta_2 X_{2,t} + ? + \beta_k X_{k,t} + ?_t,\ k > 0 \quad (3)$$

Here $k = 1,2,3, \ldots$.

The mathematical equation for the ARIMAX model can be written as Eq. (4):

$$\begin{aligned} &Y_t \\ &= \alpha + \gamma_1 Y_{t-1} + \ldots + \gamma_p Y_{t-p} \\ &\quad + \theta_1 e_{t-1} + \ldots + \theta_q e_{t-q} + \beta_1 X_{1,t} + ? + \beta_k X_{k,t} + ?_t \end{aligned} \quad (4)$$

Y_t indicates the value of the time series at time t ($t = 1,2,3, \ldots$). α is a constant or intercept term. γ_1, γ_2, γ_3 are the autoregressive parameters, representing the coefficients of the lagged values of the time series and θ_1, θ_2, θ_3 are the moving average parameters, representing the coefficients of the past forecast errors. Here, $X_{1,t}$ $X_{2,t}$ $X_{3,t}$ are exogenous variables at a time, and β_1 β_2 β_3 are the coefficients associated with the exogenous variables. p is the order of the autoregressive (AR) component. q is the order of the moving average (MA) component. k is the number of exogenous variables.

Model evaluation

After finishing our model training, we evaluate model performance using multiple techniques: mean absolute error (MAE), Root Mean Squared Logarithmic Error (RMSLE), Mean squared error (MSE), and Root mean squared error (RMSE).

Mean absolute error

The Mean Absolute Error (MAE) is derived as the average of the absolute discrepancies between the forecasted values $\widehat{Y}_t$ and the actual observed values Y_t, Mathematically denoted as follows:

$$\mathrm{MAE} = \frac{1}{n} \sum_{t=1}^{n} |Y_t - \widehat{Y}_t|$$

Mean squared error

Mean Squared Error (MSE) is calculated as the average of the squared deviations between the forecasted values $\widehat{Y}_t$ and the actual observed values Y_t, Mathematically expressed as follows:

$$\mathrm{MSE} = \frac{1}{n} \sum_{t=1}^{n} \left(Y_t - \widehat{Y}_t\right)^2$$

Root mean squared error

Root Mean Squared Error (RMSE) is calculated as the square root of the average of the squared discrepancies between the forecasted values $\widehat{Y}_t$ and the actual observed values Y_t , Mathematically stated as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n} \sum_{t=1}^{n} \left(Y_t - \widehat{Y}_t\right)^2}$$

Root mean squared logarithmic error

RMSLE stands for Root Mean Squared Logarithmic Error. It is the square root of the mean squared logarithmic error (MSLE). It is another popular statistic used to evaluate model performance, particularly in regression assignments where the target variable spans multiple orders of magnitude. Mathematically, the Root Mean Squared Logarithmic Error (RMSLE) is calculated as:

$$\mathrm{RMSLE} = \sqrt{\frac{1}{n} \sum_{t=1}^{n} \left(\log(Y_t + 1) - \log(\widehat{Y}_t + 1)\right)^2}$$

Results

The research area exhibits significant variability in environmental parameters and the prevalence of diarrhea across different places, as indicated by the descriptive data in Table 1.

The study employed correlation analysis to investigate the associations between the occurrence of diarrhea and various environmental parameters, including minimum temperature, maximum temperature, humidity, and precipitation, across diverse geographical areas. Table 2 provide a summary of the correlation coefficients for each location.

According to Fig. 2, the fourth level of Daubechies wavelet decomposition divides the information contained in the signal into several frequency bands, allowing for the observation of both the overall trend and its rapid variations. But levels 1, 2, and 3 do not perform well compared to level 4. For this reason, we take level 4, we employ wavelet decomposition to obtain detailed and approximated coefficients. Furthermore, the denoised approximation and detailed coefficients found the specific coefficient values for eliminating the trend

Table 1 Descriptive analysis on different region

Location		Diarrhea	Min temp	Max temp	Humidity	Precipitation
Dhaka	Mean	34.75	21.88	30.41	77.68	6.39
	Std	26.05	5.19	3.79	12.21	11.37
	Min	0	9.31	20	39.31	0
	Max	230	27.65	40.07	95.62	149.91
Chattogram	Mean	33.01	20.73	30.83	79.97	7.63
	Std	30.16	5.22	3.78	9.76	12.76
	Min	0	7.86	20.38	46.25	0
	Max	294	26.52	41.26	97.25	111.76
Khulna	Mean	43.61	21.54	31.55	75.14	5.09
	Std	30.17	5.49	4.39	14.36	9.82
	Min	0	7.52	20.35	28.44	0
	Max	166	28.01	43.88	95.44	143.91
Rajshahi	Mean	55.05	21.24	31.74	70.62	4.15
	Std	21.66	5.93	4.93	16.1	7.95
	Min	0	7.34	20.01	26.06	0
	Max	173	28.67	44.34	95.12	86.84

Table 2 Correlation analysis between daily diarrhea and meteorological variables

Location		Diarrhea	Mini temp	Max temp	Humidity	Precipitation
Dhaka	Diarrhea	1	0.2112	0.3483	-0.0829	-0.0232
	Min Temp	0.2112	1	0.7452	0.4467	0.3765
	Max Temp	0.3483	0.7452	1	-0.1751	0.0398
	Humidity	-0.0829	0.4467	-0.1751	1	0.4333
	Precipitation	-0.0232	0.3765	0.0398	0.4333	1
Chattogram	Diarrhea	1	0.3236	0.2825	0.0868	0.1189
	Min Temp	0.3236	1	0.7505	0.4571	0.4258
	Max Temp	0.2825	0.7505	1	-0.1488	0.0620
	Humidity	0.0868	0.4571	-0.1488	1	0.5008
	Precipitation	0.1189	0.4258	0.0620	0.5008	1
Khulna	Diarrhea	1.0000	-0.0907	0.3533	-0.4953	-0.1664
	Min Temp	-0.0907	1.0000	0.6689	0.3673	0.3324
	Max Temp	0.3533	0.6689	1.0000	-0.3672	-0.0419
	Humidity	-0.4953	0.3673	-0.3672	1.0000	0.4066
	Precipitation	-0.1664	0.3324	-0.0419	0.4066	1.0000
Rajshahi	Diarrhea	1	0.2676	0.4392	-0.2306	-0.0436
	Min Temp	0.2676	1	0.7366	0.2611	0.3743
	Max Temp	0.4392	0.7366	1	-0.3966	0.0261
	Humidity	-0.2306	0.2611	-0.3966	1	0.3998
	Precipitation	-0.0436	0.3743	0.0261	0.3998	1

and seasonality and reconstructed these values. In this instance, a scaleogram graph for cases of diarrhea was mentioned. The original data was displayed on the right side of this figure, while the denoised data signal was displayed on the left. Moreover, we see that original data have some noise, which is indicated in upper side of the images. After using wavelet, the noised is removed from the data, and its normalize the data for better outcome.

Model selection

Choosing a suitable model is essential for the precise forecasting of diarrhea occurrences. The model exhibiting the lowest AIC value indicates the optimal equilibrium between the quality of fit and the intricacy of the model. The findings mentioned above offer significant insights into the appropriateness of models in forecasting the occurrence of diarrhea in various geographical areas. This knowledge can be helpful in informing public health planning and intervention measures. Using the autoarima method, the Akaike Information Criterion (AIC) was utilized to assess and choose the most appropriate models for forecasting the occurrence of diarrhea in various geographical areas. Table 3 is a comprehensive overview of the AIC values and chosen models for each respective region.

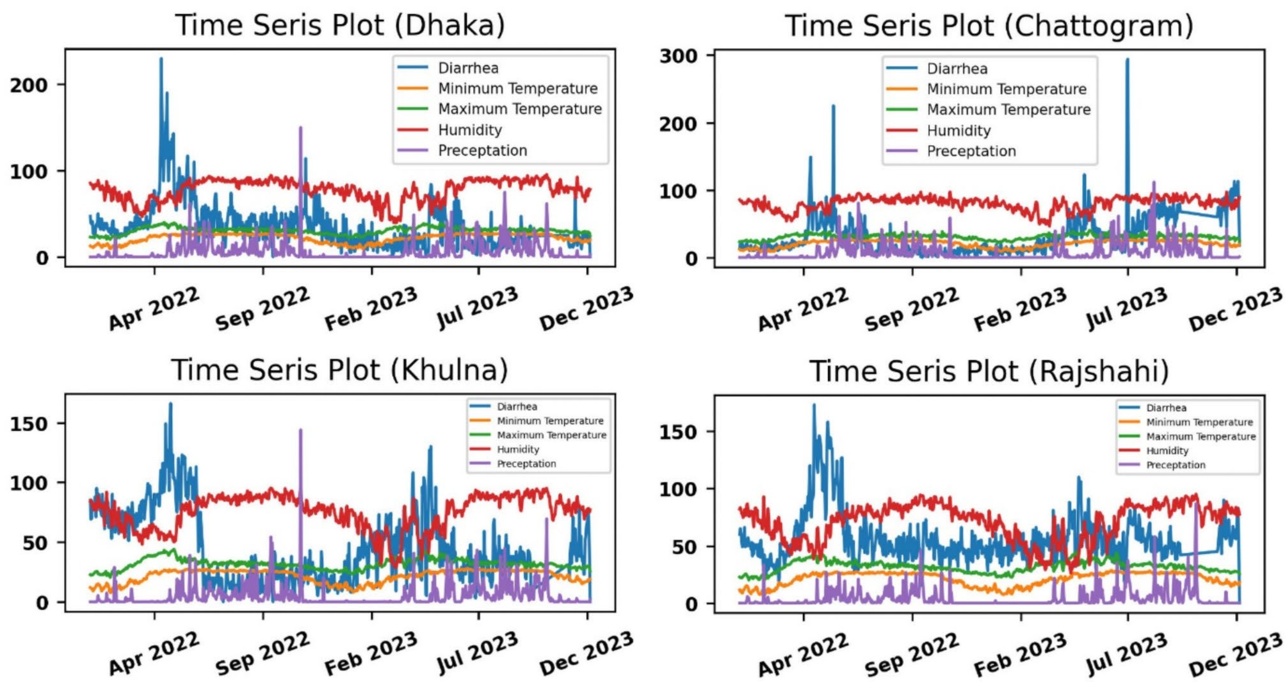

Fig. 2 Time series plot of diarrhea and weather variables

Table 3 Model selection

Region	WARIMAX		ARIMAX	
	Best model	**AIC value**	**Best model**	**AIC value**
Dhaka	(2,1,0)	582.440	(1,1,1)	4672.525
Chattogram	(2,1,0)	18.024	(0,1,2)	4933.656
Khulna	(5,1,0)	-416.062	(1,1,1)	4560.109
Rajshahi	(2,1,0)	-290.618	(1,1,1)	4411.610

Table 4 Our model performance

Division	Model	MAE	RMSE	RMSLE
Dhaka	WARIMAX	**0.067**	**0.096**	**0.005**
	ARIMAX	4.346	8.094	0.431
Chattogram	WARIMA	**0.122**	**0.193**	**0.003**
	ARIMAX	7.584	12.006	0.217
Khulna	WARIMAX	**0.084**	**0.117**	**0.005**
	ARIMAX	7.187	10.889	0.435
Rajshahi	WARIMAX	**0.112**	**0.171**	**0.003**
	ARIMAX	5.441	9.381	0.374

Model evaluation

In this study, we conducted a comparative analysis of the ARIMAX and WARIMAX models in their ability to forecast the incidence of diarrhea across several divisions. The evaluation metrics included in this analysis included the mean absolute error (MAE), root mean squared error (RMSE), and root mean squared logarithmic error (RMSLE). Smaller numbers are indicative of higher levels of model accuracy. The WARIMAX models consistently demonstrated superior performance compared to the ARIMAX models across all divisions, as indicated by lower values of MAE, RMSE, and RMSLE (in Table 4). The findings indicate that the inclusion of exogenous variables, such as weather data, in WARIMAX models enhances the precision of diarrhea incidence forecast. The significance of including external factors in time series forecasting, particularly in public health situations, is shown by the notable disparities in performance measures seen between ARIMAX and WARIMAX models. The results emphasize the potential advantages of employing sophisticated modeling tools such as WARIMAX in providing insights for public health treatments and policies on resource allocation. The wavelet processing aspect supports the model's detection of oscillating patterns, making it more useful in areas with extreme weather conditions that change seasonally. However, incorporating new health and environmental elements could improve the model's performance, allowing it to function better in various circumstances.

Model Forecast

According to Figs. 3 and 4, compare how the two models perform when forecasting where diarrhea will occur in Dhaka, Chattogram, Rajshahi, and Khulna. The WARIMAX model foresees more smoothly in line with the observed trends in reality than the ARIMAX model prognosticates, which are irregularly wild compared with actuality but show a higher number of ceremonial forms than the other. In contrast to the more stable WARIMAX forecast, the notable spikes and erratic behaviors found in the ARIMAX forecast, particularly in Chattogram and

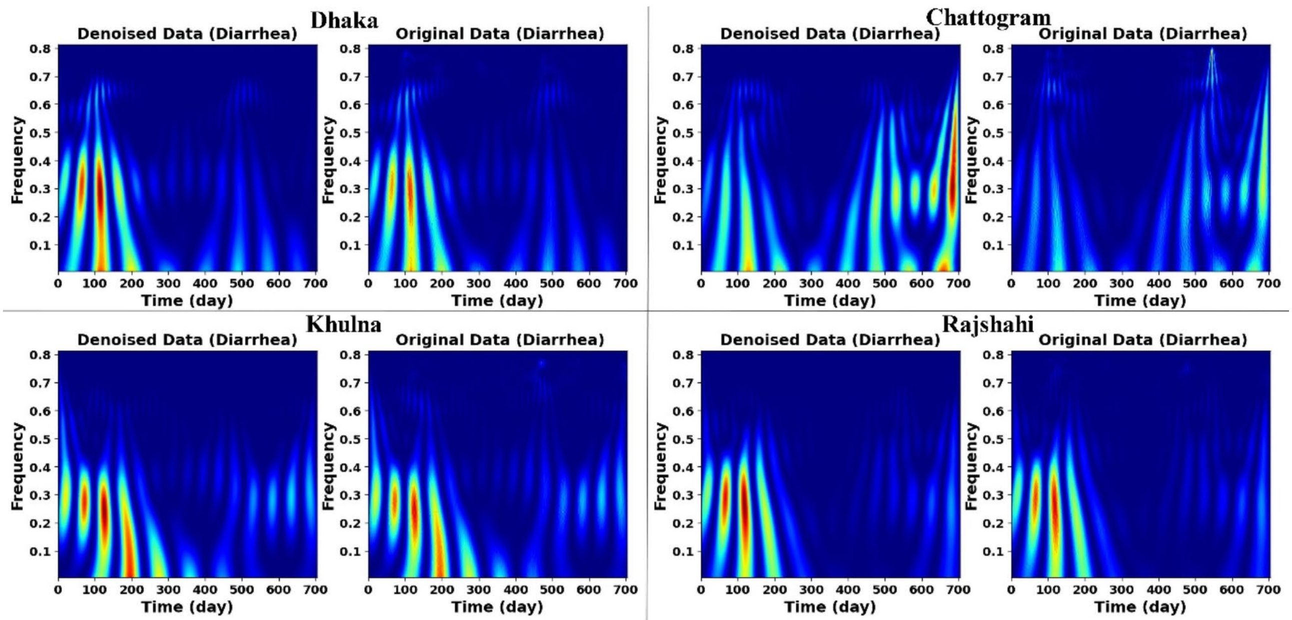

Fig. 3 Diarrhea Scaleogram Graph (De-noised by wavelet decomposition technique)

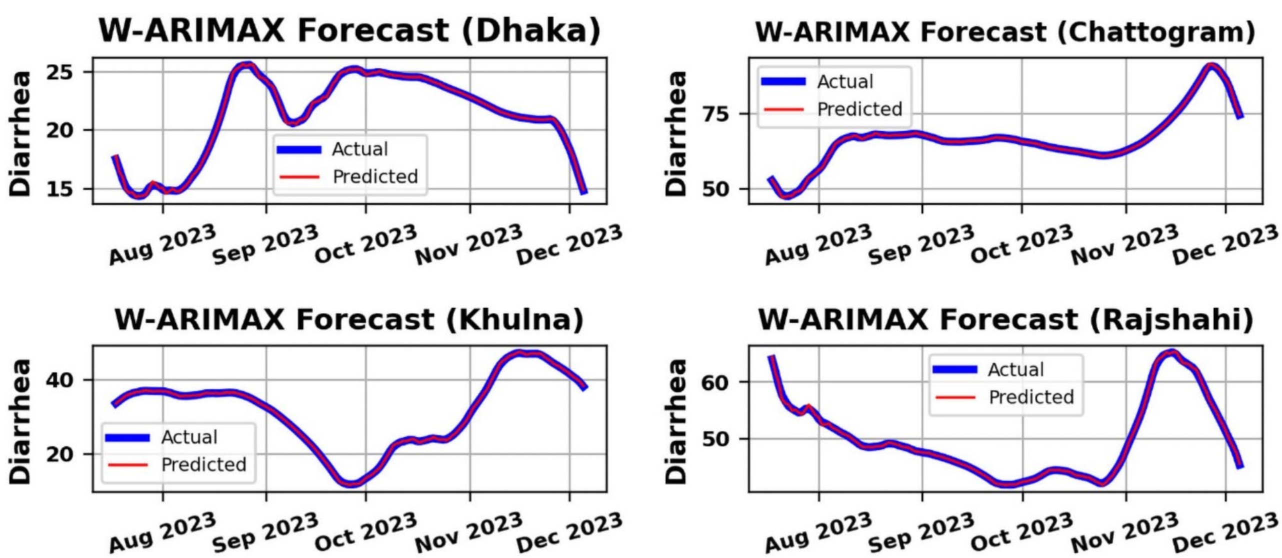

Fig. 4 Diarrhea forecasting by Wavelet-ARIMAX model

Rajshahi, suggest its susceptibility to their variations. The key result was that the ARIMAX model could not match the performance of the WARIMAX model in terms of both accuracy and stability; as such, it remains a better alternative for disease surveillance by public health officers. By giving consistent forecasts without much fluctuation in values, the WARIMAX model can greatly contribute to providing a smooth-running way to handle diarrhea cases.

Discussion

According to Table 1, Rajshahi had the most significant average prevalence of diarrhea (55.05) of the places analyzed, followed by Khulna (43.61), Dhaka (34.75), and Chattogram (33.01). The data reveals a significant variety in diarrhea rates, as evidenced by the standard deviations. Rajshahi exhibits the lowest deviation of 21.66, whereas Chattogram demonstrates the most considerable variance of 30.16. Dhaka exhibits the most significant average minimum temperature (21.88 °C), whereas Chattogram has the lowest (20.73 °C). Rajshahi has the most significant average maximum temperature, measuring 31.74 °C, while Chattogram has the lowest average maximum temperature, measuring 30.83 °C. The standard deviations indicate a high level of temperature uniformity among the several places. Differences in humidity levels are evident, as Chattogram has the highest average humidity of 79.97, while Rajshahi demonstrates the lowest average humidity of 70.62%. Significant disparities in precipitation levels are observed, as Dhaka exhibits the highest average precipitation (6.39 mm) and Chattogram demonstrates the lowest (7.63 mm).

According to Fig. 5, from 1 January 2022 to 5 December 2023, there were 23,211 diarrhea cases in the Dhaka division, 19,908 diarrhea cases in Chattogram division, 36,405 diarrhea cases in Rajshahi division, and 29,635 diarrhea cases in Khulna division. The highest number of diarrhea cases (230) were reported in Dhaka on November 4, 2022, followed by 294 in Chattogram on July 1, 2023, 166 in Khulna on April 24, 2022, and 173 in Rajshahi on April 16, 2022. In this work, the selected markers of diarrhea cases in four divisions of Bangladesh have been utilized in conjunction with daily precipitation indexes, humidity levels, and temperature (maximum and minimum). Figure 5 depict a time series plot of the number of diarrhea cases, temperature, humidity, and rainfall from January 2022 to December 2023, respectively.

From Table 2, there exists a positive link between the incidence of diarrhea and temperature across all geographical locations. Moderate positive associations have been discovered between the incidence of diarrhea and both lowest and maximum temperatures in the cities of Dhaka and Chattogram. Likewise, in the cities of Rajshahi and Khulna, there exists a moderate positive association between the frequency of diarrhea and maximum temperature. At the same time, a weaker correlation is shown between diarrhea incidence and minimum temperature. There are diverse associations between humidity and the occurrence of diarrhea in different geographical areas. A weak negative association exists between the incidence of diarrhea and humidity in Dhaka and Chattogram, indicating that higher humidity levels may be linked to reduced diarrhea incidence. Nevertheless, the association between the occurrence of diarrhea and humidity in Rajshahi and Khulna is either minimal or inconsequential. The association between precipitation and diarrhea incidence is weak to nonexistent in all locations, suggesting that rainfall may not have a substantial impact on the prevalence of diarrhea in these places.

According to Table 3, the WARIMAX model with parameters (2,1,0) demonstrated the lowest AIC value (582.440) for Dhaka, indicating a strong agreement between the model and the data in this particular location. The AIC value (18.024) of the WARIMAX model with parameters (2,1,0) was found to be the lowest, suggesting that it provides the most accurate fit for the data in Chattogram. The WARIMAX model with parameters (5,1,0) exhibited the lowest AIC value (-416.062) among the models examined, indicating its superior suitability for the data in Khulna. The WARIMAX model, equipped with parameters (2,1,0), demonstrated the most favorable fit for the data in Rajshahi, as seen by its lowest AIC value (-290.618). For Dhaka, Khulna, and Rajshahi, the ARIMAX model with parameters (1,1,1) demonstrated the lowest AIC value (4672.525), (4560.109) and (4411.610) respectively, indicating a strong agreement between the model and the data in this particular location. The AIC value (4933.656) of the ARIMAX model with parameters (0,1,2) was found to be the lowest, suggesting that it provides the most accurate fit for the data in Chattogram.

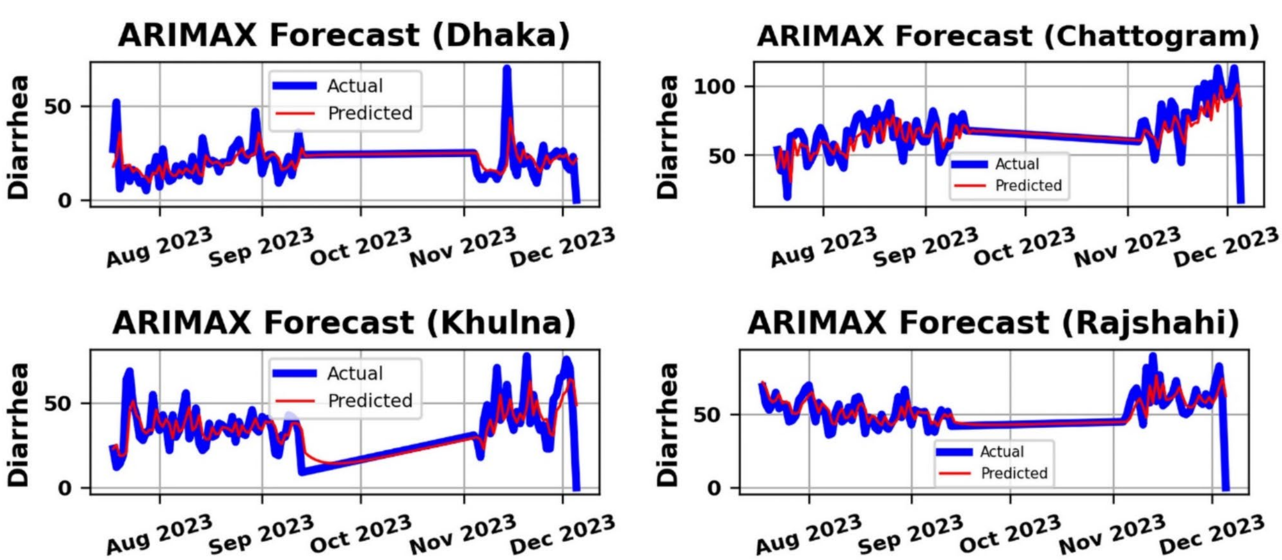

Fig. 5 Diarrhea forecasting by ARIMAX model

Table 5 Previous research model performance

Study	Model	MAE	RMSE
[47]	ARIMA	0.9173	1.1100
	GRNN	0.8266	1.3073
	ARIMA-GRNN	0.1933	0.4665
[48]	ARIMAX	-	0.46
	ARIMA	-	0.45
	RF	-	0.04
[49]	ARIMA	-	-
	LSTM	-	0.21
	SVM	-	0.22
[50]	BPNN	29.136	40.367
	SVM	38.461	49.909
	RF	35.030	48.144
[51]	SARIMA	11	14.7
[52]	ARIMA	89.0302	138.8356
	GRNN	134.5960	265.7046
	ARIMA-GRNN	85.0429	140.6426

Our models (Table 4) outperform prior studies (Table 5), as evidenced by decreased RMSE and MAE values across regions. For example, in Dhaka, the WARIMAX model had an MAE of 0.067 and an RMSE of 0.096, whereas in Chattogram, it had an MAE of 0.122 and an RMSE of 0.193. In previous studies, the ARIMA-Generalized Regression Neural Network (ARIMA-GRNN) model produced significantly higher error metrics, with RMSE values of 0.4665 [47] and 140.6426 [52], and MAE values of 0.1933 [47] and 85.0429 [52]. This considerable reduction in error statistics indicates the efficacy of our models across multiple divisions; alternatively, the RF model recorded a lower RMSE of 0.04 in another study [48]. Also, performances of the ARIMA model depend on RMSE; 1.1100, 0.45, 14.7, and 138.8356 are moderately satisfactory [47, 48, 51, 52]ss. One study used Long Short-Term Memory (LSTM) and Support Vector Machine (SVM) in their work; they found lower RMSE scores of 0.21 and 0.22 [52]. While these models are not good enough, they cannot reach the lower error rates that characterize our WARIMAX and ARIMAX models. Our new models indicate how they can be used in practical forecasting to improve accuracy in diarrhea outbreaks, therefore useful for resource allocation and planning cities.

Conclusion and recommendations

The aim of this work is to forecast the incidence of diarrhea by analyzing the influence of climate factors and justify the forecasted efficiency of the unique WARIMAX model in appropriately analyzing illness trends connected to these climate variables, for Bangladesh's four important divisions such as Dhaka, Chattogram, Khulna, and Rajshahi in order to design and test a diarrhea forecasting model. Due to its auto-regressive characteristics, seasonal behavior pattern, and influence of the weather variable on diarrhea incidence, the Wavelet-auto-regressive-integrated-moving-average with exogenous variable (WARIMAX) model was determined to be a good fit for diarrhea forecasting. The WARIMAX models demonstrated a high correlation between the incidence of diarrhea and the following climate variables: rainfall, maximum temperature, minimum temperature, and humidity. This study also showed that different regions and climate variables have different relationships between diarrhea incidence and climate variables. In comparison to the ARIMAX model, the WARIMAX model performs significantly better at forecasting. Thus, a context-sensitive model of diarrhea is one that varies its climate input features across space. Consequently, to forecast an event of diarrhea, one should study weather parameters that distinguish each place.

Health care workers and epidemiologists would get useful results from this research when making plans on how to prevent diarrhea diseases. The increased understanding of the environmental and weather variables contributing to diarrhea epidemics would benefit an epidemiologist. A medical practitioner can get ready for possible coping and adaptation mechanisms for Bangladesh's possible health hazards associated with climate change. Additionally, this research advances the creation of a diarrhea early warning system based on climate. In response to the current climatic change, decision makers may consider launching public health programs aimed at improving cleanliness. Furthermore, because climate variables and public health are inextricably linked, improved inter-sectoral collaboration is required across meteorological services, public health, and disaster management sectors. This way, climate-sensitive health-care policies and initiatives can be implemented to not only mitigate the effects of climate change on health-care systems, but also to reduce diseases. The scope of utilization of the Wavelet-ARIMAX goes beyond the geographical boundaries of Bangladesh and hence provides an analytical insight that can be used in different situations and complicated systems around the world.

Limitations and Future aspects

The study's focus on only four divisions of Bangladesh makes it difficult to generalize the findings. Over time, research on the divisions of all countries or regions with similar climates should be explored. The Wavelet-ARIMAX model is effective, but it is difficult and requires specific expertise, which may limit its applicability in public health practice. Its applicability is also quite sensitive to the model's parameters, such as the wavelet employed and the inclusion of seasonal factors. To make it more understandable and user-friendly, consider simplifying the model or comparing it to simpler methods such as machine learning methodologies. Finally, additional research may authenticate the WARIMAX model throughout include external variables such as supplementary climate variables, demographic data and socioeconomic variables or health systems to better understand the relationship between climate and health.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12889-024-20920-z.

Supplementary Material 1

Author contributions

Md. Waliullah: Conception, design of the work, acquisition, analysis, interpretation of data, drafted the work, editing and substantively revised it.Md. Jamal Hossain: Conception, design of the work, acquisition, analysis, interpretation of data, editing, substantively revised it and supervision.Md. Raqibul Hasan: Design of the work, analysis, drafted the work, editing, and substantively revised it.Abdul Hannan: Design of the work, analysis, drafted the work, editing, and substantively revised it.Mohammad Mafizur Rahman: Conception, designing of the work, substantively revised it and supervision.

Funding

The study did not receive any fund.

Data availability

Yes, I have research data to declare. The data is available in a supplementary file (Raw data.rar).

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

Received: 25 August 2024 / Accepted: 2 December 2024
Published online: 24 January 2025

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