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Long-term associations between seasonal variability and malaria transmission in Bangladesh: a 16-year national time-series analysis

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Abstract

Background Malaria transmission is strongly influenced by climatic conditions that regulate *Anopheles* mosquito survival and parasite development. However, existing studies in Bangladesh are largely short-term or region-specific, limiting understanding of long-term climate–malaria dynamics. This study addresses this gap by examining national-level, long-term associations between malaria incidence and climatic factors.

Methods A retrospective ecological time-series study was conducted using monthly malaria surveillance data from Bangladesh between January 2008 and December 2023. Climatic variables—rainfall, temperature, relative humidity, and sunshine duration—were obtained from the Bangladesh Meteorological Department for the same period ensuring full temporal alignment with malaria data. Descriptive analyses were used to assess long-term trends and seasonality. Pearson correlation was used to assess linear relationships between variables, while Spearman correlation was applied to capture potential monotonic but non-linear associations and reduce sensitivity to outliers. Multiple linear regression models incorporating one-month lagged variables were developed to identify independent climatic predictors of transmission.

Results A total of 192 monthly observations were analyzed. Malaria incidence showed a marked long-term decline, yet a consistent seasonal pattern persisted, with transmission peaking during the monsoon months (July–September). Mean relative humidity demonstrated the strongest positive correlation with malaria incidence ($p < 0.001$), followed by lagged rainfall ($p < 0.01$). In multivariate analysis, mean humidity, lagged rainfall, and lagged sunshine duration remained significant predictors, while temperature was not independently associated. The regression model accurately captured seasonal timing but underestimated peak magnitude during outbreak years.

Conclusion Despite declining incidence, malaria in Bangladesh retains a stable, climate-driven seasonal signature. Climatic variables are effective in predicting transmission timing but insufficient to explain outbreak intensity. Integrating climate indicators into surveillance systems may strengthen preparedness and support malaria elimination efforts in residual transmission settings.

Keywords Malaria, Climate variability, Seasonality, Rainfall, Humidity, Bangladesh, Time-series analysis

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Introduction

Despite substantial progress in control and elimination efforts over recent decades, malaria continues to cause significant morbidity and mortality in tropical regions [1]. South and Southeast Asia have witnessed notable reductions in malaria incidence; however, residual transmission persists in geographically and ecologically distinct pockets [2]. In Bangladesh, malaria has declined markedly at the national level, yet endemic transmission continues in specific regions, underscoring the need for sustained surveillance and climate-informed risk assessment [3].

A key operational feature of malaria transmission is parasite sporogony, the temperature-dependent developmental process within the mosquito [4]. Relative humidity and rainfall further influence mosquito survival, breeding site availability, and vector density, making malaria transmission inherently climate-sensitive [5].

In Bangladesh, malaria transmission is geographically concentrated rather than widespread. The highest burden is observed in the forested and hilly areas of the Chittagong Hill Tracts (CHT) and adjacent southeastern districts, shaped by ecological conditions, cross-border movement, and access barriers to healthcare [3, 6]. Seasonal rainfall patterns associated with the monsoon create breeding habitats for *Anopheles* mosquitoes, while humidity prolongs adult mosquito survival, thereby enhancing transmission potential [7]. Persistent hypo-endemic transmission and periodic resurgences of malaria highlight the continuing relevance of environmental factors [8].

Previous studies in Bangladesh and comparable settings have documented associations between malaria incidence and rainfall, temperature, and humidity, often with lagged effects reflecting mosquito and parasite life cycles [5, 9]. However, much of the existing literature relies on short-term datasets, localized studies, or cross-sectional designs, limiting insights into long-term seasonal stability and interannual variability [2, 5]. Furthermore, as malaria incidence declines, understanding how climate continues to shape residual transmission becomes increasingly important for elimination strategies, especially in the context of change and extreme weather events that may disrupt control efforts [10].

This study analyzed monthly malaria case data from Bangladesh spanning 2008 to 2023 alongside routinely collected—rainfall, temperature, relative humidity, and sunshine duration. The objective was to characterize long-term seasonal patterns and quantify the independent and lagged associations between rainfall, temperature, humidity, and sunshine variables and malaria incidence using correlation and multiple linear regression analyses. The study hypothesizes that, despite declining overall incidence, malaria in Bangladesh retains a consistent seasonal pattern driven by climatic factors in shaping transmission timing rather than predicting outbreak magnitude. By providing a long-term national perspective, this analysis aims to support temperature, rainfall, humidity, and sunshine informed surveillance and targeted malaria elimination efforts in residual transmission zones.

Methodology

Study design and study area

A retrospective ecological time-series study design was used to evaluate the relationship between temperature, sunshine, humidity and rainfall and malaria incidence in Bangladesh from January 2008 to December 2023. The study encompassed the entire country, with particular epidemiological relevance to malaria-endemic regions such as the Chittagong Hill Tracts. This national-scale design allowed assessment of long-term seasonal patterns and climatic influences on malaria transmission dynamics [1].

Study variables and operational definitions

The primary outcome variable was monthly malaria incidence, defined as the total number of reported malaria cases per month. Exposure variables included total monthly rainfall, mean temperature, mean relative humidity, and mean sunshine duration. Lagged rainfall, humidity, temperature, and sunshine duration were defined as climatic values recorded one month prior to malaria case reporting, consistent with *Anopheles* mosquito breeding cycles and parasite development timelines [3].

Data sources and data collection

Monthly malaria case data were collected from national surveillance records maintained by the Directorate General of Health Services (DGHS) and the National Malaria Elimination Program (NMEP). Meteorological data including rainfall, temperature, relative humidity, and sunshine duration were obtained from the Bangladesh Meteorological Department. All data were aggregated at monthly level and covered the same study period to ensure temporal comparability [2].

Data processing, management and quality control

All datasets were processed and cleaned using Python-based data management tools. Procedures included aggregation, removal of duplicate records, detection of missing values, and verification of temporal consistency. Missing data were minimal (< 1%) and were handled using linear interpolation for continuous climatic variables. Sensitivity checks confirmed that imputation did not materially alter the observed trends or associations. Climate and malaria datasets were merged by month and year to ensure precise temporal alignment. Final datasets were reviewed for plausibility and completeness before statistical analysis.

Statistical analysis

Descriptive analyses were conducted to characterize long-term trends and seasonal variation in malaria incidence. Pearson correlation analysis was used to evaluate linear relationships between climatic variables and malaria incidence, whereas Spearman rank correlation was performed to assess potential monotonic but nonlinear associations and reduce sensitivity to outliers. Multiple linear regression was subsequently employed to estimate the independent associations between climatic variables and malaria incidence, with parameters estimated using ordinary least squares (OLS). Given the time-series nature of the data, one-month lagged climatic predictors were incorporated to account for the biologically plausible delayed effects of climate on mosquito development, parasite maturation, and malaria transmission.

Because the primary objective of this study was to investigate long-term climatic associations rather than develop a forecasting model, multiple linear regression with biologically plausible lagged predictors was selected as an interpretable analytical framework. Although monthly malaria cases represent count, the analyses were based on monthly aggregated observations spanning 16 years to evaluate ecological associations rather than individual event counts. In ordinary least squares regression, the principal assumptions relate to the distribution and independence of the residuals rather than the response variable itself. Accordingly, residual normality was evaluated using normal Q–Q plots and histogram inspection of the residuals, while residual independence was assessed using the Durbin–Watson statistic. Multicollinearity among climatic predictors was assessed using variance inflation factors (VIFs), and Pearson correlation coefficients among rainfall, relative humidity, temperature, and sunshine duration were additionally examined to characterize the relationships between climatic variables. The corresponding diagnostic results are presented in Supplementary Tables S2 and Supplementary Figure S2. Collectively, these diagnostic assessments supported the adequacy of the fitted regression model for statistical inference. Nevertheless, generalized linear models based on Poisson or negative binomial distributions may provide complementary analytical approaches for future studies involving highly dispersed count data.

Interaction terms between climatic variables (rainfall × humidity) were explored during preliminary analyses but were not retained in the final model because they were not statistically significant and did not improve overall model performance. Model validity was further evaluated by comparing observed and predicted malaria trends over the study period. Statistical significance was defined as $p < 0.05$ [11]. All data management and statistical analyses were conducted using Python (version 3.11) with the pandas, NumPy, SciPy, and statsmodels libraries.

As a sensitivity analysis, temporal coefficient stability was evaluated using a Chow structural break test with 2019 specified as the breakpoint. In addition, an interaction model including period × climatic predictor interaction terms were fitted to assess whether the associations between climatic variables and malaria incidence differed before and after 2019. The results of these analyses are presented in Supplementary Tables S3 and Supplementary Tables S4.

Climatic variables were selected a priori based on established biological relevance and consistent evidence from previous malaria–climate studies rather than automated variable selection procedures. Temperature, rainfall, relative humidity, and sunshine duration were included because of their well-recognized influence on mosquito development, survival, vector abundance, parasite development, and malaria transmission dynamics. This theory-driven modeling strategy was adopted to enhance biological interpretability while minimizing the risk of overfitting.

To specify the regression framework, the following multiple linear regression model was used: $Y_t = \beta_0 + \beta_1 R_{t-1} + \beta_2 H_t + \beta_3 S_{t-1+}\ \beta_4 T_{t-1} + \varepsilon_t$, where Yt represents the number of reported malaria cases in month t, R_{t-1} denotes total rainfall in the previous month, H_t denotes mean relative humidity in the same month, S_{t-1} means sunshine hours lagged by one month. B_0 is the intercept, β_1, β_2 *and* β_3 are regression coefficients, and εt is the random error term.

Results

A total of 192 monthly malaria case observations from January 2008 to December 2023 were included in the analysis. Malaria incidence exhibited a strong declining trend over the study period, reflecting sustained control efforts, although seasonal transmission persisted. Despite inherent limitations of ecological time-series analysis, the consistency of seasonal patterns and robustness across correlation and regression analyses support the reliability of the findings.

Figure 1 illustrates a sustained decline in reported malaria cases in Bangladesh over the study period, alongside changes in species composition. The solid line represents total annual malaria cases, while the dotted line

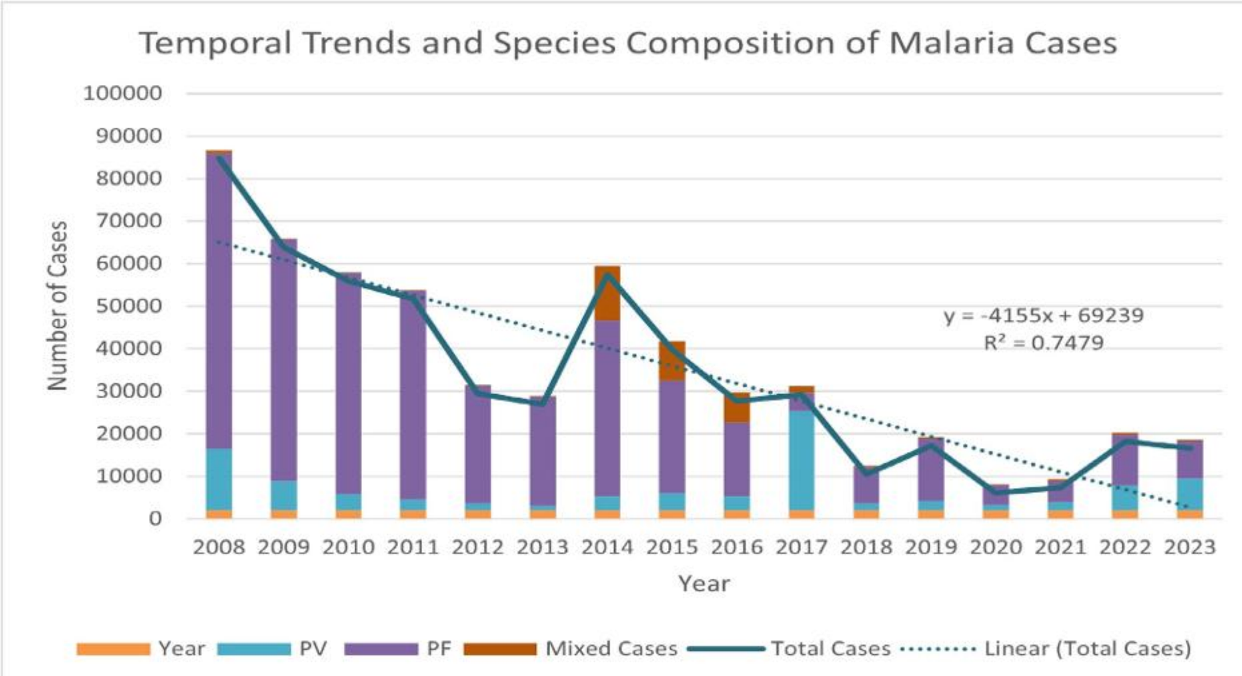

Fig. 1 Long-term trend of malaria cases in Bangladesh (2008–2023)

indicates the fitted linear trend. The linear trend equation ($y = -4155x + 69239$) shows an average annual reduction of approximately 4,155 cases, reflecting steady progress in malaria control, while 69239 is the theoretical 'starting point' of the trend line. It suggests that at the beginning of the trend (Time = 0), the model estimates there were around 69,239 cases. $R^2 = 0.7479$ is the 'Accuracy Score'. It means that 74.8% of the variation in case numbers can be explained simply by the passage of time. This is a very high score for real-world disease data, proving the decline is consistent and not random. Despite this overall reduction, intermittent increases and persistent seasonal transmission patterns were observed across multiple years (Fig. 2).

Malaria incidence increased from May, peaked between July and September, and declined sharply after October (Fig. 3). Transmission was lowest between December and February, indicating strong seasonal forcing despite reduced overall burden. Spatial–temporal intensity analysis highlighted month-wise clustering. Higher case densities were consistently observed during monsoon months, while dry-season months showed minimal transmission across years. The seasonal amplitude remained relatively stable over time despite declining annual incidence, indicating that environmental forcing continues to regulate transmission intensity. The consistent monsoon peak suggests a predictable transmission window that may be leveraged for targeted interventions.

In Fig. 4, malaria incidence increased following periods of high rainfall with an approximate one-month delay, suggesting rainfall-driven vector breeding. In Fig. 5, elevated malaria transmission coincided closely with periods of high mean humidity. Correlation analyses quantified these relationships.

Mean humidity showed the strongest positive correlation with malaria incidence ($p < 0.001$) (Table 1). Lagged rainfall also demonstrated a significant positive correlation ($p < 0.01$). Lagged sunshine duration showed weaker but statistically significant association. Multiple linear regression identified independent predictors.

The Breusch–Pagan test indicated no significant evidence of heteroscedasticity (LM statistic = 8.21, $p = 0.084$), supporting the assumption of constant residual variance. A summary of the regression diagnostic tests is presented in Supplementary Table S1, with the corresponding residual diagnostic plots shown in Supplementary Figure S1.

Multicollinearity assessment showed that all climatic predictors had VIF values below 5, including lagged sunshine (VIF = 2.39), indicating no evidence of problematic multicollinearity (Supplementary Table S2). Pairwise correlations among climatic predictors were generally low to moderate (Supplementary Figure S2), suggesting that the change in the sunshine coefficient after multivariable adjustment was more likely

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2008	2142	4050	5327	3320	5381	12590	16126	11234	8444	6741	5334	4001
2009	4076	4330	4969	4090	5067	6543	6895	6542	5368	6140	4568	5285
2010	3919	3249	3313	3697	4264	7554	7494	6213	4163	4234	4377	3396
2011	2737	1997	2033	2392	3989	8418	8168	6423	4948	4355	3647	2668
2012	2166	1624	1272	1283	1839	3529	4332	2547	3240	2959	2562	2165
2013	1220	857	667	752	1230	3993	5299	3350	2792	2431	2281	2019
2014	1042	887	677	959	1766	8547	12289	12821	6415	4977	4326	2774
2015	2024	1221	1151	1165	2541	6486	8155	4931	3649	3407	2840	2149
2016	1092	595	566	1003	2218	6432	5959	3377	1981	1544	1578	1392
2017	886	470	499	1027	2791	6049	7063	4423	2164	1654	1392	829
2018	557	259	216	229	705	1884	2050	1499	1091	920	711	402
2019	305	158	141	162	517	1795	4650	3089	2653	1580	1244	931
2020	535	203	94	97	291	888	1372	897	622	463	412	256
2021	153	99	86	94	323	1455	1823	1164	668	514	428	487
2022	320	176	118	277	1013	5155	4518	2644	1544	971	774	685
2023	533	297	240	355	891	2673	4476	2701	1373	1321	861	846

Fig. 2 Monthly average malaria cases in Bangladesh during 2008–2023 (Source DGHS)

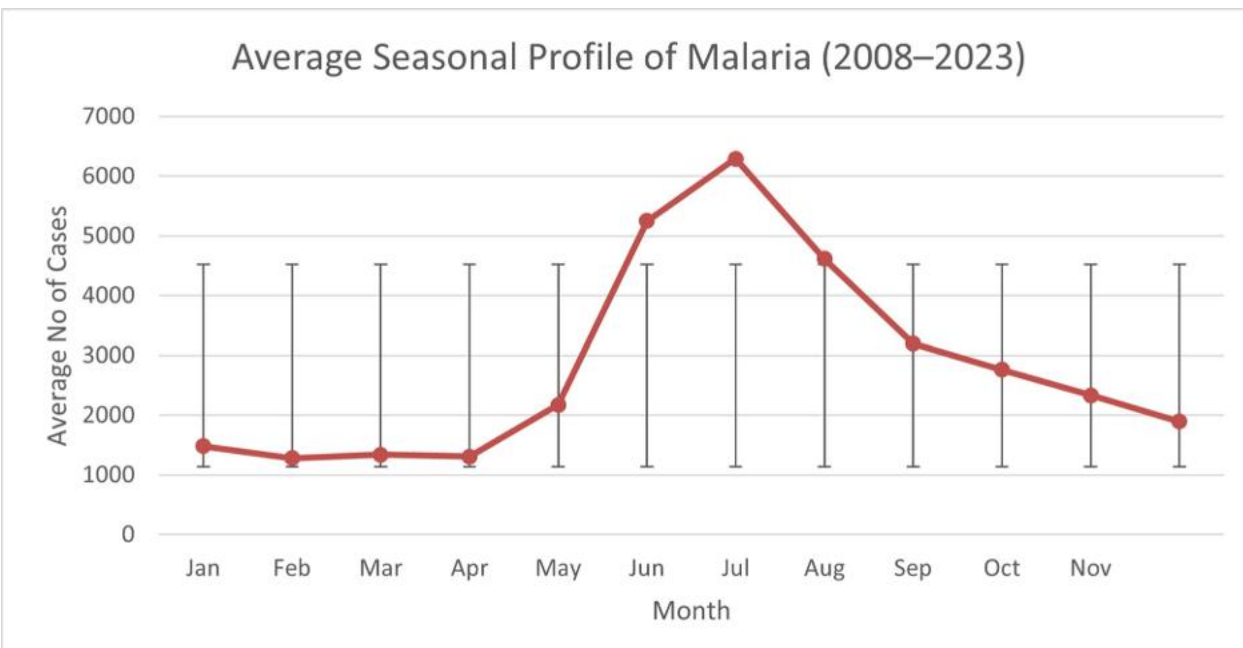

Fig. 3 Graphical presentation of average seasonal profile of malaria (2008–2023)

attributable to combined relationships among climatic predictors than to severe multicollinearity.

A sensitivity analysis was performed to evaluate temporal coefficient stability. The Chow structural break test identified a statistically significant structural break after 2019 ($F = 60.91$, df = 5,182, $p < 0.001$), indicating that the climate–malaria relationship differed between the two study periods (Supplementary Table S3). Consistent with this finding, the interaction analysis demonstrated a significant period × humidity interaction ($\beta = -0.749$, $p = 0.038$), whereas interactions involving rainfall, sunshine duration, and temperature were not statistically significant (Supplementary Table S4). These findings suggest that temporal variation in the

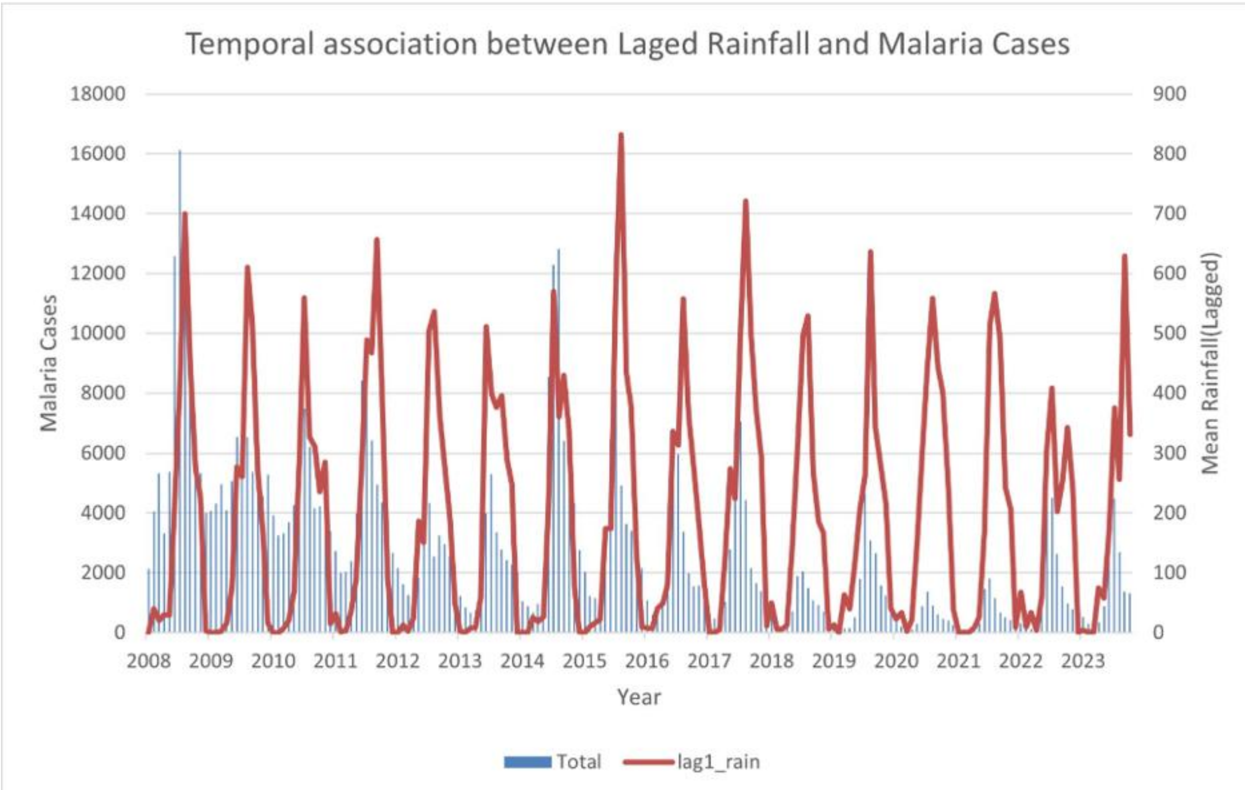

Fig. 4 Temporal association between lagged rainfall and malaria cases. Rainfall is expressed in millimeters (mm), and malaria incidence represents the monthly number of reported malaria cases

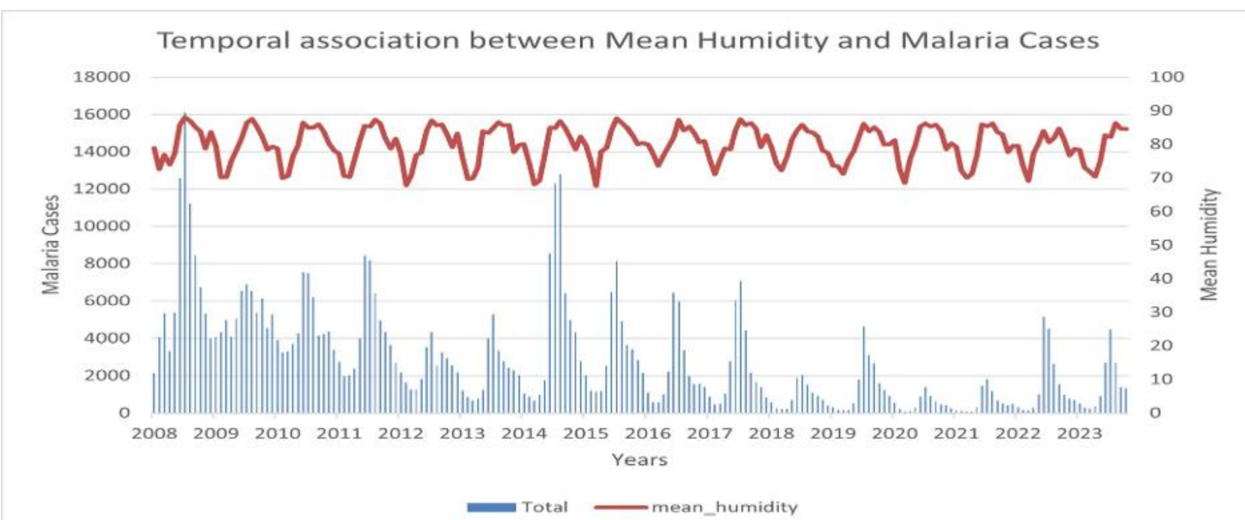

Fig. 5 Temporal association between mean relative humidity and malaria cases. Relative humidity is expressed as percentage (%), and malaria incidence represents the monthly number of reported malaria cases

climate–malaria relationship was primarily associated with humidity.

The final model retained lagged rainfall ($p=0.004$), lagged sunshine duration ($p=0.049$), and mean humidity ($p=0.0003$) as significant predictors (Table 2). Because the climatic predictors were measured using different units and scales, direct comparison of the raw regression coefficients should be interpreted with caution. Accordingly, the relative importance of each predictor was evaluated based on statistical significance, biological plausibility, and the overall correlation analyses rather than the absolute magnitude of the regression coefficients. Collectively, these findings suggest that mean humidity was the most consistently associated climatic factor with malaria transmission. Model validation further demonstrated good agreement in the temporal pattern of malaria incidence. The model closely followed seasonal timing across most years but underestimated

Table 1 Pearson and Spearman correlation coefficients between malaria cases and climatic variables

Climatic variable	Lag period	Pearson correlation (r)	Spearman correlation (ρ)	*P*-value (Spearman)	Findings
Mean humidity	0 months	0.50	0.55	< 0.001	Consistent positive: rank-based analysis yields a slightly stronger association
Rainfall	1 month	0.46	0.48	< 0.001	Robust positive: the similarity between Pearson and Spearman indicates a stable, linear relationship unaffected by extreme outliers
Sunshine	1 month	−0.25	−0.27	< 0.001	Consistent negative: both methods show a weak negative association in univariate analysis (associated with the dry season)

Table 2 Multiple linear regression model for malaria incidence

Predictor variable	Coefficient (β)	Standard error	*t*-Stat	*P*-value	Significance
Intercept	−14,196.14	3892.49	−3.65	0.0003	Sig.
Lag1 rain	4.65	1.61	2.89	0.004	Sig.
Lag1 sunshine	337.50	170.54	1.98	0.049	Sig.
Mean humidity	177.07	49.04	3.61	0.0003	Sig.

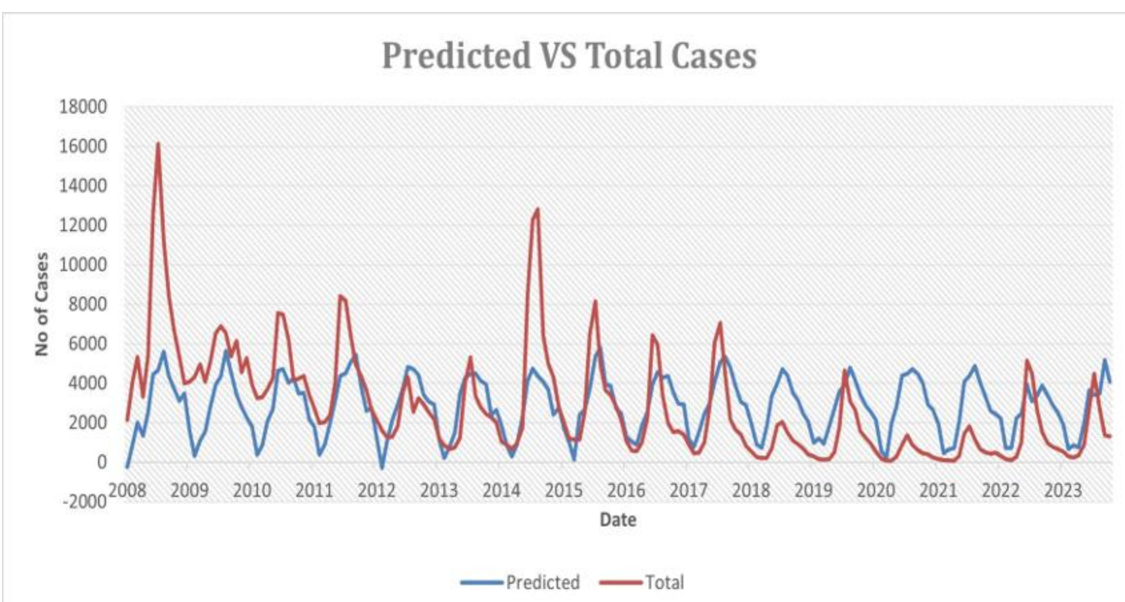

Fig. 6 Observed versus predicted malaria cases from multiple linear regression model

the magnitude of peak incidence during outbreak years, such as 2008 and 2014 (Fig. 6).

Discussion

This study provides a comprehensive analysis of seasonal influences on malaria transmission in Bangladesh. Globally, malaria transmission is recognized as highly responsive to environmental conditions that regulate *Anopheles* mosquito survival and parasite development, particularly rainfall and humidity [12, 13]. Transmission of malaria persists in ecologically suitable areas, underscoring the continued relevance of climate–malaria relationships [14].

In Bangladesh, malaria transmission has become increasingly localized in hilly regions [15]. Prior studies have documented strong associations between seasonal variability and malaria incidence, rainfall-driven breeding habitats, and humidity-related mosquito survival [16, 17]. The present analysis supports these findings by demonstrating that malaria transmission retains a clear seasonal signal despite overall reductions in case burden, reinforcing the hypothesis that climate continues to shape residual transmission dynamics. Although all retained climatic variables contributed significantly to the final model, the findings collectively suggest that relative humidity was the most consistently associated climatic factor, considering its statistical significance, biological plausibility, and overall correlation with malaria incidence. Previous studies have reported varying results depending on ecological context and temporal scale. For instance, studies conducted in arid or highland regions often identify temperature as the dominant climatic driver, whereas in humid tropical settings such as Bangladesh, moisture-related variables appear to play a more influential role [15, 16]. Differences among studies may also reflect variations in data resolution, lag structures, analytical approaches, and local vector ecology.

Earlier national and regional studies suggest that although malaria incidence has declined, the fundamental ecological factors associated with transmission have not disappeared [14, 18]. Similar patterns have been reported in other low-transmission or pre-elimination settings, where humidity and rainfall variability continue to influence seasonal risk even as overall incidence falls [19]. Interestingly, sunshine duration demonstrated a negative association with malaria incidence in the unadjusted correlation analyses but exhibited a positive independent association in the multiple regression model. This apparent discrepancy likely reflects the interrelationships among climatic predictors, particularly rainfall and humidity. While correlation analyses describe crude bivariate associations, multivariable regression estimates the independent contribution of each predictor after adjusting for the effects of the remaining variables. Consequently, directional changes in regression coefficients may arise from suppression or shared variance among correlated environmental exposures and do not necessarily indicate inconsistency in the analytical findings. These findings highlight the importance of maintaining climate-sensitive surveillance systems that incorporate humidity, rainfall, temperature, and sunshine during malaria elimination efforts, as declining case numbers may obscure persistent environmental vulnerability.

This interpretation is further supported by the multicollinearity assessment, which demonstrated low variance inflation factors and only low-to-moderate correlations among the climatic predictors, indicating that severe multicollinearity was unlikely to explain the observed coefficient changes.

The significant structural break analysis together with the observed period × humidity interaction supports the presence of temporal variation in the climate–malaria relationship after 2019. Therefore, the previously observed underestimation before 2019 and overestimation thereafter are unlikely to reflect random model error alone. Instead, these findings suggest that changes in humidity-related effects, together with unmeasured non-climatic factors such as malaria control interventions, healthcare access, surveillance practices, or population mobility, may have contributed to temporal variation in malaria transmission. Because these non-climatic variables were not directly measured, these explanations should be interpreted as plausible mechanisms rather than confirmed causal factors.

The study also aligns with international evidence indicating that seasonal variables are more effective at predicting transmission timing than outbreak magnitude [13]. Factors such as cross-border movement, access to healthcare, vector control coverage, and socio-economic conditions play a critical role in shaping malaria outcomes, particularly in marginalized populations [20]. In Bangladesh, challenges related to terrain, mobility, and service delivery in endemic regions may interact with climatic conditions to sustain transmission pockets despite national progress [21]. Consistent with these observations, the regression model accurately reproduced the seasonal timing of malaria transmission but showed a tendency to underestimate peak incidence during earlier outbreak years while overestimating transmission during some of the more recent years. This temporal pattern suggests that additional time-varying determinants beyond climatic conditions contributed to changes in malaria epidemiology over the study period. Progressive implementation of malaria control interventions, improvements in diagnosis and treatment, changes in vector control coverage, population mobility, land-use changes, and cross-border transmission dynamics may have modified malaria incidence independently of climatic variability. Consequently, although climate remained an important determinant of seasonal transmission patterns, temporal changes in programmatic and socio-environmental factors likely contributed to the observed prediction bias.

This study demonstrates that long-term seasonal influences on malaria transmission remain detectable and relevant, even in a context of declining incidence. The findings support the study hypothesis that climate-driven seasonality persists and can inform preparedness efforts, while also emphasizing the limitations of climate-only models in predicting transmission intensity. These insights are particularly important for sustaining gains toward malaria elimination and preventing resurgence. From a policy perspective, these findings support the development of climate-informed early warning systems. For example, increases in rainfall and humidity could trigger pre-emptive vector control measures such as indoor residual spraying and distribution of insecticide-treated nets. Seasonal forecasts may also guide resource allocation and surveillance intensity, particularly in high-risk districts.

Limitations

Due to the ecological and correlational design of this study, causal relationships between climatic variables and malaria incidence cannot be established. The study's ecological design and reliance on aggregated surveillance data limit its ability to capture localized transmission heterogeneity and individual-level risk factors. Additionally, non-climatic determinants such as population movement, land-use changes, vector control interventions, and socio-economic conditions were not included in the model, which may confound the observed associations and contribute to residual variability in malaria transmission.

Although preliminary analyses explored interaction terms between key climatic variables (rainfall × humidity), these were not retained in the final model due to lack of statistical significance and concerns regarding multicollinearity. Therefore, potential synergistic effects between climatic factors may not be fully captured.

The absence of programmatic and socio-environmental variables restricts interpretation of socio-environmental factors of malaria persistence. Additionally, although multiple linear regression provided an interpretable framework for examining long-term climatic associations, it does not explicitly model autocorrelation, non-stationarity, or complex temporal dependencies that commonly occur in time-series data. Advanced analytical approaches, including autoregressive integrated moving average with exogenous variables (ARIMAX), generalized additive models (GAMs), and distributed lag models, may better characterize these temporal processes and improve predictive performance. Future studies should evaluate these approaches using longer surveillance datasets. Also, the findings underscore the importance of incorporating rainfall, humidity, temperature and sunshine indicators into malaria surveillance and elimination planning. Future research should adopt more advanced analytical frameworks, including interaction modeling and integrated approaches combining climatic, entomological, and health system data at finer spatial scales, to better elucidate the complex factors of malaria transmission. Future investigations may also benefit from decomposing malaria time series into trend, seasonal, and irregular components before model development to better distinguish long-term epidemiological changes from seasonal fluctuations and random variation. Strengthening climate-informed surveillance alongside targeted interventions in endemic regions is recommended to sustain progress toward malaria elimination.

Conclusion

This study assessed the role of seasonal variability in shaping long-term malaria transmission patterns in Bangladesh. The findings confirm that malaria transmission retains a stable seasonal structure influenced by environmental conditions, supporting the hypothesis that sunshine, temperature, humidity, and rainfall continue to regulate transmission timing even as overall incidence decreases. These findings reinforce the need for sunshine, humidity, rainfall, and temperature-informed surveillance and preparedness as part of malaria elimination strategies. Integrating seasonal insights with targeted control measures, in endemic regions, may help prevent resurgence and sustain national progress toward elimination.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s41182-026-01047-w.

Supplementary material 1.

Supplementary material 2.

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Author contributions

S.A. conceptualized the study, curated the data, conducted formal analysis and investigation, developed the methodology, managed software and resources, performed visualization, and wrote the original draft of the manuscript. Z.A. contributed to formal analysis, investigation, methodology development, resource management, visualization, and participated in manuscript review and editing. R.A. was responsible for data curation, investigation, software handling, visualization, and contributed to reviewing and editing the manuscript. R.H., M.M.A. and T.M. supported the study through formal analysis and visualization and contributed to manuscript review and editing. M.M.H.S. led conceptualization, contributed to formal analysis, investigation, and methodology, performed validation and visualization, and was actively involved in writing the original draft as well as reviewing and editing the manuscript. S.K. contributed to conceptualization and methodology, provided supervision and validation, and participated in manuscript review and editing. All authors reviewed and approved the final version of the manuscript.

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Data availability
The datasets analyzed during the current study are derived from publicly available or institutionally authorized sources, including the Directorate General of Health Services and the Bangladesh Meteorological Department. All data supporting the findings of this study are presented within the article.

Declarations

Ethics approval and consent to participate
Ethical approval for this study was obtained from the Research Ethics Committee of the Faculty of Health and Life Sciences, Daffodil International University, Dhaka, Bangladesh (Ref. No: DIU/FHLS/REC/2025/28). The study utilized anonymized, aggregated secondary data obtained from national surveillance and meteorological authorities. No individual-level identifiers were accessed. Institutional permissions were obtained from the Directorate General of Health Services (DGHS) and the Bangladesh Meteorological Department (BMD) prior to data use. This study was based exclusively on secondary, aggregated data collected routinely by government agencies for surveillance and administrative purposes. No direct human participation, interaction, or intervention occurred, and no individual-level or identifiable information was used. Therefore, informed consent was not required. The study adhered to the ethical principles outlined in the Declaration of Helsinki and relevant guidelines for public health research using secondary data. No experiments on humans and/or the use of human tissue samples were conducted.

Consent for publication
Not applicable.

Competing interests
The authors declare that they have no competing interests.

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