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Research Article

Temporal Association of Climatic Factors with Dengue Incidence and Forecasting Using SARIMAX Model: A Time Series Study in Karnataka, India

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Abstract

Background: Dengue are Aedes-transmitted arboviral diseases whose transmission dynamics are strongly modulated by climatic conditions. Karnataka in India, experiences recurrent, seasonally variable dengue but region-specific forecasting models that incorporate climatic predictors remain limited.

Objectives: (1) To describe the temporal distribution of monthly dengue cases and climatic variables in Karnataka, India; (2) To develop and evaluate a SARIMAX model incorporating climatic variables for forecasting monthly dengue cases in Karnataka, India

Methods: In this retrospective time-series study, monthly dengue case counts from September 2021 to December 2025 were obtained from the Commissionerate of Health & Family Welfare Services, Government of Karnataka and matched with monthly climatic data like minimum, average and maximum temperature, relative humidity, rainfall, wind speed, and solar radiation. Series were log-transformed and rendered stationary by first-order non-seasonal and seasonal differencing. Cross-correlation function (CCF) analysis identified biologically plausible lagged climatic predictors, which were incorporated as exogenous variables in candidate SARIMAX models compared using stationary R^2, RMSE, MAPE, normalized BIC, and the Ljung-Box test, in IBM SPSS Statistics 2025, with a significance level of $p < 0.05$.

Results: Monthly dengue cases averaged 856.5 (SD 1029.0; range 8-5738), with a marked outbreak in 2023. CCF analysis identified significant positive lagged associations for rainfall (lag 7), wind speed (lag 7), solar radiation (lag 6) and humidity (lag 3) and a significant negative association for minimum temperature (lag 2). SARIMAX$(0,1,1)(0,1,1)_{12}$ was selected as the best-fitting model (stationary $R^2 = 0.218$, RMSE = 3022.6, normalized BIC = 16.894, Ljung-Box $Q = 12.98$, df = 16, $p = 0.675$), although none of the individual exogenous predictors reached conventional statistical significance (all $p > 0.05$), with minimum temperature at lag 2 showing

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the strongest, near-significant association (p = 0.098). Twelve-month forecasts indicated low dengue activity from January-April 2026 followed by a sharp monsoon-associated rise, peaking in July-August 2026, with wide prediction intervals during the peak months.

Conclusion: A SARIMAX (0,1,1) $(0,1,1)_{12}$ model incorporating lagged climatic predictors adequately captured the seasonal, monsoon-linked pattern of dengue transmission in Karnataka. Therefore, the model may be more useful for identifying periods of potentially increased dengue risk than for predicting the precise number of dengue cases in 2026, despite limited statistical power to confirm individual climatic effects. These findings support the potential value of climate-informed early-warning systems for dengue control in Karnataka, while highlighting the need for longer surveillance series to strengthen predictor level inference.

Keywords: Dengue, SARIMAX, time series forecasting, climatic factors, Karnataka, India

Introduction:

Dengue is one of the fastest-growing mosquito-borne viral diseases worldwide, causing an estimated several hundred million infections each year, particularly in tropical and subtropical regions.[1] In India, the disease has become endemic across many states and is characterised by recurrent outbreaks with a marked seasonal pattern linked to the southwest and northeast monsoon periods. Karnataka, like other states in peninsular India, experiences repeated dengue outbreaks, which continue to impose a considerable and persistent burden on the state's public health system. The transmission of dengue virus depends on the population dynamics of Aedes aegypti and Aedes albopictus mosquitoes, which are themselves highly sensitive to ambient climatic conditions. Rainfall creates and sustains larval breeding habitats, temperature governs mosquito development rate, survival and the extrinsic incubation period of the virus within the vector and relative humidity influences adult mosquito survival and biting behaviour. Because these biological processes unfold over weeks to months, the effect of a given climatic exposure on case counts is typically delayed, motivating the use of lagged climatic predictors in dengue forecasting models.

A substantial body of time-series and regression-based literature has examined climate-dengue associations in diverse settings[2,3,4,5,6,7,8,9, 10. 11.15, 16,17,18] .Across these studies, rainfall, temperature, humidity and wind speed have repeatedly emerged as relevant predictors, but the specific variables and lag lengths identified vary considerably between regions, consistent with local differences in vector ecology, land use and monsoon or rainy-season timing. This heterogeneity underscores the need for region-specific climate-informed forecasting models rather than direct extrapolation of findings from other settings.

Despite the recurrent burden of dengue in Karnataka, region-specific forecasting models that formally incorporate climatic variables as exogenous predictors remain limited. The Seasonal Autoregressive Integrated Moving Average with Exogenous Variables (SARIMAX) framework extends conventional SARIMA modelling by allowing external, and specifically lagged, climatic predictors to be incorporated directly into the forecasting structure, making it well suited to this task.

The objectives of this study were: (1) to describe the temporal distribution of monthly dengue cases and climatic variables in Karnataka state, India; and (2) to develop and evaluate a SARIMAX model incorporating climatic variables for forecasting monthly dengue cases in Karnataka state, India.

Methods:

Study design and data collection:

This was a retrospective time-series study. Two distinct datasets were used. First, monthly dengue case counts for Karnataka, India from September 2021 to December 2025 were obtained from the Commissionerate of Health & Family Welfare Services, Government of Karnataka (Dengue & Chikungunya - Malaria & H1N1 Reports) [13]. Second, monthly meteorological data minimum temperature (°C), average temperature (°C), maximum temperature (°C), relative humidity (%), rainfall (mm), wind speed (m/s) and solar radiation (W/m²) were obtained from the Karnataka Historical Weather Data & Climate archive (since 1981)[14].

Data analysis:

Outcome variable: Monthly dengue cases.

Independent variables: Minimum, average and maximum temperature (°C), relative humidity (%), rainfall (mm), wind speed (m/s), and solar radiation (W/m²).

Descriptive statistics: Descriptive statistics were calculated to summarize the characteristics of the monthly dengue case data and climatic variables. Continuous variables were described using minimum and maximum values, range, mean, standard deviation (SD), skewness and kurtosis.

Time-series plots: Time-series plots were generated to visualize temporal trends and seasonal variation in dengue incidence and climatic factors. Missing observations of the dengue cases in the month of April 2023, January 2025, February 2025 and March 2025 and climate variable solar radiation of December 2025 were handled using linear interpolation prior to analysis to maintain continuity of the monthly series.

SARIMAX model: A Seasonal Autoregressive Integrated Moving Average with Exogenous Variables (SARIMAX) model was used to forecast monthly dengue cases while incorporating climatic variables as external predictors. Monthly dengue case data and climatic variables were first transformed using the natural logarithm to stabilize variance and rainfall was transformed using ln(x+1) to accommodate zero rainfall observations. Stationarity of the transformed series was achieved through first-order non-seasonal differencing (d = 1) and first-order seasonal differencing (D = 1) with a seasonal period of 12 months.

Cross-correlation function analysis: Cross-correlation function analysis was performed between dengue cases and climatic variables to identify significant lagged relationships. Stationarity was achieved before Cross-correlation analysis of dengue cases and climatic variables. Cross-correlation functions were examined over lags from −7 to +7 months. A positive lag indicated that the climatic variable preceded dengue incidence by the corresponding number of months, whereas a negative lag indicated the reverse temporal direction. Significance limits were based on the standard 95% confidence limits provided by the CCF analysis.

For a cross-correlation function (CCF), the approximate 95% confidence limits are commonly calculated as:

$$\pm 1.96/\sqrt{N}$$

where:

N = number of observations used in the CCF

1.96 = the standard normal critical value for a two-sided 95% confidence level.

$\pm 1.96/\sqrt{52}$

The range is from −0.272 to +0.272

Therefore, a CCF coefficient outside approximately ± **0.272** would be considered statistically significant at the 5% level under this approximate method, which is exactly the same as a critical value or table value of r = 0.27 at p=0.05.[12] Dengue cross-correlation functions (CCFs) were examined to assess temporal associations between incidence and climatic variables at different lags. The CCF plots included approximate 95% confidence limits, with cross-correlation coefficients extending beyond these limits considered statistically significant at the 5% level. Pre-whitening was not performed; therefore, the observed CCF associations were interpreted as exploratory temporal associations.

The lag periods included in the SARIMAX model were selected based on statistically significant cross-correlations observed in the exploratory CCF analysis. The seven-month lag identified for rainfall, wind speed and solar radiation represents a statistical temporal association and should not be interpreted as evidence of a direct biological effect persisting for seven months.

SARIMAX model evaluation: Candidate models were identified using the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots and compared using model-selection criteria, including the Bayesian Information Criterion (BIC), root mean square error (RMSE), mean absolute percentage error (MAPE), The final model was selected based on the highest stationary R^2, lowest RMSE, MAPE and normalized BIC, together with satisfactory residual diagnostics. The non-significant Ljung–Box test provided no evidence of significant residual autocorrelation. Forecasts of monthly dengue cases were generated for the study forecast period using projected values of the selected climatic variables.

Statistical analysis: Analyses were performed using IBM SPSS Statistics 2025, with a significance level of $p < 0.05$.

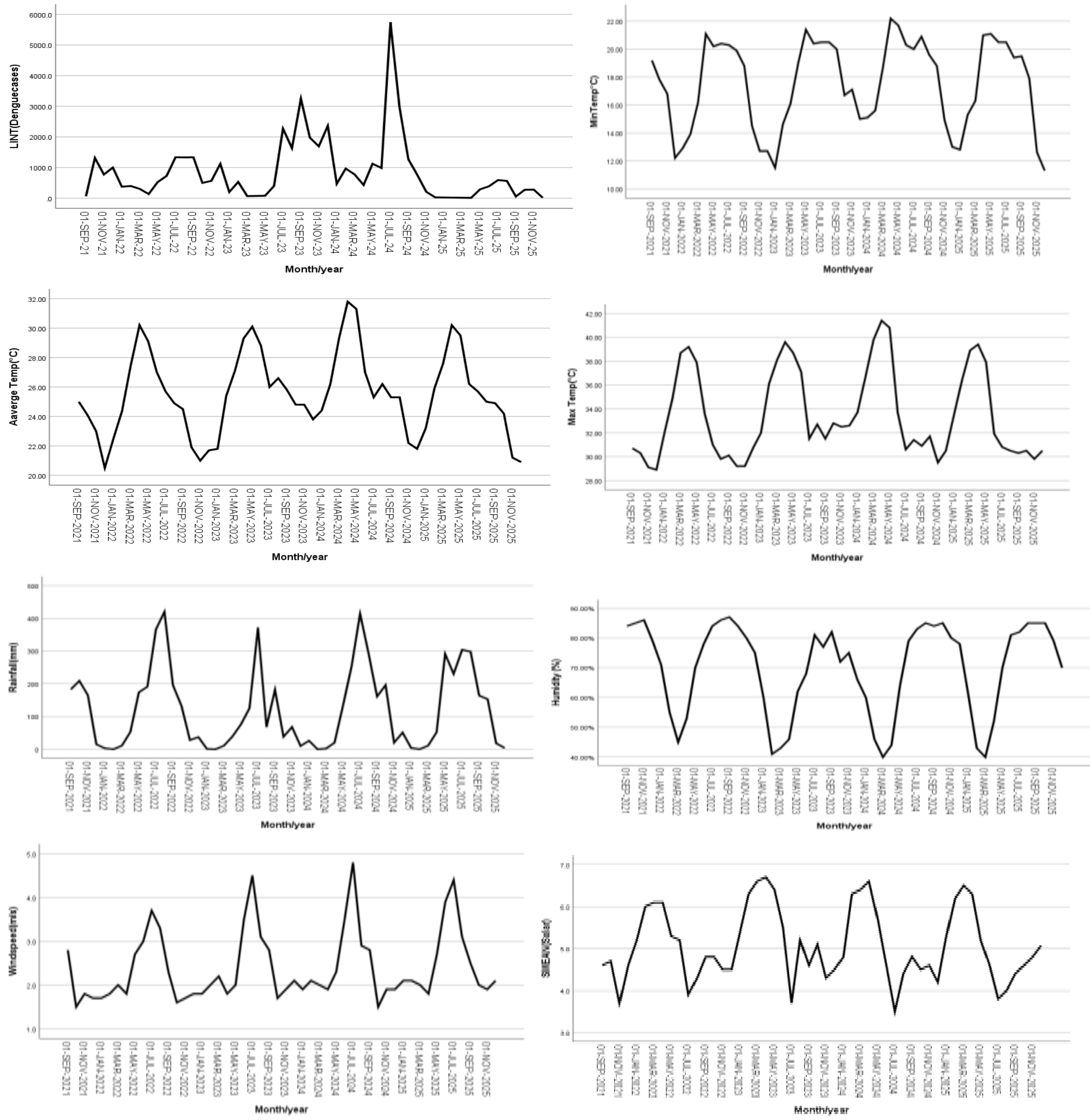
Results :

Table 1: Temporal pattern of dengue cases and climatic variables from September 2021 to December 2025.

Variable	Range	Minimum	Maximum	Sum	Mean	SD	Skewness	Kurtosis
Dengue cases	5730.00	8.00	5738.00	44539.0	856.52	1029.04	2.63	9.38
Min. Temp (°C)	10.90	11.30	22.20	911.40	17.53	3.20	-0.46	-1.16
Avg. Temp (°C)	11.30	20.50	31.80	1327.90	25.54	2.83	0.26	-0.46
Max. Temp (°C)	12.50	28.90	41.40	1741.60	33.49	3.711	0.68	-0.96
Rainfall (mm)	420	0	420	6273	120.63	122.99	0.89	-0.22
Humidity (%)	47.00	40.00	87.00	3636.00	69.92	15.40	-0.75	-0.85
Wind speed (m/s)	3.3	1.5	4.8	124.7	2.40	0.81	1.37	1.23
Solar radiation (W/m²)	3.2	3.5	6.7	263.8	5.07	0.87	0.35	-0.88

Monthly dengue cases from September 2021 to December 2025 had a mean of 856.52 (SD = 1029.04), ranging from 8 to 5738 cases. Dengue incidence exhibited marked positive skewness (2.63) and high kurtosis (9.38), indicating occasional epidemic peaks. Mean minimum, average, and maximum temperatures were 17.53°C (SD = 3.20), 25.54°C (SD = 2.83), and 33.49°C (SD = 3.71), respectively. Mean monthly rainfall was 120.63 mm (SD = 122.99), and relative humidity averaged 69.92% (SD = 15.40). Wind speed and solar radiation had mean values of 2.40 m/s (SD = 0.81) and 5.07 W/m² (SD = 0.87) respectively. Most climatic variables showed approximately symmetric distributions, whereas rainfall and wind speed showed positive skewness.

Figure 1: Sequential charts of dengue cases and climatic factors.



The sequential charts (Figure 1) illustrate the temporal trends of monthly dengue incidence and climatic variables during the study period. Dengue incidence demonstrated marked seasonal and interannual variation, with relatively few cases during the early months of each year, followed by a gradual increase during the monsoon and post-monsoon seasons. The highest dengue incidence was observed in 2023, indicating a major outbreak, after which cases declined in 2024 and remained comparatively lower during 2025.

The climatic variables exhibited distinct seasonal patterns. Rainfall showed sharp peaks during the monsoon months and low values during the dry season. Maximum, minimum, and mean temperatures displayed regular annual cycles with moderate fluctuations. Relative humidity remained high during the monsoon season and decreased during the dry months. Wind speed showed moderate fluctuations with less pronounced seasonality than rainfall and humidity. Solar radiation demonstrated a clear seasonal cycle, with higher values during summer months and lower values during the monsoon, reflecting changes in cloud cover and sunshine duration.

Visual inspection of the sequential charts suggested that increases in dengue incidence generally followed periods of high rainfall and relative humidity, while temperature, solar radiation and wind speed appeared to influence dengue transmission indirectly through seasonal environmental conditions. These temporal patterns indicated a likely lagged relationship between climatic factors and dengue incidence, supporting the inclusion of lagged climatic variables in the subsequent cross-correlation and SARIMAX analyses.

Figure 2: Stationarity achievement of dengue cases and climatic factors.

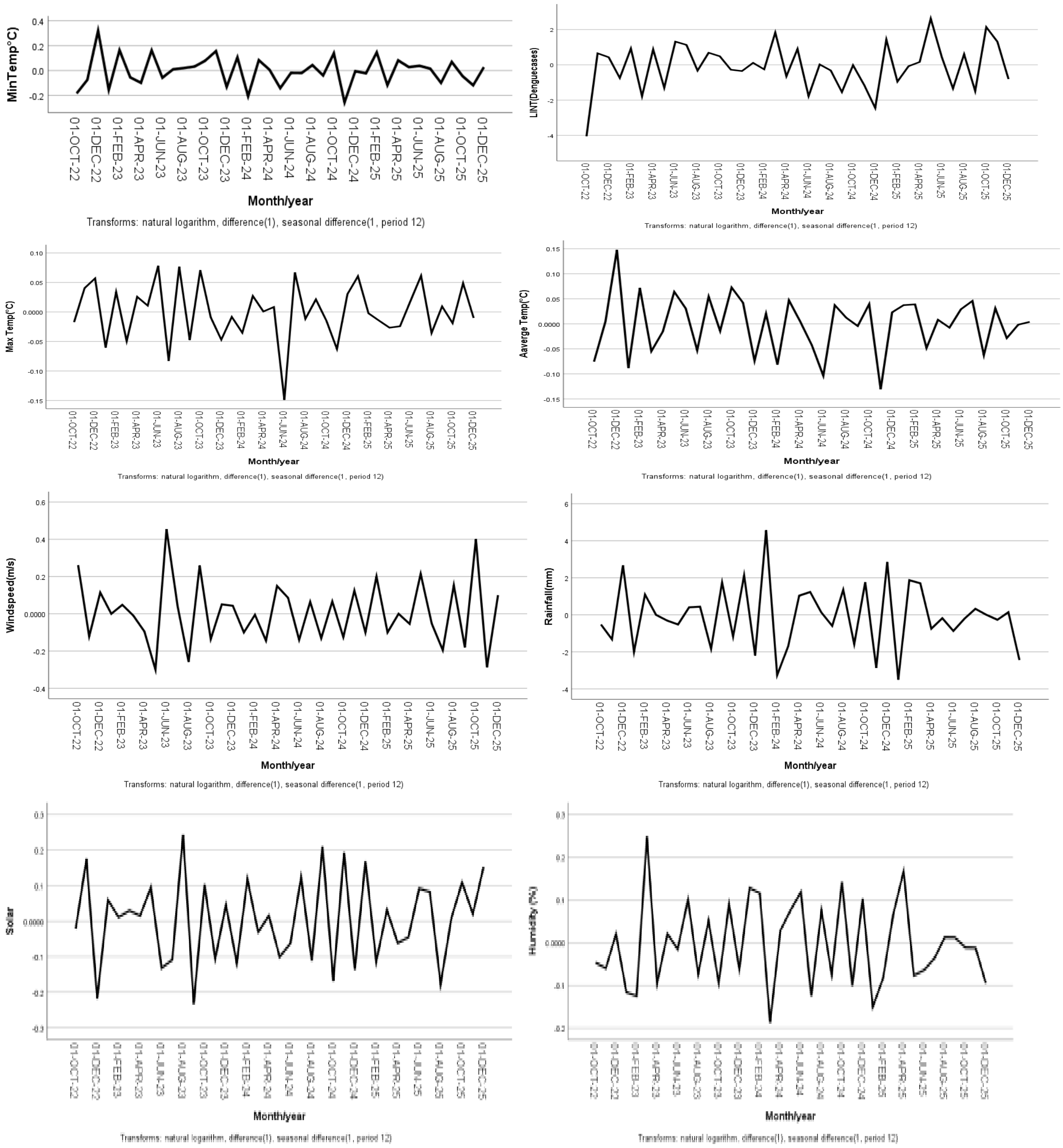
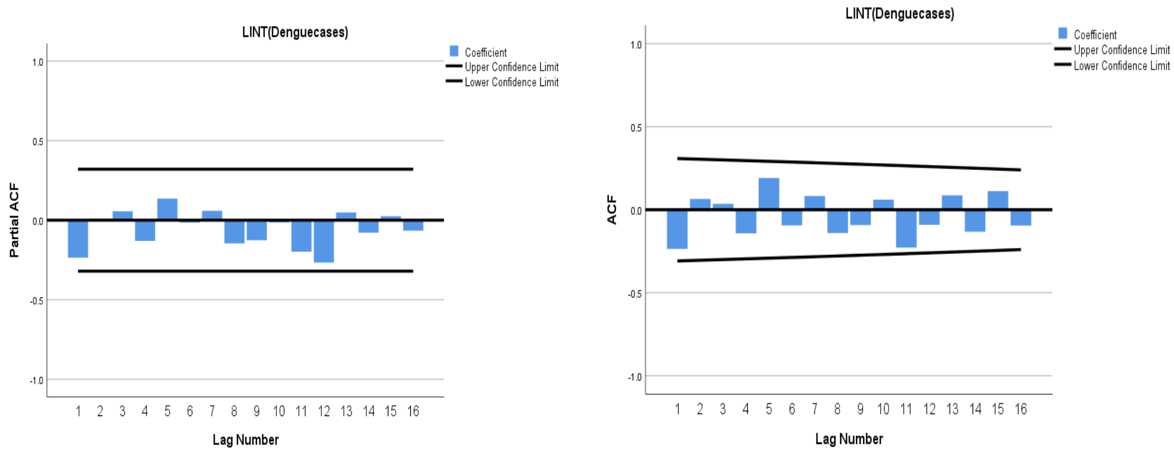
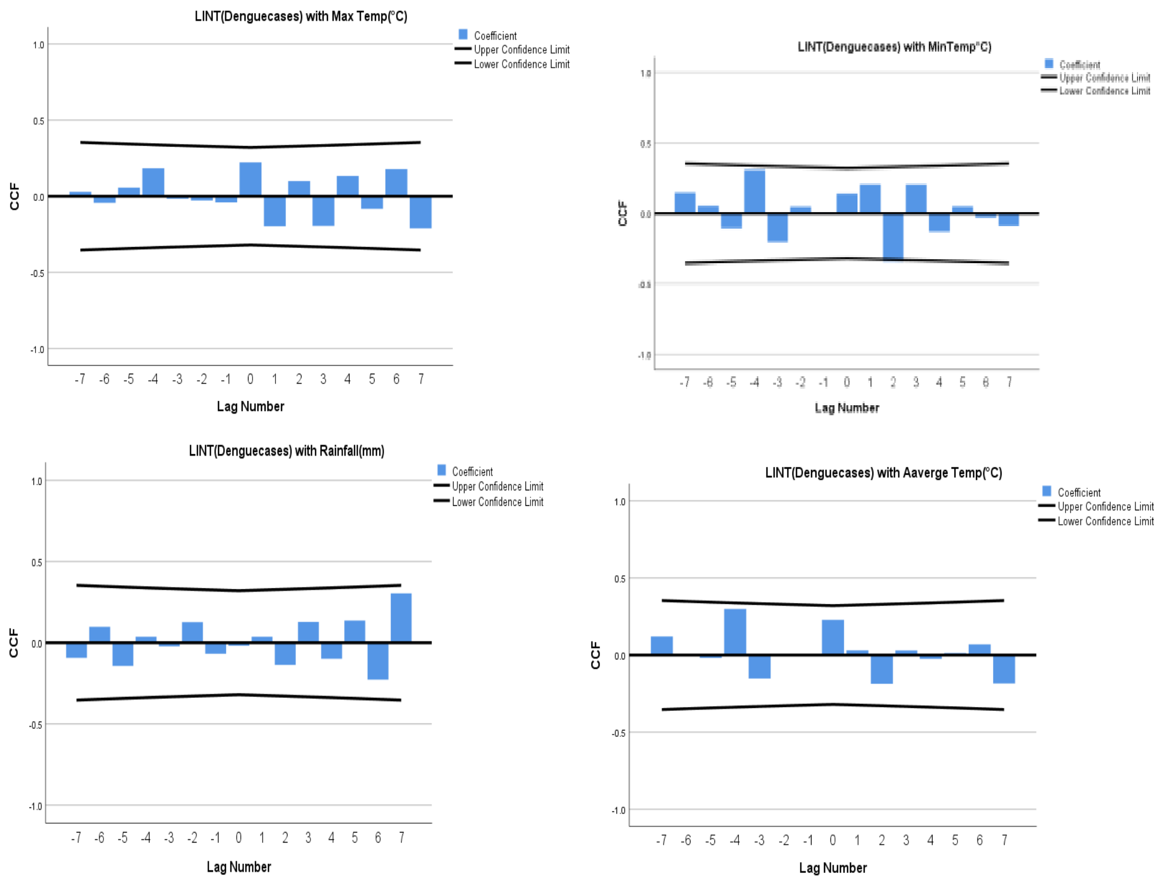


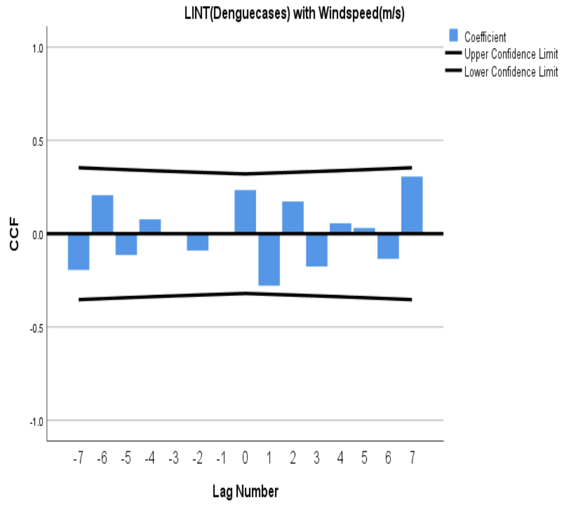
Figure 3: Autocorrelation of dengue cases.

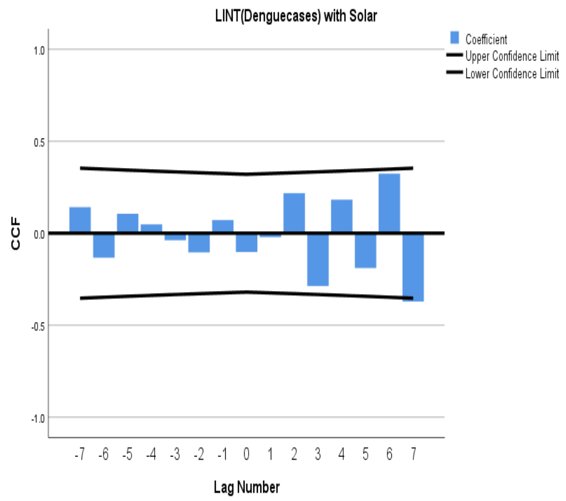


With first-order non-seasonal differencing (d = 1) and first-order seasonal differencing (D = 1) applied to the natural log-transformed series (Figure 2), the series achieved stationarity. The ACF and PACF plots of the differenced series (Figure 3) displayed rapid decay to insignificance, confirming successful stationarity transformation and enabling reliable model identification for dengue cases.[12]

Figure 4: Cross-correlation of dengue cases and climatic factors.







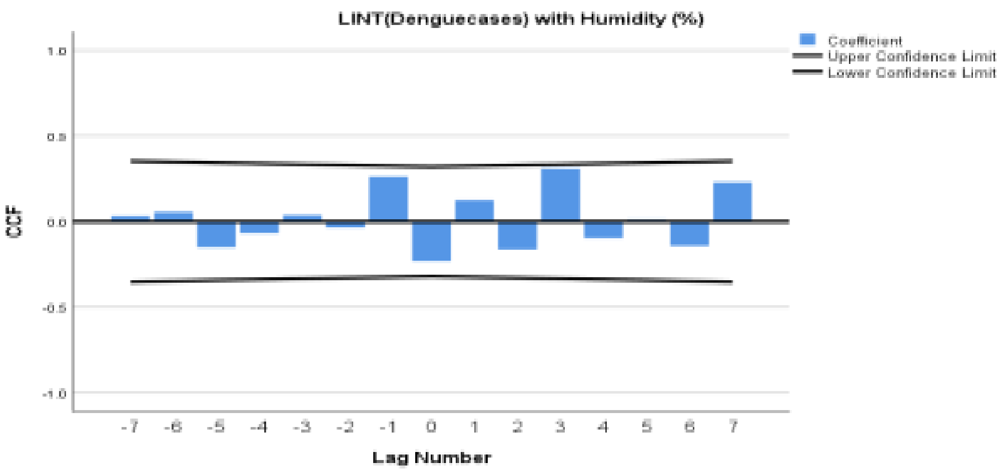


Table 2: Significant cross-correlations between dengue cases and climatic variables.

Variables	Lag (months)	Correlation (r)	Standard error	P-value	Interpretation
Min. Temp	-4	0.310	0.169	P<0.05	Significant
Min. Temp	2	-0.343	0.164	P<0.05	Significant
Rainfall	7	0.304	0.177	P<0.05	Significant
Wind Speed	1	-0.280	0.162	P<0.05	Significant
Wind Speed	7	0.306	0.177	P<0.05	Significant
Solar	6	0.324	0.174	P<0.05	Significant
Solar	7	-0.371	0.177	P<0.05	Significant
Humidity	3	0.309	0.167	P<0.05	Significant

Cross-correlation analysis identified significant associations between dengue incidence and several climatic variables at different time lags (Figure 4, Table 2). Minimum temperature showed a significant positive correlation at lag -4 months ($r = 0.310$, $p < 0.05$) and a significant negative correlation at lag 2 months ($r = -0.343$, $p < 0.05$). Rainfall showed a significant positive correlation at lag 7 months ($r = 0.304$, $p < 0.05$). Wind speed was significantly negatively correlated at lag 1 month ($r = -0.280$, $p < 0.05$) and positively correlated at lag 7 months ($r = 0.306$, $p < 0.05$). Solar radiation showed a significant positive correlation at lag 6 months ($r = 0.324$, $p < 0.05$) and a significant negative correlation at lag 7 months ($r = -0.371$, $p < 0.05$). Relative humidity showed a significant positive correlation at lag 3 months ($r = 0.309$, $p < 0.05$).

For the SARIMAX model, climatic variables with biologically plausible positive time lags were considered as candidate exogenous variables. Accordingly, minimum temperature (lag 2), rainfall (lag 7), wind speed (lag 7), solar radiation (lag 7), and relative humidity (lag 3) were selected for model development. Variables with negative lags were not included in the forecasting model, as they do not represent preceding climatic conditions capable of influencing future dengue incidence.

Table 3: Comparison and selection of SARIMAX models.

SARIMAX**(p,d,q)(P,D,Q)12**	**Stationary R²**	**RMSE**	**MAPE**	**MAE**	**Norm. BIC**	**Ljung-Box Q (df, p)**
SARIMAX(0,1,0)(0,1,0)	0.152	3452.22	277.73	1650.75	16.94	11.02(df=18, p=0.894)
SARIMAX(1,1,0)(0,1,0)	0.171	3711.73	291.32	1748.93	17.20	10.66 (df=17, p=0.894)
SARIMAX(0,1,1)(0,1,0)	0.175	3709.38	294.84	1732.14	17.19	10.81(df=17, p=0.866)
SARIMAX(1,1,1)(0,1,0)	0.190	3388.09	299.61	1554.34	17.12	11.88(df=16, p=0.758)
SARIMAX(1,1,1)(0,1,1)	0.206	3067.21	308.22	1427.30	17.03	12.53 (df=15, p=0.640)
SARIMAX(0,1,1)(0,1,1)	0.218	3022.62	306.50	1476.01	16.89	12.98 (df=16, p=0.675)
SARIMAX(1,1,0)(0,1,1)	0.195	3218.20	298.41	1583.57	17.02	12.45 (df=16, p=0.712)
SARIMAX(0,1,0)(0,1,1)	0.152	3545.45	286.87	1682.74	17.11	11.31 (df=17, p=0.840)

Among the evaluated SARIMAX models, SARIMAX (0,1,1) $(0,1,1)_{12}$ was selected as the optimal forecasting model (Table 3). This model demonstrated the highest stationary R^2 (0.218), the lowest RMSE (3022.62) and the lowest normalized BIC (16.89). The Ljung-Box test was non-significant $Q = 12.98$ ($df = 16$, $p = 0.675$), indicating that residuals were independently distributed and that the model adequately captured temporal dependence in the dengue case series. This model was therefore considered the most appropriate for forecasting monthly dengue cases.

Table 4: SARIMAX (0,1,1) $(0,1,1)_{12}$ model parameter estimates and model adequacy (natural log-transformed dengue cases).

Parameter	**Estimate**	**Standard error**	**T - test**	**P-value**
Constant	5.212	4.398	1.185	0.248
MA (1)	0.373	0.221	1.683	0.105
Seasonal MA (1)	0.427	0.446	0.959	0.347
Min. Temp, lag 2	-0.249	0.145	-1.720	0.098
Rainfall, lag 7	-0.004	0.005	-0.836	0.411
Wind speed, lag 7	0.107	0.536	0.200	0.843
Solar radiation, lag 7	0.208	0.548	0.380	0.707
Humidity, lag 3	-0.023	0.027	-0.862	0.397

Table 4 presents the parameter estimates of the SARIMAX (0,1,1) $(0,1,1)_{12}$ model fitted to the natural log-transformed monthly dengue cases, with meteorological variables included as exogenous predictors. The model incorporated first-order non-seasonal differencing ($d = 1$) and first-order seasonal differencing ($D = 1$) to achieve stationarity.

The estimated intercept ($\beta = 5.212$, $SE = 4.398$) was not statistically significant ($t = 1.185$, $p = 0.248$). The non-seasonal moving average component, MA(1), had a positive coefficient ($\beta = 0.373$, $SE = 0.221$)

that was not statistically significant (t = 1.683, p = 0.105). The seasonal moving average component, SMA(1), had a positive estimate (β = 0.427, SE = 0.446) that was also not statistically significant (t = 0.959, p = 0.347).

Among the meteorological variables, minimum temperature at a two-month lag showed a negative association with dengue incidence (β = -0.249, SE = 0.145), approaching statistical significance (t = -1.720, p = 0.098). Rainfall at a seven-month lag showed a very small negative effect (β = -0.004, SE = 0.005; p = 0.411), while wind speed at a seven-month lag showed a weak positive association (β = 0.107, SE = 0.536; p = 0.843). Solar radiation at a seven-month lag was also positively associated with dengue incidence (β = 0.208, SE = 0.548; p = 0.707), whereas relative humidity at a three-month lag showed a weak negative association (β = -0.023, SE = 0.027; p = 0.397). None of the meteorological predictors reached the conventional level of statistical significance ($p < 0.05$); minimum temperature at a two-month lag showed the strongest, though non-significant, association with dengue incidence.

Figure 5: Observed and forecasted dengue cases for January 2026 to December 2026, with 95% confidence intervals.

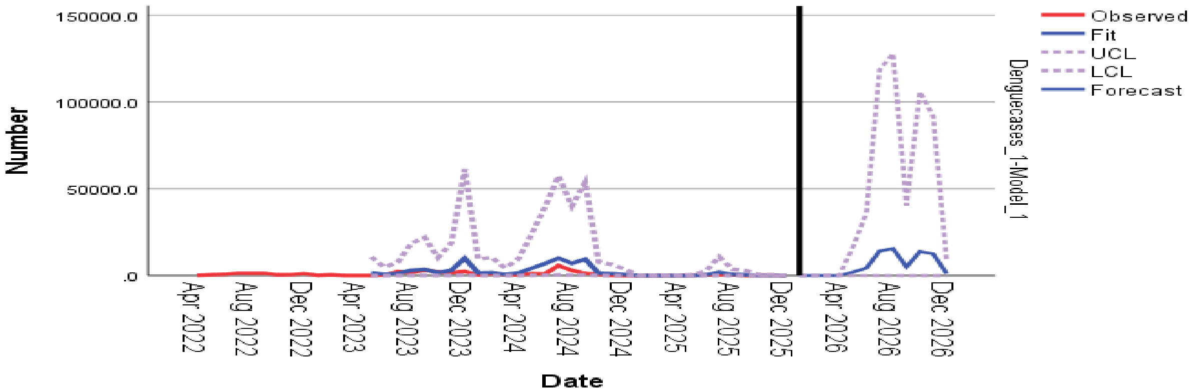


Figure 5 shows the observed, fitted and forecasted monthly dengue cases together with the 95% prediction intervals. The fitted values closely followed the observed dengue trend during the historical period, indicating adequate model fit. The vertical line separates observed data from the forecast period beginning January 2026. The forecast showed a clear seasonal pattern, with relatively low case numbers during the first four months of 2026 followed by a substantial rise from May onward. The highest predicted incidence occurred during July and August, after which cases gradually declined toward the end of the year. The upper and lower confidence limits widened considerably during the peak transmission period, indicating increased uncertainty in the magnitude of future outbreaks while maintaining the expected seasonal trend.

Table 5: Twelve-month dengue case forecast with 95% prediction intervals for SARIMAX$(0,1,1)(0,1,1)_{12}$.

Month/Year	Forecast	95% LCL	95% UCL
January-2026	12	0.5	66.7
February-2026	12	0.3	82.7
March-2026	20	0.2	150.5
April-2026	50	0.3	398.3
May-2026	1984	7.2	16395.7
June-2026	4273	8.9	35899

Month/Year	Forecast	95% LCL	95% UCL
July-2026	14142	17.3	118636.5
August-2026	15495	11.3	127843.4
September-2026	5047	2.2	40429.2
October-2026	13776	3.7	105988
November-2026	12548	2.1	91825.2
December-2026	1165	0.1	8040.3

Table 5 presents the monthly forecasted dengue cases for January-December 2026 from the SARIMAX$(0,1,1)(0,1,1)_{12}$ model, with corresponding 95% prediction intervals. The model predicted relatively low dengue incidence during the initial months of 2026 (12, 12, 20, and 50 cases from January to April, respectively). A sharp increase was projected from May onward, reaching 1984 cases in May and 4273 cases in June, with a seasonal peak in July (14,142 cases) and August (15,495 cases), followed by a gradual decline to 5047 cases in September, 13,776 in October, 12,548 in November and 1165 in December. The wide 95% prediction intervals, particularly during the peak transmission months, indicate greater forecasting uncertainty during periods of high dengue activity while still reflecting the expected seasonal pattern.

Discussion:

This study described the temporal pattern of monthly dengue cases and climatic variables in Karnataka, India, over a 52-month period and developed a SARIMAX$(0,1,1)(0,1,1)_{12}$ model incorporating lagged rainfall, wind speed, solar radiation, minimum temperature, and humidity as exogenous predictors. The model reproduced the seasonal, monsoon-associated pattern of dengue transmission and projected a marked rise in cases from May 2026, peaking in July-August, consistent with the well-established biological link between monsoon rainfall, vector breeding and dengue transmission intensity.

The direction and lag structure of the significant cross-correlations were broadly consistent with the known ecology of Aedes-borne transmission. Rainfall and humidity showed positive associations with dengue at intermediate lags (7 and 3 months, respectively), plausibly reflecting the time required for rainfall-created breeding sites to translate into adult mosquito populations and subsequent transmission, while wind speed and solar radiation showed mixed positive and negative associations at different lags, consistent with their more indirect influence on vector survival and human exposure. This general pattern - climatic variables shaping dengue transmission through lagged, non-linear pathways - mirrors findings reported in dengue time-series studies; however, the specific variables and optimal lags identified have varied across these settings, likely reflecting differences in monsoon timing, vector species composition and local ecology[2,4,5,6,7,8,9,10,11,15,16,17,18].

A time-series analysis from the study[3] that combined SARIMA, XGBoost, and Poisson regression similarly found that temperature, humidity, and wind speed were significantly associated with increased dengue incidence, reinforcing the broad relevance of these climatic drivers across South Asian dengue-endemic settings, even though the specific incidence rate ratios and optimal lag structures differed from those identified in the present study. Such cross-country variation is consistent with the view that climate-dengue relationships, while directionally similar in many settings, require local calibration rather than direct transfer of model parameters between regions.

Notably, none of the climatic predictors in the final SARIMAX model reached conventional statistical significance, although minimum temperature at a two-month lag approached significance and showed the largest effect size.

This attenuation of predictor-level significance within the fully specified model, despite significant bivariate cross-correlations, likely reflects several factors: the relatively short 52-month series limited statistical power to detect exogenous effects once autoregressive and seasonal moving-average terms were included; correlated climatic variables (for example, temperature, humidity, and rainfall) may have shared overlapping explanatory variance and the seasonal differencing and moving-average terms themselves may have absorbed much of the recurring seasonal climatic signal, leaving comparatively little residual variance for the exogenous predictors to explain. Similar challenges in isolating independent climatic effects within multivariable time-series or regression frameworks have been noted in other dengue-climate studies, underscoring a recurring methodological tension between model parsimony and the inclusion of biologically motivated but individually weak predictors[7,8].

The wide 95% prediction intervals surrounding the forecasted peak months are consistent with the marked positive skewness (2.63) and high kurtosis (9.38) observed in the dengue case series, reflecting the episodic, outbreak-prone nature of dengue transmission. Comparable forecasting uncertainty during high-incidence periods has been reported in other SARIMA- and machine-learning-based dengue forecasting studies, which have similarly found that peak-season predictions carry substantially wider uncertainty than low-transmission periods, and that model performance during outbreak years can be difficult to capture fully even with well-fitting overall models[3,10,18].

This study has several strengths, including the use of a rigorous, sequential analytical workflow (stationarity testing, cross-correlation analysis with pre-differencing and systematic model comparison), the incorporation of five biologically plausible climatic predictors and the surveillance of dengue, which are frequently co-circulating in Karnataka. Nonetheless, several limitations should be noted. of the present study was the relatively short time series comprising 52 monthly observations. The inclusion of seasonal and non-seasonal components together with multiple climatic predictors may have reduced the statistical power and stability of parameter estimates. Therefore, the findings should be interpreted cautiously and require validation using longer time-series datasets.

Conclusion:

A SARIMAX(0,1,1)(0,1,1)$_{12}$ model incorporating lagged rainfall, wind speed, solar radiation, minimum temperature, and humidity reproduced the seasonal, monsoon-linked pattern of dengue transmission in Karnataka, India and although the model captured the projected seasonal pattern of dengue incidence, the wide prediction intervals indicated substantial uncertainty in the quantitative forecasts Therefore, the model may be more useful for identifying periods of potentially increased dengue risk than for predicting the precise number of dengue cases.

Although none of the individual climatic predictors reached statistical significance in the final model, their biologically plausible direction and lag structure, together with the model's overall fit, support the potential value of climate-informed, SARIMAX-based forecasting as a component of dengue early-warning systems in Karnataka. Future work incorporating longer surveillance series, sub-regional data and entomological indices and comparing SARIMAX performance against alternative forecasting approaches may help to strengthen predictor-level inference and improve forecast precision.

Declarations

Competing Interests

The authors declare that they have no competing interests.

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Use of Artificial Intelligence
The authors declare that artificial intelligence (AI) tools were used only for language editing, grammar correction, and improvement of the clarity and readability of the manuscript. AI tools were not used to generate, analyse, or interpret the study data, develop the statistical methodology, or draw scientific conclusions. The authors take full responsibility for the accuracy, originality, and integrity of the final manuscript.

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