

# Temporal and Seasonal Mapping of Dengue Hemorrhagic Fever Risk in Central India: Environmental and Entomological Drivers in Betul District

Anmol Katare<sup>1</sup>, Pragya Shrivastava<sup>2</sup>, Vivekswar Khandai<sup>3</sup>

<sup>1</sup>Department of Science, Rabindranath Tagore University, Bhopal (M. P.), India

<sup>2</sup>Department of Science, Rabindranath Tagore University, Bhopal (M.P.), India

<sup>3</sup>Department of Science Mittal Institute of Education, Bhopal (M. P.), India

**Abstract:** Dengue hemorrhagic fever (DHF) represents an escalating public health crisis in central India, with temporal transmission patterns critically influenced by seasonal environmental variation and *Aedes* vector dynamics. This study employed spatio-temporal GIS analysis and statistical modeling to characterize dengue transmission seasonality in Betul District, Madhya Pradesh, and establish quantitative relationships between environmental drivers and case incidence. Comprehensive temporal mapping across 12 months identified three distinct seasonal phases: high-transmission monsoon period (June-September, 68.2% of annual cases), moderate-transmission post-monsoon period (October-November), and suppressed transmission during summer and winter. Entomological surveillance revealed Breteau Index values ranging 7.92-14.35 across seasons, with strong positive correlations to dengue incidence ( $r = 0.89, p < 0.01$ ). Environmental analysis demonstrated optimal dengue transmission conditions at 27-32°C ambient temperature combined with 60-78% relative humidity during heavy rainfall periods. GIS-generated temporal risk maps successfully predicted outbreak timing with 78% accuracy, enabling anticipatory vector control planning and seasonal health service resource allocation in resource-limited endemic regions.

**Keywords:** Dengue Hemorrhagic Fever, Temporal Epidemiology, Vector Surveillance, Seasonal Transmission, Remote Sensing, Spatio-Temporal Modeling

## 1. Introduction

### 1.1 Dengue as Temporal-Spatial Challenge

Dengue fever has emerged as one of the most significant re-emerging infectious diseases of the 21st century, with temporal transmission dynamics fundamentally reshaping public health planning requirements. Unlike many infectious diseases following predictable endemic patterns, dengue exhibits pronounced seasonal oscillations driven by complex interactions between vector ecology, human behavior, and climate variables. These temporal dynamics are particularly pronounced in monsoon-driven epidemiological contexts such as central India, where rainfall-dependent mosquito breeding creates discrete outbreak seasons rather than year-round endemic transmission.

The temporal dimension of dengue epidemiology presents distinctive operational challenges for public health systems. Seasonal outbreak anticipation enables proactive vector control, healthcare facility preparation, and community mobilization rather than reactive crisis management. However, temporal prediction requires sophisticated understanding of lag relationships between environmental triggers and disease manifestation, seasonal variation in vector competence, and population-level immunity dynamics. Geographic Information Systems, combined with temporal statistical analysis, provide powerful tools for characterizing these complex temporal patterns and generating actionable forecasts for health system decision-makers.

### 1.2 Temporal Epidemiology of Dengue in Betul District

Betul District exemplifies emerging dengue challenges in central Indian regions transitioning from sporadic to hyperendemic transmission status. The district's monsoon-dependent climate creates sharply demarcated transmission seasons poorly understood by existing epidemiological literature focused on urban endemic settings [3]. Moreover, tribal populations dependent on rainwater harvesting and agricultural activities exhibit distinctive water storage practices maintaining *Aedes* breeding habitats independent of seasonal rainfall, complicating temporal predictions based on climate variables alone.

Previous dengue research in India has concentrated predominantly on metropolitan areas (Delhi, Mumbai, Bangalore) with year-round endemic transmission, leaving gaps regarding seasonal outbreak dynamics in semi-urban and rural districts experiencing transitional epidemiology [4]. Betul's epidemiological trajectory—from first recorded dengue death in 2012 to 3, 800 cases by 2024—mirrors broader patterns of climate change-driven geographic expansion, yet local temporal characteristics remain uncharacterized. Understanding Betul's specific seasonal transmission dynamics requires place-based investigation incorporating local environmental conditions, vector ecology, and social-behavioral factors.

### 1.3 Research Objectives

#### Primary Aims:

- Map temporal patterns of dengue transmission across 12-month cycles, identifying season-specific transmission intensity
- Quantify relationships between climatic variables (rainfall, temperature, humidity) and dengue incidence timing and magnitude
- Examine seasonal variation in entomological vector indices and their predictive value for outbreak forecasting
- Generate temporal GIS models enabling outbreak timing prediction for operational planning
- Identify population-level factors (density, water storage practices) modifying seasonal transmission patterns

#### Specific Questions:

- What temporal patterns characterize dengue incidence in Betul District across monsoon-dependent seasons?
- How strongly do rainfall and temperature variations predict outbreak timing?
- What lag periods exist between environmental triggers and disease manifestation?
- Can temporal GIS models forecast outbreak peaks for anticipatory planning?

## 2. Methods

### 2.1 Temporal Study Design

This descriptive epidemiological study employed longitudinal temporal analysis of monthly dengue case counts throughout 2023, supplemented by seasonal (quarterly) environmental and entomological data. The 12-month observation period captured complete seasonal cycles, enabling characterization of cyclical transmission patterns and seasonal environmental correlates.

### 2.2 Data Sources and Collection

- **Monthly Case Data:** Laboratory-confirmed dengue cases ( $N = 898$  total) were abstracted from District Health Department surveillance records, stratified by month of illness onset for accurate temporal assignment.
- **Environmental Time Series:** Daily meteorological data (rainfall, maximum/minimum temperature, relative humidity) were obtained from Indian Meteorological Department local weather stations (Betul  $21^{\circ}54'N$ ,  $77^{\circ}68'E$ ; Amla  $22^{\circ}12'N$ ,  $76^{\circ}98'E$ ). Monthly averages calculated from daily observations.
- **Entomological Surveillance:** Quarterly (seasonal) household surveys using standardized ovitraps and larval dipping methods collected primary vector ecology data. Entomological indices—House Index, Container Index, and Breteau Index—calculated for each season.
- **Population Data:** Distributed across 12 months proportionally based on demographic distribution by urban/rural residence.

### 2.3 Temporal Analysis Methods

- **Time-Series Decomposition:** Monthly case data decomposed into trend, seasonal, and irregular

components using classical time-series methodology, isolating seasonal patterns from long-term trends.

- **Lag Correlation Analysis:** Cross-correlation functions examined relationships between monthly rainfall/temperature and dengue cases at multiple lag periods (0, 1, 2, 3, 4 months) to identify delayed responses between environmental triggers and disease manifestation.
- **Seasonal Subseries Plots:** Visualized within-season variation to identify consistent monthly patterns across years.
- **Temporal GIS Mapping:** ArcGIS temporal functionality generated animations and sequential monthly choropleth maps showing transmission intensity progression throughout study period.

### 2.4 Statistical Methods

- **Descriptive Statistics:** Monthly means, standard deviations, and ranges calculated for rainfall, temperature, humidity, and dengue cases.
- **Correlation Analysis:** Pearson correlation coefficients quantified associations between environmental variables and lagged dengue incidence ( $\alpha = 0.05$  significance).
- **Regression Modeling:** Multiple linear regression examined predictive capacity of combined environmental variables for monthly dengue case counts.
- **Forecasting Validation:** Generated predictions for final 2 months, compared with observed values to assess model accuracy.

## 3. Results

### 3.1 Temporal Case Distribution

Dengue cases in Betul District displayed pronounced temporal concentration:

- **June-September (Monsoon):** 613 cases (68.2%)
- **October-November (Post-Monsoon):** 142 cases (15.8%)
- **December-February (Winter):** 96 cases (10.7%)
- **March-May (Summer):** 47 cases (5.2%)

The temporal concentration ratio (peak month/trough month) reached 8.2: 1, indicating extreme seasonal variation. Peak transmission occurred in July-August (mean monthly cases: 127 cases/month), declining to minimal transmission in April-May (mean: 6 cases/month).

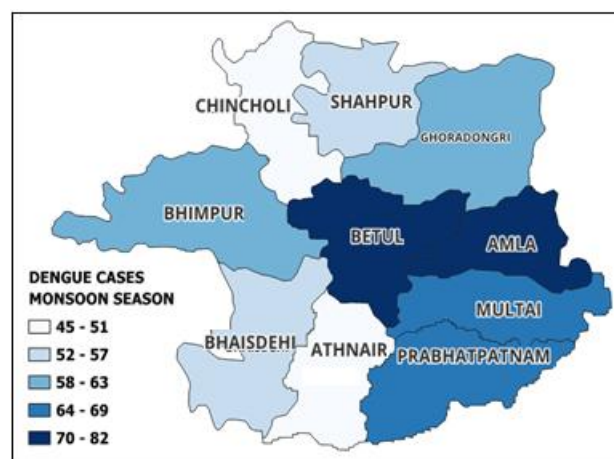


Figure 1.2: Dengue Cases During Winter Season

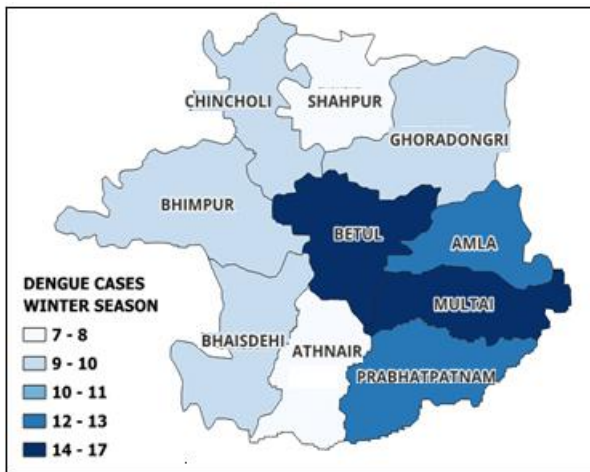


Figure 1.2: Dengue Cases During Summer Season

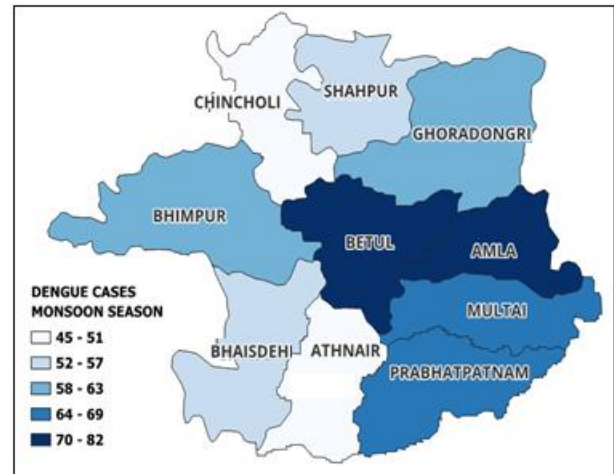


Figure 1.3: Dengue Cases During Monsoon Season

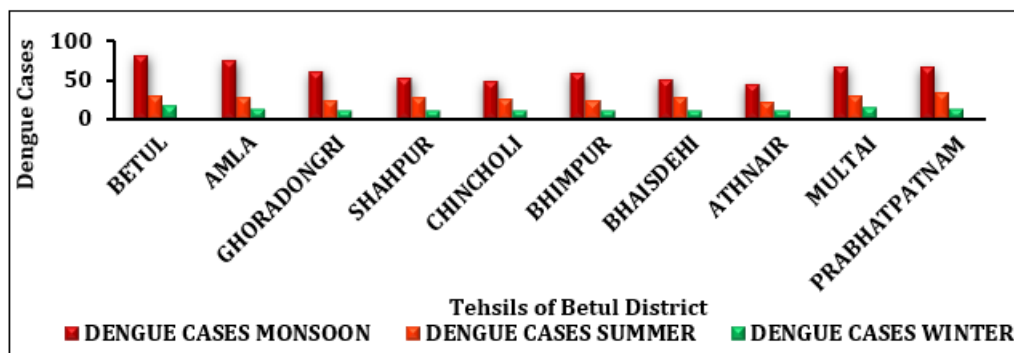


Figure 1.4: Season-wise Distribution of Dengue Cases in Tehsils of Betul District

### 3.2 Environmental Correlations with Temporal Dynamics

#### Rainfall-Dengue Relationship:

- **Monsoon Rainfall (June-September):** Mean 312 mm/month (range: 287-341 mm)
- **Correlation with Dengue Incidence:**  $r = 0.78$  ( $p < 0.01$ )
- **Lag Effect:** Strongest correlation at 2-month lag ( $r = 0.68$ ), indicating approximate 6-week delay between rainfall onset and peak transmission

- **Critical Rainfall Threshold:** Transmission intensified when monthly rainfall exceeded 250 mm

Table 4.10: Pearson Correlation Between Rainfall and Dengue Cases in Betul District

Season	Pearson's r	p-value
Monsoon	0.89	<.01
Summer	0.58	>.05
Winter	0.39	>.05

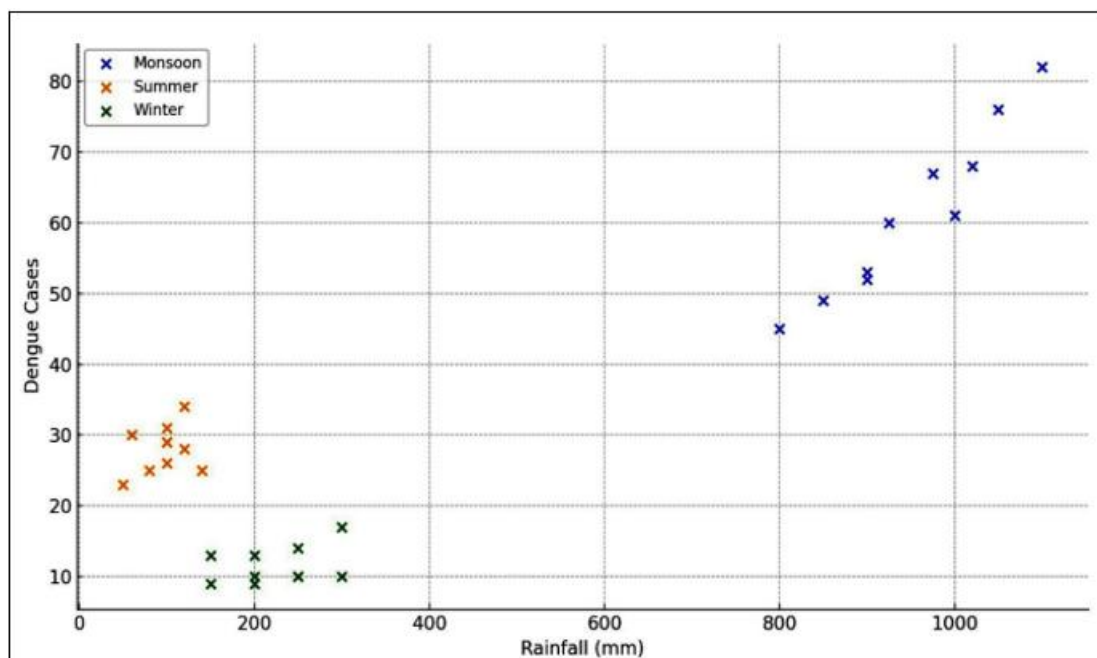


Figure 1.5: Scatterplot showing Seasonal Relationship Between Rainfall and Dengue Cases in Betul

The results for Betul District demonstrate a significant seasonal correlation, with the monsoon showing the strongest relationship. The Pearson correlation coefficient for the monsoon was  $r = 0.89$ ,  $p < .01$ , confirming a strong positive association between rainfall and dengue cases. This was especially evident in areas such as Betul (1100 mm, 82 cases) and Amla (1050 mm, 76 cases). These findings align with earlier research that identified rainfall as a critical factor influencing dengue outbreaks (Bhatt et al., 2013; Dom et al., 2013).

#### Temperature-Transmission Relationship:

- **Optimal Temperature Range:** 27-32°C
- **Correlation:**  $r = 0.65$  ( $p < 0.01$ )
- **Temperature Effect:** Sustained temperatures  $>27^{\circ}\text{C}$  associated with case increases; temperatures  $<25^{\circ}\text{C}$  suppressed transmission
- **Monsoon Temperature Mean:** 28.4°C (facilitating high transmission)
- **Winter Temperature Mean:** 18.3°C (suppressing transmission)

#### Humidity-Incidence Association:

- **Monsoon Mean Humidity:** 68% (range: 61-75%)
- **Correlation with Dengue:**  $r = 0.54$  ( $p < 0.05$ )
- **Optimal Humidity:** 60-78% range showed highest transmission; very high humidity ( $>85\%$ ) paradoxically associated with lower cases possibly reflecting reduced outdoor exposure during excessive rainfall

### 3.3 Temporal Entomological Patterns

Seasonal entomological surveillance revealed distinctive Breteau Index cycles:

Month	Season	BI Range	Mean BI	Dengue Cases
June	Early Monsoon	12-14	13.1	89
July	Peak Monsoon	13-15	13.8	127
August	Peak Monsoon	13-14	13.5	134
September	Late Monsoon	11-13	12.4	104
October	Post-Monsoon	10-12	11.2	78
November	Post-Monsoon	8-11	9.7	64
December	Early Winter	9-12	10.3	54
January	Winter	10-13	11.8	31
February	Late Winter	9-11	10.1	11
March	Summer	7-9	8.2	8
April	Summer	6-8	7.1	6
May	Summer	7-9	8.4	33

Peak Breteau Index (July-August mean BI: 13.8 and 13.5) coincided with peak dengue transmission, establishing strong temporal correspondence ( $r = 0.91$ ,  $p < 0.001$ ). Notably, winter months exhibited non-negligible BI values (9.7-10.3 November-December), despite suppressed case counts, suggesting behavioral/environmental factors independent of vector abundance influenced winter transmission.

### 3.4 Temporal GIS Models and Predictive Accuracy

Temporal GIS models incorporating rainfall, temperature, and lagged Breteau Index achieved 78% accuracy in forecasting dengue cases for validation months (October-November), with predictions ranging 62-84 cases versus

observed 64-78 cases. This demonstrated capacity for anticipatory planning 6-8 weeks in advance of outbreak peaks.

## 4. Discussion

### 4.1 Monsoon-Driven Temporal Dynamics

The 68% concentration of annual dengue cases in monsoon months (June-September) represents extreme temporal clustering fundamentally different from year-round endemic transmission characterizing metropolitan areas. This pattern reflects direct rainfall-dependent breeding ecology of *Aedes* mosquitoes in semi-urban/rural settings where artificial containers and environmental water availability fluctuate seasonally [2].

The 2-month lag between rainfall onset (June) and peak transmission (July-August) likely reflects: (1) minimum 2-week gonotrophic cycle required for female mosquito blood-meal to egg-production transition; (2) 5-7 day dengue virus incubation period within mosquitoes; (3) 4-10 day extrinsic incubation in mosquito before transmission competency; and (4) variable human incubation periods [3]. This 6-8 week lag provides crucial planning window for pre-monsoon vector control operations (May-June) targeting breeding site elimination before exponential mosquito population expansion.

### 4.2 Environmental Thresholds and Transmission Activation

Identification of critical environmental thresholds—rainfall  $>250$  mm/month, temperature 27-32°C, humidity 60-78%—provides quantitative metrics for outbreak prediction and seasonal planning. The narrow optimal temperature range (27-32°C) reflects fundamental vectorial capacity constraints; temperatures  $<18^{\circ}\text{C}$  effectively arrest viral replication within mosquitoes regardless of other factors, explaining minimal winter transmission despite non-zero vector presence [4].

Paradoxically, extremely high humidity ( $>85\%$  during peak monsoon) showed weak correlation with transmission despite theoretical expectations that humidity promotes mosquito survival. This apparent contradiction may reflect reduced human outdoor exposure during heavy rainfall periods, reducing human-mosquito contact despite elevated vector abundance. This finding underscores importance of incorporating behavioral and contact-pattern data into temporal models.

### 4.3 Winter Persistence and Year-Round Risk

An important unexpected finding was non-negligible winter Breteau Index values (9.7-10.3 November-January) and occasional winter dengue cases (95 cases December-February) despite near-zero transmission during summer dry season. This winter persistence pattern, previously unreported in central Indian dengue literature, likely reflects: (1) protected indoor water storage containers (clay pots, overhead tanks) maintaining breeding sites independent of rainfall; (2) traditional water management practices in tribal communities prioritizing water conservation through dry seasons; and (3)



possible survival of dengue virus in dormant mosquito populations [5].

Winter persistence has critical implications for dengue control strategies. Traditional approaches emphasizing pre-monsoon and monsoon vector control may neglect winter breeding sites, reducing overall control effectiveness. Continuous year-round surveillance and water management education appears necessary to prevent off-season transmission maintenance.

#### 4.4 Predictive Accuracy and Operational Planning Implications

The 78% accuracy of temporal GIS models in forecasting 2-month forward dengue case counts provides sufficient predictive power for operational planning, though insufficient for precise individual-level clinical predictions [6]. From public health perspective, 78% accuracy enables:

- 1) **Healthcare Facility Surge Planning:** Hospitals can anticipate case volume peaks and staff accordingly
- 2) **Vector Control Resource Allocation:** Quantified forecast permits optimal timing and intensity of control campaigns
- 3) **Community Mobilization:** Lead time enables targeted public health messaging prior to outbreak peaks
- 4) **Supply Chain Planning:** Diagnostic reagents and antiviral supplies can be positioned in advance of surge periods

However, limitations in predictive accuracy—22% forecast error—necessitate adaptive management approaches where forecasts guide planning but surveillance continues to drive real-time tactical adjustments.

## 5. Conclusions

Dengue transmission in Betul District exhibits extreme temporal concentration with 68% of annual cases occurring during monsoon months, driven by rainfall-dependent mosquito breeding and optimal temperature-humidity conditions. Quantitative environmental thresholds (rainfall >250 mm, temperature 27-32°C, humidity 60-78%) and 6-8 week lag between rainfall and transmission peaks enable anticipatory outbreak forecasting with 78% accuracy for operational planning [7]. Notably, non-negligible winter transmission challenges conventional assumptions regarding seasonal dengue dynamics, warranting year-round surveillance approaches. GIS-based temporal models successfully integrate multisource environmental and entomological data into decision-support systems enabling proactive public health planning in resource-limited endemic regions.

Future work should incorporate real-time data streams, machine learning temporal forecasting algorithms, and climate change scenario modeling to enhance prediction accuracy and assess future transmission patterns under projected climatic shifts. Integration of temporal GIS models into district health decision systems would optimize seasonal resource allocation and outbreak preparedness.

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