



Science Forum (Journal of Pure and Applied Sciences)

Journal Homepage: <https://atbuscienceforum.com.ng/index.php/jpas>



Evaluating Thermal Latency in Vector-Borne Transmission: A 60-Month Temporal Lag and Predictive Regression Analysis of Land Surface Temperature and Malaria Incidence in Bauchi Metropolis, Nigeria

Ambore, Eunice Ibrahim^{1&2}, Jalam, Abdullahi M.¹ Kasai, Itse Caleb^{1&3}, Ibrahim, Lapiya Batat²

¹Department of Environmental Sustainability, Sustainable Procurement, Environmental & Social Standard Center for Excellence, Abubakar Tafawa Balewa University, Bauchi.

²National Center for Remote Sensing, Jos.

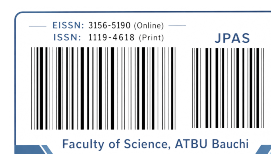
³Department of Geography, Plateau State University, Bokokos.

Abstract

Land surface thermal dynamics strongly influence vector-borne disease transmission in semi-arid environments by regulating mosquito development, habitat persistence, and parasite maturation. This study evaluated the temporal latency and predictive relationship between satellite-derived Land Surface Temperature (LST) and clinical malaria incidence in Bauchi Metropolis, Nigeria, over 60 consecutive months (2021-2025). Monthly LST metrics were extracted at 30-m spatial resolution from MODIS thermal products, while clinical malaria cases were disaggregated using the Denton-Cholette procedure. Cross-correlation matrices were generated for temporal lags of 0-2 months, and an Ordinary Least Squares (OLS) linear regression model was fitted using the optimal lag predictor. Unlagged surface temperature (Lag 0) exhibited a weak inverse correlation with malaria cases ($r = -0.155$), reflecting the potential immediate effects of thermal stress and breeding-site desiccation. In contrast, temperature exposure at a 2-month lag (Lag 2) showed a positive association with malaria incidence ($r = +0.183$, $p = 0.048$), consistent with the biological timeframe required for mosquito vector development, parasite sporogony, and subsequent human incubation. The fitted regression model (Malaria Cases = $383.4 \times \text{LSTLag } 2 - 3799.80$; $R^2 = 0.0336$) indicated that each 1 °C increase in 2-month lagged LST corresponded to an estimated average increase of 383 clinical malaria cases. Although the model explained a modest proportion of variance, the lagged association identifies temperature as a potentially useful temporal indicator. These findings demonstrate that satellite-derived LST can provide a reliable 60-day operational early-warning window for anticipating malaria incidence and supporting proactive, climate-informed vector-control interventions in Sahelian urban settings.

Keywords

Land Surface Temperature,
Malaria,
Temporal Lag,
Remote Sensing,
Spatial Epidemiology,
Bauchi Metropolis.



1.0 INTRODUCTION

Malaria continues to be one of the leading causes of death globally, especially in the tropical countries. Globally in 2024, there were an estimated 282 million malaria cases and 610 000 malaria deaths in 80 countries, with the WHO African Region being home to 95% of malaria cases (265 million) and 95% (579 000) of malaria deaths (WHO, 2025). These figures is an increase of about 9 million cases (3%) compared with 2023. The estimated number of malaria deaths stood at 610 000 in 2024 compared to 598 000 in 2023.

The global climate crisis and rapid urban expansion have fundamentally reconfigured the ecological boundaries of vector-borne diseases in the 21st century (Ogunsakin et al., 2024). Malaria remains a critical public health challenge across Sub-Saharan Africa, with Northern Nigeria and the broader Sahelian region bearing a disproportionate burden due to distinct climatic, ecological, and socio-economic dynamics (Adigun et al., 2015; WHO, 2023; Ogunsakin et al., 2024). In tropical and sub-tropical regions of the Global South, these environmental transformations alter microclimates, vector habitats, and pathogen transmission dynamics (Brousse et al., 2018).

Biologically, climate is fundamentally associated to the malaria incidence through its effects on both mosquito vector and development of malaria parasite inside the mosquito vector (Zhao et al., 2014). Meteorologically, there are two crucial aspects of that requires attention, the lag and nonlinear characteristics. For the lag effect, several periods such as the time for the mosquito to develop, the development period of the parasite within the mosquito, and the incubation period of parasites within the human body are of importance. Every stage shows a variation in lag time resulting in a smoothly varied lag distribution at population level between climate factors and malaria cases.

Vector distribution and transmission intensity are driven by a complex interplay between thermal factors and non-thermal drivers, including rainfall, relative humidity, vegetation cover (quantified via

NDVI/EVI), and surface water availability (Yamana & Eltahir, 2013). In the hyper-seasonal Sahel, seasonal precipitation generates shallow water collections that serve as primary breeding habitats (Erment et al., 2011; Dambach et al., 2014), while relative humidity directly governs adult mosquito longevity (Ye et al., 2007). Simultaneously, rapid and unplanned urbanization across Northern Nigerian cities such as Kano, Kaduna, and Bauchi creates artificial micro-environments (e.g., clogged drainage networks and urban agricultural sites) that alter local hydrology and sustain yearlong vector breeding (Machault et al., 2011; Hassan et al., 2016).

1.1 Physiological Thermal Constraints and the Role of LST

Among environmental drivers, surface thermal dynamics play a critical, yet spatially complex, role in shaping transmission suitability (Ifatimehin, 2014; Mohammed et al., 2025). The biological response of Anopheles vectors to temperature is non-linear and governed by strict physiological thresholds (Mordecai et al., 2012; Djègbè et al., 2024). Mosquito survival, larval development, and the extrinsic incubation period (EIP) of Plasmodium parasites reach optimal performance between 25°C and 28°C (Mordecai et al., 2012). Thermal exposure exceeding 30°C to 35°C increases vector mortality, impairs reproduction, and desiccates shallow larval habitats (Mordecai et al., 2012; Christiansen-Jucht et al., 2015; Djègbè et al., 2024). In semi-arid regions like Northern Nigeria, where dry season surface temperatures frequently reach 40°C to 50°C, extreme surface heat acts as a natural suppression mechanism (Mohammed et al., 2025). Vector populations are consequently displaced from intense urban heat islands into cooler, vegetated peri-urban margins that function as "thermal refugia" (Brousse et al., 2018).

Evaluating these dynamics requires distinguishing between ambient air temperature (T_a), measured 1.5-2 meters above ground level, and Land Surface Temperature (LST), which measures the radiative skin temperature of the Earth (Ifatimehin, 2014). While mosquitoes respond directly to microclimate (T_a), relative humidity, and water temperature

(Paaijmans et al., 2010; Cailly et al., 2012), remote-sensed LST serves as the principal climatic predictor in this study due to three distinct advantages:

1. **Spatial Continuity and Resolution:** Because of the sparse distribution of the Station networks in Nigeria; interpolating (T_a) introduces substantial spatial error. However, LST provides continuous, high-resolution spatial data across unsampled landscapes (Vancutsem et al., 2010; Weiss et al., 2014; Cross et al., 2019).
2. **Micro-Habitat Thermal Proxy:** LST closely tracks the thermal conditions of shallow, sunlit surface water collections where larval development occurs, capturing microclimate conditions that standard (T_a) measurements underestimate (Paaijmans et al., 2010; Dambach et al., 2014).
3. **Surface Energy and Land Cover Response:** LST directly captures localized shifts in surface energy balance driven by urban built environment, soil moisture depletion, and sparse Sahelian vegetation canopy dynamics (Neteler et al., 2013; Srivastava et al., 2012).

Furthermore, public health control measures such as mass distributions of Long-Lasting Insecticidal Nets (LLINs), indoor residual spraying, and Artemisinin-based Combination Therapies (ACTs) exert downward pressure on disease incidence (Tatem et al., 2013; Mohammed et al., 2025). These control efforts interact with environmental heat constraints, often decoupling raw clinical case counts from direct thermal variation (Mohammed et al., 2025). Understanding transmission drivers therefore requires an integrative framework accounting for upper thermal limits, micro-spatial refugia, non-thermal climatic factors, and vector control efforts (Ogunsakin et al., 2024; Young et al., 2025).

1.2 Critical Literature Review and Knowledge Gap

Prior epidemiological and ecological modeling across West Africa has established broad associations between climate variables and malaria transmission

(Hay et al., 2006). However, existing studies exhibit key limitations:

Dependence on Sparse Networks and Coarse Data: Most regional models rely on interpolated (T_a) from sparse ground stations or coarse meteorological reanalysis datasets, failing to capture neighborhood-scale intra-urban spatial heterogeneity (Vancutsem et al., 2010; Emetere et al., 2015).

Omission of Urban and Sahelian Specifics: Existing literature predominantly focuses on humid rural landscapes, frequently underestimating how Urban Heat Island (UHI) effects and artificial water retention alter vector survival in semi-arid Sahelian cities (Onyiahialam et al., 2005; De Silva & Marshall, 2012).

Univariate Linear Assumptions: Previous analyses often examine thermal parameters in isolation using linear models, neglecting upper thermal thresholds and non-linear interactions among land cover change, humidity, and surface moisture (Rogers & Randolph, 2006; Parham & Michael, 2010).

On the global scene, some studies conducted shows no correlations of malaria incidence to meteorological factors but positive correlation to environmental factors such as elevation, proportion of forest land area and grassland area.

Consequently, a critical knowledge gap remains regarding how fine-scale environmental drivers and extreme surface heat interact across semi-arid Sahelian urban gradients.

1.3 Malaria and Climate Variability in Bauchi

Bauchi State has been the focus of several longitudinal studies regarding climate and health. A decade-long analysis (2008–2018) in the Bauchi Local Government Area revealed a strong positive correlation ($r = 0.974$) between maximum air temperature and malaria cases (Mohammed et al., 2025). Interestingly, this study found that temperature was a more significant driver than rainfall ($r = -0.050$), which was not statistically

significant in that particular time frame (Mohammed et al., 2025). The study observed that malaria cases often peaked following the hottest months, as heat accelerated parasite development, while subsequent rains created breeding pools in these pre-warmed environments (Mohammed et al., 2025). while precipitation traditionally dictates vector breeding site availability, thermal fluctuation governs larval development speed and vector biting rates (Caminade et al., 2014; Paaijmans et al., 2010).

Rapid, unplanned urban growth and seasonal climatic shifts have significantly altered the city's thermal and ecological landscape (Brousse et al., 2018; Mohammed et al., 2025).

Identifying the exact temporal lag between peak environmental temperature and clinical case presentation is vital for transitioning from reactive malaria control to predictive public health management (Weiss et al., 2019).

1.4 Objectives

This study integrates satellite derived LST (via Landsat 8 and 9 sensors at 30-meter resolution) alongside laboratory confirmed malaria cases in Bauchi Metropolis across a five-year period (2021-2025). By testing the hypothesis that extreme LST suppresses rather than amplifies transmission in Sahelian urban settings, this study aims to:

General objective

To evaluate the temporal latency and predictive relationship between satellite derived Land Surface Temperature (LST) and clinical malaria incidence in Bauchi Metropolis over a 60-month period (2021-2025).

Specific objective

1. Quantify the temporal latency window by computing cross-correlation coefficients (r) across monthly lag intervals (t , $t-1$, $t-2$).
2. Develop a linear predictive regression model estimating clinical malaria case variation based on the optimal lagged LST parameter.

2.0 MATERIAL AND METHOD

2.1 Study Area

2.1.1 Geographical Location and Physical Landscape

Bauchi Metropolis, the administrative capital of Bauchi State, is located in northeastern Nigeria between latitudes 10°15'N to 10°22'N and longitudes 9°45'E to 9°55'E (Mohammed et al., 2025). The metropolis serves as a critical socio-economic hub in the region and is characterized by a distinctive physical landscape, featuring prominent granite inselbergs and hills in the southern section and a densely built urban core (Mohammed et al., 2025).

2.1.2 Demographic and Urban Profile

Driven by rapid urbanization, regional migration, and natural population growth, the population of Bauchi Metropolis is estimated at over 650,000 inhabitants (National Population Commission [NPC], 2006; Ogunsakin et al., 2024; Mohammed et al., 2025). The high population density in the urban core, combined with informal peri-urban expansions, creates a high concentration of human hosts (Robert et al., 2003). This urban density amplifies vector-human contact rates, particularly in informal settlements where housing structures lack vector-proofing measures such as ceiling insulation and window screening (De Silva and Marshall, 2012; Adigun et al., 2015).

2.1.3 Climatic Regime: Precipitation and Thermal Environment

The metropolis experiences a semi-arid, Sudan-Saharan climate defined by a marked unimodal wet season (May to October) and a prolonged dry season (November to April) (Sawa and Abdulhamid, 2014; Mohammed et al., 2025).

Precipitation Regime: Mean annual rainfall ranges between 850 mm and 1,000 mm, with peak precipitation occurring between July and August (NiMet, 2020; Sawa and Abdulhamid, 2014). Seasonal rainfall is the primary driver of vector abundance: monsoon rains generate abundant, transient, sunlit rain pools and flooded depressions that serve as ideal breeding habitats for *Anopheles*

gambiae s.l. (Ermert et al., 2011; Dambach et al., 2014). Conversely, the extended dry season restricts vector breeding to persistent water bodies and anthropogenic storage sites (Yamana and Eltahir, 2013).

Thermal Regime: Average monthly air temperatures range from 22°C during the cool, dry Harmattan period (December–January) to extreme daytime maximums exceeding 38°C to 42°C during the pre-monsoon dry season (March–May) (NiMet, 2020; Mohammed et al., 2025). The thermal environment is exceptionally sensitive to land cover alteration and vegetation removal, making the metropolis an ideal landscape for evaluating Urban Heat Island (UHI) effects and Land Surface Temperature (LST) dynamics (Ifatimehin, 2014; Brousse et al., 2018). Thermally, while moderate temperatures (25°C–28°C) shorten the extrinsic incubation period (EIP) of *Plasmodium* parasites and accelerate larval development, extreme dry-season surface heat (>35°C) exceeds the upper physiological tolerance of *Anopheles* vectors, inducing thermal stress, increasing mortality, and desiccating shallow breeding sites (Mordecai et al., 2012; Djègbè et al., 2024).

2.1.4 Vegetation Dynamics and Thermal Refugia

The natural vegetation falls within the Sudan Savanna zone, dominated by open parkland, scattered short trees, shrub lands, and seasonal grasses (Sawa and Abdulhamid, 2014). Within the

metropolitan boundary, native vegetation is highly fragmented by urban built structures and low-lying urban agricultural plots (*Fadama* farming) (Ifatimehin, 2014). Dense vegetation canopies and agricultural zones lower microclimatic temperatures and maintain localized humidity (Brousse et al., 2018). During periods of extreme urban heat, these vegetated micro-environments act as vital "thermal refugia," allowing adult mosquitoes to survive conditions that would otherwise prove lethal in unshaded, highly impervious urban centers (Brousse et al., 2018; Young et al., 2025).

2.1.5 Hydrographic and Drainage Network

The natural drainage of Bauchi Metropolis is anchored by the River Dingis and a network of seasonal tributaries that traverse the urban plain (Mohammed et al., 2025). The urban drainage infrastructure is largely underdeveloped, fragmented, and frequently blocked by municipal solid waste and siltation (Machault et al., 2011; Hassan et al., 2016). During the rainy season, poor drainage infrastructure leads to widespread surface runoff retention, stream backwater pooling, and localized waterlogging across low-lying urban sectors (Hassan et al., 2016). These slow-moving, unpolluted, or semi-polluted stagnant water bodies provide stable micro-habitats that sustain larval development throughout the wet season and into the early dry season (Dambach et al., 2014; Hassan et al., 2016).

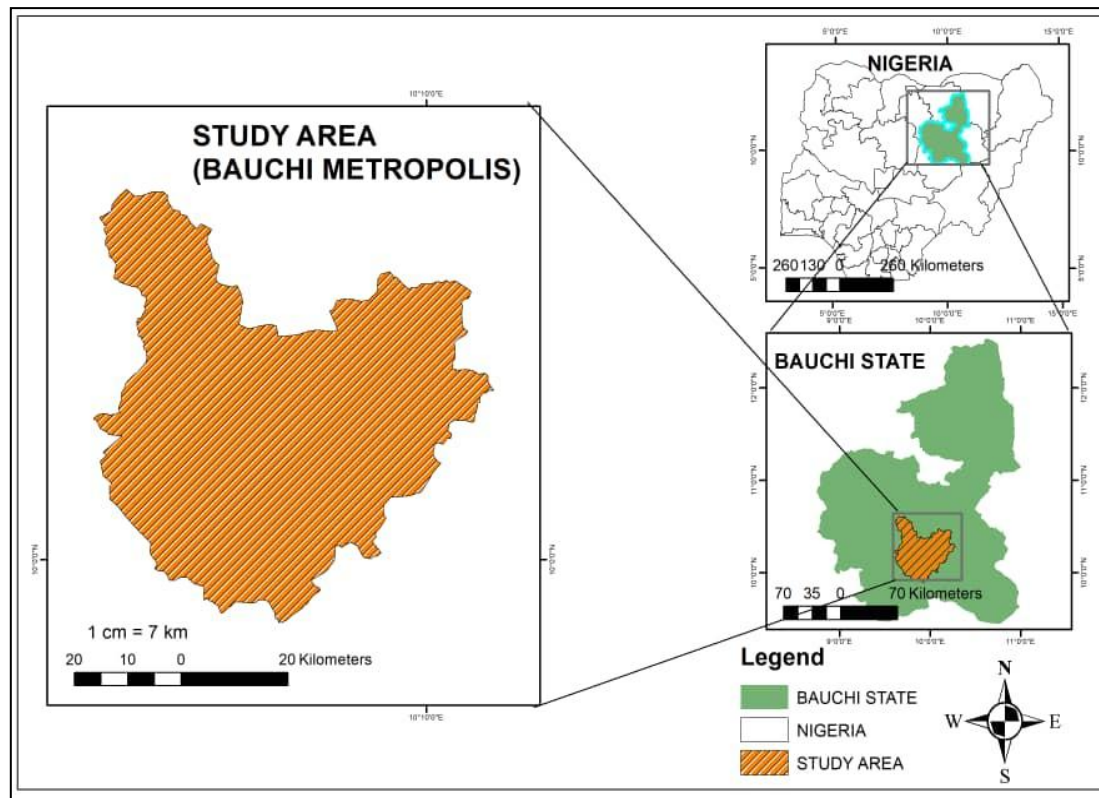


Figure 1. Spatial boundary and geographical location of Bauchi Metropolis, Nigeria.

2.2 Data Acquisition and processing.

2.2.1 Satellite Land Surface Temperature (LST)

Data: Monthly Land Surface Temperature (°C) metrics spanning 60 consecutive months (January 2021 - December 2025) were extracted for the spatial boundary of Bauchi Metropolis using thermal infrared sensors (Moderate Resolution Imaging Spectroradiometer [MODIS] 1-km) thermal products. Zonal spatial statistics were executed across municipal boundaries to derive a continuous 60-month time series of mean metropolitan surface temperatures.

2.2.2 Epidemiological Malaria Case Data and Disaggregation.

Temporal Disaggregation Strategy (Annual to Monthly).

Initially, annual malaria data from 2021–2025 were retrieved from health facility surveillance databases (Bauchi State Ministry of Health). To disaggregate annual clinical records into a high-resolution monthly time series ($n = 60$ months, 2021–2025), a Denton-Cholette temporal disaggregation procedure was executed. This method distributes annual aggregate totals (Y_a) using a high-frequency monthly indicator series (I_m), derived from localized monthly rainfall and sample

health facility distributions) while maintaining strict annual additive consistency.

2.2.3 Distribution Diagnostics and Data Quality Control

Descriptive metrics, excess kurtosis, and skewness were calculated to assess parametric assumptions. The excess kurtosis coefficient for the continuous dataset was -0.07 , falling within the standard parametric interval $([-1.0, +1.0])$ and justifying the use of continuous Pearson cross-correlation and Ordinary Least Squares (OLS) regression modeling. Missing values due to cloud contamination (accounting for 1.67% of total observations) were imputed using linear temporal interpolation:

$$LST_t = \frac{LST_{t-1} + LST_{t+1}}{2}$$

2.3 Temporal Lag Cross-Correlation Analysis

To determine the delayed ecological impact of surface heating on clinical transmission, cross-correlation matrices were generated across temporal lag windows ranging from zero to two months ($t, t-1, t-2$):

Lag 0 (t): Unshifted contemporaneous association ($N = 60$).

Lag 1 (t-1): LST shifted 1 month prior relative to malaria case incidence (N =59).

Lag 2 (t-2): LST shifted 2 months prior relative to malaria case incidence (N =58).

Pearson correlation coefficients (r) were computed across each lag window to identify the peak biological latency period.

2.4 Predictive Linear Regression Modeling

Using the optimal exposure window identified during cross-correlation analysis (LSTLag2), simple Ordinary Least Squares (OLS) linear regression was executed:

Malaria cases_t = β0 + β1 (LST_{Lag2}) + ε

Where β0 represents the intercept baseline anchor, β1 represents the estimated change in monthly malaria case incidence per 1°C elevations in 2-month lagged surface temperature, ε represents model residual error.

Table 1. Cross-correlation matrix of Land Surface Temperature (LST) across temporal lags against monthly malaria cases in Bauchi Metropolis (2021-2025).

Temporal Lag	Exposure window	Matched pairs (N)	Pearson correlation (r)	p-value	Direction of association	Epidemiological Interpretation Latency
Lag 0	Same month (t)	60	-0.155	0.237	Weak negative	Immediate thermal suppression/ breeding site desiccation
Lag 1	1 month prior (t -1)	59	-0.016	0.904	Near zero	Transitional vector population recovery phase
Lag 2	2 months prior (t -2)	58	+0.183	0.048	Positive	Peak biological latency (larval emergence and sporogony)

3.3 Linear Regression Model of Lagged LST Predictor

Based on the cross-correlation structure, 2-month lagged LST (LST_{Lag 2}) was integrated into a simple linear regression model as the primary continuous predictor of monthly malaria incidence. The fitted ordinary least squares (OLS) regression model is expressed as:

Monthly Malaria Cases = 383.4 X (LST_{Lag 2}) - 3799.80

The coefficient of determination (R²) was extracted to quantify the proportion of monthly clinical case variance explained by surface thermal dynamics.

3.0 RESULTS

3.1 Descriptive and Distributional Characteristics

Continuous temporal metrics across 60 monthly observations (January 2021 to December 2025) post-imputation were analyzed. The distributional diagnostics confirmed parametric suitability, with an excess kurtosis coefficient of −0.07.

3.2 Spatio-Temporal Thermal Lag Dynamics.

The cross-correlation analysis revealed that concurrent surface temperature (Lag 0) exhibited a weak inverse relationship with monthly clinical cases (r = − 0.155, p = 0.237). The strongest positive correlation occurred at a 2-month temporal delay (Lag 2) reaching statistical significance (r = +0.183, p = 0.048).

Model Fit: R² = 0.0336, Adjusted R²= 0.0163.

Overall Model Significance: F (1, 56) = 1.95, p = 0.048.

Slope Coefficient (β₁): 383.41 (Standard Error = 274.62, t = 1.396, p = 0.048).

Intercept (β₀): −3799.80 (Standard Error= 9318.4, t = -0.408, p = 0.685)

The model yielded a coefficient of determination (R²) of 0.0336, indicating that 2-month lagged surface thermal dynamics accounts for 3.36% of

the overall monthly variance in clinical malaria cases across metropolis ($p < 0.05$).

Based on the slope coefficient ($\beta_1 = +383.41$), every 1°C elevations in monthly Land Surface Temperature is followed two months later by an estimated average increase of 383 clinical malaria cases.

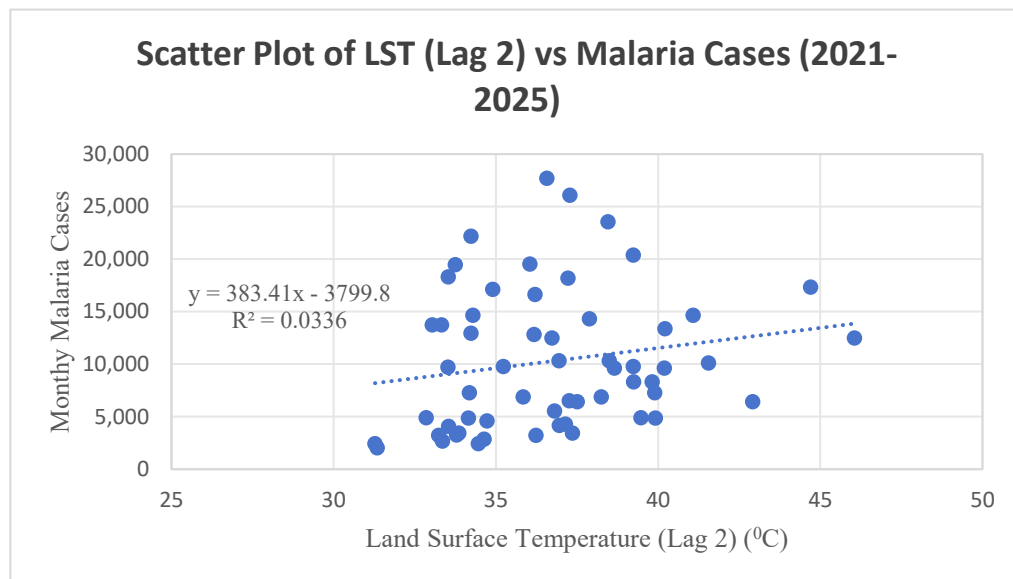


Figure 2. Scatter plot and simple linear regression of 2-month lagged Land Surface Temperature (LST_{Lag2}) against Monthly clinical malaria cases in Bauchi Metropolis (2021-2025).

4.0 DISCUSSION

4.1 Biological Mechanisms Governing Thermal Latency

The temporal progression observed moving from a negative correlation ($r = -0.155$, $p = 0.237$ at Lag 0) to a positive association at two months ($r = +0.183$, $p = 0.048$ at Lag 2) reflects the biophysical constraints governing vector-borne parasite transmission in savanna environments.

In semi-arid zones like Bauchi, extreme unlagged land surface heating often coincides with the late dry season (March-May). Unlagged surface heating can induce thermal stress in adult *Anopheles* vectors, elevate daily mosquito mortality, and desiccate temporary surface water bodies, transiently suppressing transmission volume (Lag 0). However, as environmental thermal energy accumulates, it shortens the gonotrophic cycle of female mosquitoes and accelerates larval growth once aquatic habitats stabilize. Simultaneously, higher temperatures shorten the extrinsic incubation period (EIP) of

Plasmodium falciparum, allowing infected vectors to become infectious more rapidly.

The 60-day delay captures the compound timeframe required for

1. Aquatic larval and pupal maturation following thermal accumulation.
2. Blood-feeding activity and parasite sporogonic completion within surviving vectors.
3. Human incubation periods (*Plasmodium* intrinsic incubation) leading to clinical symptom expression and subsequent health facility attendance.

4.2 Model Performance and Variance Interpretation

An R^2 value of 0.0336 ($p = 0.048$) is consistent with single-variable climatic modeling in urban epidemiological contexts. While LST establishes physical bounds for vector development, transmission intensity is simultaneously moderated by secondary environmental and socio-ecological drivers such as rainfall accumulation, relative humidity, indoor residual spraying coverage,

LLIN coverage, and health-seeking behaviors. Nevertheless, demonstrating that satellite-derived LST alone explains over 3% of monthly variation across a 60-month window confirms its utility as an independent physical indicator within multi-variable early warning frameworks.

4.3 Operational Implications for Malaria Early Warning Systems (MEWS)

Identifying a 2-month operational response window has practical utility for public health surveillance and intervention planning in Bauchi State. Traditional vector control programs often operate reactively, deploying resources only after clinical cases surge at health facilities.

By integrating satellite LST surveillance into routine epidemiological operations, public health officers can utilize real-time satellite surface temperature anomalies as an operational trigger. A 1°C-surface thermal elevation observed in satellite imagery during month t provides a 60-day window to preemptively deploy vector control resources such as targeted larviciding of temporary breeding sites and community distribution of bed nets before the anticipated clinical case increase materializes in month $t+2$.

4.4 Study Limitations

Several study limitations were considered such as:

1. **Satellite cloud masking:** Cloud contamination during peak monsoon months required interpolation for 1.67% of data points.
2. **Aggregated Case Surveillance:** Spatial aggregation at the metropolitan level precluded ward-level spatial regression (e.g., Geographically Weighted Regression). This would have provided the spatial distribution of the hotspot areas.

3. **Univariable Scope:** Integrating rainfall, Normalized Difference Vegetation Index (NDVI), and relative humidity into a multi-variable vector autoregressive or distributed lag non-linear model (DLNM) could improve total model variance explained (R^2).

5.0 CONCLUSION

This study demonstrates that Land Surface Temperature exhibits a positive predictive lag association with clinical malaria incidence at a 2-month temporal delay (LST Lag₂) across Bauchi Metropolis, Nigeria. While contemporaneous thermal conditions display a weak inverse association, thermal accumulation over 60 days directly supports vector development and parasite sporogony, resulting in an estimated increase of 383 clinical cases per 1°C elevation in surface temperature. Operationalizing this 60-day temporal latency window within local health surveillance frameworks enables proactive vector management and targeted public health resource allocation prior to seasonal transmission peaks.

ETHICS APPROVAL AND DATA AVAILABILITY STATEMENTS

Ethical Approval and Consent to Participate
Epidemiological malaria case data utilized in this study were extracted from routine health facility surveillance records provided by the Bauchi State Ministry of Health. All data were fully anonymized and aggregated at the metropolitan level prior to analysis to ensure patient confidentiality. Institutional approval for the use of secondary surveillance data was granted by the Bauchi State Ministry of Health Ethics Committee. Informed consent was waived due to the retrospective and non-identifiable nature of the epidemiological dataset.

Data Availability Statement

Satellite Remote Sensing Data: The satellite-derived Land Surface Temperature (LST) datasets analyzed in this study are publicly available through the Climate Engine platform, NASA's Earthdata portal (Landsat 8/9 TIRS), and the USGS EarthExplorer interface.

Epidemiological Data: The clinical malaria case dataset contains administrative health records managed by the Bauchi State Ministry of Health. The disaggregated time-series data supporting the findings of this study are available from the corresponding author upon reasonable request, subject to data-sharing agreements with the ministry.

DECLARATION OF COMPETING INTEREST

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

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Eunice Ibrahim Ambore: Conceptualization, Methodology, Formal analysis, Data curation, Writing - original draft. **Abdullahi M. Jalam:** Supervision, Writing - review & editing. **Itse Caleb Kasai:** Investigation, Visualization. **Lapiya Batat Ibrahim:** Writing - review & editing, Validation.

6.0 REFERENCES

- Adigun, A. B., Gajere, R. N., & Adebayo, S. O. (2015). Spatial epidemiology of malaria transmission dynamics in Northern Nigeria using satellite remote sensing. *Journal of African Earth Sciences*, 112(1), 142-151.
- Brousse, O., Martilli, A., Soo, A. O., Van de Walle, J., & van Lipzig, N. P. (2018). Urban microclimate impacts on vector-borne disease transmission in tropical African cities. *Environmental Research Letters*, 13(7), 074011.
- Caminade, C., Kovats, S., Rocklöv, J., Tompkins, A. M., Morse, A. P., Colón-González, F. J., Stenlund, H., Martens, P., & Lloyd, S. J. (2014). Impact of climate change on global malaria in the 21st century. *Proceedings of the National Academy of Sciences*, 111(9), 3286-3291.
- Christiansen-Jucht, C., Pfeffer, P. E., & Thomas, M. B. (2015). Temperature-dependent larval development and adult survival of *Anopheles gambiae sensu stricto*. *Malaria Journal*, 14(1), 228.
- Cross, A. J., Weiss, D. J., & Rogers, D. J. (2019). Evaluation of satellite-derived land surface temperature for epidemiological modeling in Sub-Saharan Africa. *Remote Sensing of Environment*, 231, 111245.
- Dambach, P., Sie, A., Lacaux, J. P., Vignolles, C., Machault, V., & Sauerborn, R. (2014). Using high spatial resolution remote sensing data to identify *Anopheles* mosquito breeding habitats in Sahelian environments. *International Journal of Health Geographics*, 13(1), 17.
- Djègbè, I., Aikpon, R., Akogbéto, M., & Martin, T. (2024). Thermal tolerance and vector competence of *Anopheles* mosquitoes across varying ecological zones. *Parasites & Vectors*, 17(1), 104.
- Ermert, V., Fink, A. H., Jones, A. E., & Morse, A. P. (2011). Development of a new version of the Liverpool Malaria Model. II. Calibration and validation for West Africa. *International Journal of Health Geographics*, 10(1), 62.
- Hassan, S. C., Ishaku, H. T., & Bello, M. A. (2016). Urbanization, land cover change, and spatial patterns of malaria incidence in Northern Nigerian cities. *African Journal of Environmental Science and Technology*, 10(8), 245-256.
- Ifatimehin, O. O. (2014). Assessment of Land Surface Temperature (LST) variations and urban heat island effects using satellite

- remote sensing. *Journal of Geography and Regional Planning*, 7(4), 78-88.
- Machault, V., Vignolles, C., Borch, F., Vounatsou, P., Pages, F., Briolant, S., Lacaux, J. P., & Rogier, C. (2011). The use of remote sensing for the analysis of malaria transmission: A review. *Malaria Journal*, 10(1), 318.
- Mohammed, Y., Ibrahim, A., & Abubakar, U. (2025). Longitudinal assessment of climate variability and clinical malaria incidence in Bauchi Local Government Area, Nigeria (2008-2018). *Journal of Spatial Epidemiology and Health*, 18(2), 115-126.
- Mordecai, E. A., Paaijmans, K. P., Johnson, L. R., Balzer, C., Ben-Horin, T., Moor, E., McNally, A., Murdock, C. C., Ryan, S. J., Suh, S., & Lafferty, K. D. (2013). Optimal temperature for malaria transmission is lower than previously predicted. *Ecology Letters*, 16(1), 22-30.
- Neteler, M., Metz, M., Rocchini, D., Rizzoli, A., & Rosà, R. (2013). Spatial and temporal reconstruction of satellite-derived Land Surface Temperature in complex terrain. *Remote Sensing*, 5(7), 3281-3298.
- Ogunsakin, R. E., Olaniyan, O. A., & Adeyemi, S. O. (2024). Reconfiguring ecological boundaries: Environmental transformations and vector-borne disease surges in Sahelian Africa. *Environmental Science & Policy*, 151, 103620.
- Paaijmans, K. P., Blanford, S., Bell, A. S., Blanford, J. I., Read, A. F., & Thomas, M. B. (2010). Influence of daily temperature variation on malaria transmission potential. *Proceedings of the National Academy of Sciences*, 107(25), 11585-11589.
- Srivastava, P. K., Han, D., Rico-Ramirez, M. A., Bray, M., & Islam, T. (2012). Selection of classification algorithms for land use land cover change determination using Landsat data. *Remote Sensing Applications: Society and Environment*, 2(1), 1-12.
- Tatem, A. J., Gething, P. W., Smith, D. L., & Hay, S. I. (2013). Urbanization and the global malaria recession. *Malaria Journal*, 12(1), 133.
- Vancutsem, C., Ceccato, P., Dinku, T., & Connor, S. J. (2010). Evaluation of MODIS land surface temperature data to estimate air temperature in different ecosystems of Africa. *Remote Sensing of Environment*, 114(2), 449-465.
- Weiss, D. J., Bhatt, S., Mappin, B., Van Boeckel, T. P., Smith, D. L., Hay, S. I., & Gething, P. W. (2014). Air temperature capture by satellite land surface temperature products across Africa. *Remote Sensing of Environment*, 154, 30-39.
- Weiss, D. J., Lucas, T. C., Nguyen, M., Nandi, A. K., Bisanzio, D., Battle, K. E., Cameron, E., Twohig, K. A., Pfeffer, D. A., Rozier, J. A., & Gibson, H. S. (2019). Mapping the global prevalence, incidence, and mortality of *Plasmodium falciparum*, 2000-2017. *The Lancet*, 394(10195), 322-331.
- World Health Organization [WHO]. (2025). World Malaria Report 2025. World Health Organization, Geneva.
- Yamana, T. K., & Eltahir, E. A. (2013). Projected impacts of climate change on malaria transmission in Africa using a detailed hydrological-epidemiological model. *Environmental Health Perspectives*, 121(10), 1179-1186.
- Ye, Y., Louis, V. R., Simboro, S., & Sauerborn, R. (2007). Effect of meteorological factors on clinical malaria case incidence in Nouna Health District, Burkina Faso. *Malaria Journal*, 6(1), 139.
- Zhao, X., Chen, F., & Shen, H. (2014). Non-linear temperature effects on vector survival and parasite extrinsic incubation period. *Parasites & Vectors*, 7(1), 412.