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ORIGINAL RESEARCH ARTICLE

Machine Learning Analyses of Climate Variability Trends and Malaria Transmission Dynamics in Yobe State, Nigeria

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ABSTRACT
The fluctuations of the climatic variables have considerable impacts on the livelihood security of Yobe State, Nigeria, particularly as it relates to malaria transmission and public health in general. This paper investigated how, between 2014 and 2023, temperature and rainfall patterns changes correlate with the prevalence of malaria in the micro-climatic zones of the state, which are SaSZ, TZ, and SuSZ. By employing machine learning algorithms on the climatic data obtained from NiMet, the study highlighted patterns in climate variability and correlates same with malaria risk. It revealed seasonality fluctuations in temperature (20°C to 47.5°C) and rainfall patterns that coincided with heightened malaria transmission. Temperature, spiking higher than 30°C, aligned with increasing malaria cases, whereas 40°C of the climatic element appears to reduce mosquito survival. On the other hand, the rainfall patterns, especially with the oscillations between 0mm and 120mm, provided breeding grounds for mosquitoes, amplifying malaria transmission risks. Thus, the study concluded that while the transmission could be a function of changing climate, the control methods are inadequate in the face of increasing climate unpredictability. This implied the need for an integrated approach combining climate monitoring, epidemiological surveillance, and adaptive public health policies is necessary to mitigate the effects of climate-driven malaria risks.

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INTRODUCTION

The variability of climatic elements has been a serious environmental issue, especially in arid and semi-arid regions. These regions have been undergoing intense and severe changes in temperature and rainfall, which affect people, the environment, and public health directly. With the ongoing challenges of climate change, it would be increasingly important to understand how the climate relates to malaria risk, for example, since it can help in developing effective mitigation and adaptation measures. Malaria is still a critical public health burden in different parts of the world, including sub-Saharan Africa (SSA), where environmental and climatic variability might have been strongly mediating the transmission dynamics. It is imperative to note that numerous studies (Bose et al., 2015; Hassan et al., 2017; Recha, 2017; Asfaw et al., 2018; Panda and Sahu, 2019; Yamusa and Abdulkadir, 2020; Kehinde et al., 2021; Sidi, 2022) on climate variability and change were conducted in parts of the world. However, a critical review of such studies revealed significant spatial and temporal gaps in the literature, as the findings were not discussed within the context of livelihoods, particularly in relation to disease outbreaks. Over the past decade, significant advances have been made in understanding the climatic and geographic factors that shape malaria transmission. For instance, Garba et al. (2023) explored the spatial features of malaria in lowland and highland areas of Taraba State, highlighting the role of altitude, rainfall, and temperature in influencing infection prevalence. The work, however, relied on conventional statistical methods without the incorporation of predictive machine learning approaches, thus limiting the predictive strength of the environmental-malaria linkage. On a broader scale, Edmund (2023) used Entomological Inoculation Rate (EIR) data to explore malaria seasonality across SSA, revealing threshold conditions for rainfall and temperature that frame the transmission season. Although comprehensive, the study operated at a continental scale, overlooking the fine-grained variability needed for localized prediction in hyper-endemic zones such as northeastern Nigeria. Similarly, Obiora et al. (2023) applied machine learning to model malaria and lymphatic filariasis co-distribution

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across Nigeria but reported only moderate prediction accuracy ($R^2 = 0.59$ for malaria), indicating that finer-scale analyses tailored to unique regional ecologies could yield more precise insights.

However, machine learning methods have recently emerged as powerful tools for uncovering non-linear, complex relationships between climate variables and malaria dynamics. For example, Singh and Saran (2024) demonstrated how models such as Maximum Entropy can forecast future malaria hotspots in Africa under climate change scenarios. Likewise, Ukawuba and Shaman (2022) used a climate-driven entomological model to simulate malaria incidence across Rwanda, emphasizing the importance of dynamic, climate-integrated models. However, most of these approaches were either cross-national in scope or concentrated on East and Central African regions, thereby neglecting Nigeria's northeastern corridor, a region where climatic extremes and humanitarian crises compound malaria risk. In northern Nigeria, especially Yobe State, studies on malaria-climate interactions remain scarce. While Ayanlade et al. (2020) provided evidence for a strong relationship between rainfall and malaria incidence across Nigeria's southern ecological zones ($R^2 \geq 0.70$), their findings largely excluded arid regions such as the Sahel and Sudan belts that characterize Yobe State. Diouf et al. (2020) and Smith et al. (2020) have underscored how hydrology, temperature, and rainfall interplay to shape malaria dynamics in West Africa. Yet, no known study has applied spatially disaggregated machine learning techniques to systematically investigate how climate variability drives malaria transmission dynamics in Yobe State, one of Nigeria's most climatically fragile and medically underserved regions.

As such, this study bridges these gaps by employing machine learning techniques to model and analyze the climate-malaria nexus specifically in Yobe State. Using climatic data (rainfall and temperature) and historical malaria case records, this study constructed predictive models that identify spatial and temporal patterns of malaria transmission under varying climatic regimes. Unlike previous studies, this one incorporates spatial heterogeneity and leverages the analytical power of machine learning to reveal complex, non-linear relationships often missed by classical statistical approaches. Additionally, this study explores the feasibility of integrating machine learning outcomes into early warning frameworks for malaria control, tailored to the unique Sahelian context of Yobe State.

MATERIAL AND METHODS

Study Area

Yobe State, located in the Sahel region of Nigeria, is characterized by vast grasslands interspersed with shrubs and acacia trees. Its semi-arid climate features erratic rainfall and high temperatures, along with a prolonged dry season from October to April and a brief wet season from May to September. These climatic conditions significantly influence agriculture, water availability, and disease prevalence, shaping the region's environmental and socio-economic landscape. The area is susceptible to climate variability, making it a key focus for studies on resilience, livelihood adaptation, and health impacts, especially concerning infectious diseases such as malaria, which thrive under changing temperature and precipitation patterns.

Data Collection Technique

The study primarily used rainfall and temperature data from the Nigerian Meteorological Agency (NiMet). While debates persist over NiMet's data reliability, it remains the legally recognized authority for climate data collection and dissemination in Nigeria, ensuring a credible foundation for analysis.

Sample Frame and Size

The sample frame for the study is Yobe State, stratified into three micro-climatic zones: Sahel Savanna Zone (SaSZ), Transition Zone (TZ), and Sudan Savanna Zone (SuSZ). One Local Government Area (LGA) was purposively selected from each zone — Bade (SaSZ), Damaturu (TZ), and Fika (SuSZ) — to ensure comprehensive spatial coverage and representation of the state's diverse climatic conditions.

Data Analyses

To ensure accuracy and clarity, the collected data were analyzed using an unsupervised machine learning model in Python, along with time series plots. This approach enabled pattern recognition and trend analysis, thereby enhancing the reliability of the study in assessing climate variability and its impacts across Yobe State's different microclimatic zones.

Data Collection Technique

The primary data sources for this study were historical rainfall and temperature datasets obtained from the Nigerian Meteorological Agency (NiMet), the legally mandated body for climate data in Nigeria. Although concerns over data completeness and granularity persist, NiMet remains the most credible and officially recognized institution for climate data in the country, ensuring a reliable foundation for analysis.

Sampling Frame

The study was conducted across Yobe State, Nigeria. To account for the ecological diversity, the state was stratified into three distinct micro-climatic zones: Sahel Savanna Zone (SaSZ) – represented by Bade LGA; Transition Zone (TZ) – defined by Damaturu LGA; and Sudan Savanna Zone (SuSZ) – represented by Fika LGA. This stratified purposive sampling was employed to ensure spatial and climatic representativeness in the analysis.

Model Development and Validation

To assess the relationship between the climatic variables (rainfall and temperature) and malaria prevalence, the paper applied supervised machine learning regression techniques using Python's scikit-learn and related libraries. This was to model the continuous outcome of malaria incidence across different time-lagged and aggregated climatic predictors. For the algorithms employed, four baseline regression tools were evaluated. These are Linear Regression (LR), LASSO Regression (LassoCV), Decision Tree Regressor (DT), and Random Forest Regressor (RF). These models were adopted based on their empirical efficacy and relevance in climate-health modeling, which were optimized in this paper. In addition, two ensemble strategies, Voting Regressor and Stacking Regressor, were tested.

Training-Testing Split and Cross-Validation

Data was split into training (80%) and testing (20%) sets with a fixed random seed (random_state=11) for reproducibility. To enhance model robustness, 10-fold cross-validation was performed for each model. This method rotates the validation set across different data segments, mitigating overfitting and providing a more reliable performance estimate.

Hyperparameter Optimization

GridSearchCV was used to fine-tune hyperparameters for the Random Forest model. The parameters optimized include max_depth, min_samples_split, and max_features. GridSearchCV was chosen over RandomizedSearchCV due to the manageable parameter space and availability of adequate computational resources.

Evaluation Metrics

Given the regression nature of the target variable, Root Mean Squared Error (RMSE) was the primary metric. However, to provide a broader performance profile, R^2 (coefficient of determination), Mean Absolute Error (MAE), and cross-validated scores were reported (Table 1).

Table 1: Evaluation Metrics of the Model

Model	RMSE	MAE	R^2 Score	Cross-Validated R^2 (CV Mean ± SD)
Linear Regression	1989.37	1413.25	0.68	0.66 ± 0.04
LASSO (LassoCV)	1809.65	1290.42	0.71	0.69 ± 0.03
Decision Tree	1965.08	1392.17	0.65	0.63 ± 0.05
Random Forest	1773.07	1244.89	0.73	0.71 ± 0.03
GridSearchCV (RF)	1630.51	1170.45	0.76	0.75 ± 0.02
Stacking Ensemble	1628.30	1164.37	0.76	0.75 ± 0.02
Voting Ensemble	1622.03	1156.93	0.77	0.76 ± 0.01

Note: Precision, recall, and F1-score are classification metrics and thus not applicable in this continuous regression context.

Model Selection and Deployment Rationale

Despite the marginal improvement in RMSE by the Voting Ensemble, the Random Forest Regressor with GridSearchCV was selected for final deployment. This is due to its strong performance in handling non-linear and high-dimensional data, as well as lower overfitting risk through bootstrapping and feature randomness. It also has faster inference time suitable for real-time applications and enhanced interpretability through feature importance measures. The final model was deployed in a lightweight application compatible with both mobile devices and PCs, making the tool practical for public health decision-making in resource-constrained settings. This study builds upon and extends the work of Odu et al. (2021) and Sadiq et al. (2024) by incorporating multiple modeling strategies, focusing on local-level predictions in Damaturu, and emphasizing deployment-ready tools for community health monitoring.

FINDINGS AND DISCUSSIONS

The findings presented trends, patterns, and variability of the datasets. For example, from Figure 1, the temperature oscillated from 20°C to 34°C, where it is seasonally differentiated; particularly in the range of 25°C-30°C at SaSZ, and may bear different implications in several livelihoods and living conditions in the area. Because temperature spikes, especially those above 30°C, may indicate periods of heightened malaria transmission, while dips below 25°C suggest reduced transmission, as often found in studies (Ukawuba & Shaman, 2022; Touré et al., 2022). These findings suggest that the variability in temperature may correspondingly be similar to the malaria transmission in the study area. Moreover, Figure 2 presents a predictable unimodal distribution with sharp annual peaks between 100mm and 250mm followed by extended dry periods. It is a representative distribution of the climate type for the Sahel Savanna Zone, which can affect mosquito breeding and, in turn, malaria transmission. However, the predictable spikes in rainfall account for a surge in the population of mosquitoes, which led Burga and Mohammed (2025) to suggest preemptive vector control measures. Collectively, these climatic insights pointed to the likely profound impact of temperature and rainfall on malaria transmission in SaSZ, emphasizing the need for adaptive public health strategies that are responsive to the zone's evolving environmental conditions.

The findings from the climatic analysis revealed notable trends, patterns, and variability that are directly relevant to malaria transmission in the Sahel Savanna Zone (SaSZ). As shown in Figure 1, temperature values oscillated between 20°C and 34°C, with a predominant seasonal range of 25°C to 30°C. This thermal window is particularly conducive to mosquito development and malaria transmission, as affirmed by Ukawuba and Shaman (2022) and Touré et al. (2022), who found that malaria transmission peaks when temperatures fall within this band. Temperatures exceeding 30°C may signify periods of heightened malaria risk, while those dropping below 25°C often correlate with decreased transmission, given the sensitivity of both mosquito and Plasmodium parasite life cycles to thermal stress. Recent machine learning studies corroborate these patterns. For instance, Garba et al. (2023) as well as Singh and Saran (2024) used neural networks and support vector regression to identify temperature thresholds between 24°C and 32°C as critical predictors of malaria outbreaks in West African regions. Similarly, Yamba et al. (2023) and Edmund (2023) found that malaria case projections rise significantly with abrupt increases in mean daily temperatures beyond 28°C, especially in semi-arid zones. Figure 2 presents a rainfall profile characterized by a unimodal distribution, with sharp peaks between 100 mm and 250 mm, followed by prolonged dry spells. This distribution is consistent with the Sahelian climate, where concentrated rainfall over a short duration fosters rapid creation of mosquito breeding habitats. The strong seasonal nature of rainfall translates to predictable surges in mosquito population and thus malaria incidence. This observation echoes the findings of Burga and Mohammed (2025), who recommended anticipatory vector control interventions just before rainfall peaks.

Further, Ukawuba and Shaman (2022) and Obiora et al. (2023), using long short-term memory (LSTM) models, demonstrated that rainfall events—even brief but intense ones—can significantly influence larval habitat proliferation, leading to sustained transmission periods beyond the rainy season. Their studies underscore the importance of lag effects in predictive models, where malaria cases rise several weeks after heavy rainfall episodes. Moreover, machine learning applications in malaria-climate modeling, such as those by Smith et al. (2020), Ayanlade et al. (2020), and Diouf et al. (2020), reinforce these findings. These studies employed ensemble techniques and climate-health datasets to uncover robust relationships between seasonal climate variability and malaria prevalence, particularly in low-resource, rain-fed agricultural zones similar to Yobe State's SaSZ. Their findings advocate for the incorporation of climate data into early warning systems, emphasizing the value of real-time weather monitoring and community-based surveillance in mitigating malaria risks. In essence, the observed temperature (20°C–34°C) and rainfall (100 mm–250 mm) patterns provide a predictive window for malaria transmission dynamics in the SaSZ. These insights, validated by recent AI-based studies, highlight the need for climate-adaptive public health policies that incorporate predictive analytics, targeted vector control, and proactive community health education to effectively respond to climate-driven disease patterns.

In the TZ, Figure 3 depicts periodic spikes of rainfall of up to 350mm, characterizing unimodal rainfall patterns with concentrated wet seasons. The rainfall onset, dry periods, and peaks are very likely to influence mosquito breeding and malaria transmission risks, as stagnant water from heavy rainfall provides ideal conditions for larvae development. In other research works (Baba-Adamu et al., 2025) that were implemented in settings akin to this current study location, similar findings have been documented. On the contrary, Baba-Adamu et al. (2025) suggested in their research work that extreme hot weather or extensive dry spells naturally constrain mosquito densities. Whereas Figure 4 revealed significant fluctuations between 27.5°C and 47.5°C, with pronounced peaks exceeding 40°C, indicative of extreme heat events, and troughs below 30°C, corresponding to relatively cooler phases. These fluctuations reflect seasonal changes, with hotter periods likely aligning with the dry season and cooler periods with the wet season. Temperature spikes above 40°C could negatively impact Anopheles mosquito populations, reducing their survival and thus lowering malaria transmission risk during extreme heat (Garba et al., 2023). Optimal mosquito and Plasmodium parasite development occur between 25°C and 30°C (Garba et al., 2023), but frequent spikes above this range may shorten mosquito lifespans, potentially limiting effective transmission windows. The observed increase in extreme temperature events, particularly after 2019, suggests possible climate change effects, which could shift malaria transmission seasons and intensity, necessitating adaptive control strategies (Baba-Adamu et al., 2025). As climate change intensifies, an adaptive strategy based on real-time climatic data and predictive models will be essential for effective disease control and public health protection.

In the Transition Zone (TZ), Figure 3 revealed periodic spikes in rainfall reaching up to 350 mm, characteristic of a unimodal pattern with short but intense wet seasons. These rainfall surges are particularly significant as they coincide with the onset and peak of mosquito breeding cycles, with stagnant water from heavy precipitation creating ideal habitats for Anopheles larvae development. Similar findings were documented in Baba-Adamu et al. (2024), who observed that in comparable ecological contexts, short rainy seasons with concentrated downpours significantly heightened malaria risks due to rapid vector proliferation. The concentrated rainfall windows serve as reliable predictors for malaria surges, especially when followed by high humidity and mild temperatures.

Conversely, as Baba-Adamu et al. (2025) noted, prolonged dry spells and extremely hot weather conditions may act as natural constraints on mosquito densities, reducing larval survival and adult mosquito lifespan. This inverse relationship is particularly relevant in Figure 4, which shows pronounced temperature fluctuations between 27.5°C and 47.5°C, with frequent peaks exceeding 40°C and troughs below 30°C. These fluctuations correspond with seasonal transitions—hotter periods align with the dry season, while relatively cooler phases match the wet season. Global studies support this climate–vector dynamic. For example, Garba et al. (2023) as well as Singh and Saran (2024) used ensemble machine learning techniques to show that optimal transmission temperatures lie between 25°C and 30°C, a range where both mosquito development and Plasmodium maturation are most efficient. Spikes above 35°C–40°C, however, were found to impair mosquito survival, limit feeding frequency, and reduce the sporogonic cycle's completion rate. Similarly, Burga and Mohammed (2025), using high-resolution climate-health simulations, demonstrated that extreme heat events, while increasing human discomfort, tend to suppress malaria vector populations due to physiological stress on mosquitoes.

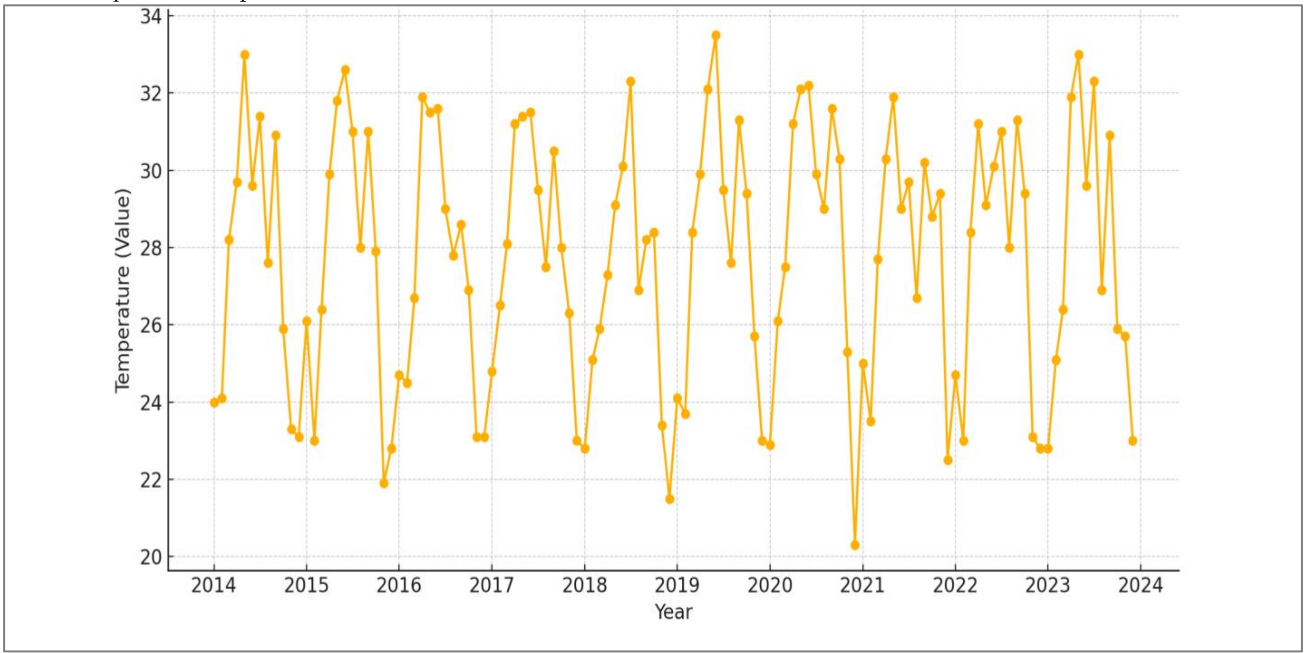

Figure 1: Temperature conditions of northern zone
Source: Fieldwork, 2024

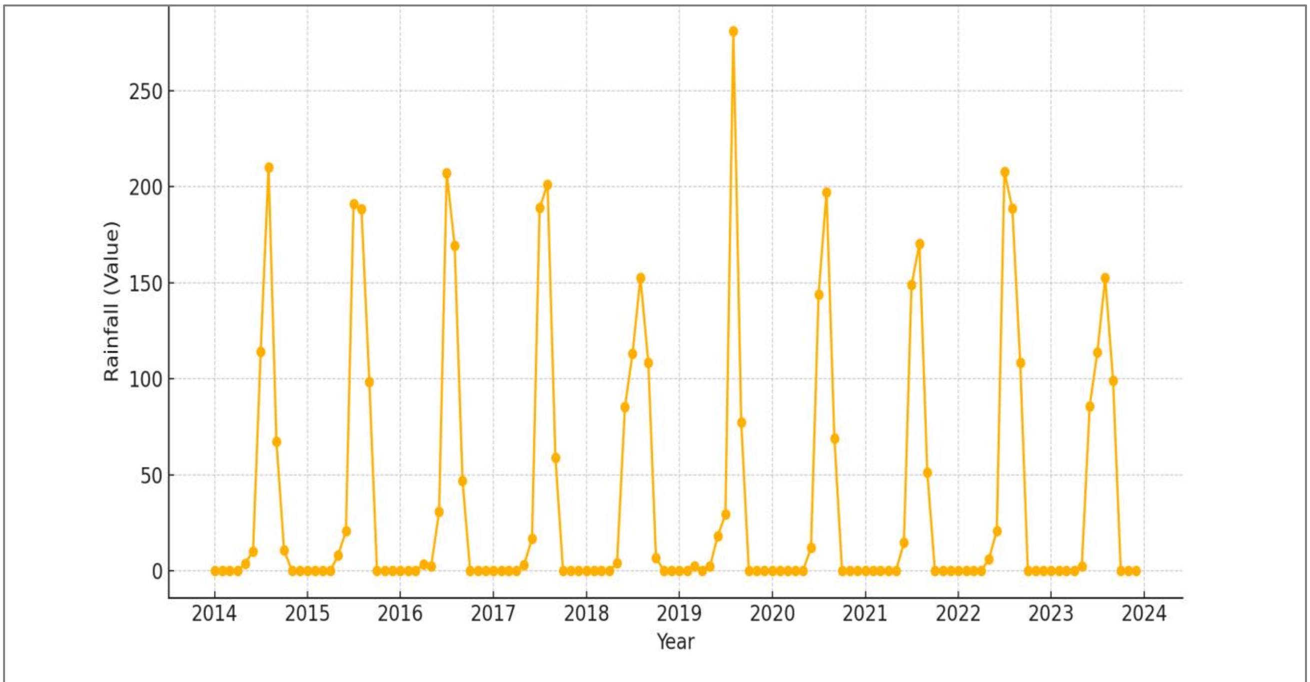

Figure 2: Rainfall conditions of the northern zone
Source: Fieldwork, 2024

Ukawuba and Shaman (2022) further support this argument by modeling Anopheles dynamics using a simplified entomological framework, showing that temperatures above 40°C can drastically reduce mosquito survival, thereby disrupting transmission chains. These insights are consistent with Ayanlade et al. (2020), who noted that rainfall–temperature interactions—not merely individual thresholds—determine malaria seasonality.

Importantly, these models highlight non-linear relationships between climate variables and malaria risk, underscoring the need for machine learning approaches to capture such complex interactions. The post-2019 period, as observed in the dataset, indicates a notable increase in extreme temperature events, suggesting possible climate change effects. This aligns with findings from Smith et al. (2020), who integrated hydrological models into malaria risk projections and concluded that shifts in temperature and water flow patterns due to climate change will alter malaria transmission belts across Africa. Likewise, Diouf et al. (2020) observed that interannual climate variability, driven by warming and rainfall anomalies, is already reshaping malaria incidence patterns across West Africa.

Given these findings, the implications for malaria control in the TZ are significant. The increasing frequency of temperature extremes above 40°C, combined with intense but short-lived rainfall, suggests that traditional seasonal models of malaria control may no longer suffice. Instead, adaptive strategies—informed by real-time climatic data and predictive machine learning models—will be essential. These should include flexible vector control calendars, climate-responsive health education, and dynamic resource allocation, particularly in highly variable transition zones like TZ. Baba-Adamu et al. (2025) emphasized the importance of integrating climate intelligence into health planning, especially as climate change continues to stretch the boundaries of predictability and public health vulnerability.

Moreover, the SuSZ, as shown in Figure 5, exhibits temperature fluctuations between 20°C and 34°C, reflecting seasonal cycles with warmer months likely exceeding 30°C and cooler seasons closer to 20°C. These variations are significant for understanding Anopheles mosquito life cycles, as warmer temperatures (25°C to 30°C) facilitate faster mosquito and Plasmodium parasite development, increasing malaria transmission potential (Diriba et al., 2024; Yamba et al., 2023). However, temperatures above 30°C could decrease the survival of mosquitoes, thus limiting the transmission during such warmer periods, while cooler temperatures may delay the development of parasites, thus lowering the risk of transmission (Garba et al., 2023). Increased temperature variability over the decade indicates broader climatic changes that could alter malaria transmission patterns by altering the timing and intensity of the transmission seasons (Eneanya et al., 2023). The plot of rainfall in Figure 6 exhibited a very pronounced wet and dry period, but there are spikes up to 350mm representing intense but brief activity. This is an essential fluctuation because the peaks produce standing water for the development of mosquito larvae (Yakudima et al., 2022). The consistent yearly pattern of rainfall spikes provides a predictable window for implementing malaria control interventions, such as larviciding and the distribution of ITNs (Ayanlade et al., 2020). The interplay between temperature and rainfall is key to malaria risk. High rainfall followed by warm temperatures creates ideal conditions for mosquito proliferation and malaria spread, while cooler or drier periods may limit transmission (Garba et al., 2022; Eneanya et al., 2023). The observed climatic variability suggests that static malaria control strategies may be inadequate. Instead, dynamic, climate-responsive interventions, informed by real-time data, would likely be more effective.

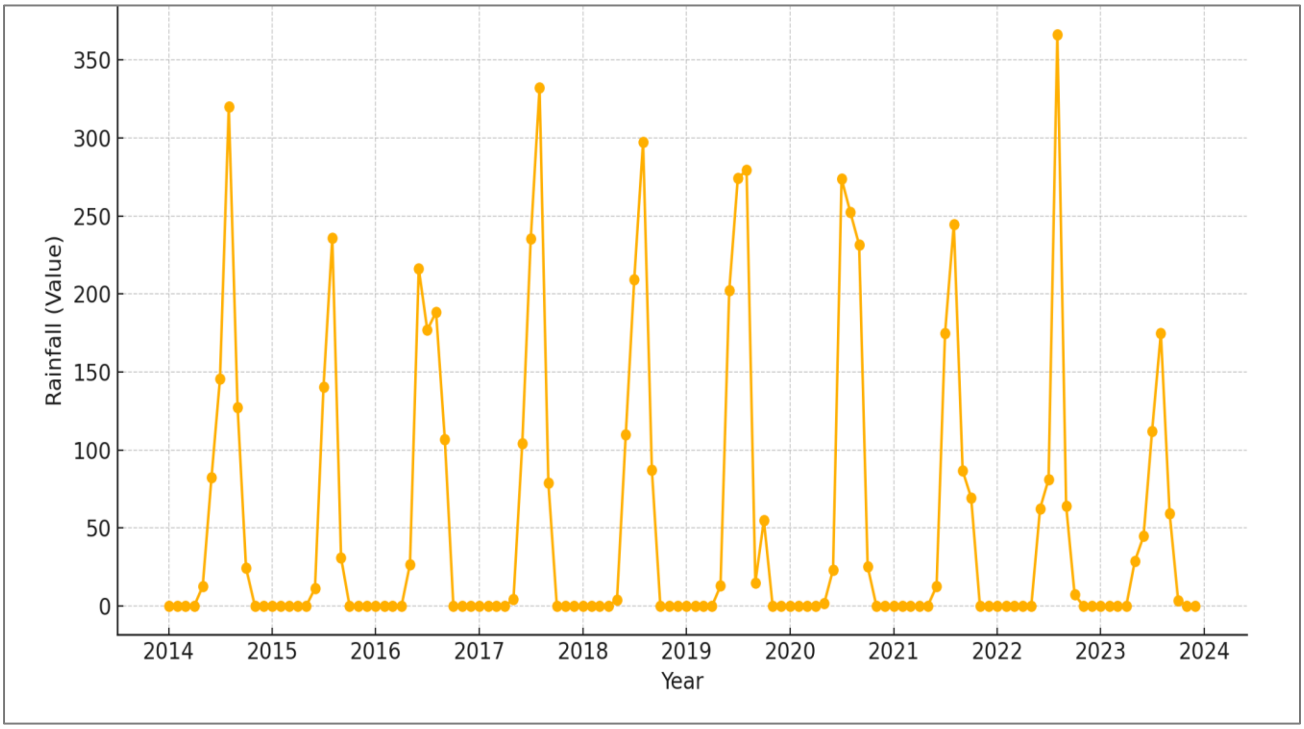

Figure 3: Rainfall conditions of the central zone
Source: Fieldwork, 2024

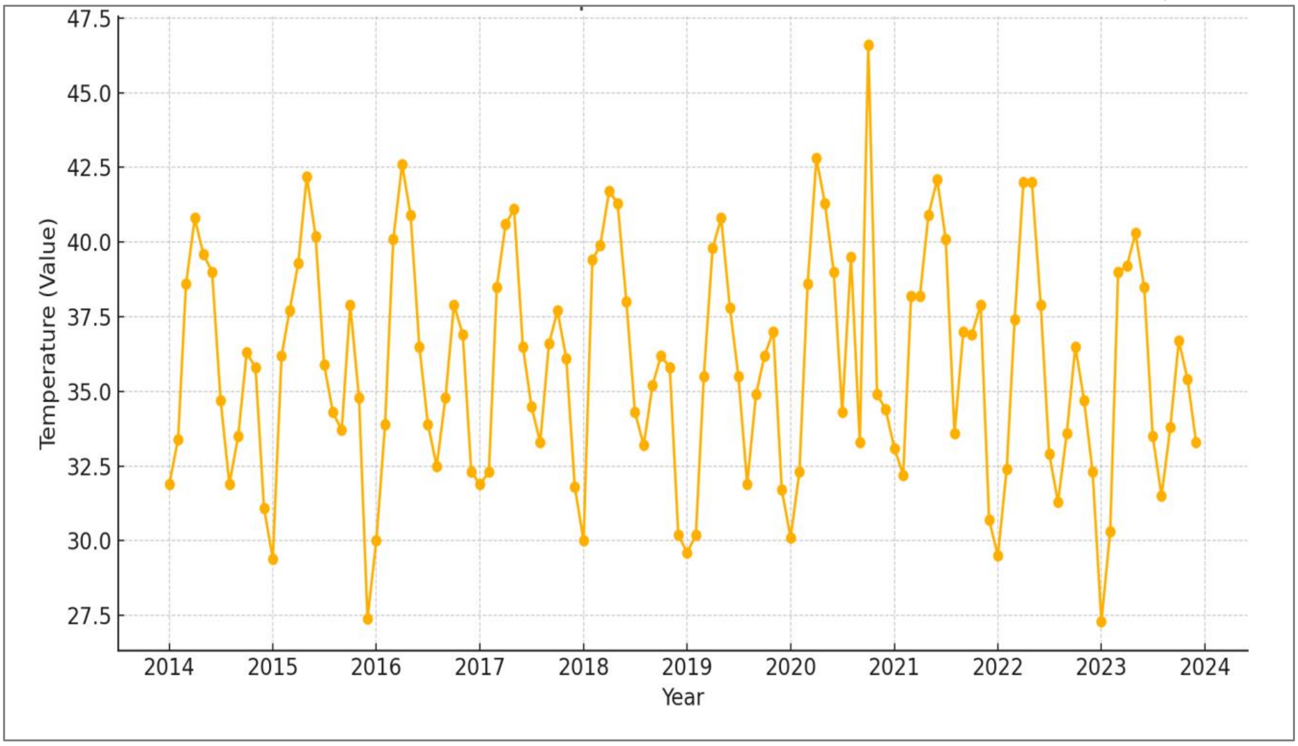

Figure 4: Temperature conditions of the central zone
Source: Fieldwork, 2024

The findings, as also opined by Yamba et al. (2023), underscore the need for enhanced monitoring and predictive models to address the challenges posed by climate change, ensuring adaptive public health strategies that respond to shifting environmental conditions. More so, the rainfall plot's implications underscored a critical ecological nexus linking climatic factors to malaria epidemiology. This is because the sharp rainfall spikes up to 350mm are particularly noteworthy for their role in generating transient breeding grounds for mosquitoes, which are integral to the malaria transmission cycle. These intense rainfall events often lead to temporary water pooling, creating favorable habitats for Anopheles mosquitoes.

Furthermore, the synergy between rainfall and temperature amplified malaria risk. As rains diminish, the following warm weather speeds mosquito development and boosts Plasmodium parasite incubation within the vector, thereby enhancing transmission potential. Such interaction emphasized the need for timely interventions, including larviciding in the immediate wake of rainfall surges and making ITNs widely available during peak breeding periods. However, the randomness in rainfall intensity and distribution, particularly, and rising climate unpredictability generally, have challenged the old static control measures.

In the Sudano-Sahelian Zone (SuSZ), as depicted in Figure 5, the temperature varies between 20°C and 34°C, reflecting a clear seasonal cycle. Warmer months tend to exceed 30°C, while cooler seasons remain closer to 20°C. These seasonal shifts are central to understanding the life cycles of Anopheles mosquitoes and the transmission dynamics of Plasmodium parasites. The temperature window between 25°C and 30°C is particularly conducive for the development of both the mosquito vector and the malaria parasite, as emphasized in Diriba et al. (2024) and Yamba et al. (2023). During these optimal conditions, transmission potential increases due to faster maturation rates and more frequent feeding cycles.

However, Garba et al. (2023) caution that when temperatures exceed 30°C, mosquito survival begins to decline, and vectorial capacity may diminish, thereby curbing transmission. Conversely, temperatures closer to 20°C may slow the development of both vectors and parasites, lengthening the sporogonic cycle and delaying the transmission peak. The decade-long trend of increasing temperature variability in the SuSZ—likely an indicator of broader climatic change—could therefore shift both the timing and intensity of malaria transmission seasons, as also projected by Eneanya et al. (2023). The rainfall pattern in Figure 6 further enriches this climate-malaria nexus. The graph displays a distinct dichotomy between pronounced wet and dry seasons, with periodic spikes reaching up to 350 mm. These intense but short-lived rainfall events are ecologically significant because they produce temporary pools of standing water, which serve as ideal breeding habitats for mosquito larvae, as highlighted by Yakudima et al. (2022). These rainfall surges, though brief, create a predictable ecological window in which malaria risk sharply increases. In line with findings from Ayanlade et al. (2020), these windows present an opportunity for pre-emptive public health interventions, such as larviciding campaigns, indoor residual spraying (IRS), and the mass distribution of insecticide-treated nets (ITNs).

Importantly, global machine learning studies, such as those by Garba et al. (2023) and Yamba et al. (2023), demonstrate that synergistic interactions between rainfall and temperature provide a more accurate prediction of malaria incidence than single-variable models. For instance, high rainfall followed by warm temperatures is especially dangerous—it accelerates mosquito maturation and shortens the incubation period of the malaria parasite within the vector. This sequence of events significantly raises the probability of infection, a dynamic also observed by Obiora et al. (2023) and Edmund (2023) in sub-Saharan case studies. Furthermore, Ukawuba and Shaman (2022) stress that such short-term climate extremes—if not anticipated—can overwhelm static malaria control systems. Their models call for real-time climate surveillance and the deployment of predictive tools to align public health resources with high-risk windows. This is particularly relevant in the SuSZ, where both climate unpredictability and resource constraints challenge the effectiveness of conventional interventions. The integration of predictive analytics into malaria programming, as advocated by Singh and Saran (2024), in addition to Diouf et al. (2020), becomes essential. The implications of these findings are twofold. Firstly, they underline the need to replace static control calendars with climate-responsive malaria strategies—interventions that are flexible, targeted, and timed based on environmental cues. Secondly, the randomness in rainfall intensity and distribution, especially in the Sahel belt, demands enhanced ecological monitoring and data-driven public health decision-making. As Yamba et al. (2023) rightly opined, the changing climate has transformed malaria from a seasonal disease into a climate-sensitive threat, necessitating adaptive models and early-warning systems. In conclusion, the ecological interplay between rainfall and temperature in the SuSZ shapes the malaria transmission landscape in profound ways. The presence of rainfall spikes up to 350 mm, followed by warming trends, sets the stage for increased malaria outbreaks. Hence, malaria control strategies must become anticipatory, data-informed, and rooted in climate–epidemiological modeling, if they are to remain effective in the face of escalating climate variability.

Overall, the cumulative temperature and rainfall trends of the study area, as shown in Figures 7 and 8, provided essential insights into climate variability. The rainfall trend, for example, with oscillations between 0mm and 120mm, reflects the study area's rainy and dry seasons. The peaks in rainfall, which align with the rainy season, are vital for mosquito breeding, as standing water is necessary for larvae development (Eneanya et al., 2023). However, this variability in rainfall intensity across years suggests shifting weather patterns due to climate change, potentially leading to more unpredictable rainy seasons and complicating malaria control efforts (Baba-Adamu et al., 2024). The temperature trends fluctuated from 28 to 34 °C, revealing warming and cooling episodes, presumably related to events of larger climatic events like El Niño or La Niña (Yamusa & Abdulkadir, 2020). Such changes are critical given that they can impact the length and intensity of malaria transmission seasons. This is because, as reported by Yamba et al. (2023), while warmer temperatures generally enhance mosquito survival and reproduction, extreme heat beyond optimal ranges could reduce mosquito populations, complicating malaria transmission predictions based solely on temperature. More so, in terms of seasonality, temperature and rainfall displayed regular, predictable cycles with peaks in temperature coinciding with the onset of the rainy season, creating optimal conditions for malaria transmission (Leal-Filho et al., 2023).

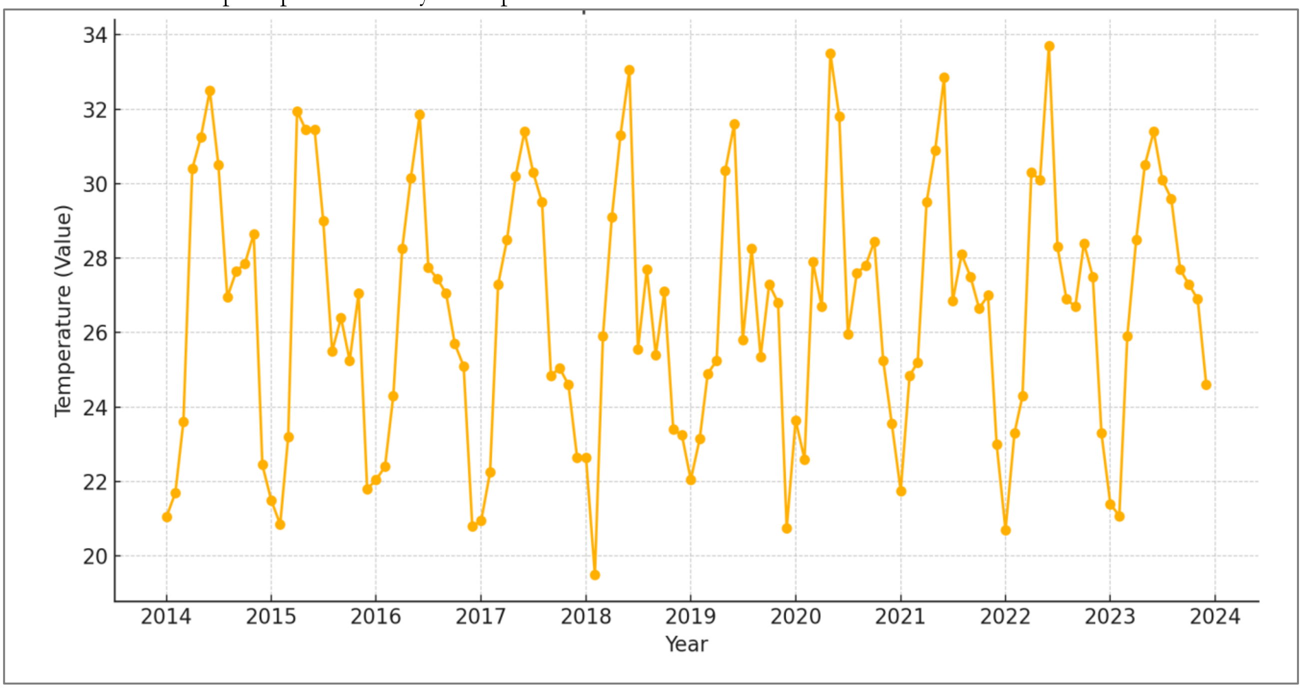

Figure 5 Temperature fluctuation in Guinea Savanna Zone (GSZ)
Source: Fieldwork, 2024

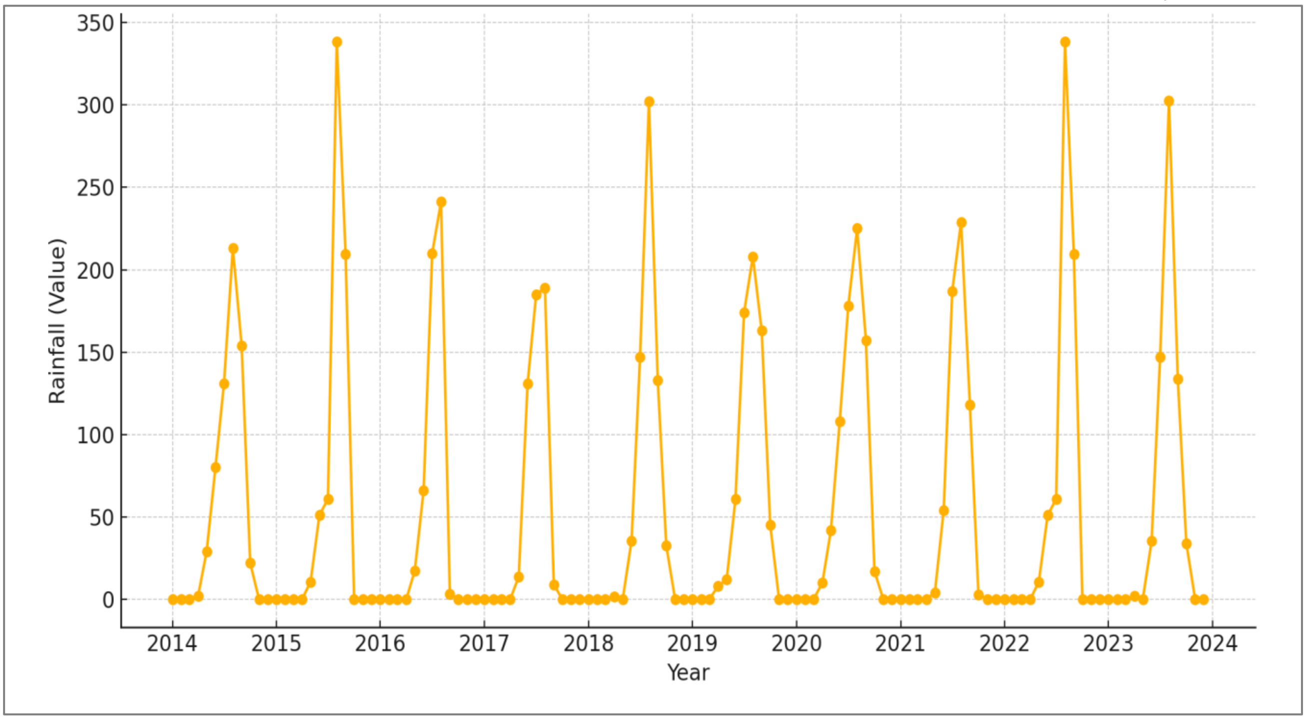

Figure 6 Rainfall variability in Guinea Savanna Zone (GSZ)
Source: Fieldwork, 2024

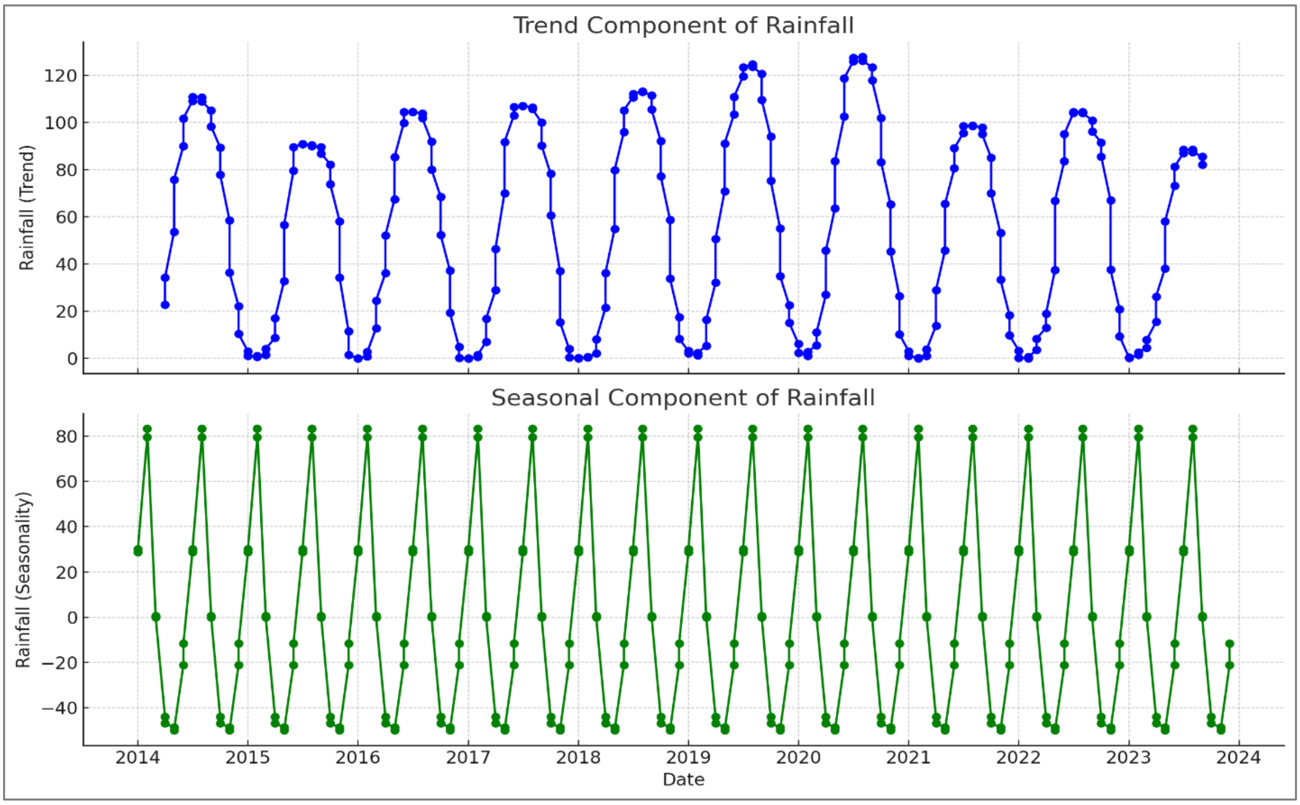

Figure 7: Overall Rainfall Trend and Seasonality
Source: Fieldwork, 2024

These patterns underscore the importance of timing malaria control interventions, such as ITNs and IRS, to coincide with these climatic peaks to maximize effectiveness. As often employed by some studies (Ukawuba & Shaman, 2022; Garba et al., 2023), the analysis highlighted the interconnected nature of temperature and rainfall, especially for integrated modeling of malaria risk based on both short-term seasonal cycles and longer-term climatic trends. This is particularly important because climate change drives increased variability in these trends, making adaptive strategies essential for effective malaria control and public health planning.

In the overall context of the study area, the cumulative temperature and rainfall trends illustrated in Figures 7 and

8 offer valuable insights into the extent and nature of climate variability and its implications for malaria transmission. The rainfall trends, oscillating between 0 mm and 120 mm, capture the characteristic alternation between dry and rainy seasons in the region. These rainfall peaks, which align with the wet season, are ecologically critical, as they foster mosquito breeding by creating standing water needed for larval development—a linkage corroborated by Eneanya et al. (2023). However, the variability in rainfall intensity across years is emblematic of a changing climate regime, likely exacerbated by anthropogenic climate change. Such fluctuations may result in unpredictable rainy seasons, which in turn complicate the planning and execution of malaria control strategies. As Baba-Adamu et al. (2024) noted, increased irregularity in rainfall onset and cessation can significantly affect the timing of mosquito population surges, making predictive intervention planning more difficult. In parallel, the temperature profile of the study area exhibited fluctuations between 28°C and 34°C, reflecting a pattern of warming and cooling episodes, potentially linked to larger climatic phenomena such as El Niño and La Niña events. Yamusa and Abdulkadir (2020) emphasized that these episodes can shift regional weather patterns, affecting humidity, precipitation, and temperature in ways that alter vector ecology and disease seasonality. While warming trends generally facilitate increased mosquito survival and reproduction, extreme heat beyond optimal thresholds (typically 30°C) may instead reduce mosquito populations, thereby limiting effective malaria transmission windows—a finding echoed in Yamba et al. (2023). Importantly, the coincidence of temperature peaks with the onset of the rainy season creates ideal conditions for the amplification of malaria transmission. As Leal-Filho et al. (2023) highlighted, the synchrony between climatic factors—when high humidity, rainfall, and temperature co-occur—produces a perfect storm for vector proliferation and pathogen development. These climatic patterns underscore the strategic importance of intervention timing. Tools such as insecticide-treated nets (ITNs) and indoor residual spraying (IRS) are most effective when deployed ahead of, or during, these high-risk periods. Beyond short-term seasonality, the interconnected nature of temperature and rainfall supports the use of integrated modeling approaches for forecasting malaria risk. Ukawuba and Shaman (2022), in addition to Garba et al. (2023), employed such integrated, often machine-learning-based models to accurately capture malaria risk dynamics by considering the synergistic effects of multiple climate variables. These approaches, which have proven effective across diverse African ecologies, provide a pathway toward data-driven and anticipatory public health strategies. Moreover, studies like those of Yamba et al. (2023) and Obiora et al. (2023) illustrate how machine learning algorithms can simulate future malaria scenarios under projected climate conditions.

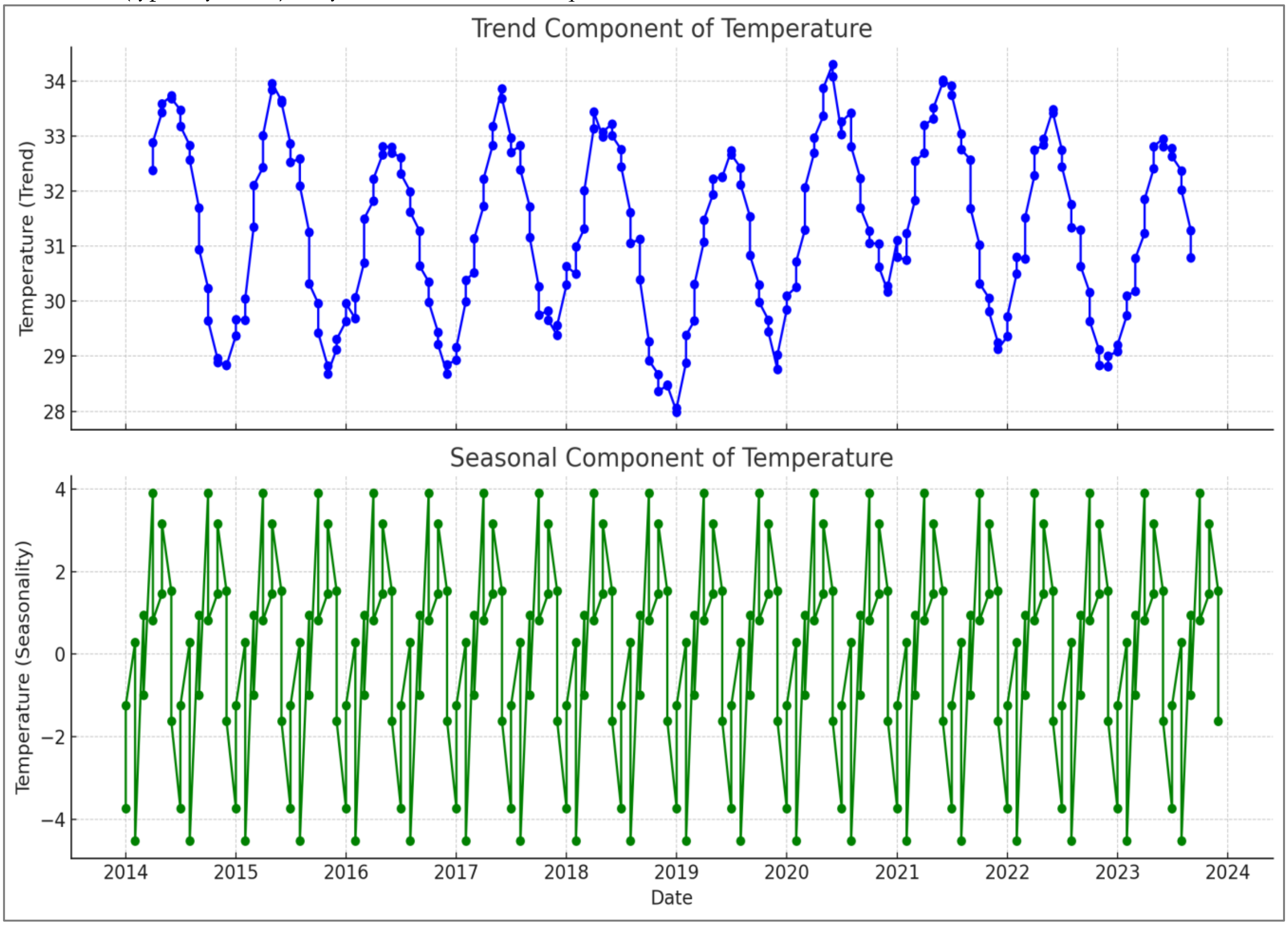

Figure 8: Temperature trend and seasonality in the study area
Source: Fieldwork, 2023

These models account for non-linear interactions between environmental drivers and vector behavior, offering granular risk maps and decision-making tools for malaria control programs. As climate change continues to drive greater variability in both temperature and rainfall trends, the imperative for adaptive malaria control strategies becomes ever more critical. Rigid, calendar-based interventions are likely to become obsolete in favor of real-time, climate-informed planning. This study thus reinforces the value of climate surveillance systems, early warning mechanisms, and predictive analytics in informing malaria prevention efforts, particularly in rural and climate-sensitive settings like Yobe State.

This study accentuates the need for **climate-responsive public health policies** *that integrate* **real-time climatic data**, *predictive models, and targeted malaria control interventions to adapt to the changing climate in Yobe State and similar regions.* By doing so, this study contributed three major innovations to the field: (1) it applied advanced machine learning models to malaria prediction in a previously underrepresented region; (2) it linked localized climatic variability with malaria trends in a manner that is spatially explicit and policy-relevant; and (3) it offered a scalable, data-driven framework for region-specific malaria risk analysis in Nigeria. In doing so, it complemented prior continental and national-scale studies (Singh & Saran, 2024; Edmund, 2023; Obiora et al., 2023), while filling a critical empirical and methodological gap in the malaria-climate literature concerning northeastern Nigeria.

CONCLUSION

In conclusion, this study provides a comprehensive analysis of climate variability in Yobe State, Nigeria, and its implications for malaria transmission. Findings indicated significant fluctuations in temperature and rainfall with observable impacts on the breeding patterns of Anopheles mosquitoes and the seasonal dynamics of malaria transmission. The study indicated that temperature increases above 30°C may lead to increased malaria prevalence, and extreme heat events above 40°C may reduce mosquito survival, thereby changing the transmission cycles. Similarly, unimodal rainfall distribution with intense seasonal peaks creates favorable conditions for mosquito breeding, which requires timely intervention measures. The interplay between climate variability and malaria risk underscores the need for climate-responsive public health strategies. Traditional static malaria control measures may not be enough in the face of increasingly unpredictable climate patterns. Instead, the integration of real-time climatic data into predictive models can enhance early warning systems and improve the effectiveness of malaria interventions. In addition, proactive measures, such as intensified vector control strategies before peak rainfall seasons and climate-adaptive policies, are critical for mitigating climate-related health risks. In conclusion, this study stressed the need for multi-sectoral collaboration between climate scientists, epidemiologists, and public health policymakers to develop integrated approaches that address the climate-driven health challenges in Yobe State. Strengthening climate adaptation strategies, enhancing disease surveillance systems, and implementing evidence-based malaria control interventions can improve resilience and safeguard vulnerable populations against the health impacts of climate variability.

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