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GEOSTATISTICAL EVALUATION OF THE IMPACT OF CLIMATE VARIABILITY ON MALARIA INCIDENCE IN THE SOUTH-WEST OF NIGERIA

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Abstract

Malaria remains a significant health concern in Nigeria, particularly in the South-West region. This study assesses the impact of temperature and rainfall on malaria incidence and prevalence in South-West Nigeria using remotely sensed and modelled data sourced from the Malaria Atlas Project and NASA's POWER database covering 2000 to 2020. The study adopts the Geographically Weighted Regression geostatistical model to establish the relationship between malaria and rainfall and temperature in the study area. The result shows a rising oscillating annual mean temperature trend of 0.0088oC/yr-1 from 2000 to 2020. The malaria incidence exceeds 8 million cases annually, peaking in 2020 at almost 10 million cases. The rising trend of malaria incidence highlights the inadequacy of the malaria intervention programmes to meet their goal of reducing malaria incidence by 40% by 2020. The study highlights the spatial variations, with high incidence in urban centres like Lagos and Ibadan metropolises, their satellite towns, as well as other prominent and capital towns including Oshogbo, Ilesa, Akure, Ijebu-Ode and Abeokuta. Contrary to this, the greater malaria prevalence was recorded in less densely populated areas of Oyo state, Imeko-Afon, Odeda, Yewa and Ijebu-Waterside areas in Ogun state as well as Ose and Idanre in Ondo state. The Geographically Weighted Regression equation model shows a strong positive correlation between malaria prevalence and temperature at a significance of 0.76 compared to rainfall which exhibits no association indicating the relevance of temperature as an explanatory indicator of malaria. With the continuous endemicity of malaria in the South-West, malaria management and control efforts should be focused on high-incidence areas in the South-West and Nigeria in general to fulfil the Sustainable Development Goal of Good health and well-being and the eradication of malaria by 2030.

Keywords: Climate Variability, Geostatistics, Malaria Incidence; Malaria Prevalence; Rainfall; South-West; Temperature

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INTRODUCTION

With over 3.4 billion people at risk of contracting the disease, malaria is the largest infectious disease and source of death in the entire world Arab et al., 2014; Lubinda et al., 2021). In 2020, there were 627,000 malaria-related fatalities in 85 endemic nations, with an expected 241 million cases of the infection (WHO, 2022). Pregnant women and children under five make up the majority of the casualties (WHO, 2020). Malaria prevalence has been steadily declining globally in the twenty-first century, but it is still widespread in Sub-Saharan Africa, which accounts for 92% of all instances worldwide (WHO, 2019). The persistent endemicity of malaria in tropical areas, particularly in Africa, has been related to the region's poor public health infrastructure and the severe consequences of Plasmodium infections (Caminade et al., 2014).

The anthropogenic changes to our environment, such as rising greenhouse gas pollution and a rise in the frequency of severe events brought on by climate variability, add to this situation (Efe and Ojoh, 2013). (Kim et al., 2012; Mohammadkhani et al., 2016; Akinbobola and Hamisu, 2022) argued that while temperature affects the malaria parasite's and mosquito's lifecycle (Mohammadkhani et al., 2016), rainfall creates an environment conducive to mosquito fertilisation and breeding (Mohammadkhani et al., 2016). The greatest mix of sufficient rainfall and temperature for anopheline mosquito reproduction and survival exists in tropical regions like the southwest of Nigeria (Efe and Ojoh, 2013).

Our understanding of the mechanisms underlying the linkage between malaria and climate remains lacking because of their complicated interaction (Wickremasinghe, et al., 2012). In areas where the disease has been successfully controlled as well as in new, historically non-malarious areas, studies have shown that the changing climate will increase the opportunities for malaria transmission in historically malarious areas like the southwestern region of Nigeria (Ajayi et al., 2017; Oheneba-Dornyo et al., 2022; Wickremasinghe, et al., 2012; Santos-Vega et al., 2016; Lubinda et al., 2021). Increased temperatures and rainfall may encourage the growth of malaria-carrying mosquitoes at higher elevations, increasing malaria spread in previously low-incidence regions (Arab et al., 2014; Escobar et al., 2016). Warmer temperatures will influence the evolution of the parasite in the mosquito and enable it to develop quicker in low-altitude regions like the coastal region of Nigeria where malaria is extremely prevalent, boosting spread and having an impact on the burden of the disease (Efe and Ojoh, 2013; Arab et al., 2014; Wanjala and Kweka, 2016).

The relationship between malaria prevalence, rainfall and temperature was determined using the Geographic Weighted Regression (GWR). The GWR is an important local method for analysing spatial varying relationships (Ge et al., 2017). Unlike other regression analyses, the GWR allows the regression parameters to vary locally by providing location-wise parameter estimates for each variable in spatial regression problems (Ge et al., 2017). Its results are thus, significantly better fir for all tested combinations of variables (Ndiath et al., 2015). The GWR allows for the display and visualization of parameters estimates of each explanatory variable on a raster surface, this allows for an easy presentation and understanding of the complex relationships that have spatial variations (Ndiath et al., 2015; Jasim et al., 2022).

GWR has been applied in various fields including environment and meteorology (Pasculli et al., 2014; Tewara et al., 2019; Tesfamicheal et al., 2022), land use and landcover (Su et al., 2012), in health, disease and related studies (Black 2014; Liu et al., 2021; Jasim et al., 2022) and malaria (Ndiath et al., 2015; Ge et al., 2017). The application of GWR methods to health and related studies, especially malaria has enabled complex scenarios of malaria disease to be visualized through the creation of spatial maps within the Geographic Information System (GIS) technology (Tewara et al., 2019).

Few studies are available on the regional aspect of the diseases, especially in a highly heterogeneous and socially and environmentally diverse region like the South-West. Studies on the relationship between malaria incidence and rainfall and temperature are rare and infrequent and are mostly restricted to state and national levels (Ojoh and Efe, 2013; Okunlola and Oyeyemi, 2019; Segun et al., 2020; Akinbobola and Hamisu, 2022; Oluwatimileyin et al., 2022; Ekpa et al., 2023). The lack of continuous spatiotemporal data coverage on malaria, rainfall, and temperature covering several years is the main obstacle impeding these studies from being conducted. The study overcame these problems by utilizing rainfall and temperature data from the Prediction of Worldwide Energy Resource (POWER) project from 2000 to 2020, as well as parasite rate survey data collected at the LGA level in the southwest area of Nigeria. Many nations, including Nigeria, have implemented control plans and eradication strategies that are based on mapping the prevalence and geographic spread of malaria (Weiss et al., 2019). The research will influence the malaria strategy for controlling malaria as well as future adaptations to climate change. It would also fill in any voids on malaria and the environment in Nigeria.

MATERIALS AND METHODS

Study Area

South-West Nigeria spans about 77815 Km^2 into the hinterland of Lagos, Ogun and Ondo axis of the Atlantic Ocean, from Latitude 6.35^o to 8.617^o North and Longitude 2.52^o to 6.11^o East of the Greenwich Meridian, including Lagos, Ogun, Osun, Ondo, Oyo and Ekiti States (Figure 1; Faleyimu et al., 2013). It is bounded by the Kogi and Kwara States, Edo and Delta States, the Gulf of Guinea, and the Republic of Benin form its northern, eastern, southern, southern, and western borders, respectively (Fasona et al., 2020a). prominent settlements in the study area include the Lagos and Ibadan Metropolis, Abeokuta, Ijebu-Ode, and Sagamu in Ogun State, Ilesa, Oshogbo, and Ogbomosho in Osun state, Ondo Town, Akure, Owo and Ore in Ondo state as well as Ado-Ekiti, Ikere, Ifaki, Oye in Ekiti state. According to the Köppen climate classification scheme, the region is located in the lowlands of the humid tropics of southern Nigeria (Ojo et al., 2001). It has distinct rainy and dry seasons, an all-year average temperature of 27°C, and double maximum yearly rainfall that can be as low as 900mm in the northern highlands and 3000mm along the coast (Kottek et al., 2006; Fasona et al., 2020b). Based on the cool and humid South-Westerlies from the Atlantic, the first rainy season, which is stronger, lasts from April to July, and the second, which is weakened, lasts from October to November. There is a comparatively dry period between the peaks that is known as the "August Break." However, harmattan North-Easterly winds typically occur from December through February, interrupting the primary dry season, which lasts from December to March (Omotosho and Abiodun, 2007).

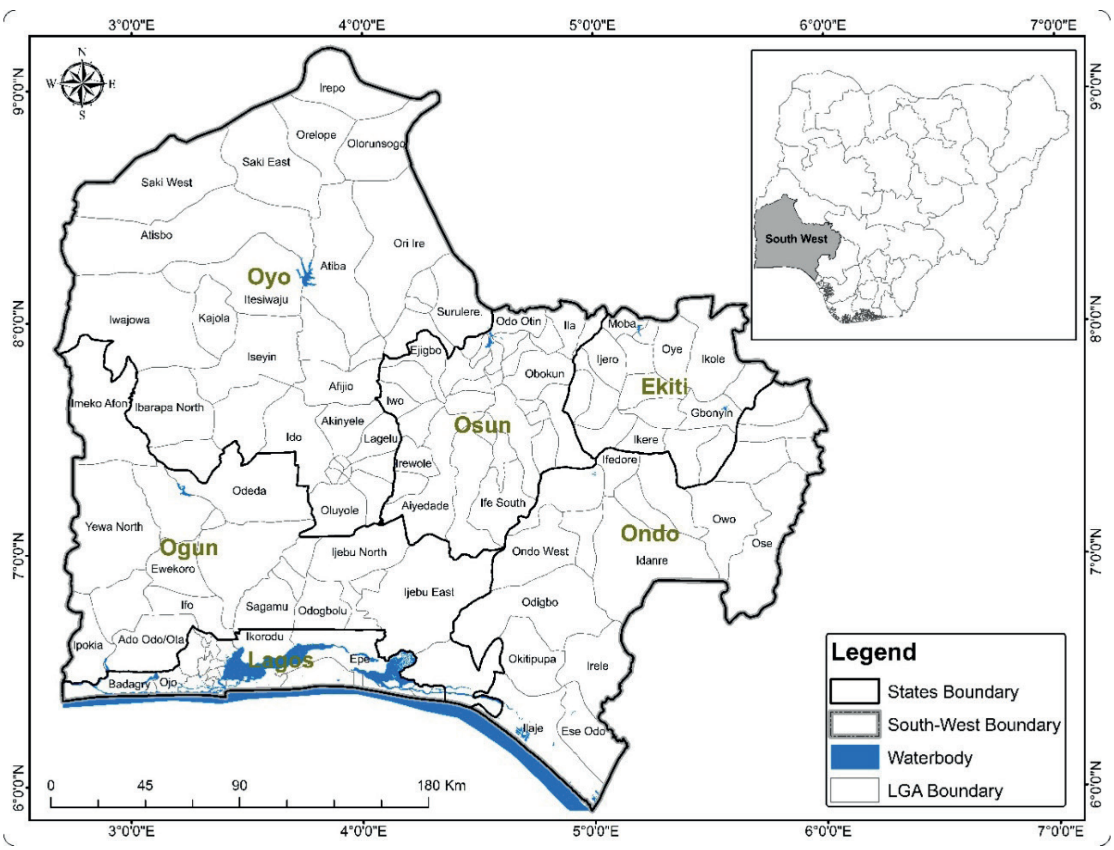

Figure 1: South-West Nigeria

Data Source and Characteristics

The National Aeronautics and Space Administration's POWER database (NASA, https://power.larc.nasa.gov/) provided the temperature and rainfall data for the study. The applicability of the data, particularly to environmental studies requiring geographic scales outside the scope of traditional weather locations, as well as its availability and high quality of documented long-term meteorological data, made it the preferred choice for the study (White et al., (2011). Additionally, there are limitations in the localisation in the Southwest due to a variety of factors that are general limitations of meteorological stations as argued by Davey and Pielke, (2005) and White et al., (2011).

The Malaria Atlas Project (MAP) database (http://www.map.ox.ac.uk/), which allows users to download, view, and modify parasite rates, administrative borders, and an extensive collection of raster's files spanning South-west Nigeria, served as the study's primary source of data on malaria incidence and prevalence (Pfeffer et al., 2018). The MAP has been adopted by numerous studies (Amoah et al., 2018; Korenromp et al., 2017; Golding et al., 2017; WHO, 2015) and has continued to support important international research such as the World Malaria Report (WHO, 2017) and the Global Burden of Disease study (Fene et al., 2020). The MAP was preferred over the conventional reported malaria case data sourced from the state's Ministry of Health because it is easier to access and is open access (Piel et al., 2013; Moyes et al., 2013). The MAP also keeps a regularly updated collection of national and subnational malariometric data, which is supported by academic journals, national health departments, foreign papers, and surveys like the DHS. (DHS, 2018). The United States Census Bureau's PEPFAR programme (https://www.census.gov/geographies/mapping-files/time-series/demo/international-programs/subnationalpopulation.html) used baseline population data from the 2006 Population Census to calculate the 2020 population estimates adopted for the study, at the local government level for the southwest region of Nigeria.

DATA ANALYSIS AND ANALYTICAL TECHNIQUES

To illustrate the spatial and temporal variation in rainfall, temperature, and malaria incidence in the southwest of Nigeria, the results were shown in surface maps and yearly trend charts. To demonstrate the time and geographical dimensions of the two meteorological variables, the yearly rainfall and annual mean temperature were specifically depicted in chats and surface maps (using the Inverse Distance Weight option of the Spatial Analysis Tool of the ArcGIS Pro software). Similarly, Charts and surface maps were used to display the yearly malaria incidence as well as the spatial distribution of the incidence (malaria incidence/1000 persons). Additionally, the prevalence of malaria in the southwest was shown on surface maps based on population forecasts for the year 2020. The prevalence of malaria was computed as cases per 1,000 people, and the malaria prevalence was depicted as in Eqn. 1.

$$MP = \frac{Malaria\ cases}{P \times Annual\ Grouth\ Rate} \times 1{,}000 \text{ .... Eqn. 1}$$

Where MP= Malaria Prevalence; P= 2020 Population estimate

(Source: Adapted from Oheneba-Dornyo et al., 2022)

The Geographically Weighted Regression (GWR) spatial statistics were employed for exploring the geo-statistical relationship between malaria prevalence, rainfall and average temperature. The linear regression was used as a diagnostic tool for selecting the appropriate predictors for the GWR model. The GWR model was developed using the ArcGIS Pro, via the **Spatial Statistics Tools>Modelling Spatial Relationships>Geographically Weighted Regression.** The model was calibrated using a weighting scheme, Continuous kernel function (Gaussian), where the number of neighbouring spatial units is used to define "varying" magnitude as actual bandwidth for each regression location. The optimal number of neighbours was determined by minimizing the Akaike Information Criterion (AICc). Malaria prevalence was the dependent variable while rainfall and average temperature were the explanatory variables (Ge et al., 2017; Ndiath et al., 2015).

A scatterplot with linear regression lines and local regression curves was used to analyse the link between malaria, rainfall, and temperature. Using the methods described by Torres-Reyna (2010) and Croissant and Millo (2008), the Panel Data Analysis was used to determine the effect of rainfall and temperature on the incidence of malaria.

RESULT

Average Temperature and Rainfall of South-West Nigeria

The annual mean temperature trend for South-West Nigeria during the period of 2000-2020 (Figure 2) shows an oscillating and rising trend of 0.0088°C/yr^{-1} or 0.088°C per decade. Additionally, the highest annual mean temperature was recorded in 2016 and 2006 with 26.53°C and 26.42°C respectively. On the other hand, the lowest temperature in the region was recorded in 2008, 2011 and 2012 at 25.59 °C, 25.64 °C and 25.65 °C respectively. The long-term trend in annual mean rainfall from 2000-2020 shows a positive trend of 15.008mm/yr^{-1} or 150.08mm per decade. In the 21 years, there has been an average annual rainfall of about 1351.6mm of rainfall per year in South-West Nigeria.

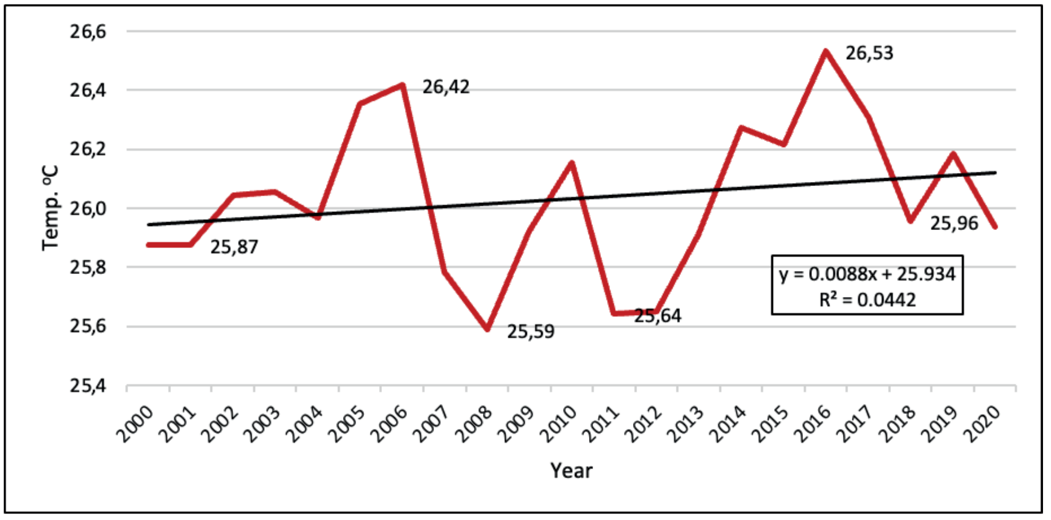

Figure 2: Annual mean temperature trend for the South-West region of Nigeria

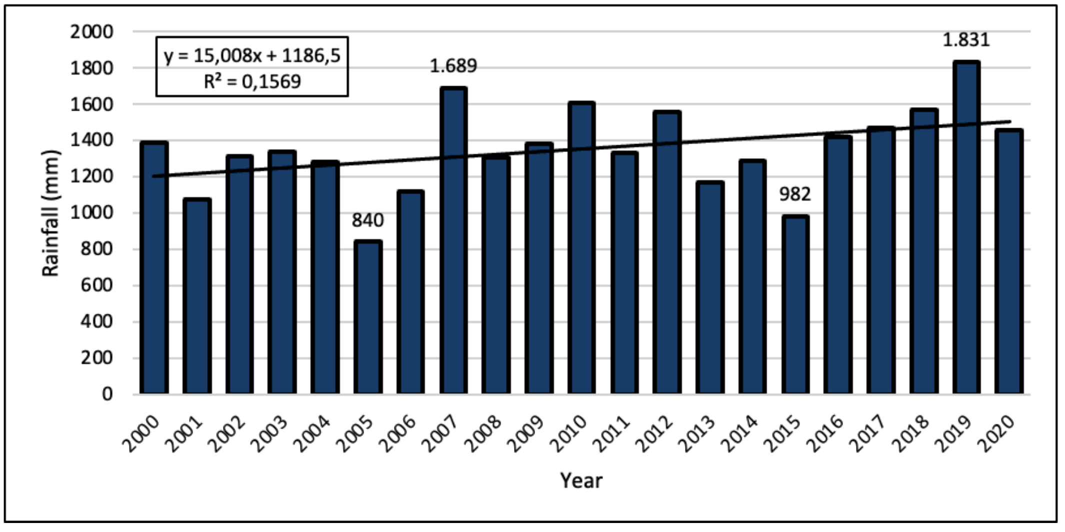

Figure 3: Annual rainfall trend for the South-West of Nigeria

The spatial pattern of the average temperature (Figure 4a) for the South-West of Nigeria shows that the coastal region recorded the highest temperature of between 26.0-26.6°C, this covers the entire Lagos state the riverine areas of Ondo and Ogun states, the south-eastern stretch of Ogun and Oyo states. The windward highland areas in Osun, Ondo and Ekiti states recorded the lowest temperatures of below 24.9°C from 2000-2020. As regards rainfall (Figure 4b), an annual average of 1352mm of rainfall was recorded from 2000-2020. The largest portion of the rainfall falls in the southern part of the region and reduces northwards towards the southwestern highland stretch. The highland areas above Oyo's west and east local government areas, as well as the north and northeastern stretch of Ondo and Ekiti states, received between 940 and 1310mm of rainfall. Inversely, the south-easter parts of Lagos, Ondo and Ogun states, including Ese-Odo, Ilaje, Irele, Odigbo, Okitipupa, and Ilaje in Ondo, Ogun waterside, Ijebu East and Aiyedaade LGA in Ogun state and some part of Epe LGA in Lagos state received between 1648-1752 annual rainfall from 2000-2021.

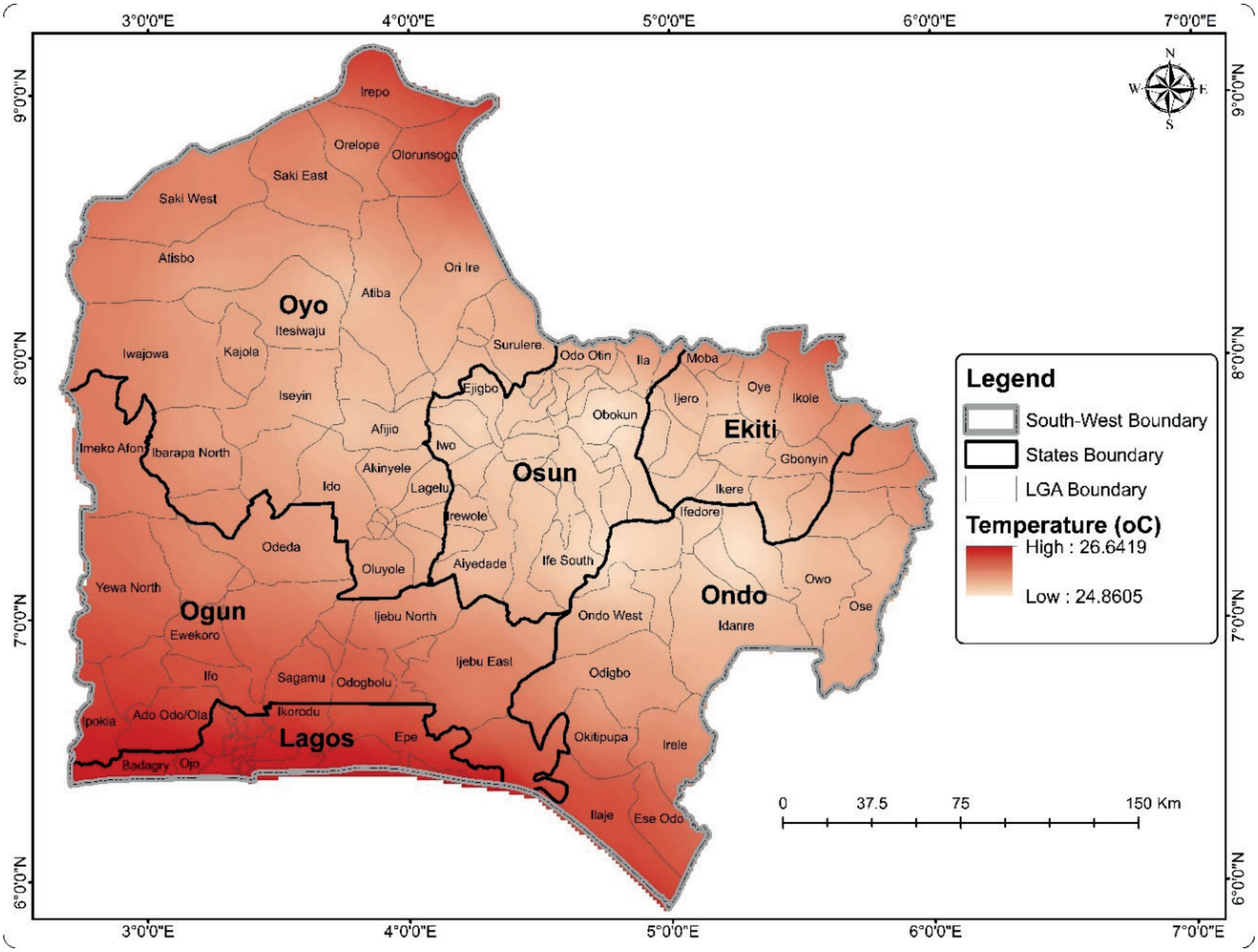

Figure 4(a): Spatial Distribution of Temperature for the Study Area

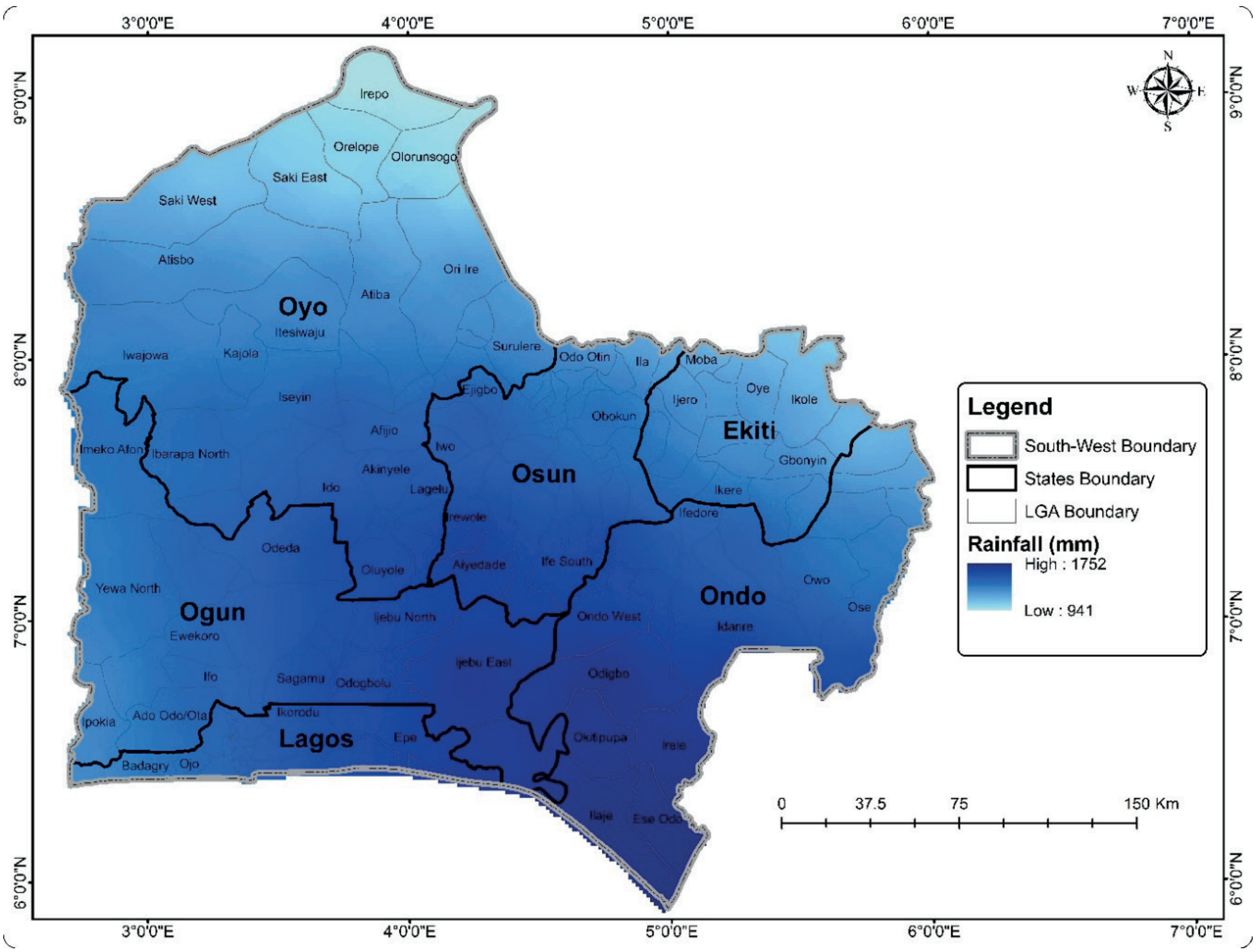

Figure 4(b): Spatial Distribution of Rainfall for the Study Area

Similar to the findings of Fasona et al., (2019) the standardized rainfall and temperature anomaly (Figure 5&6) across South-western Nigeria reveals near-annual variations. The anomaly suggests 2 distinct rainfall periods; a general dry period from 2001-2015, which was broken by wet years in 2007, 2010 and 2012. Form 2016-2020 marked a wet period that peaked in 2019. The trend points to a nonlinear trend in rainfall in the area and suggests oscillation and variability in the rainfall, which might have an impact on the region's ecosystems and human activities (Fasona et al., 2019).

The temperature anomaly of the area shows persistent oscillating low and high-temperature intermissions in the area with the low temperatures bottoming in 2008, 2011 and 2012 and peaking in 2005, 2006 and from 2014-2017. Generally, the period from 2000-2021 was regarded as a prolonged period of high temperature, following the global warming trend seen in the region are both congruent (IPCC, 2021).

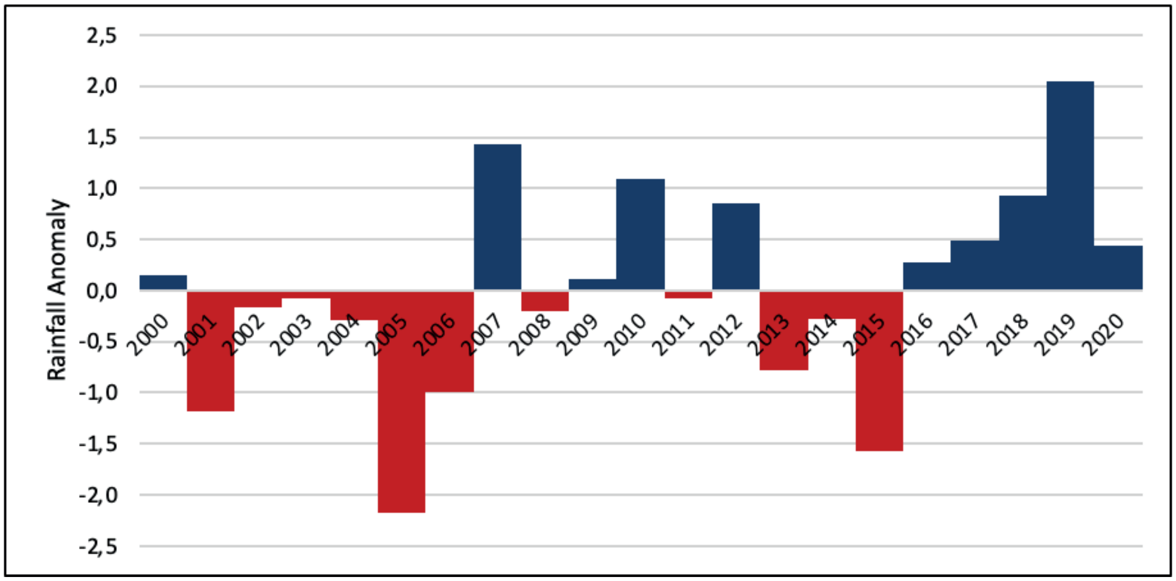

Figure 5: Standardized Rainfall Anomaly

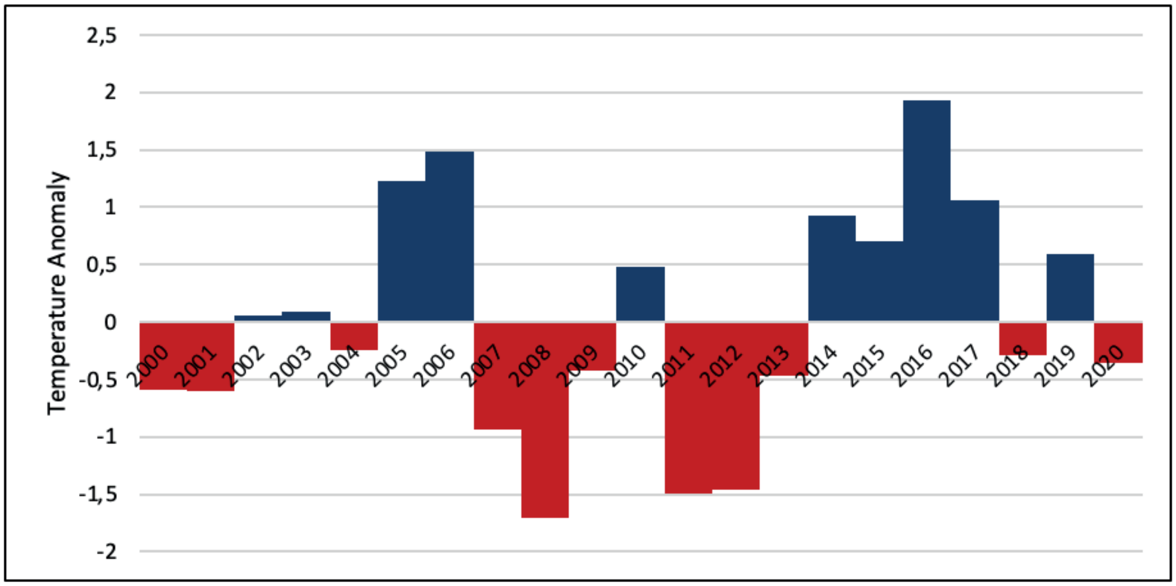

Figure 6: Standardized Average Temperature Anomaly

Malaria Prevalence and Distribution in the South-West of Nigeria

The prevalence/incidence trend and pattern of *P. falciparum* malaria are presented in Figure 7 the uncertainty interval for the study was calculated to show endemicity levels across states and local government areas in the study with 95% uncertainty intervals. From 2000-2020, the southwest region of Nigeria recorded an annual average malaria case of 8,223,758 at a 21.2% uncertainty interval (*UI*) across all age groups in the 6 states in the study area. The incidence peaked in 2009 and 2020 with about 9,310,262 and 9,942,714 cases at 95% *UI* of 22.5% in 2009 and 23.3% in 2020 respectively. This illustrates the progress made in malaria intervention in the region, especially the 2009-2013 and 2014-2020 Malaria Intervention Program, as well as the impact of the COVID-19 pandemic on the endemicity of malaria in the region.

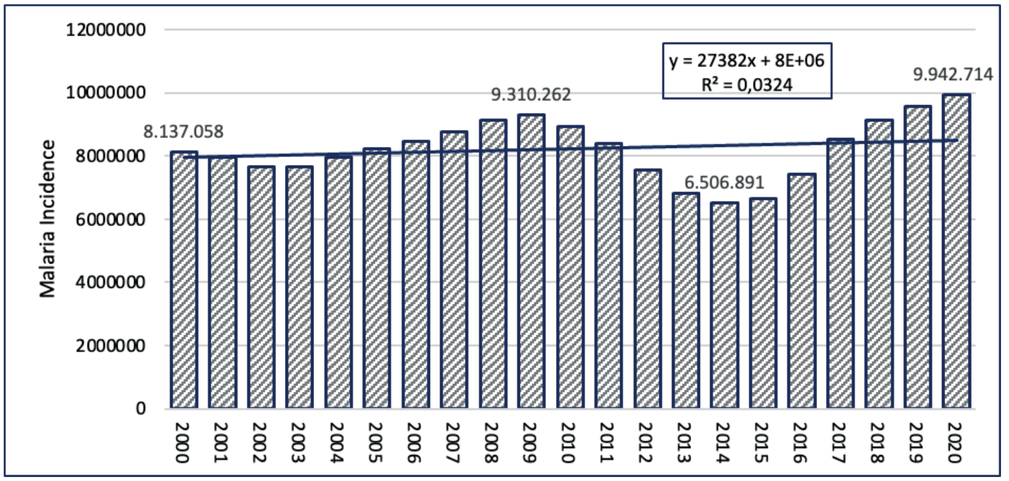

Figure 7: Malaria incidence in the southwestern region of Nigeria

The spatial distribution of malaria (Figure 8) shows a high concentration in Ibadan and Lagos metropolis ranging from 150-420 thousand cases, followed by surrounding areas like Epe, Ibeju-Lekki, Eti-Osa, Badagry, Ojo, Ikorodu, Ado-Odo-Ota, Ipokia, Sagamu and the entire Ijebu-towns peaking in areas around Alimosho, Agege, Ifako-Ijaye, Ikeja and Kosofe in Lagos state and Ifo, Ado-Odo-Ota have average malaria counts of between 100-150 thousand. Also, the North-eastern highland areas of Osun, Ekiti and Ondo states recorded an average malaria incidence of between 5-75 thousand cases and peaked in areas like Ife-East, Ado-Ekiti, and Ondo town woodland areas with a relatively high population density.

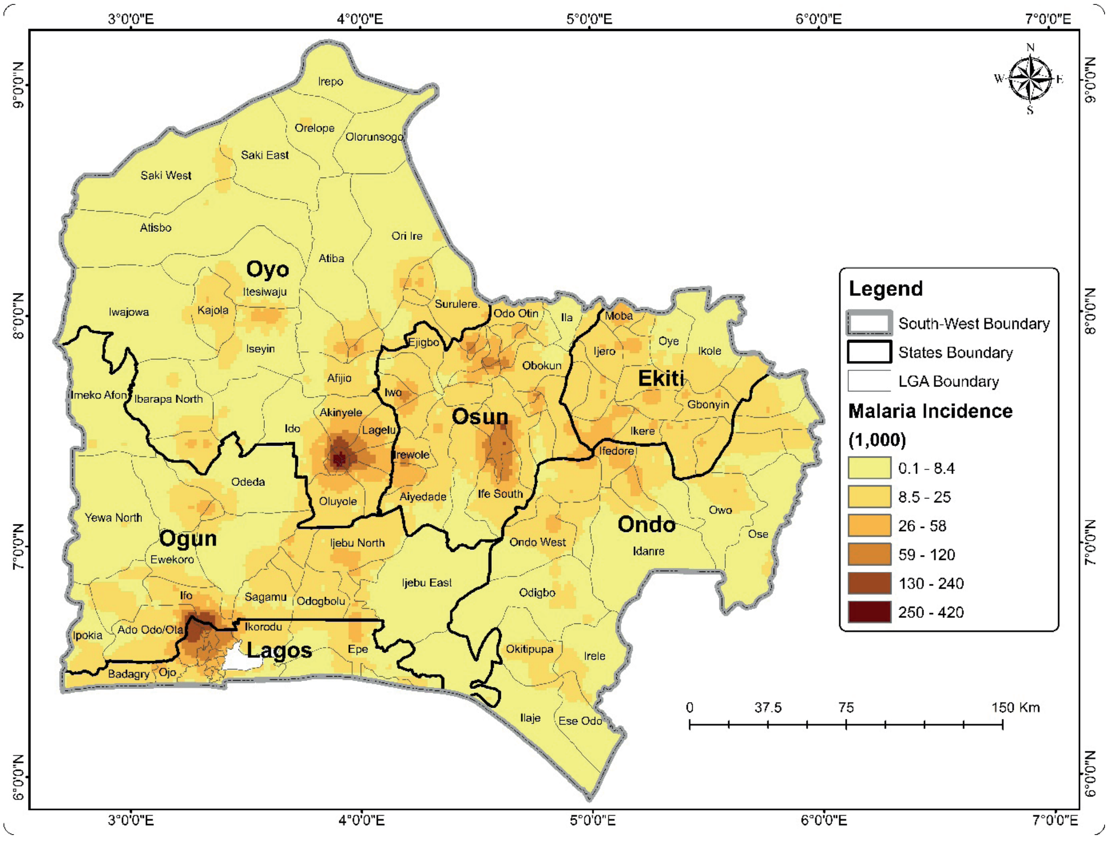

Figure 8: Spatial distribution of Malaria incidence in the southwest region of Nigeria

The malaria incidence counts above might be misleading, especially because of the high value recorded in the Lagos and Ibadan metropolitan areas. However, because malaria incidence is greatly influenced by population and population density (Alemu et al., 2011), a re-evaluation of the result is needed. When the population is factored into the situation, the malaria prevalence rate (per 1,000 inhabitants) in the South-West (Figure 9&10) of Nigeria shows a different picture. Ibadan, and especially Lagos metropolitan areas and their surrounding communities with the highest population and population density recorded the lowest malaria prevalence compared to other areas in South-West Nigeria. With Odeda (313), Yewa North (249), Ijebu-Ode (245), Ijebu East (243) and Aiyedaade (241) Local Government Areas recording the highest malaria prevalence in the South-West of the country.

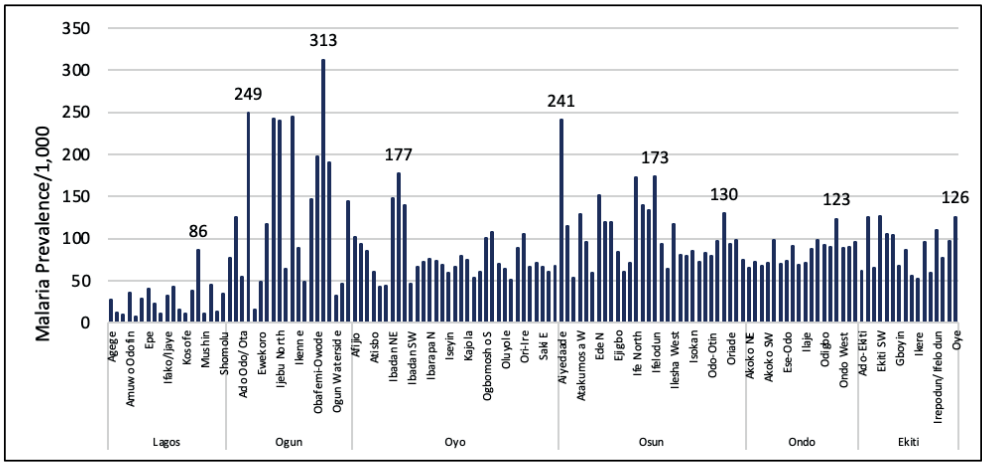

Figure 9: Malaria Prevalence in South-West Nigeria

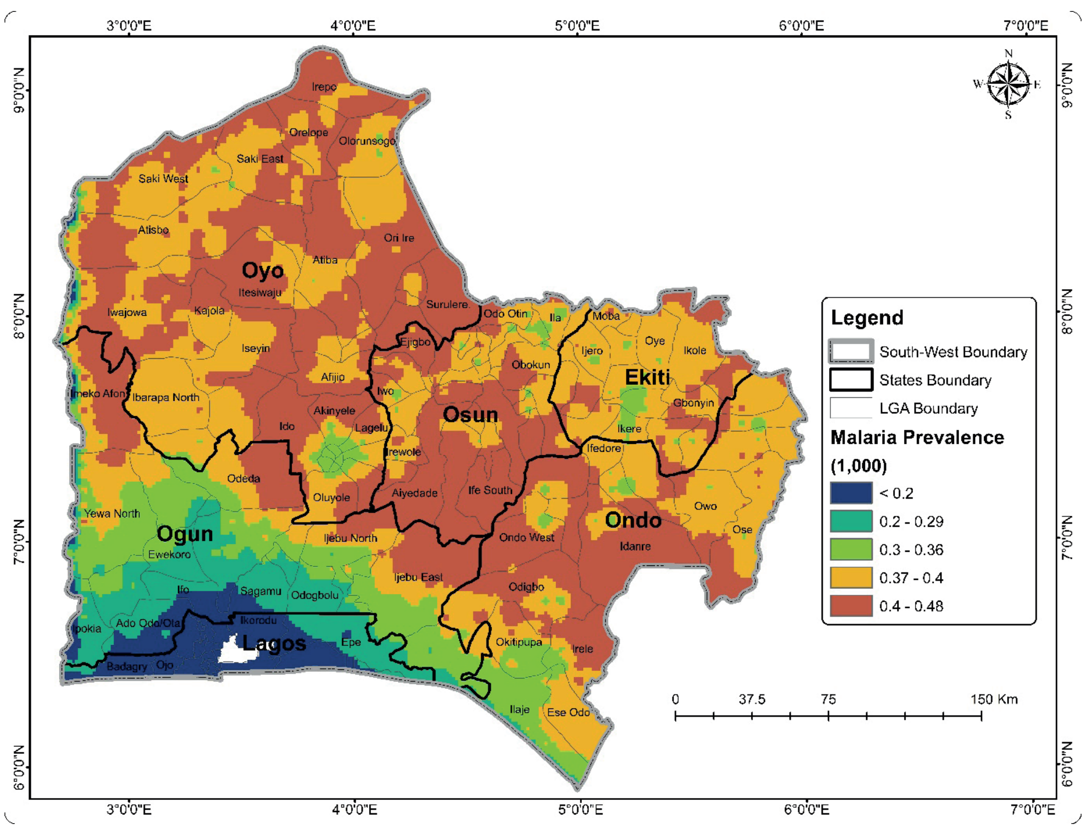

Figure 10: Malaria Prevalence in the South-West Nigeria

Geographically Weighted Regression of Malaria Prevalence, Rainfall and Temperature

The two explanatory variables (rainfall and average temperature) were examined locally for their influence on malaria prevalence in southwest Nigeria using the Geographically Weighted Regression (GWR). Figure 11 depicts the GWR at each local government area in the southwest. At a 95% level of significance, the true confidential relationship (R^2) value for average temperature and rainfall was 0.76 and 0.00, respectively (Figure 12 a&b). This suggests that in contrast to rainfall, which has little effect on malaria prevalence, the average temperature has a strong association with or influence over malaria prevalence in the South-West of Nigeria.

The residual value is geographically uniformly distributed over the South-West, with each explanatory variable's standard deviation reflecting its spatial variance, and a low standard deviation implies a strong GWR fit. The raw residuals are divided by the estimated standard residual to get the standard residual. It measures the degree of divergence between observed and anticipated variables. In other words, it is the discrepancy between the expected malaria prevalence and those seen. The differing values show diversity and unpredictability in the data, proving the GWR models unbiased. The predicted and actual malaria prevalence differ significantly in LGAs where the standard deviation is less than 2.5. In contrast, the opposite is true in LGAs where the standard deviation is more than 2.5.

Indicating a statistically significant correlation between rainfall, temperature, and malaria prevalence, the GWR revealed a mean value of 0.19064. The data match the GWR model, as shown by the standard deviation of 0.98. Saki West LGA presented the only area with less than – 2.5 standardised residual values indicating the closest gap between predicted and actual malaria prevalence followed by Yewa North, Ikorodu and Kosofe respectively. Iwajowa and Irepo LGAs on the other hand, exhibited standardized residual values that are larger than 2.5, suggesting the widest gap between the predicted and actual prevalence of malaria in the area.

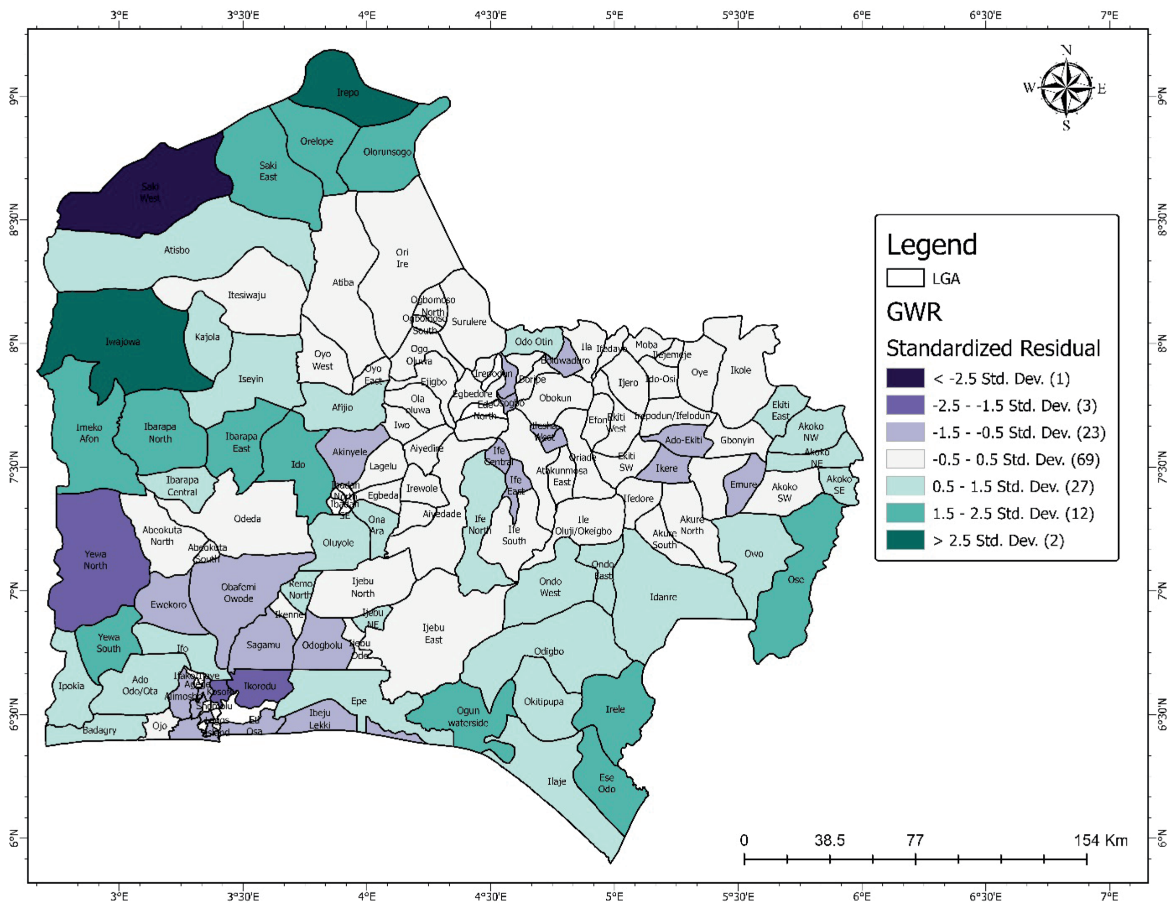

Figure 11: Geographically Weighted Regression (GWR)

Figure 12 a&b: Correlation between malaria prevalence, rainfall and temperature for the South-West of Nigeria.

DISCUSSION

In Sub-Saharan Africa, Nigeria, and the southwest, malaria is still a significant public health concern. As such, it has remained a key area of emphasis for Sustainable Development Goals (Okunlola and Oluyemi, 2019). The research offers a geostatistical assessment of the effects of temperature and precipitation on the incidence of malaria in the southwest of Nigeria from 2000 to 2020. The South-West of Nigeria's annual mean temperature pattern from 2000 to 2020 exhibits a fluctuating and rising trend of 0.0088°C per year. This shows a tendency towards increasing temperatures, comparable to those observed globally (IPCC, 2021), in Nigeria (Abiodun et al., 2013), and in the southwest (Fasona et al., 2019). The area's lowest reported annual average temperatures were 25.59°C, 25.64°C, and 25.65°C in 2008, 2011, and 2012, respectively. The information reveals an ongoing increase in the average temperature of the area, which has been associated with climate change among other things in reports from around the globe (IPCC, 2021). A positive long-term propensity of 15.008mm/yr-1 and 0.0088oC/yr^{-1} can be seen in the annual mean rainfall and average temperature from 2000 to 2020, respectively. This conflicts with studies by Fasona et al. (2019) and Oguntunde et al. (2011), which both found a 1.75 mm/yr^{-1} decrease in rainfall between 1892 and 2015 and 1901 and 2000, respectively. This is a consequence of the study's limited sample size of rainfall data years compared to the contradictory studies' which span more than 100 years.

The rainfall figures for the region exhibit an oscillating pattern that reflects both local and worldwide patterns, peaking in 2019 with about 1831.5mm of rainfall (IPCC, 2021), much like the temperature values do. With 840.5 and 981.5mm, respectively, 2005 and 2015 had the lowest amounts of rainfall in the region from 2000 to 2020. The temperature range observed for the study falls within the ideal range for malaria transmission, which is important for malaria prevalence and incidence simply because Kumar et al. (2014) and Mordecai et al. (2013) modelling of malaria studies indicate that temperatures between 16 and 34^{o}C are potential temperature ranges for malaria transmission. This suggests the possible effects of climate change on the prevalence and distribution of malaria (Dale and Knight, 2008). The impact of temperature change on malaria incidence is consistent with the prediction made by Githeko et al. (2000) that by 2100, the global mean temperature would have significantly increased by 1.0–3.5°C. The causes of the observed slowdown in the temperature for the southwestern region are unclear and warrant further investigation, even though the rising tendency in global temperature has usually been ascribed to anthropogenic effects (IPCC, 2014).

Fasona et al. (2019), assert that the trend indicates a nonlinear trend in rainfall and suggests oscillation and variability in the rainfall, which might have an impact on the region's ecosystems and human activities, the standardised rainfall and temperature anomaly for the southwest of Nigeria exhibits near-annual variations. In general, the years 2000 to 2021 were considered a prolonged period of high temperatures, consistent with the regional warming pattern (IPCC, 2021).

From 2000 to 2020, the incidence of malaria in South-West Nigeria averaged 8,223,758 cases per year, spiking in 2009 and 2020 with almost 10 million cases in 2020. The region's malaria intervention programs, particularly the 2009-2013 and 2014-2020 Malaria Intervention Programs, which were affected by the COVID-19 pandemic, are making consistent but unsustainable progress, as evidenced by a modest positive pattern of 0.0324 cases/yr-1. Despite this, the study asserts that the Global Technical Strategy for Malaria's two most important objectives—to reduce death and illness by at least 40% by 2020—were unachievable (WHO, 2021). Reducing the number of cases in regions with the greatest incidence is the primary objective in the worldwide eradication of malaria (Talapko et al., 2019), a goal that the South-west and Nigeria, in general, are still battling to accomplish. Contrary to popular belief (Santos-Vega et al., 2016), malaria still appears to be prevalent in urban areas based on the high incidence of the disease in the populated regions of Lagos and Ibadan metropolis as well as other major cities. This is likely due to the female Anopheles gambiae's preference for tiny, open, and temporal pools, which are common in metropolitan regions and include wayside ditches, footprints, and man-made openings (Opoku and Ansa-Asare, 2009).

However, the prevalence of malaria in less populated areas is also a sign that the disease, at least in the southwestern region, is endemic in less populated remote areas and calls for attention and action (Kabaria et al., 2017). This supports the claim made by Tatem et al. (2008) that population density influences malaria spread, which has significant effects on the impact of the disease.

The Geographically Weighted Regression (GWR) is an effective model for the study because it allows for the display and visualization of parameter estimates of each explanatory variable on a raster surface, allowing for easy visualization of complex relationships over space (Ndiath et al., 2015). The GWR shows a strong and positive correlation with malaria prevalence indicating that as the average temperature value strongly increases, malaria prevalence equally reduces.

This was confirmed by the works of Omogunloye et al. (2018) on the modelling of malaria incidence in Lagos who reported a negligible relationship between malaria and rainfall and a strong relationship between malaria and temperature. According to Weiss et al. (2014), there is a high correlation between temperature and the prevalence of malaria. He asserted that temperature is a better predictor of malaria prevalence than rainfall or other climatic factors. Intense rainfall may reduce malaria transition by destroying mosquito breeding sites, resulting in a drop in the prevalence of malaria and making it less of a malaria indicator, even though rainfall increases malaria transmission and incidence by increasing mosquito breeding sites (Yamana and Eltahir, 2013; Wu et al., 2017; Oheneba-Dornyo et al., 2022).

CONCLUSION

Nigeria's biggest health problem continues to be malaria, which is prevalent in the nation. According to the study, malaria is prevalent in the entire southwestern part of the nation, with high incidence rates in densely populated areas. The Geographically Weighted Regression shows that temperature influences malaria incidence and prevalence more than rainfall in South-West Nigeria. A deeper knowledge of the impact of temperature on malaria's prevalence, incidence, and spread is recommended given the study's statistically significant link between malaria prevalence and temperature. The data also demonstrates that the country's various malaria intervention programmes have not met their target of reducing malaria mortality and morbidity by 40% by 2020. As a result, improvements should be made to ensure that the Sustainable Development Goal (3) of promoting global health and wellbeing, as well as the eradication of malaria by 2030, is met. Understanding the Spatiotemporal patterns of malaria about climate variability can equip students and researchers with the analytical skills necessary to predict and mitigate disease outbreaks. Additionally, the study is crucial for developing targeted interventions that can reduce the burden of malaria and improve overall community health resilience in the face of climatic shifts.

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