Geospatial Analysis of Malaria Prevalence among Children Under Five Years in Jigawa State, North West, Nigeria

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Abstract

Malaria is one of the leading causes of illness and death in developing countries. Despite growing international concern and efforts to provide effective treatment through the development and improvement of vector control mechanisms, malaria infection continues to remain a leading health problem in Africa, particularly south of the Sahara. At present, however, very few studies have been undertaken that investigate the spatial distribution of malaria cases. This study, therefore, aims to employ geospatial tools to map out areas of high and low malaria prevalence among children under the age of five years. Annual malaria prevalence was computed using confirmed cases from 2014 to 2019 in Jigawa state. Spatial autocorrelation techniques using global Moran's I and Getis-Ord Gi* statistics were applied. Overall malaria prevalence ranged between 2,743 and 12,916 per 100,000 populations. Results of the overall global Moran's I indicate a statistically significant degree of positive autocorrelation ($I = 0.358122$, $Z = 3.721018$, $P = 0.000198$) and all the years under study showed clustered patterns. Hotspot analysis was further explored to show the location of clusters. The results of the analysis detected high prevalence clusters in central and north-western parts of the state. The study recommends targeting hotspot areas in the design and implementation of malaria control activities.

Introduction

Malaria is one of the leading causes of illness and death in developing countries, especially in sub-Saharan Africa (Sachs and Malaney, 2002. Who, 2018; Rumisha et al. 2019). It is a vector-borne infectious disease transmitted from one person to another through the bite of an infected female anopheles mosquito (Kim et al.2020). It therefore, remains one of the highest public health concerns in tropical and subtropical regions of the world, especially in South and Latin America, Africa, and Southeast and Central Asia (Prothero, 1995; WHO, 2008). Most cases occur in Sub-Saharan Africa (Carter and Mandis, 2002; Sachs and Malaney, 2002; Patz et al. 2005; WHO. 2014). Malaria is caused by protozoan parasites of the genus plasmodium. Human malaria is normally caused by four different species of plasmodium; they are p. falciparum, p. malariae, p. ovale, and p. vivax. Among these species, p. falciparum is the most significant and deadly form of malaria presenting severe health risks, especially in sub-Saharan Africa, which is preventable (WHO, 2011; Paton, et al. 2021).

An estimated 3.4 billion people in 92 countries are at risk of contracting malaria, with 1.1 billion at high risk (a likelihood of obtaining malaria in a year greater than one in 1000) (WHO, 2019). A more recent report indicated that there are expected to be 241 million cases of malaria worldwide, with 627 000 malaria fatalities in 2020 (WHO, 2021) indicating an increase in the number of cases and deaths reported in 2019. The WHO African Region is responsible for a disproportionately large amount of the worldwide malaria burden. In 2020, 95 percent of malaria cases and 96 percent of malaria deaths occurred in the region (WHO, 2021). In 2017, it was estimated that there were 219 million clinical malaria cases worldwide. 92% of the cases occurred in the WHO African region. Global malaria-related deaths in 2017 were estimated at 435,000, of which 93% were in Africa, and children under the age of five years are particularly high risk accounting for 61% of all deaths (WHO, 2018). According to a WHO report in 2013, more than 90% of the population in Africa lives in areas exposed to the risk of malaria infection, with 74% of the population living in highly endemic areas where malaria transmission is greatest and perennial (WHO, 2014).

The vector Anopheles mosquito is generally influenced by environmental conditions. Climate, through the influence of factors such as temperature, precipitation, and relative humidity, has a significant influence on malaria transmission (Dahal, 2008; Oluleye and Akinbobola, 2010). It influences the development, reproduction, and survival of Anopheles mosquitoes and malaria parasites. Other environmental factors including altitude, topography, land use/land cover, and human settlement patterns have a significant impact on the spatial distribution of vectors and the disease they transmit (Abeku et al. 2004; Van Der Hoek et al. 2003; Kibret et al. 2019).

The malaria situation in Africa is becoming more and more complex as the disease is now extended to include previously non-endemic or low transmission areas of the eastern and southern parts of the continents (Chala, 2007). In fact, malaria globally is responsible for about 7.8% disease burden (WHO, 2021) with Africa accounting for the majority. A recent study reveals that malaria transmission is higher in rural areas than in urban areas (Doumbe-Belisse, et al. 2021).

Concerning Nigeria, malaria is endemic in all parts of the country, with year-round transmission and the rates of Transmission differ from place to place being slightly lower in Sahelian areas and high mountain areas of the plateau (National Population Commission, National Malaria Control Programme and ICF International, 2012). Nigeria` accounted for 25% and 19% of the global estimate of malaria cases and deaths in 2017 (WHO, 2018). The system for control and prevention of malaria now faces major challenges in endemic countries like Nigeria due wide range of factors. Among the factors are increasing resistance of the parasite to anti-malarial drugs, the resistance of mosquito to insecticides, poor coverage of health infrastructure for diagnosis and treatment of the disease especially in rural areas, shortage of well-trained personnel, scarce financial resources, high cost of the control program and weak strategic planning effective malaria control (Traore, 2003; Alemu, 2006; Ranson 2018).

In all malaria-endemic regions, malaria tends to form a cluster known as “hot spots” and “hot populations” that become sources of continued infections (Rulisa et al. 2003; Shahandeh and Basseri, 2019). Active and prompt identification of clusters and specific locations of clusters, as well as associated risk factors, is essential for assisting government and private partners interested in malaria control and prevention to provide appropriate intervention strategies and resource allocation (WHO, 2007).

Recent development in geographical information system (GIS) and spatial statistical tools provide new methodologies to analyze the generated clinical data by detecting spatial patterns of disease distribution and delineation of hot spots to assess the true situation for better public surveillance and for improving our understanding of the transmission dynamics of disease such as malaria (Osterholt et al. 2006; Yeshiwondim et al. 2009; Saxena et al. 2009). Geospatial statistics have been increasingly applied in analyzing and mapping malaria case data (Gebreslasie, 2015; Kirk, et al. 2015; Ahmad, Goparaju, and

Qayum, 2017; Zandian et al. 2019; Gambo, et al. 2020). They provide an opportunity for medical geographers to better understand and explain the spatial distribution of diseases and the possible association between risk factors. Spatial autocorrelation statistics analyze the correlation of a variable in relation to the location that that variable is. Moran's I is a more popular tool for measuring spatial autocorrelation (Huo et al. 2012). Global Moran's I measure and analyze the degree of dependency among observations in geographic space. On the other hand, local spatial autocorrelation statistics such as local Moran's I and Getis and Ord are useful in identifying locations of spatial clusters or "Hot spots" and outliers (Huo et al. 2012).

Currently, despite the endemic situation of malaria in Jigawa State, the application of GIS and spatial statistics to study malaria and provide information to assist in the control and elimination of the disease in the state is sparse in published literature. Thus, this study applied GIS and spatial statistical techniques on confirmed malaria cases to identify spatio-temporal patterns of hotspots of malaria cases in Jigawa state.

Materials And Methods

Study Area

Jigawa State is located in the northwest geopolitical zone of Nigeria, consisting of 27 local government areas. The state lies roughly between latitude 10^{o} N and 12^{o} N and longitude 7^{o} E to 10^{o} E. It shares its western border with Kano and Katsina States, Bauchi State to the east, and Yobe State to the northeast. To the north, Jigawa State shares an international border with the Niger Republic. It covers an approximate land area of about 22, 410 Km2 (Fig 1).
The study area experiences a tropical wet and dry type of climate coded as "Aw" in the Koppen classification system. The wet season commences from June through September, although mid-May and mid-October are usually regarded as part of the wet season. The normal annual rainfall is higher in the southern parts, where it is between 1000 and 1100 mm and decreases to about 500 to 550 mm as one moves to the north and north-eastern parts of the state Olofin, 2008). Maximum temperatures (above 42^{o} C) are recorded during the hottest months of March and April and may extend to mid-May, while lower temperatures as low as 10o C are normally recorded in the coolest months (December to February). The mean annual temperature is about 26^{o} C, but the mean monthly values range between 21^{o} C and 23^{o} C in the coolest months and over 30^{o} C in the hottest months (Olofin, 2008). The Hadejia river system forms the major drainage accounting for about 80% of the historic flow of the river system in the area (Abdulhamid, 2014) and drains essentially north-eastwards into Lake Chad. However, in some parts of the north, the river ceases to flow in a proper channel but wanders across the formation. As a consequence, the area gets flooded in the rainy seasons, which becomes a breeding site for malaria vectors.

Jigawa state ranked 8th among the most populous states in Nigeria based on the 2006 population census. Its population stood at 4,348,649 (Federal Republic of Nigeria, 2007) with an average density of about 194 persons/km2. The projected population figure for the area as of 2019, stood at 6, 526, 432

(NPC, 2020). Agriculture, which is regarded as one of the occupational malaria risk factors, is the dominant economic activity in the state employing 70% of the inhabitants (Jigawa State Ministry of Health {JSMoH}, 2010).

Malaria and Population Data

Data on malaria were obtained from the Jigawa State Ministry of Health. The data includes all malaria cases among under-five years old, confirmed by microscopic or Rapid Diagnostic Test (RDT) kits, and clinically diagnosed at various public health facilities across the 27 LGAs. Malaria cases were recorded daily for each facility and later transferred to National Health Management Information System (NHMIS) monthly summary form for health facilities version 2013 at the local government level for onward submission to the state ministry of health. Monthly malaria cases for the period of six years (2014 - 2019) were extracted from the database of the ministry. The choice of this period was based on data availability for the entire state.

Data on population were collected from National Population Commission, Jigawa state. Data from population censuses conducted in 1991 and 2006 were collected and used to compute the inter-census growth rate for each local government area of the state. The population was projected for the years 2014 to 2019 and the data were used to calculate malaria prevalence rates and produce hotspot maps.

Data analysis

Prevalence Rate

Malaria case data were standardized as prevalence rather than total cases. The essence was to give a better representation of the data due to the varying population size of the LGAs in the state. Prevalence is one of the measures of disease frequency and burden. It is often useful to assess the burden of disease in a given population. This is not limited to burden in relation to resources; it also reflects burden in terms of life expectancy, morbidity, quality of life, or other indicators (Noordzij, et al. 2010). For this study, malaria prevalence data were generated by dividing the total number of malaria cases for each year of study for the 27 LGAs by the population of each LGA. The following formula was used to compute the prevalence rate:

$$\text{Prevalence rate} = \frac{\text{Total Number of Malaria cases}}{\text{Total Population of the area}} X\ 100{,}000 \quad \text{..} \quad (1)$$

Cluster Analysis

Spatial and temporal cluster analyses were conducted to detect spatial clustering of malaria prevalence using the spatial autocorrelation technique. The technique represents the correlation between a variable at a location and the values of the same variable at a neighbouring location (Zhang et al. 2009). Spatial autocorrelation statistics measure and analyze the degree of similarity among observations in geographic space. Two forms of analysis were employed. The first was to determine the degree of the spatial pattern of malaria cases in the area, which may either be clustered; dispersed, or random using Global Moran's I.

The global Moran's I statistics provide a summary for each feature in the dataset consisting of I, z-score, and p-value. The tool compares the values of neighbouring locations and strong positive autocorrelation (clustered) existed when neighbouring areas over the entire area under study have similar values. If neighbouring areas have dissimilar values, then the tool yielded strong negative spatial autocorrelation (dispersed). The value of I, therefore, ranges from +1 (indicating positive autocorrelation) to -1 (representing negative autocorrelation). A 'Z' value is computed to assess whether clustering/dispersing is statistically significant or otherwise. The statistical test, therefore, is capable of determining the degree of spatial autocorrelation of a given phenomenon. It measures the degree to which a phenomenon is clustered in space (Osayomi, 2015). However, the tool is not powerful to indicate the location of clusters and outliers. The formula for Moran's I statistics is given below:

$$I = \frac{N}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij}(X_i - \overline{X})(X_j - \overline{X})}{\sum_i (X_i - \overline{X})^2} \qquad (2)$$

Where N is the number of spatial units (LGAs) indexed by *i* and *j*. X represents the study variable (malaria prevalence rate), is the mean value of malaria cases. W*ij* is an element of a matrix of spatial weights which defines the degree of proximity between local governments areas *i* and *j*.

The second analysis is to show the location of hotspots/cold spots using Local Getis-Ord statistics (Gi*). The Getis-Ord Gi* statistical analysis, on the other hand, was employed to supplement Moran's I. The tool identifies different spatial clustering patterns like hot spots and cold spots, with statistical significance (Getis and Ord, 2010). The statistics reflect whether differences between the local mean (i.e., cases for a local government and it's nearest neighbouring local government in the state) were significantly different from the global mean (i.e., the overall cases of all local governments in the state). The resultant "z" score is an indicator of a high or low malaria prevalence cluster. High and positive z-score values above 1.96 indicate the occurrence of malaria hotspots, while values below 1.96 represent cold spot areas. Therefore, the higher/lower the z-score is, the stronger or weaker the relationship would be. Scores closer to zero indicate the absence of clusters.

The formula for calculating hot spots using Getis-ord Gi* is given as:

$$I_i = \frac{(y_i - \overline{y}) \sum_{j-i}^{n} w_{ij} (y_j - \overline{y})^2}{m_2} \qquad (3)$$

Where *yi* is the value of the variable (malaria prevalence rate) at the location *i*th, n is the number of LGAs, *wij* is a weight representing the spatial relationship of LGAs *i,* and *j,* m_2 is the average of the squared deviations from the mean of malaria cases.

Results And Discussion

Descriptive Statistics

The statistical summary of malaria prevalence over the period 2014 - 2019 is presented in Table 1. According to the Table, malaria prevalence among children below the age of five years ranged from 2743/100,000 population to 12,916/100,000 with an average rate of 5952/100,000 individuals. The standard deviation of malaria prevalence (δ = 2261.92) which measures the degree of dispersion of cases from the mean, shows that there is wide variation in the prevalence rate of malaria under five years.

Table 1: Descriptive statistics of malaria prevalence among under-five years old

Mean	Minimum	Maximum	Std. Deviation
5952	2743	12,916	2261.92

Source: JSMoH, 2020 and Author's analysis, 2021

The mean annual prevalence rate among those under-five years (5,952 per 100,000 or 5.95%) observed in this study is higher than 1.8% and 1.92% reported by Dawaki *et al.* (2016) and Solomon *et al.* (2020) respectively. However, our result (5.95%) is close to that of Alemu *et al.* (2012) and Nanvyat *et al.* (2017) who found 7.8% and 7.4% in Kola Diba, North Gondar, Ethiopia, and Jos Plateau State, Nigeria. In contrast, other studies have reported a high prevalence of 27.7% by Elechi *et al.* (2015) in Maiduguri, Borno State, Nigeria; 61.7% by West and Okari (2018) in Port Harcourt, Nigeria and 63% by Simon-Oke *et al.* (2019) in Ekiti State, Nigeria. Similarly, other high prevalence rates were reported in Africa and Asia. They include: 11.97% in Tanzania (Paul and Msengwa, 2018), 22.1% in Ghana (Yankson *et al.* {2019}), 22.1% in Ethiopia (Abossie *et al.* {2020}), 37.4% in Malawi (Gaston and Ramroop, 2020), 35.4% in Malawi (Chilanga *et al.* {2020}) and 42.3% in Indonesia (Jiero and Pasaribu, 2021). This variation in the results might be due to differences in climatic conditions, altitudinal variations, type of the study design employed, variations in the methods of malaria detection, differences in the coverage of intervention activities, and other factors that affect transmission.

The low prevalence rate among under-five children reported in this study might be related to increased awareness of the inhabitant of the state on the use of ITNs. This finding is not surprising considering the 2018 Nigeria Health Demography Survey Report, which revealed that household ownership of ITNs in the country is highest in Jigawa (the study area) and Kebbi States (98%) which is above the national target (NPC and ICF International, 2019). The report further disclosed that in Jigawa State, 90.5% of the surveyed children who are below five years of age slept under ITNs the night before the survey. This shows that the vast majority of the younger children are well protected from the infective bites by mosquitoes.

Spatial Patterns of Malaria Prevalence

Global spatial statistics using the Moran's I measure were used to test for the significant pattern in the prevalence of malaria among under-five children in the study area. The test results (Table 2) showed overall positive and statistically significant Moran's *I* (Moran's *I* = 0.358122, *Z* score = 3.721018. *P* = 0.000198), suggesting a significant concentration of high prevalence rates (clustering). The result in Table 2 further shows a similar level of autocorrelation for the years under study. The clustering was strongest in the year 2018 (Moran's *I* = 0.406459, *Z* score = 4.023251. *P* = 0.000057) followed by 2019 (Moran's *I* = 0.310412, *Z* score = 3.263420, *P* = 0.001101).

Table 2: Spatial pattern of malaria prevalence

Years	Moran's Index	Z-score	P value	Pattern
Under-five years:				
2014	0.235427	2.614904	0.008925	Clustered
2015	0.214774	2.461729	0.013827	Clustered
2016	0.237812	2.501937	0.012352	Clustered
2017	0.287145	2.914179	0.003566	Clustered
2018	0.406459	4.023251	0.000057	Clustered
2019	0.310412	3.263420	0.001101	Clustered
2014-2019	0.358122	3.721018	0.000198	Clustered

Source: Author's computation (2021)

The presence of significant positive autocorrelation for the years under study shows the extent to which neighbouring rates are correlated. Thus, LGAs sharing a border is more similar with respect to malaria than those that are distantly apart. However, the occurrence of malaria prevalence in these years in specific areas is not by chance. The statistically established spatial dependency of the disease implies the presence of similar risk factors in neighbouring areas thereby influencing the spatial transmission of the disease. This finding is not surprising since malaria is an environmental disease, and environmental variables are spatially related. Other similar studies (Sexena *et al.* 2012; Osayomi, 2014; Osei and Yibile, 2015; Yakudima and Adamu, 2019; Bizimana and Nduwayezu, 2020) had also revealed spatial clustering of malaria cases in their studies. However, these global test results indicate a need for further investigation using local spatial statistics (hotspot analysis).

Hotspot Analysis of Malaria for Children Under Five Years

Local spatial statistics using Getis-Ord Gi* was applied to detect the locations of clusters over the study periods. Figure 2 represents the result of the cumulative (2014 – 2019) hotspot analysis for the under-five years population group. The figure showed central and north-western parts of the state as the hotspot regions. Hotspots of 90% and 95% confidence levels were noted in the following LGAs: Kiyawa, Jahun, Dutse, Gwiwa, Roni, Kazaure, and Yan-kwashi. North-eastern part of the state (comprising Kaugama, Auyo, Hadejia, Malam Madori, Kiri Kasamma, Guri, and Birniwa LGAs) on the other hand formed the cold spot region.

The year-wise hotspot analysis results (figure 3a) showed a hotspot cluster at all three confidence levels in 2014. LGAs like Gwiwa, Roni, Yan-kwashi, Kazaure, and Kiyawa LGA formed the hotspot clusters. In 2015, only three LGAs (Jahun, Gwiwa, and Roni) showed hotspots at 95% and 90% confidence levels (figure 3b). For the remaining years of the study (2016-2019) four LGAs exhibit hotspot clusters (figures 3c-3f). Gwiwa, Roni, and Kiyawa LGAs appear as hotspot areas at 99% confidence level for two years of the analysis, while four LGAs including Birnin Kudu, Buji, Kazaure, and Yan-kwashi appear in the group (99% C.I.) in only one year. For 95% confidence level Dutse LGA consistently appears for the three years of the analysis, Jahun LGA appears in two years while Yan-kwashi, Kazaure, and Kiyawa each appeared in only one year. Six LGAs formed hotspot clusters at 90% confidence level, they are Kiyawa, Gwiwa, Roni, Jahun, Ringim, and Birnin Kudu, and each appeared in only one year.

On the other hand, the overall result (2014-2019) of hotspot analysis established a cold spot cluster in the north-eastern part of the state with Guri, Birniwa, and Kiri Kasamma at 99% confidence interval, while Kaugama, Malam Madori, and Hadejia fall under 95% confidence level (figure 2). Auyo LGA belongs to the cold spot at 90% confidence interval (figure 2). The yearly results show that Birniwa LGA consistently emerges as a significant cold spot (99%) for five consecutive years, Kiri Kasamma appears in three years, Malam Madori and Hadejia two years each, while Guri and Kaugama each appeared in only one year (figure 3a-3f). At 95% confidence level Guri LGA occurs under a cold spot for five years, Kiri Kasamma and Kaugama (3 years), Malam Madori (2 years), while Hadejia, Auyo, and Birniwa had emerged in only one year.

Identification of a hotspot cluster consistently located in the central and the north-western parts of the state was the most significant outcome of cluster analysis. A possible explanation for the consistent clustering of malaria in these areas could be the presence of favourable conditions for malaria transmission. Some LGAs like Jahun and Kiyawa shared borders with other LGAs that have wetlands where traditional rice cultivation is practiced. Rice fields according to Gurthmann *et al.* (2002) are the most favourable sites for the mosquito to breed. In addition, most of the LGAs that fall within and surrounding the clusters have water streams that allow for the cultivation of vegetables and other crops. These water agro-systems may provide significant habitat for mosquito breeding and thus, increase the vector population for malaria transmission. This finding is confirmed by the works of Rulisa *et al.* (2013) and Bizimana & Nduwayezu (2020) that discovered significant malaria hotspots located close to water-based agro-ecosystems.

The second likely factor is urbanization. Jigawa State is made up of five emirate districts. The headquarters of these districts are considered the major towns in the state and are therefore providing employment opportunities and other services, hence attracting people from other areas. Three out of the five emirate headquarters were part of the identified clusters. Osayomi (2014) established an association between malaria and urbanization in Nigeria. This association was due to the fact that most towns are characterized by poor sanitary conditions, such as improper disposal of waste, poor condition of drainage, and an unclean housing environment among others. All these encourage the breeding of mosquitoes and thus, promote the transmission of malaria.

The availability of formal healthcare centres in these 11 LGAs may partly explain the emergence of hotspot clusters in the areas. This finding was supported by a study on the distribution of healthcare facilities in Jigawa state by Yakudima (2018) who found that nearly 60% of modern health facilities in the state are concentrated in these areas. Another likely reason for a stable hotspot in these areas is that the existing malaria control and intervention measures might have not been taken correctly or might have not been applied appropriately.

Our analysis further showed that the coldspots are majorly concentrated in the north-eastern part of the state. This area is characterized by low rainfall and high temperature. Adequate rainfall is required to recharge existing water bodies or create new ones which serve as breeding sites. The low rainfall receives in this area makes mosquito breeding habitats so scarce thus, low transmission intensity of malaria. Temperature is also considered a key determinant of transmission. This area (north-east) is associated with high temperatures for most of the year. The high temperature at 40^{o}c reduces mosquito abundance due to the long larval duration (Dale *et al.* {2005}). Low rainfall coupled with high temperature affects the development of vegetation cover in the area. Adequate vegetation cover provides favourable conditions for malaria vectors to rest. The sparse nature of vegetation cover in the area can reduce mosquito density. All these factors could partly explain the low transmission of malaria in the area leading to cold spot conditions.

Table 3 summarized the number of LGAs identified as hotspots and coldspots for each year. From the table, the number of LGAs reported as hotspots cluster across the state was highest in the year 2014 and slightly lower during the 2016-2019 periods.

Table 3: Number of LGAs per type and intensity of malaria cluster

Confidence Interval	2014	2015	2016	2017	2018	2019	2014-2019
Under-five years:							
Coldspots 99% C.I.	1	3	1	1	5	3	3
Coldspots 95% C.I.	2	-	5	4	2	3	3
Coldspots 90% C.I.	-	-	1	1	1	1	1
Not significant	19	21	16	17	15	16	13
Hotspots 90% C.I.	1	2	2	1	-	-	6
Hotspots 95% C.I.	2	1	2	2	1	-	1
Hotspots 99% C.I.	2	-	-	1	3	4	-

Source: Author's computation (2021)

High-intensity clustering was reported in 2018 and 2019 in three and four LGAs respectively. This pattern of high-intensity clustering in these years could be related to high rainfall which brings about serious flooding in many parts of the state. Thus, stagnant water points tend to occur in many places and favoured ecological conditions suitable for malaria pathogens and vectors to develop and proliferate. These findings corroborate the works of Okunola and Oyeyemi, (2019) who reported malaria clusters in the 6 geopolitical zones of Nigeria, and Gambo, *et al*. (2020) who reported environmental influences, for example, Climate change, which has a favourable impact on the vector's ecology, habitat, and breeding grounds, as well as the study area's geographical position and poorly coordinated settlement pattern and environmental cleanliness, to have all contributed to an increase in malaria cases in Nigeria.

Conclusion

In this study, the spatial autocorrelation technique has been explored to identify and map the geographical distribution of malaria prevalence clusters. Further, the study highlighted the role of GIS and spatial data analysis in explaining disease dynamics. The results discovered statistically significant clustering of high malaria prevalence in the central and north-western parts of the state while coldspot LGAs were persistently detected in the north-eastern part of the area. This finding suggests the provision of adequate malaria intervention services including vaccination to the identified high malaria prevalence clusters.

Declarations

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Figures

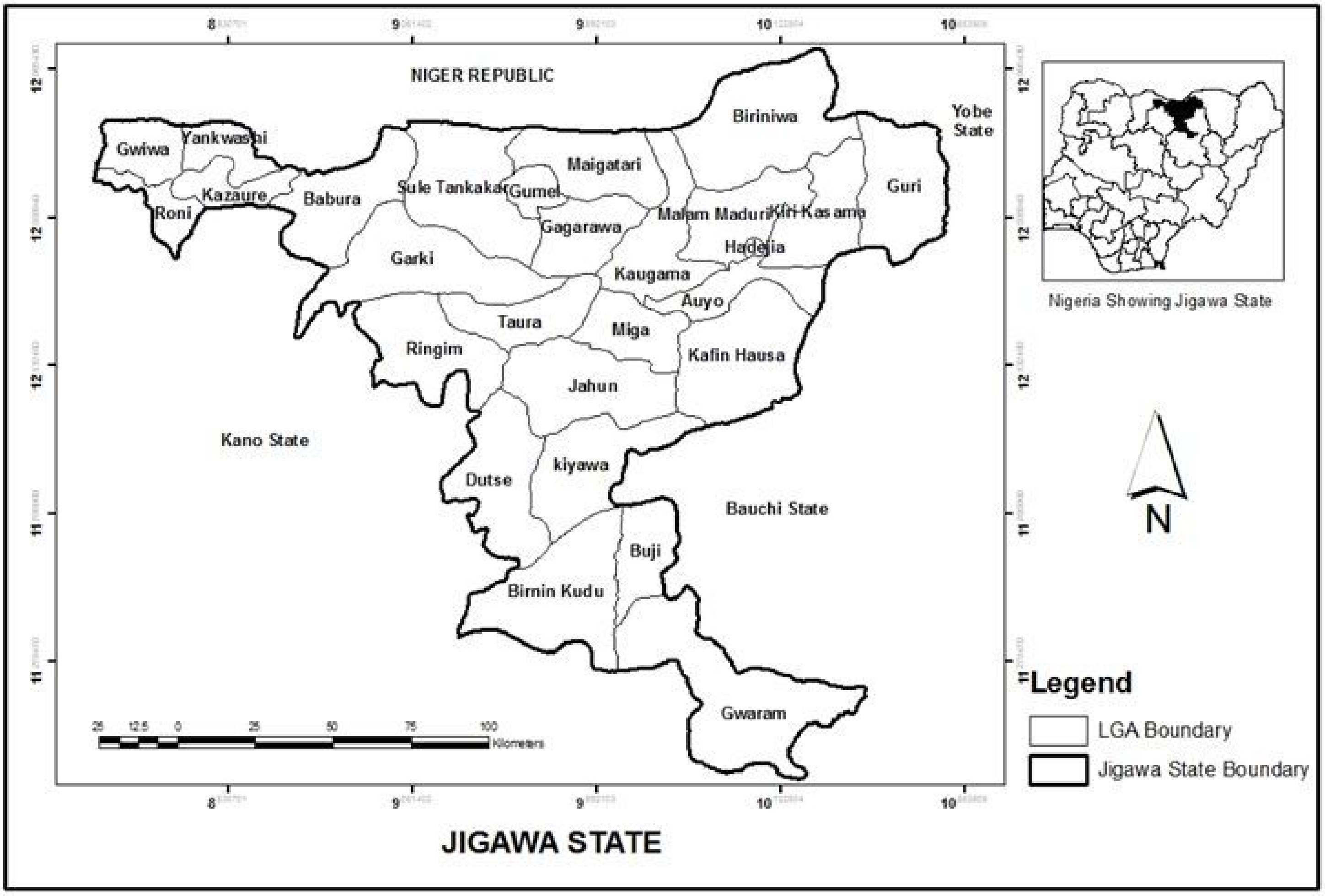

Figure 1

Jigawa State (Study Area)

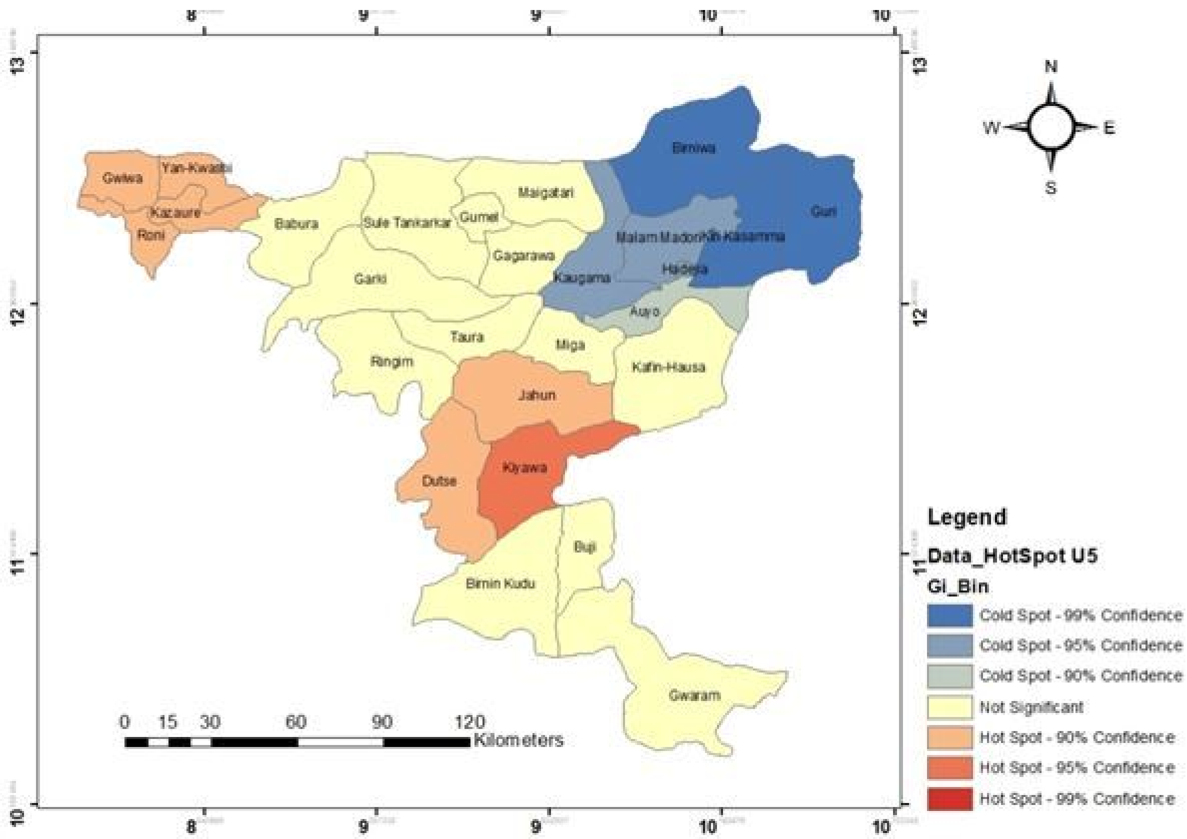

Figure 2: Hotspot of malaria prevalence (2014-2019)

Figure 2

Hotspot of malaria prevalence (2014-2019)

Figure 3

Fig 3a: Hotspot of malaria prevalence (2014) Fig3b: Hotspot of malaria prevalence (2015). Fig 3c: Hotspot of malaria prevalence (2016) Fig 3d: Hotspot of malaria prevalence (2017). Fig 3e: Hotspot of malaria prevalence (2018) Fig 3f: Hotspot of malaria prevalence (2019)