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Research Article

Detecting Hotspots Clusters of Malaria Prevalence Among Pregnant Women in Jigawa State, North-West, Nigeria

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ABSTRACT

Malaria during pregnancy is considered a serious public health challenge in tropical and subtropical regions. In 2020, there were an estimated 33.8 million pregnancies in the WHO African Region, of which 11.6 million (34%) were at risk of malaria infection during pregnancy, and the West African sub-region bears the highest prevalence (39.8%) of exposure to malaria during pregnancy. Due to the high prevalence of malaria infection among pregnant women, this study aimed to explore the pattern of malaria prevalence among pregnant women using clinically confirmed hospital data from 2014 to 2019 in Jigawa State, Northwest Nigeria. ArcGIS version 10.3 was used for database development and spatial data analysis. Spatial statistics namely Global Moran's I and Local Getis-Ord statistics (Gi*) were used to conduct data analysis. The former was employed to detect the existence of clusters while the latter was used to show the location of clusters. Results show that there is a statistically significant cluster pattern of malaria prevalence from the year 2014 to 2018, while the year 2019 had a random distribution. The clustering was strongest in the year 2016 with Moran's I 0.387680, Z-score 3.946283, and P value 0.000079. The detected hotspots concentrate in the central part of the study area while cold spots occurred in the northern part. The study suggests that proper attention should be given to hot spot locations in the allocation of resources for malaria control.

Keywords: *Cluster, Malaria prevalence, Pregnancy, Prevalence, Spatial statistics, Jigawa,*

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INTRODUCTION

Malaria is a mosquito-borne infectious disease that causes illness and death to humans and other animals. In humans, malaria is caused by one of the four Protozoan parasites of the genus *plasmodium*. These four species are *p. falciparum, p. malariae, p. ovale* and *p. vivax* though humans occasionally become infected with *Plasmodium* species that normally infect animals, such as *P*. knowlesi (WHO, 2013). Of the four species, *p. falciparum* is the most dangerous one due to its high mortality rate, widespread resistance to anti-malaria drugs, and dominance in the world's most endemic malaria region, Africa (Deponte and Beeker, 2004; Mayxay *et al.* 2004; WHO, 2011; Paton, *et al.* 2021). Malaria parasites are predominantly transmitted through the bite of an infected female *anopheles* mosquito. It is responsible for about 80%and 90% of morbidity and mortality in humans (Alemu and Mama, 2016).

Malaria continues to remain the leading cause of morbidity and mortality in many developing countries (Rumisha *et al.* 2019; Romero *et al.* 2021). It presents adverse health, social and economic consequences to a number of countries, especially in tropical and sub-tropical regions of the world. According to World Health Organization (WHO) report, there were an estimated 241 million malaria cases and 627,000 malaria-related deaths in 2020 in 85 malaria-endemic countries (WHO, 2021). This represents an increase of 6% and 12% in the number of cases and deaths compared to 2019. The WHO African Region bears the greatest burden of malaria with an estimated 228 million cases in 2020, accounting for about 95% of cases and Nigeria suffered more than any other country contributing 27% of global cases and deaths (WHO, 2021).

Malaria infection during pregnancy is considered a serious public health challenge in tropical and subtropical regions (Feleke *et al.* 2020). In 2020, there were an estimated 33.8 million pregnancies in the WHO African Region, of which 11.6 million (34%) were at risk of malaria infection during pregnancy and the West African sub-region bears the highest prevalence (39.8%) of exposure to malaria during pregnancy (WHO, 2021). In malaria-endemic areas, malaria is responsible for almost one-quarter of the yearly maternal mortality, (Chaponda *et al.*2015) and the risk of developing severe malaria for pregnant women is 2-3 times higher than that of non-pregnant women living in the same area (Schantz-Dunn and Nour, 2009). Pregnancy-associated malaria can cause critical anaemia and other adverse birth outcomes including placental accumulation of parasites, low birth weight from prematurity and intrauterine growth retardation, spontaneous abortion, congenital infection, and infant mortality (Bader *et al.* 2010; Yatich *et al.* 2010; Cornelio and Seriano, 2011).

Prevalence of malaria varies across geographical areas over time. The burden of the disease, therefore, differs between geographical locations and population groups. Understanding the location and distribution pattern of the disease will enhance disease control and management practice. As a result, the WHO recommends the surveillance of malaria cases to identify areas or population groups that are most affected by the disease, and for planning resource allocation for maximum impact (WHO, 2018).

Presently, Geographical Information Systems (GIS) and spatial statistics have been used to address disease clusters and hotspots. The global spatial autocorrelation technique is employed to measure and analyzed the degree of similarity among observations in geographic space. Moran's I and Getis-Ord Gi* statistics are commonly applied to identify whether observations are clustered in space or not and show the locations of clusters. Spatial statistical techniques are increasingly gaining their application in the analysis and mapping of malaria-related studies among other fields. The application of spatial clustering and mapping techniques in studying mosquito-borne infections has been demonstrated in spatial clustering and risk factors of malaria infections in Equatorial Guinea (Gomez-Barroso *et al*. 2017), spatio-temporal clustering of malaria cases in Nigeria (Yakudima and Adamu 2019), GIS Determination of Malaria Hot Spots in Iran (Zandian *et al.* 2019), spatio-temporal patterns of malaria incidence in Rwanda (Bizimana and Nduwayezu, 2020) and Geospatial analysis of malaria mortality in Ghana (Kenneth *et al.* 2021).

The aim of this paper is to use the spatial autocorrelation technique to analyze malaria cases among pregnant women in Jigawa State and to map the distribution of significant malaria hotspot areas.

MATERIALS AND METHODS

Study Site: Jigawa is one of the seven States that formed the northwest geo-political zone of Nigeria. It has 27 local government areas (LGAs) and five Emirate councils. The state is located approximately between latitude 10^o N and 12^o N and longitude 7^o E to 10^o E. It borders Kano and Katsina States to the west, 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 24, 515 Km^2 (Plate 1).

The climate of the area is tropical wet and dry type coded as "Aw" in the Koppen classification system. The normal rainy season starts in June and lasts until September although mid-May and mid-October are usually regarded as part of the rainy season. The dry season commences in October and ends in May. 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).

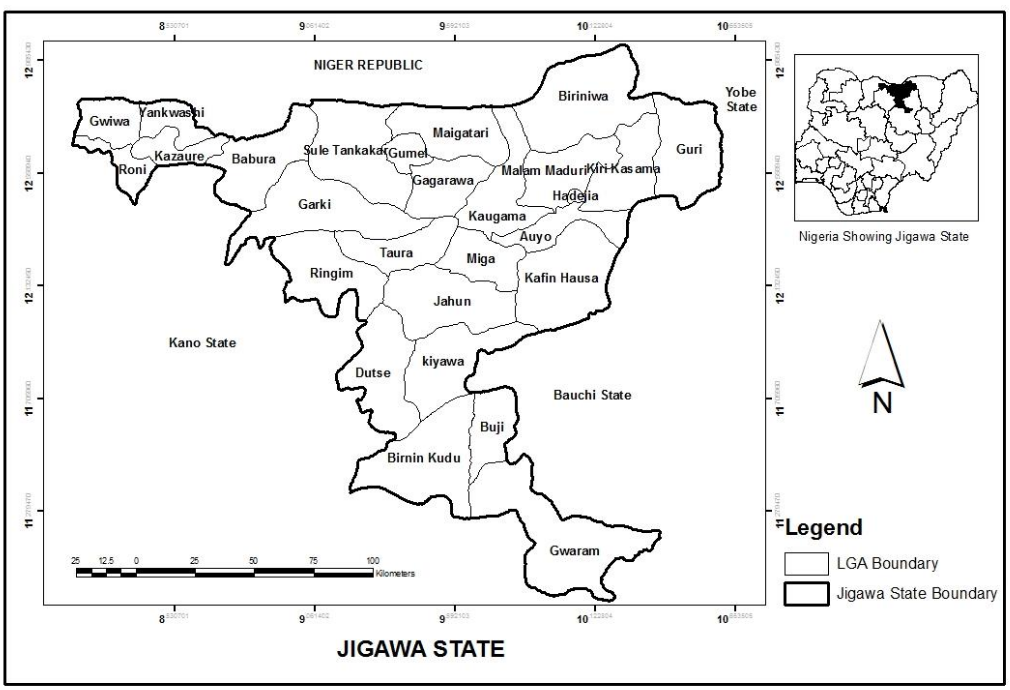

Plate 1:
Jigawa State (the study area)

Maximum temperature (above 42^{o} C) is recorded during the hottest months of March and April and may extend to mid-May, while lower temperature as low as 10^{o} C is normally recorded in the coolest months (December to February). The mean annual rainfall is higher (1000 - 1100 mm) in the southern parts and lower (500 - 550 mm) in the northern and northeastern parts of the state (Olofin, 2008). The area hosted a number of streams, rivers, stagnant water bodies, irrigated lands, wetlands, blocked drainages, and garbage dumps among other features that promote mosquito breeding. The 2006 population census figure for the Jigawa State stood at 4,348,649 (Federal Republic of Nigeria, 2007) with an average density of about 177 persons/km^2. The projected population figure for the area as of 2019, stood at 6, 526, 432 (National Population Commission, 2009). Agriculture which is regarded as one of the occupational malaria risk factors is the dominant economic activity in the state employing 70% of the inhabitant (Jigawa State Ministry of Health {JSMoH}, 2010).

Data Sources

Malaria Case Data: Clinically confirmed pregnancy malaria case data for the state from 2014 – 2019 was collected from the Jigawa State Ministry of Health. The data was aggregated by month and year at local government areas levels. The data is for confirmed cases using microscopic or Rapid Diagnostic Test (RDT) kits and clinically diagnosed at various public health facilities across the state. In each facility, daily records of confirmed malaria case events were sent to the health office of their local government where cases are transferred to the National Health Management Information System (NHMIS) monthly summary form for health facilities version 2013 for onward submission to the State Ministry of Health. The State Ministry of Health used to feed the National Malaria Control Office with routine malaria data obtained from various local governments. The data were categorized into three population groups: under five years, above five years, and pregnant women. Cases were further grouped into uncomplicated and severe for each population group. For this study, only uncomplicated cases of malaria among pregnant women were used. Monthly malaria cases for the period of six years (2014 - 2019) were extracted from the database of the ministry.

Population Data: Population data used in this study were collected from the National Population Commission, Jigawa state. Data on the population census conducted in 1991 and 2006 were collected and used to calculate the inter-census growth rate for each local government area in the state. The computed result was to determine the projected population figures for the years 2014 to 2019 and the data were used to calculate malaria prevalence rates and produced hotspot maps.

Data Analysis

Prevalence Rate: To ensure a better representation of clinically confirmed malaria cases, data were standardized as prevalence instead of total cases. This was due to the unequal 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 the burden of resources, it also reflects the burden in terms of life expectancy, morbidity, quality of life, or other indicators (Noordzij, *et al.* 2010). In this study, malaria prevalence data was computed by dividing the total number of malaria cases for each year of study for the 27 LGAs by the population of each LGA. The formula used in the computation is:

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

Spatial Pattern: Moran's *I* statistical technique was used to explore the spatial pattern of malaria prevalence among pregnant women in the state, which may either be clustered; dispersed, or random. The technique measures the degree to which a phenomenon is clustered in space. Clustering is the occurrence of unusual aggregation of a phenomenon in a sub-district (Wangdi *et al.* 2020). Clusters are determined by comparing Moran's *I* values of the target sub-districts and their neighbouring sub-districts to Moran's *I* values of all sub-districts in the study area (Anselin, 1995). The value of Moran's index ranges from +1 (indicating positive autocorrelation) to -1 (representing negative autocorrelation) with a zero value indicating the absence of clustering.

The Moran's index formula is given below:

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

Where N is the number of spatial units (LGAs) indexed by i and j, X represents the study variable (malaria prevalence rate), $\bar{X}$ *is the mean value of malaria cases,* w_{ij} *is an element of a matrix of spatial weights which defined as the degree of proximity between local governments areas i and j*

Hotspot Analysis: Understanding the location of where diseases such as malaria are concentrated is highly essential for controlling, managing, and monitoring reasons. Different spatial statistical tools such as Getis-Ord Gi* statistics, local indicators of spatial association (LISA) statistics, multi-logistic regression, and local Moran's I and Geary's, have been developed to measure the degree of dependency and identify areas of the hot spot and cold spot of events. The hot spot is a type of clustering where the target sub-district had a higher rate of events than the study area average (Wangdi *et al.* 2020).

In our study, the Getis-Ord Gi* statistical analysis was employed to identify different spatial clustering patterns like hot spots and cold spots with statistical significance. This type of statistics is can show whether the differences between the local mean (i.e., cases for a local government and its nearest neighbouring local government in the state) was significantly different from the global mean (i.e., the overall cases of all local government in the state).

The statistic returns a Z score for each feature in the dataset. The resultant "z" score is an indicator of hot or cold spots malaria prevalence cluster. For a statistically significant positive Z score, the larger the Z score is, the more intense the clustering of high values (hot spots). For statistically significant negative Z score, the smaller the Z score is, the more intense the clustering of low values (cold spot) 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 Getis-ord Gi* has the following formula:

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

Where *yi* is the value of a 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

Monthly Malaria Prevalence: The study analyzed monthly malaria prevalence as presented in Figure 1. The figure shows a fluctuating and increasing trend, with cases occurring in almost every month. The peak period of high cases begins in June and ended in October after the rainy season. The highest mean monthly prevalence rates of 73 and 71 per 100,000 people were observed in the months of September and October respectively. In contrast, the lowest mean monthly rates were reported in the months of May and June with 31 and 33 per 100,000 individuals respectively.

Annual Malaria Prevalence: Further analysis of the annual malarial prevalence among pregnant women indicated an annual declining trend in malaria prevalence (refer to Figure 2). Over the study period, the highest prevalence (768 per 100,000 population) occurred in the year 2014 while the lowest (410 per 100,000) was reported in 2016. The mean cumulative prevalence was calculated as 524 per 100,000 population.

Spatial Autocorrelation Pattern of Malaria Prevalence: Further analysis was undertaken to evaluate the spatial pattern of malaria prevalence among pregnant women in Jigawa State using Global Moran's *I* statistics. The test results (Table 1) based on the annual prevalence rates showed that there was a strong positive spatial autocorrelation in all the years under study except 2019 which showed a random pattern of distribution. The clustering was greatest in the 2016 with Moran's index 0.387680, *Z* score = 3.946283, *P* = 0.000079. This was closely followed by the year 2014 (Moran's index = 0.309075, *Z* score = 3.210292, *P* = 0.001326). Table 2 further indicates evidence of significant spatial autocorrelation of malaria prevalence for the overall years of study. The result shows that Moran's index was 0.229 which is greater than 0.00 indicating a positive clustered pattern. The Z-score was 2.94, which is higher than 2.58 with a *p-value* of 0.003. In general, the distribution of malaria prevalence among pregnant women in the study area for the period under observation had a clustered pattern.

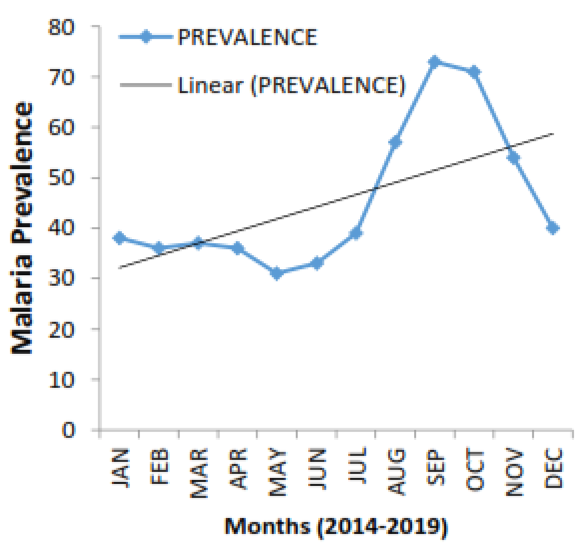

Figure 1:
Mean monthly malaria prevalence among pregnant women

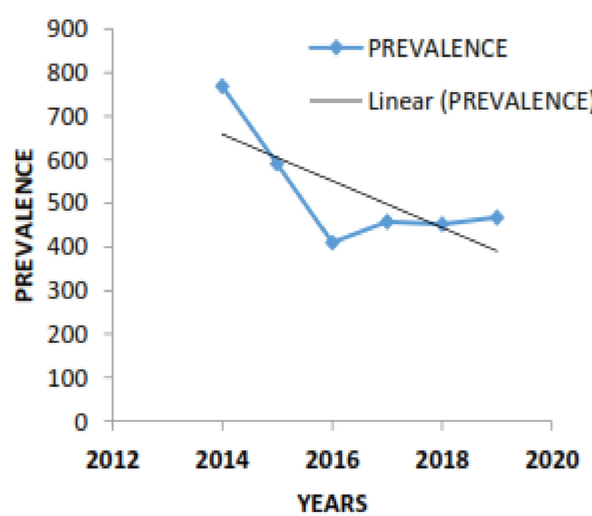

Figure 2:
Annual distribution of malaria prevalence among pregnant

Table1:
Spatial autocorrelation test result on malaria prevalence from 2014-2019

Year	Moran's I	Expected Index	Variance	Z-score	P- value	Pattern
2014	0.309075	-0.38462	0.011720	3.210292	0.001326	Clustered
2015	0.297063	-0.38462	0.011052	3.191531	0.001415	Clustered
2016	0.387680	-0.38462	0.011661	3.946283	0.000079	Clustered
2017	0.220340	-0.38462	0.008177	2.862072	0.004209	Clustered
2018	0.100961	-0.38462	0.005420	1.893879	0.058241	Clustered
2019	0.000877	-0.38462	0.006268	0.496864	0.619285	Random
2014-2019	0.228767	-0.38462	0.008258	2.940614	0.003276	Clustered

Source: Data analysis, 2021

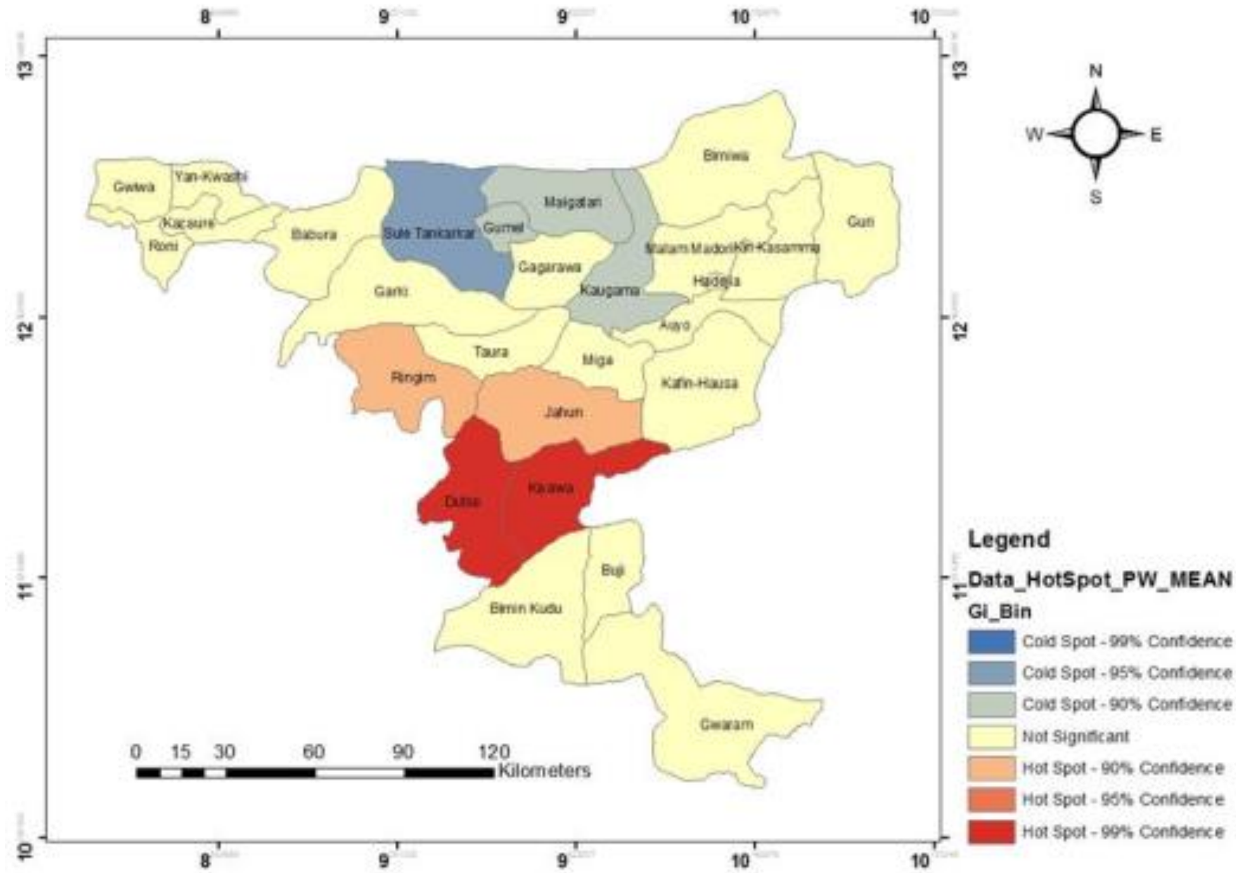

Plate 2
Hotspot of malaria prevalence among pregnant women (2014-2019)

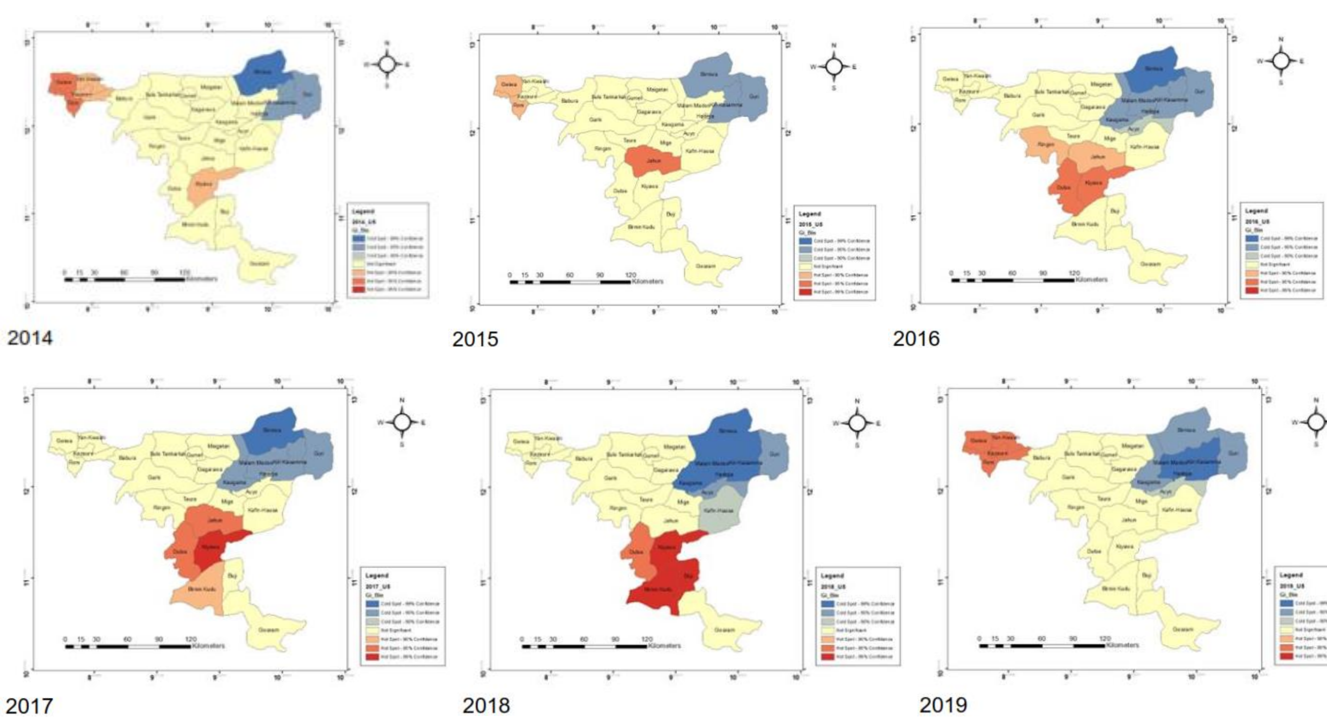

Plate 3
Yearly hotspots of malaria prevalence among pregnant women

Table 2:
Summary of type and intensity level hot and cold spot clusters

		Hotspot 99% C.I	Hotspot 95% C.I	Hotspot 90% C.I	Coldspot 99% C.I	Coldspot 95% C.I	Coldspot 90% C.I
2014	LGA (%)	-	11.1	-	3.7	3.7	11.1
	POP (%)	-	9.6	-	2.3	4.3	9.0
2015	LGA (%)	3.7	7.4	-	3.7	-	14.8
	POP (%)	3.9	11.0	-	2.3	-	13.3
2016	LGA (%)	11.1	7.4	3.7	14.8	-	3.7
	POP (%)	16.8	6.7	3.5	12.5	-	4.8
2017	LGA (%)	7.4	-	7.4	-	-	7.4
	POP (%)	10.6	-	7.9	-	-	6.9
2018	LGA (%)	7.4	-	3.7	-	-	3.7
	POP (%)	10.6	-	3.5	-	-	2.6
2019	LGA (%)	3.7	-	11.1	-	-	-
	POP (%)	3.9	-	16.8	-	-	-

Hot/Cold Spots of Malaria Prevalence

In order to plan for a proper intervention strategy, information on the locations of malaria hot spots among pregnant women is very important. The study, therefore, detected the location of hot and cold spots areas of malaria in pregnant using the Getis Ord-Gi* statistic estimation measure. Areas with different risk levels for different years were detected

Based on the analysis undertaken on the overall (2014-2019) data, hotspot analysis of malaria prevalence indicates statistically significant local clustering in the area. Plate 2 revealed significant clustering of malaria (99% confidence interval) in Kiyawa and Dutse LGAs. This level of risk accounts for 7.4% of the total LGAs for the state and 10.6% of the population under study. A hotspot at a 90% confidence level on the other hand was detected in Ringim and Jahun LGAs. These two LGAs also account for 7.4% of the LGAs in the state with 7.9% of the population in the state. Plate 2 also indicates that cold spots at 99% can only be detected in Sule Tankarkar LGA which formed 3.7% of the entire LGAs in the state with only 2.3% of the whole population of the study. However, three LGAs (Gumel, Maigatari, and Kaugama) formed cold spots at a 90% confidence interval and these constitute 11.1% of the LGAs under observation (Figure 3). In general, 14% of the LGAs in the state constitute the cold spot zone and accommodate 12.5% of the state population.

The yearly analyses were presented in Plate 3. It was observed from the figures that Kiyawa LGA appears under the hotspot zone at 99% in good five years, Dutse LGA (3 years) while Gwiwa, Roni, and Birnin Kudu LGAs each appeared in only one year. At a 95% confidence level, a hotspot was detected in Jahun in two years while Dutse and Buji had one year each. For a 90% confidence level, the hotspot was detected in Ringim LGA (3 years), Kiyawa, Jahun, Dutse, and Kafin Hausa LGAs (1 year each). Furthermore, Plate 3 showed Sule Tankarkar as the coldest LGA for appearing under cold spots at a 99% confidence level for consecutive three years. Gumel, Maigatari, and Kaugama LGAs each formed a cold spot at a 99% confidence level in only one year. At a 95% confidence level, Garki, Gumel, and Maigatari each had appeared twice in the three years of the analysis. However, Kaugama LGA had appeared only once at this confidence level. At a 90% confidence level, Kaugama had appeared in three years, while Babura and Maigatari had only one year each. Table 2 summarizes the proportion of LGAs and the number of people within the different zone of malaria for each year.

DISCUSSION

This study employed a Geographical Information System and spatial statistical technique to identify the spatial patterns and detect the locations of hot and cold spots of malaria prevalence among pregnant women. Our finding revealed that malaria cases occur throughout the year with seasonal variations. This finding indicates that the study area is an endemic malaria region. The concentration of higher cases in June – October throughout the period under investigation coincides with the rainy season. During this period alternative breeding sites are numerous because of rainfall. Similarly, temperature condition is suitable for a mosquito to reproduce, their ability to transmit the disease, and parasite development (Noden *et al.* 1996; Apiwathnasorn, 2012).

Similarly, studies undertaken by Nanvyat *et al.* (2017); Epopo *et al.* (2019); Okonlola and Oyeyemi (2019); and Wangdi *et al.* (2020) also found a concentration of malaria cases in the rainy season (May - October) in their respective study area. Low malaria prevalence was surprisingly reported in the period of higher temperature in the area which is between May and June. However, apart from higher temperatures during those months, another reason for the low prevalence of malaria has not yet been ascertained. On the other hand, studies undertaken in Nigeria by (Nanvyat *et al.* (2017); Yakudima and Adamu (2017); Okonlola and Oyeyemi (2019); Yakudima and Adamu (2019)) reported low transmission of malaria between December and February when the temperature condition is low. Thus, the temperature is one of the factors that influence the prevalence of malaria in this study area.

Another pattern observed from this study indicated that the highest prevalence occurred in the year 2014 while the lowest was reported in 2016 with a declining trend. First, the decreasing trend in malaria prevalence among pregnant women could be related to the intervention strategies undertaken. For example, during the observed period, there was increased use of ITNs and Intermittent Preventive Treatment (using Sulphadoxine-pyrimethamine {SP}) in the area. According to NPC and ICF International (2014; 2019), 95.7% of pregnant women in Jigawa State slept under an ITNs the night before their survey compared to 26.1% in 2013. This represents a significant increase. This is probably due to in 2013, 24.6% of pregnant women received one or more doses of SP during an antenatal care visit (NPC and ICF International, 2014) and it increased to 66.9% in 2018 (NPC and ICF International, 2019). Therefore, it contributed to the drastic reduction in the incidence of malaria in pregnancy in the state.

The overall mean annual prevalence (524 per 100,000 or 0.524%) of malaria among pregnant women revealed in this study is relatively much lower than that reported in other areas in Nigeria. For instance, Maureen *et al.* (2016), Inah *et al.* (2017), Joseph *et al.* (2017), Simon-Oke (2019), and Onyemechi and Malann (2020) reported 66.7%, 40.7%, 24.1%, 40.2%, and 61.3% respectively as prevalence rate among pregnant women in their study areas. Additionally, much higher prevalence rates were reported elsewhere in Africa: 22.4% in Mount Cameroun, Cameroun (Anchang-Kimbi *et al.* 2015), 19.6% in Blantyre, Malawi (Boudova *et al.* 2015), 31.8% in Nchelenge, Zambia (Chaponda *et al.* 2015) and 20.4% in the middle belt, Ghana (Dosoo *et al.* 2020) respectively. The variation in the observed prevalence across the various studies might be due to differences in climatic and topographical conditions as well as malaria prevention measures adopted. The very low prevalence rate (524 per 100,000 populations) observed in this study could be linked to increased attention to malaria intervention measures in the state, especially among pregnant women. For example, Nigeria Demographic Health Survey reported that in 2018 the overall coverage and utilization of ITNs among pregnant women reached 95.7% in Jigawa State (NPC and ICF International, 2019).

Furthermore, the result of our study discovered that the spatial distribution patterns of malaria prevalence in pregnancy occurred in clustered. The presence of significant positive autocorrelation for the period under investigation except the year 2019 revealed the level to which cases of neighbouring areas are correlated. This result suggests that the prevalence of malaria in pregnancy between LGAs that share a border is more similar than those that are further apart. Thus, the occurrence of malaria prevalence in these years in specific areas is not by chance. The statistically established spatial dependency of the disease further implies the presence of similar risk factors in neighbouring areas thereby influencing the spatial transmission of the disease. This finding confirmed the results of previous studies by (Sexena *et al.* 2012; Osayomi, 2014; Yakudima and Adamu, 2019; Bizimana and Nduwayezu, 2020; Gwitira *et al.* 2020; Rouambo *et al.* 2020) that observed clustering of malaria cases in particular geographic areas. Previous studies relate the spatial heterogeneity of malaria to variation in environmental determinants at the macro and micro spatial levels (Stresman, 2010; Gwitira *et al.* 2020). However, these global test results indicate a need for further investigation using local spatial statistics (hotspot analysis).

Furthermore, the hotspot analyses presented in this study give evidence of statistically significant clustering of LGAs into ‘hotspots’ and ‘cold spots’ of malaria prevalence in pregnancy and significant variation over time. This result indicated that hotspots of malaria prevalence were mainly detected in the central, northwest, and southern parts of the state. Furthermore, it also shows consistently over the study period malaria clusters occur in varying intensity levels and at different geographic areas. A persistent and stable cluster of malaria in pregnancy was detected in Kiyawa LGAs, though with a varying magnitude of risks. Dutse and Jahun LGAs located in the central part of the state are also reported as significant hot spot areas. These findings indicated hot spot corroborates with those studies conducted by Bousema *et al.* (2013) and Kamuliwo *et al*. (2015) for malaria in pregnancy.

Moreover, the consistent hotspots identified in the central part and a few other pockets imply that local factors have contributed significantly to the local transmission of the disease in the area. There are a number of plausible reasons for the existence of hotspots in the detected areas.

One of the most important factors is the presence of potential breeding grounds. The major identified hotspot areas (Kiyawa, Dutse, and Jahun) bordered other LGAs that have wetlands where vegetable (onion, cabbage, tomato) cereals such as rice and maize were grown. Rice fields according to Gurthmann *et al.* (2002) are the most favourable sites for mosquitoes to breed and increase in density. According to Chan *et al.* (2022), malaria vector densities were six times higher in rice-growing than non-rice-growing areas, because the ecological conditions of the early stages of rice fields are what exactly required by larvae of A *gambiae* sl. In addition, irrigated lands provide ideal sites for resting and enhancing the longevity of mosquitoes (Alemu, 2007). Within these hot spots and other neighbouring LGAs streams and groundwater sources are equally used by farmers to irrigate their land. This also ensures the availability of soil moisture which attracts mosquitoes. These water agro-systems may provide significant habitat for mosquito breeding and thus, increase vector population for malaria transmission. This finding is confirmed by studies conducted by Rulisa *et al.* (2013) and Bizimana & Nduwayezu (2020) that discovered significant malaria hotspots located close to water-based agroecosystems. Other studies (such as Oguoma and Ikpeze (2008); Mwangangi *et al.* (2010); and Demissew *et al.* 2020) suggested that irrigation agricultural practices influence *Anopheles* species diversity and such diversified malaria-transmitting *Anopheles* species might affect the risk of malaria transmission and affect control effort around irrigation sites.

The second reason is due to population concentration. The local government areas that have appeared in hotspot cells are associated with a high population. The findings suggested that hotspot locations are connected to high-population areas. This finding is in line with the result of studies by Kabaria *et al.* (2017) and Tewara *et al.* (2018) who identified hot spots of malaria cases in highly populated areas. This explanation for the existence of a malaria hot spot in these local government areas is that in most African towns locations characterized by high populations are mainly associated with 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.

Another reason for the occurrence of hotspots of malaria in pregnancy might be due to increased access to healthcare services by pregnant women through support Medicine Saint Frontier (MSF) support. MSF is an international organization responding to disease outbreaks and emergency health needs in Nigeria for many years. It runs the maternity and neonatal departments of Jahun General Hospital. The organization provides financial and technical support to reduce maternal complications. All antenatal and maternity services such as scanning and Caesarean Section (CS) are given to the patients free of charge at the facility. The center has a Neonatal Intensive Care Unit which is one of the best in the country. The unit is responsible for taking care of babies that were born with problems such as neonatal jaundice, neonatal sepsis, congenital anomaly, and other complications that required medical attention. Services related to maternal problems such as Eclampsia, Vesico-vaginal fistula (VVF), Recto-vaginal fistula and many others are all given free. These attract pregnant women from neighbouring local government areas and other parts of the state to enjoy the services. Thus, making the center of the state experience elevated malaria cases.

Although our study achieved its goal by identifying and locating locations of hotspot clusters of malaria among pregnant women, it has some limitations. The study used aggregated data collected by health professionals on patients at health facilities. And the data did not capture vital information about the patients such as a patient's address, age, and parity, among other others. In addition, the data did not capture cases registered at private health institutions and those treated at home. Hence, the picture of the disease among the studied population may not be ascertained. The study was conducted in Jigawa state, its findings therefore may not be generalizable to the whole country. Finally, the study did not include some known risk factors of malaria (biological, environmental, and climatic factors) which might have a significant impact on the transmission of malaria due to the nature of the study. Despite these potential limitations, the results of this study are still important and may be useful for planning disease surveillance, particularly in areas of limited resources by focusing on high-risk areas.

In conclusion, this study analyzed the spatial distribution of malaria infection among pregnant women in Jigawa state. This was investigated through spatial statistics using global Moran's I and Local Getis-Ord statistics (G*i**). The results revealed that the significant hot spot areas for malaria among pregnant women are concentrated in the central part of the state. Hotspots were detected for five out of six years of the observation, with a year-to-year variation in the risk levels. The results of this study could be used for effective malaria control and will equally assist national, state, and local stakeholders in planning and undertaking future malaria intervention strategies aimed at targeting hot spot cells. In addition, the results can be used as a baseline to assess the impacts of malaria programs implemented so far. It is recommended that further studies be conducted to look into the risk factors of malaria transmission among pregnant women in the area.

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