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Influence of Environmental Factors on Malaria Incidence in Jigawa State, Nigeria

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Abstract: Malaria has become a significant health disaster, particularly in developing countries, where physical and built environments are poorly improved. This paper aims to assess the influence of climatic and non-climatic environmental variables on malaria incidence. Climatic variables (rainfall, temperature, and humidity), physical environmental variables (distance to mosquito breeding sites and vegetation cover), built environmental variables (condition of sewers, distance to garbage dumpsite, type of house, availability, and condition of water storage containers, type of plant cover within residential houses and type of animal kept in residential compound) were analysed to determine their relationship with malaria incidence using correlation and multiple regression analyses. The results showed that all the variables except temperature and condition of water storage containers showed a positive correlation with malaria incidence. Furthermore, relative humidity, rainfall, and distance to mosquito breeding sites were the most significant factors, and the correlation coefficients are 0.424, 0.333, and 0.383 ($P < 0.0001$), respectively. Moreover, climatic and non-climatic environmental factors accounted for 18.9% and 19.0% of the malaria incidence. Our findings identified the most significant environmental determinants for malaria incidence in the area. This will help in the planning of malaria control activities in the area.

Keywords: Climate; Environment; Incidence; Jigawa; Malaria

1.0 Introduction

Disasters are severe occurrences with a quick onset that affect a significant portion of the local population (European Union, 2013). Because of this, disasters place a heavy weight on the community and the government to reduce the destruction, suffering, and fatalities. Natural occurrences like earthquakes, tsunamis, floods, tornadoes, hurricanes, and pandemics can cause disasters, as can human-caused catastrophes like industrial accidents, traffic accidents, and terrorist attacks (European Union, 2013).

Malaria outbreaks can be regarded as disasters due to their catastrophic effects. There are significant public health and socioeconomic burden connected with the disease. Numerous people who survive death could experience subsequent consequences such as recurrent fever, starvation, cognitive (mental) delay, and severe anaemia (if not promptly treated), which may cause brain damage. Malaria also causes severe anaemia, unfavourable pregnancy outcomes include spontaneous abortion, stillbirth, preterm birth, low birth weight, and total maternal death in pregnant women (Cornelio and Seriano, 2011).

Although malaria has been successfully eradicated in developed nations, it remains a significant health threat in Africa (Sachs & Malaney 2002). In tropical Africa, it is one of the most frequent causes of serious sickness. According to the World Health Organization's 2021 World Malaria Report, there were 241 million cases and 627,000 fatalities worldwide from malaria in 2020, which is higher by 14 million cases and 69,000 deaths compared to 2019 records (WHO, 2021). This rise was primarily attributed to the diverse COVID-19 disruption. Africa, south of the Sahara bears a disproportionately heavy burden from malaria, in particular, Nigeria, where 27% and 32% of the estimated global cases and deaths were recorded in 2020, (WHO, 2021).

In Nigeria, where 76% of residents live in high- and 24% in low-malaria transmission zones, malaria transmission and risk are both considered to be high (WHO, 2017). According to the National Malaria Eradication Programme (NMEP), National Population Commission (NPC), National Bureau of Statistics (NBS), and ICF International (2016), hospitalization due to malaria account for 30% while outpatient visits to Nigerian hospitals make up 60%. Additionally, up to 11% of maternal deaths, 25% of infant deaths, and 30% of under-5 deaths are attributed to malaria. Each year, it is estimated that there are close to 300,000 paediatric deaths from malaria and around 110 million clinically diagnosed cases of the disease. The disease stresses the already-weak health system, slows the GDP by 40% yearly, and costs over 480 billion Naira (about 1.11 billion US dollars) in treatment, prevention, and lost man hours (FMoH and National Malaria Elimination Programme [NMEP] 2014).

Environmental factors generally have an impact on the vector Anopheles mosquito. The spatial distribution of vectors and the diseases they transmit are significantly influenced by climatic factors (particularly temperature, rainfall, and relative humidity), altitude, terrain, land use and land cover, and human settlement patterns (Darkoh et al., 2017). While numerous studies (Alemu et al., 2011a; Upadhayayula et al., 2015; Kibret et al., 2019) have demonstrated a link between climatic parameters and malaria transmission, others examine how non-climatic environmental factors affect malaria transmission (Ojua et al., 2013; Ngatu et al., 2019; Pullan et al., 2010).

Available literature shows that quite a number of studies on malaria have been conducted in Jigawa State (Bello and Adamu 2015; Abubakar et al., 2016; Jennifer and Musa 2016; Dauda and Muhammad 2017; Shuaibu et al., 2017; and Michael et al., 2019). However, the focus of these investigations was from a clinical, entomological, and epidemiological standpoint. In addition, none of the research that was evaluated looked into the connection between environmental factors and the spread of malaria in the state. Therefore, making wise policy and management decisions requires an understanding of how environmental factors affect malaria prevalence. This study looked into whether environmental factors, both climatic and non-climatic, were linked to malaria transmission in Jigawa State.

2.0 Study Area

The study was conducted in Jigawa State, located in the northwest geo-political zone of Nigeria. The area lies between latitudes 11° N and 13° N and longitudes 8° E and 10.15° E, and covers an approximate land area of about 24, 515 Km2 (Figure 1). The area is characterised by a savanna type of vegetation and experiences a tropical wet and dry type of climate. The 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 part of the state. The mean annual temperature is about 26o C but the mean monthly values range between 21o C and 23o C in the coolest months and over 30o C in the hottest months (Olofin, 2008). Agriculture is the dominant economic activity of the state employing 70% of the inhabitants (Jigawa State Ministry of Health, 2010). The 2021 population projection of the area was 7, 246, 906, made up of 49% males and 51% females (National Population commission, 2009). As of 2010, there were 614 healthcare facilities, both public and private.

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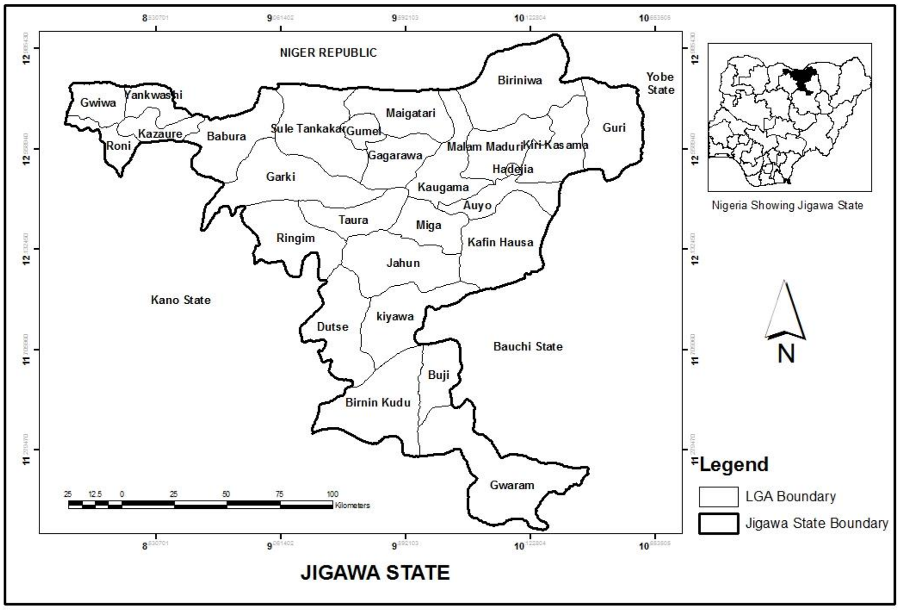

Figure 1: Jigawa State

3.0 Materials and Methods

3.1 Data Collection

The following instruments were used for the study: (1) Structured questionnaire for eliciting responses from the respondents on malaria occurrence in households and environmental issues related to malaria; (2) SPSS version 21 for statistical analysis; and (3) personal computer for data storage and analysis. Clinically confirmed malaria data were collected from the Jigawa State Ministry of Health. The data consist of all clinically diagnosed malaria cases at various public health facilities across the 27 LGAs. Monthly cases for six years (2014 - 2019) were extracted from the database. The choice of this period was based on data availability for the entire state. However, there were a few missing data in the record, but they were estimated using nearest neighbour analysis.

Data on meteorological elements, including total monthly rainfall, mean monthly temperature, and relative humidity from August 2017 to October 2019 for the entire 27 LGAs, were collected from the Jigawa State Agricultural Rural Development Authority (JARDA). Monthly averages of meteorological variables data were correlated with mean monthly malaria data to examine the relationship between the two variables, if it exists. Like malaria case data, records of some variables in a few LGAs were missed and estimated using nearest neighbour analysis.

The data on population were collected from National Population Commission, Jigawa state office. Data on the population census 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 2014 to 2019. The data were used to calculate malaria prevalence rates and form the basis for sample size determination for questionnaire administration.

Data on household physical environmental variables (distance to breeding sites such as wetlands, stagnant water bodies, and rivers and distance to over ground vegetation like grasses, shrubs, and bushes), built environmental variables (functional status of sewers, distance to garbage dump sites, nature of the house, availability and condition of water storage containers, type of plant cover within residential compound and type of animal kept in the house), and history of malaria occurrence (number cases recorded in the past six months) were obtained using a structured questionnaire. Multi-stage sampling method was employed in selecting respondents for the questionnaire survey. The area was first divided into three distinct ecological zones: Guinea, Sudan, and the Sahel savanna. Two (Gumel and Ringim) out of ten LGAs from the Sahel and three (Kafin Hausa, Ringim, and Roni) out of fifteen LGAs from the Sudan savanna were randomly selected, representing 20% of the total LGAs from these ecological zones. However, one (Gwaram) out of two LGAs was selected in the Guinea savanna, representing 50%, since two LGAs have no 20%. In each sampled LGA, 20% of its locality (settlements) was selected for further in-depth study. The idea of taking 20% of the LGAs and localities as sample size was suggested by Arlosoroff et al., (1987). They judged 20% as adequate to yield a meaningful statistical validity of results from any population. to this end, seven (7), thirteen (13), and six (6) localities were selected from Guinea, Sudan, and Sahel ecological zones respectively. The sample size for the study was determined based on Krejcie and Morgan's (1970) criteria. The calculator uses the following formula:

$$n= c2Np(1-p)/(A2N)+(c2p[1-p] \qquad \text{Eq. 1}$$

where n represents the sample size required, N is the total study population, p is the average proportion of records expected to meet the various criteria, (1-p) is the average proportion of records not expected to meet the criteria, A is the margin error deemed to be acceptable (calculated as a proportion) e.g. 0.05, c is a mathematical constant defined by the Confidence Interval chosen.

Therefore, using the formula, a sample of 322 respondents was drawn from each zone, giving a total of 966 respondents. The stratified sample formula by Stat (2012) was used to determine the sample size for each sampled locality. The formula is given below:

$$nh = (Nh/N) \times n \qquad \text{Eq. 2}$$

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where, nh represents sample size in each village, Nh is total population size in each village, N is total population size, n is total sample size.

Housing units were considered as the sampling units and were selected using a systematic random sampling technique. In all housing units where multiple household heads are identified, only one was considered for the study.

3.2 Prevalence Rate

The prevalence rate a measure of assessing the disease burden in a given population was used to standardize malaria case data. This was to give a better representation of the data due to the varying population size of the local government areas (LGAs). The following formula was used to compute the prevalence rate:

$$\text{Prevalence rate} = \frac{\text{Total Number of Malaria cases}}{\text{Total Population of the area}} X\ 100{,}000 \qquad \text{Eq. 3}$$

The nearest neighbour analysis was employed using XLSTAT 2014 add-in Software to estimate missing values in the dataset of malaria cases and meteorological variables. The technique is capable to predict unknown values using the known values at neighbouring locations (Junninen *at al.* 2004). The formula is expressed as:

$$Y=Y_1 \text{ if } X\leq X_1+[(X_2-X_1)/2] \text{ or } Y=Y_1 \text{ if } X\geq X_1+[(X_2-X_1)/2] \qquad \text{Eq. 4}$$

Where Y represents the interpolate, X is the time point of the interpolate, Y_1 and X_1 are coordinates of the starting point of the gap, and Y_2 and X_2 are the endpoints of the gaps.

Pearson product-moment correlation analysis was employed to explore the relationship between meteorological variables (temperature, rainfall, and relative humidity) and clinically confirmed malaria cases in Jigawa State. A separate analysis was then conducted to investigate the relationship between the number of malaria cases recorded in the last six months and household physical and built environmental factors. Where *r* is the correlation coefficient value, *x* and *y* are the bivariate, *n* is the sampling size.

Malaria prevalence was used as the dependent variable while meteorological variables were considered as independent variables.

Multiple linear regression is a statistical tool that is used to predict the variability that occurs between dependent and independent variables. This tool was used to determine the relative effects of climatic and non-climatic environmental variables on malaria incidence. Multiple linear regressions can be expressed using the equation:

$$Y = \beta o + \beta 1x1 + \beta 2x2 + \ldots\ldots\ldots\ldots\ldots\ldots + \beta mxm + eij \qquad \text{Eq. 5}$$

Where Y represents the dependent variables, *x1* to *xm* represents the multiple independent variables, β0 to βm represents the regression coefficients, and *e* represents the random error.

The number of malaria cases experienced in the last six months was the dependent variable while physical and built environmental variables are the predictors. Prior to the above analyses, preliminary assumption testing was conducted to ensure that assumptions of normality, linearity, and equality were not violated.

The level of significance was set at $P > 0.05$. All analyses were conducted using SPSS version 21.

4.0 Results

4.1 Climatic variables and Malaria Prevalence

Table 1 gives the statistical summary of meteorological variables and malaria cases. From the Table, the mean monthly temperature ranged from 14.3^{o}C to 45.6^{o}C with a standard deviation of 4.709oC. This shows a slight variation in the distribution.

Table 1: Summary of meteorological variables and malaria cases in Jigawa state

Variables	Minimum	Maximum	Mean	Std. Deviation
Temperature (^{o}C)	14.3	45.6	29.017	4.709
Rainfall (mm)	0	1056	95.886	138.703
Humidity (%)	2.13	96	38.779	24.077
Malaria cases	108	8221	1230.33	879.479

The monthly rainfall had minimum and maximum values of 0.00 mm and 1056. 0 mm respectively. A huge variation (δ = 134.055) in the total monthly rainfall occurred as many months went without rain. The average relative humidity ranged from 2.13% to 96%. Table 1 further shows that the monthly malaria prevalence rate in Jigawa State across the six-year study period ranged from 108 to 8221/100,000 population, with a mean prevalence of 1230/100,000 individuals. The standard deviation of the malaria prevalence rate (σ = 879.479) indicates high variability in the number of cases reported.

4.2 Correlation Analysis

An association between the monthly prevalence rate of malaria and meteorological variables using Pearson correlation analysis was established. As shown in Table 2, the correlations were both positive and negative. From the Table, monthly malaria prevalence was positively and significantly correlated (0.01 level of significance) with total monthly rainfall ($r = 0.331$, $p = 0.000$) and mean monthly relative humidity (r =

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0.424, p = 0.000). However, the mean monthly temperature shows a negative non-statistically significant correlation with monthly malaria prevalence (Table 2). This indicates that an increase in temperature decreases malaria prevalence in the area monthly.

Table 2: Summary of meteorological variables and malaria cases in Jigawa state

	Malaria Cases	Temperature	Rainfall	Humidity
Malaria Cases	1			
Temperature	-0.034	1		
Rainfall	**0.331****	0.004	1	
Humidity	**0.424****	-0.005	0.614	1

** Correlation is significant at the 0.01level (2-tailed)

4.3 Multiple Regression Analysis

To observe the independent effect of each independent variable on malaria occurrence, linear regression analysis was employed. The result of linear regression shown in Table 3 gives 43.5% as the correlation coefficient (R) between the criterion (malaria) and predictors (temperature, rainfall, and relative humidity) and an R2 value of 0.189, which implies that rainfall, humidity, and temperature have jointly accounted for 18.9% of the malaria occurrence in Jigawa state. The F-statistics, which measures the overall significance of the regression model, is F = 56.285 with a significant p-value of 0.000, indicating that our model is a good fit.

Table 3: Model summary for climatic factors

R	.435
R Square	.189
Adj. R Square	.186
Std. Error of the Estimate	793.703
R Square Change	.189

** Correlation is significant at the 0.01level (2-tailed)

As depicted in Table 4, the variable with the largest beta coefficients was relative humidity with 0.354; this means that relative humidity makes the strongest unique contribution in explaining the variation of malaria prevalence. However, rainfall and relative humidity are positively and significantly related to malaria prevalence. The temperature, however, had a negative standardized coefficient beta value (Table 4).

Table 4: Standardized beta coefficients for climatic factors

	Unstandardized Coefficient		Standardized Coefficient		
	B	Std. Error	Beta	T	Sig.
(Constant)	839.452	190.302		4.411	.000
Temperature	-6.189	6.247	-0.033	-0.991	0.322
Rainfall	0.723	0.269	0.114	2.688	0.007
Humidity	12.924	1.549	0.354	8.345	.000

4.4 Environmental variables and Malaria occurrence

Correlation analysis was also performed to explore the possible relationship between environmental variables and malaria occurrence in the last six months at the household level. The result of the analysis detected a significant relationship between household physical and built environmental variables with malaria occurrence at the household level (Table 5). The table shows that seven out of the eight variables are positively correlated. They are distance to breeding sites (r= .383, p= .000), distance to vegetation cover (r= .137, p= .000), condition of sewers (r= .109, p= 0.000), distance to garbage dumpsites (r= .159, p= .000), types of houses (r= .132, p= .000), type of vegetation within residential houses (r= .088, p= .003), and type of animal kept in residential houses (r= .057, p= .037). The condition of water storage containers in the house is the only variable that is negatively correlated with malaria incidence (r= -.039, p= .112).

Table 5: Correlation matrix of environmental variables

	MI	DBS	DVC	CS	DGS	TH	CSC	VH	AK
MI	1								
DBS	**.383****	1							
DVC	**.137****	.374	1						
CS	**.109****	-.021	-.004	1					
DGS	**.159****	.318	.456	-.097	1				
TH	**.132****	.077	.046	.222	-.042	1			
CSC	-.039	.136	.179	-.014	.145	.069	1		
VH	.088	-.013	-.080	.135	-.019	.070	-.075	1	
AK	.057	-.053	-.111	-.015	-.091	.001	-.076	.033	1

** Correlation is significant at the 0.01level (2-tailed). MI= Malaria incidence, DBS= Distance to breeding sites, DVC= Distance to vegetation cover, CS= Condition of sewers, DGS= Distance to garbage dumpsites, TH= Type of house, CSC= Condition of water storage containers, VH= Type of vegetation within the house, AK= Type of animal kept in the house.

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Table 6: Model summary for enviromental factors

R	.436
R Square	.190
Adj. R Square	.184
Std. Error of the Estimate	2.74778
R Square Change	.190
F Change	28.111
Sig. F Change	.000

** Correlation is significant at the 0.01level (2-tailed)

The Beta standardized coefficients (Table 7) indicated that distance to vegetation cover and condition of water storage containers have an inverse relationship, while the remaining six variables showed a positive relationship. Among the environmental factors distance to the breeding sites is the most significant determinant of malaria occurrence at the household level.

Table 7: Standardized beta coefficients for environmental factors

	Unstandardized Coefficient		Standardized Coefficient		
	B	Std. Error	Beta	T	Sig.
(Constant)	.665	.563		1.181	.238
DBG	1.416	.121	.375	11.703	.000
DVC	-.047	.125	-.013	-.377	.707
CS	.345	.109	.096	3.169	.002
DGS	.334	.140	.080	2.390	.017
NH	.436	.150	.088	2.914	.004
CSC	-.642	.205	-.094	-3.138	.002
VH	.149	.068	.065	2.200	.028
AK	.229	.088	.075	2.564	.010

5.0 Discussion

This study discovered that climatic factors and household environmental factors play a significant role in the transmission of malaria in Jigawa State. The monthly distribution of malaria prevalence in the study area revealed a fluctuating trend, with cases occurring almost every month and season. However, higher cases were concentrated during the rainy months and reached their peak in September. The possible reason for higher cases during this period is the availability of alternative breeding sites produced by rainfall. This finding agreed with that of Epopo et al. (2019); Okonlola and Oyeyemi (2019); and Wangdi et al. (2020) that found the concentration of malaria cases during the rainy season (May - October) in their respective study area.

Similarly, this study confirmed an association between climatic parameters and malaria occurrence in the area. From the correlation analysis, relative humidity and rainfall have been positively related to malaria occurrence in the area. The relative humidity is directly dependent on rainfall and temperature and determines the life span of the Anopheles mosquito and, thus, its ability to transmit the malaria parasite to humans (Ita et al., 2017). Generally, increased humidity is believed to enhance mosquito survival (Haque et al., 2010). It explains why mosquitoes are more active and prefer blood-feeding at night (Ita, et al., 2017). The positive correlation between humidity and malaria could be due to the concentration of cases in the rainy season when the humidity is above 60%. Studies have shown that relative humidity above 60% will significantly increase the infection rate of malaria (Xiang et al., 2018). Moreover, the finding of this study corroborates that of Alemu et al., (2011a), Efe and Ojo (2013), Upadhayayula et al., (2015), Msugh-Ter et al., (2017), who found relative humidity to have a significantly positive impact on the incidence of malaria. On the contrary, a negative association between malaria incidence and relative humidity was observed by Devi et al., (2013).

Rainfall is another determinant factor for malaria transmission by providing additional breeding sites and moisture needed to sustain mosquito habitat. In addition, rainfall increases the relative humidity and longevity of the adult mosquito (Bi et al., 2003). Rainfall is considered beneficial to mosquito breeding if moderate but may be harmful and destructive by flushing away the mosquito larvae when it occurs in excess (Bi et al., 2003). The finding of this study reveals a positive correlation between total monthly rainfalls with malaria prevalence in Jigawa state. The possible explanation was that rainfall creates numerous pools in the area, creating suitable conditions for mosquito breeding, thereby increasing the mosquito population. A similar result was found by other researchers (Alemu et al., 2011a; Weli and Efe, 2015; Upadhayayula et al.,, 2015; Msugh-Ter et al., 2017; Kibret et al., 2019). However, our finding contradicts that of Haque et al., (2010), Arab et al., (2014), and Klutse et al., (2014), who obtained a negative correlation between malaria cases and rainfall in their respective studies. The interpretation was that likely high and intensive rainfall flushed out breeding sites. It may also be that community members are well aware of the risk of malaria during high rainfall and therefore, take appropriate preventive measures.

The temperature has a significant effect on the transmission of malaria. It affects the larval development rate, the survival rate of adult mosquitoes, and the extrinsic incubation period of parasites (Mordecai et al., 2013). For instance, a temperature above 30oC slows down the parasite development rate and reduces mosquito longevity and its ability to transmit the disease (Akinbobola and Omotosho 2013). Furthermore, this study discovered a negative association and absence of a statistically significant relationship between temperature and malaria cases in the study area. This could result from high temperatures over 30oC recorded for most of the months in many stations in the area. This finding is in agreement with the results of previous studies (Alemu et al., 2011a; Arab et al.,, 2014; Weli and Efe, 2015; Msugh-Ter et al., 2017; Segun et al., 2020). In contrast, many researchers (Efe and Ojo, 2013; Upadhayayula et al., 2015) reported a positive and significant association between monthly malaria cases and mean monthly temperature.

In the same vein, the result of multiple linear regression shows that the investigated climatic variables contributed about 19% to the prevalence of malaria in Jigawa state. Other variables not included in the model, such as housing conditions, poor environmental conditions, population immunity and movement, local ecological factors (vegetation, irrigation structures), government policy, and availability of healthcare facilities, among others, accounted for the remaining 81%. The result of regression analysis obtained in this study (19%) is lower than the 75.3%

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reported in Huang-Huai River, China by Zhou et al., (2010), 66% obtained in Warri Metropolis by Efe and Ojoh (2013), and 65% found in Port Harcourt Region by Weli et al., (2015). The variation could be due to the differences in the local climate conditions between the areas.

Several physical and built environmental factors were observed to have a significant influence on the transmission of malaria. In this study, the effects of distance to breeding sites, distance to vegetation cover, condition of sewers, and distance to garbage dumpsites among others on malaria transmission were investigated.

The potential sites for mosquito breeding were stagnant water bodies, wetlands, slow-moving rivers, and streams. As a result, having such habitats adjacent to residential areas may result in a rise in mosquito populations and the spread of malaria. The association between malaria infection and the vicinity of possible vector breeding sites has been observed in earlier studies (Matthys et al., 2006; Peterson et al., 2009; Alemu et al., 2011b), and entomological studies imply that mosquitoes tend not to move far from breeding sites when blood meals (i.e., humans) and aquatic habitats are close by (Machault et al., 2009). Our results show that there is a statistically significant link between malaria and being close to places where mosquitoes lay their eggs, which backs up the previous finding.

Vegetation cover affects microclimatic conditions by offering a shade that potentially reduces evaporation, minimizes wind speed, moderating temperature and humidity (Shankar et al., 2016). Cumulatively, these factors enhance vector population and longevity, and malaria transmissions are likely to increase with increased vector survival (Kabaria et al., 2016). Distance to vegetation sites and different forms of vegetation available within residential compounds positively and significantly correlated with malaria incidence at household levels.

Another built environment factor that was examined to establish its impact on malaria incidence is the condition of sewer system. It was investigated to find out if the open drain system is functionally fast-moving, slow-moving, or stagnant. Standing water and poodles can be caused by non-moving drains, which is ideal for mosquito breeding. As a result, residential areas with blocked open drains may be recognized for having high mosquito breeding rates and thus be linked to higher malaria transmission rates. From our finding over 60% of the study participants claim that their sewers do not move quickly. This was most likely the cause of the apparent strong positive association between the prevalence of malaria and the state of the local sewers.in this regard, our findings are in line with those of Adekia (2008), who discovered that drains in the Kano Municipal local government area retained unpleasant brackish water, acting as a breeding ground for a variety of disease vectors.

Garbage dumps are recognized to serve as favourable breeding grounds for insect vectors, including the potential to produce water stagnation that supports the development of mosquito larvae (Fobil et al., 2011). The likelihood of malaria incidence in a region increases as the number of these trash dumps increases. This is due to the possibility that any abandoned tyres, tins, or other containers discovered in trash streams may collect water and provide a favourable habitat for the growth of malaria vectors. As a result, mosquito populations grew, which raised the risk of malaria. Families residing close to waste sites are therefore at a higher risk of contracting malaria. This study found a statistically significant positive association between malaria and the distance to garbage dumps. Similar findings have been found in studies by Nasir et al., (2015) and Fobil et al., (2011).

The spread of malaria can be reduced by modern homes since they have fewer mosquito entry points. Compared to those who lived in better housing, those who regularly resided in non-improved and partially improved housing were more frequently infected with malaria (Morakinyo et al., 2018). Poorly built mud and mixed-material homes are likely to have a number of gaps and holes through which a vector mosquito could readily enter after smelling human hosts. In this study, it was discovered that the type of dwelling was statistically and positively significant. Most of the respondents who reported that there were more cases of malaria in their homes lived in traditional and mixed-race homes, which are less mosquito-proof. Again our findings also support past studies that found links between malaria risk and substandard housing (Alemu et al., 2011b; Liu et al., 2014).

Domestic water containers are major breeding sources for vectors in Nigerian cities (Olayemi et al., 2011), indicating elevated malaria risks. The risk of developing malaria is enhanced when water is kept in the home in open containers. In the current study, there was a negative correlation between malaria incidence and water storage in household containers. This could be because mosquitoes have limited access to the water since the great majority of the containers are covered. Additionally, if the water is used up and refreshed every day, there may not be a chance for it to remain idle for long enough to support anopheles breeding. Likewise, keeping domestic animals in homesteads has also encouraged malaria transmission in communities (Peters, 2010). Our findings showed a strong correlation between the occurrence of malaria and animal presence. This is supported by earlier studies by Temu et al. (2012), and Liu et al. (2014), who also discovered a significant positive correlation between the animal presence and malaria infection.

From the results of multiple linear regression analysis, the eight monitored environmental parameters contribute 19% with distance to breeding habitats having the strongest positive influence on the occurrence of malaria at the household level. This is a result of high mosquito population density at locations close to the breeding sites. The condition of sewers and the nature of the house are also noted to have a positive influence on malaria incidence at the household level. The result of our study is in line with previous studies by Pullan et al. (2010), and Alemu et al. (2011b) that discovered a strong association between malaria incidence and proximity to the potential mosquito breeding habitats.

6.0 Conclusions

Our study found that despite increasing efforts to fight malaria, the disease remained endemic in Jigawa State with cases occurring throughout the year. High cases of the disease are concentrated in the rainy months when alternative breeding sites are numerous. The study revealed that climatic and non-climatic environmental factors are the major determinants of malaria transmission in the area. The results of the study established a strong positive association between rainfall, relative humidity, and malaria incidence. Findings also indicate that infection risk is influenced by proximity to potential mosquito breeding grounds, nearness to garbage dump sites, poor management of drainage systems, and poor housing condition. For effective malaria control, the rainy season should be given priority in the allocation of intervention. In addition, campaign awareness should be strengthened or established to educate local communities about personal protection measures and environmental management to avoid the risk of mosquito-borne diseases. More studies are required on sociocultural determinants for further exploration of malaria risk factors, for effective control and prevention of the disease in the area.

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