MULTICRITERIA DECISION AND GEOSPATIAL TECHNIQUES FOR MAPPING AND ANALYSIS OF MALARIA VULNERABLE AREAS IN BORNO STATE, NIGERIA

BY

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ABSTRACT

The need to study the spatial pattern of malaria prevalence and vulnerability emanates from the fact that malaria prevalence is not evenly distributed in any geographical area but heavily depends on the prevailing of both environmental and socioeconomic factors. Multi-Criteria Decision Analysis (MCDA) and geospatial techniques were employed in this study to assess the vulnerable areas to malaria occurrence [based on suitable breeding sites for mosquitoes] in Borno State. Seven environmental factors [rainfall, temperature and humidity [climatic factors, obtained online] as well as relief, water body and slope [processed from ASTERDEM data] and vegetation which was generated from Landsat Imageries of 2020 were used. The seven criteria were processed and integrated to model malaria vulnerable areas in the state. Reported cases of malaria in each of the Local Government Areas (LGAs) in the state during the periods [2011-2013 and 2016-2018] were also obtained from the Epidemiological unit of Borno State Ministry of Health for the determination of malaria reported cases and prevalence among the LGAs. The results were analyzed based on the three ecological zones in the State. The study revealed that vulnerable land area to malaria decreases from Guinea Savannah in the south through Sudan Savannah at the central to Sahel Savannah in the North. The spatial pattern of the malaria vulnerability was found to be the same pattern with the number of reported cases and the pattern of malaria prevalence in the State. This similar pattern shows the reliability of the generated malaria vulnerability map. Lake Chad, Jere bowl and the valleys of major rivers like Komadougou-Yobe and Hawul with dense vegetation and water body which are more suitable to the breeding of mosquitoes were found to be more vulnerable to malaria occurrence than the dry land areas. High relief areas like Biu Plateau and Gwoza hills with cooler temperature and scanty vegetation are less vulnerable. It was recommended that the use of online climatic data should be encouraged because of its wider coverage, up-to-date and reliability, while digital mapping for malaria vulnerability assessment should be embraced for generation of quick, consistent, good visual impression and reliable malaria vulnerability maps.

Key words: Borno State, Ecological Zones, Geospatial techniques, Malaria vulnerability, Multi-Criteria Decision Analysis.

INTRODUCTION

The pattern of malaria transmission varies markedly from region to region in Sub-Saharan Africa, depending on climatic, ecologic, hydrologic and topographic variations which determine malaria endemic and prevalence patterns. The need to study the spatial pattern of malaria prevalence and vulnerability emanates from the fact that malaria prevalence is not evenly distributed in any geographical area but heavily depends on the prevailing environmental and socioeconomic factors (Homan et al., 2016). Nearly half of the world's population is at risk of malaria. In 2016, an estimated 216 million cases of malaria occurred worldwide. This disease causes about one million deaths annually of which approximately 90% of cases occur in Sub-Saharan Africa. Every two minutes one child dies of malaria and vast majority are young children in Sub Saharan Africa especially in Nigeria and the Democratic Republic of Congo (WHO, 2017). In Nigeria, malaria is a major public health problem where it accounts for more cases and deaths than any other country in the world. Malaria is a risk for 97% of Nigeria's population. The remaining 3% of the population live in the malaria free highlands. In 2016, Nigeria accounted for 27% of all malaria cases in the world and 52% of the cases in West Africa (WHO, 2017).

It is widely acknowledged that malaria transmission dynamics are closely related to socio-economic and environmental factors; the environmental factors include altitude, precipitation, temperature, land use and land cover (McMahon et al., 2021). Malaria has, therefore, been defined as an environmental disease (Castro, 2017). About 70-90% of the risk of malaria is considered due to environmental factors which in turn influence the abundance and survival of the vectors (Kibret et al., 2019). Borno State is the second largest State in terms of land mass after Niger State according to National Bureau of Statistics (NBS, 2010), and National Population Commission (NPC, 2009). With this large land area, expectedly, the state will have variations in ecology, vegetation, climate, drainage system, relief among others. Due to these variations, the level of vulnerability of any part of the state to malaria must definitely depend on the existing environment, because malaria variability largely depends on the prevailing environmental factors.

Mapping the spatial patterns of malaria distribution has been an important epidemiological tool (Kleinschmidt, 2000; Omumbo et al., 2015; Odhiambo et al., 2020). Hardly has any technological advancement had a profound and rapid impact on any field of enquiry, like the Geographic Information System (GIS) has had on Medical Geography (Aghajani, 2017). The GIS has allowed the replacement of paper maps with digital maps and descriptive speculation about disease has been replaced with scientific analysis of spatial patterns of diseases. The tool helps to solve health research questions from a geographical perspective such as "What is the spatial distribution of diseases under consideration?" and "Can patterns be detected?". It also provides a digital lens for exploring the dynamic connections between people, their health and well-being and changing physical and social environments. It makes it easy to link disease data to other information about the environment including geographic distribution of risk factors, GIS provides a powerful tool for medical geographers (Aghajani, 2017; Mishra and Kumar, 2021).

One of the problems responsible for the ineffectiveness in the control of malaria is the non-availability of data in most areas, and where available, most of them are in analogue format which are always difficult to keep, they also occupy large space, difficult to update and therefore, subject to excommunication. Moreover, extraction of information for quick visual impression and comparative studies from analogue data is always cumbersome and subject to inaccuracies (Ikusemoran, 2009).

Therefore, this study focuses on the use of GIS techniques to generate digital maps for the assessment of the vulnerable areas to malaria endemicity in Borno State where potential severity of malaria can easily be visualized and analyzed comparatively. The lack of a contemporary vulnerability map of malaria prevalence in Borno state forms the fulcrum of this study considering the high prevalence of malaria in the state. Only few studies on malaria covering the entire Borno state exist, among the few ones are Akawu et al. (2018), on the prevalence of malaria in Borno State, and Ambe et al. (2020), on impacts of seasonal malaria Chemoprevention on malaria burden among under five-year-old children in Borno State. None of these existing works was able to provide malaria vulnerability map of the state. In this paper, environmental factors such as climatic [rainfall, temperature and relative humidity], relief, vegetation, slope and water body were generated and integrated using geospatial tools for creation of digital malaria vulnerable maps for the State for proper malaria control which can easily be visualized and analyzed comparatively.

THE STUDY AREA

Borno State is located between Latitudes 10˚ 0' 13.473"N and 13˚ 44' 40.23"N and Longitudes 11˚ 26' 20.555"E and 14˚ 34' 11.581"N (Fig.1). The State shares international boundaries with three countries, that is, Republics of Cameroon in the East, Chad in the North East and Niger in the North. The State also has boundaries with three States in Nigeria: Adamawa State in the South, Gombe State in South-West and Yobe State in the West. The present Borno State consists of twenty-seven (27) Local Government Areas (LGAs). Borno State covers a total land area of 72,363.40 km^2. Borno State is very diverse in terms of its physical characteristics. Different parts of the state exhibit unique characteristics in terms of rainfall, temperature, soil, relief and drainage which collectively define her ecology (Ijere and Daura, 2000; Lazarus 2012). To study geographical variations, ecological zones present great advantages especially with respect to studying disease patterns.

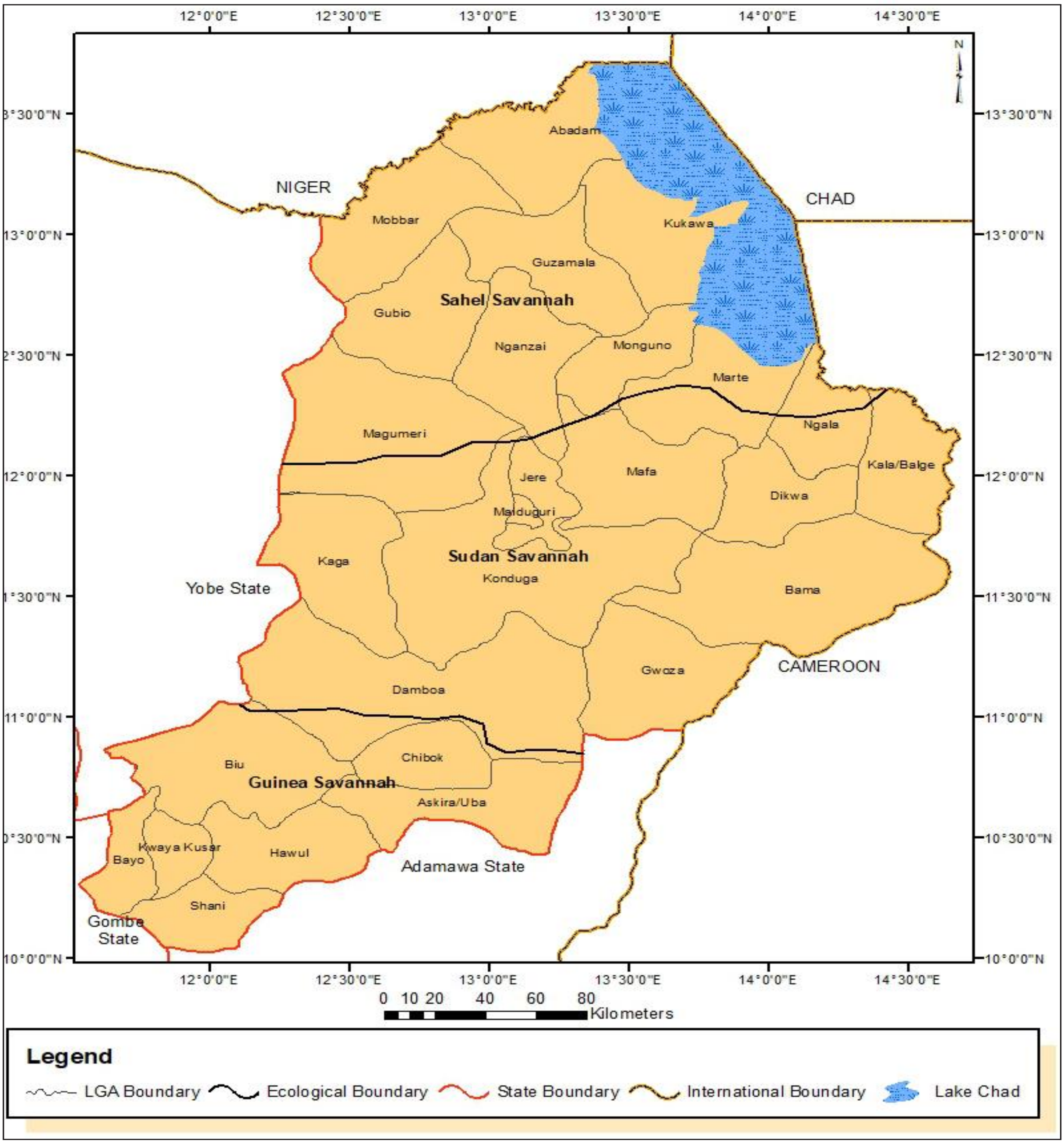

Figure 1: The Study Area
Source: UN_OCHA (2018)

MATERIALS AND METHODS

Modeling Vulnerable Areas to Malaria in Borno State

The following seven (7) criteria were integrated to map the vulnerable areas to malaria in the state: (i) rainfall, (ii) temperature, (iii) relative humidity, (iv) relief, (v) vegetation cover, (vi) slope and (vii) water body. These seven criteria were considered to be the most important environmental factors responsible for malaria vulnerability in an environment (Adigun et al., 2015; Simeon-Oke et al., 2016). Mean annual climatic data (rainfall, temperature and humidity) were obtained online from World's Climate data (1983-2014). In-situ climatic data for verification of the reliability of the online data were acquired from Nigerian Metrological Agency (NIMET). Relief, slope and drainage maps of the state were generated form ASTERGDEMv2 DEM Data, while Normalized Difference Vegetation Index (NDVI) and

Normalized Difference Water Index (NWDI) processes were used for delineating vegetation and water body within the state using Landsat Images of 2019 acquired from earthexplorer.usgs.gov. The NDVI of Dec 2019 (Landsat 8) was used to extract the vegetation of the area in ArcGIS 10.5 software by using the formula (Kshetri, 2018):

$$NDVI = \frac{(IR - R)}{(IR + R)} \quad (1)$$

Where: IR = Infrared Band (Band 5) and R = Red Band (Band 4)
The formula and the bands were expressed as (for Landsat 8):

$$NDVI = \frac{Band\ 5 - Band\ 4}{Band\ 5 + Band\ 4}$$

NDVI values ranges from -1 to 1.
The same Landsat that was processed to generate NDVI was also used to generate NWDI

$$NDWI = \frac{Green - NIR}{Green + NIR} \quad (2)$$

Where: Green = Green Band (Band 3) and NIR = Near Infrared Band (Band 5). The formula and the bands are therefore expressed as:

$$NDWI = \frac{Band\ 3 - Band\ 5}{Band\ 3 + Band\ 5}$$

The Raster Calculator of the Map Algebra module in the Arc toolbox of ArcGIS 10.6 was used to calculate the bands based on the formula. The output maps give the NDVI and NDWI of Borno State.
Epidemiological data covering the periods (2011-2013 and 2016-2018) of malaria reported cases were obtained from Epidemiological unit of Borno State for comparison of the generated vulnerable land areas and the actual reported cases in each of the vulnerability classes and for the determination of malaria prevalence among the LGAs in the state. Using the obtained data as input, the spatial pattern of each of the seven criteria was created and classified into four (4) classes. The values of vulnerability from lowest of one (1) and highest of four (4) were assigned to each of the classified seven maps based on the level of impact of each of the classes on malaria vulnerability. The seven (7) criteria were integrated using Multi-Criteria Decision Analysis (MCDA) method. The criteria were weighted using Analytic Hierarchy Process (AHP) methods of weighting (Saaty, 2015) as shown in Table 1.

Table 1: Classifications and Ratings of the Criteria
Source: Saaty, (2015), Fieldwork (2021)

Criteria	Requirements	Classes		Ratings
Rainfall	Precipitation is a key player in malaria occurrence and that increased precipitation provides more breeding sites for mosquitoes (Joao *et al.* 2018). Short duration but high intensity of rainfall provides more pools of stagnant water suitable for the breeding of anopheles' mosquito, increasing the vulnerability of the people in these areas to malaria infection (Akawu, et al. 2018).	(i)	775.51-958mm = High	4
		(ii)	593.01-775.5mm = Moderately High	3
		(iii)	410.51-593mm = Moderately Low	2
		(iv)	228-410.5mm = Low	1
Temperature	Range of temperature requirements of minimum of 18°C and maximum of 40°C for mosquito breeding in tropical regions have been postulated (Bruce- Chwatt, 2011, WHO 2020, Lazarus, 2015). All species have the shortest development cycle around 27-31°C (Bruce-Chwatt, 2011).	(i)	30-31.5 = High	1
		(ii)	28.3-29.9 = Moderately High	2
		(iii)	26.7-28.2 = Moderately Low	3
		(iv)	25-26.6 = Low	4
Relative Humidity	Mosquitoes survive better under conditions of high humidity and more active when humidity rises (Lazarus, 2015). Mosquitoes survive best where relative humidity is above 60% (OU, 2019). Relative humidity affects malaria transmission through its effect on the activity and survival of mosquitoes.	(i)	48-55.5 = High	4
		(ii)	40.5-47.9 = Moderately High	3
		(iii)	32.9-40.4 = Moderately Low	2
		(iv)	25.3-32.8 = Low	1
Vegetation	Vegetation provides a suitable environment for breeding with certain types of plant cover playing an important role in determining vector abundance and thereby increasing the number of aquatic larval habitats and extending the duration of the transmission season (Ceccato et al. 2015).	(i)	Woodlands	4
		(ii)	Grassland/Shrubs	3
		(iii)	Bare Surfaces/Scanty Vegetation	1
Relief	Elevation less than 650m is suitable for mosquito breeding, and lower in areas with higher altitude of 650m. Though, beyond 2013m altitude, temperature will not be high enough to support malaria transmission, hence malaria prevalence will be very low if it exists at all (Joao et al. 2018). Plains are more prone to accumulation of water which forms ponds or lakes and thereby increase the risk of malaria prevalence.	(i)	569.1-1327m = Mountain/Highlands	1
		(ii)	416.1-569m = Upland	2
		(iii)	328.1-416m = High Plains	3
		(iv)	188-328 = Low Plains	4
Waterbody	Water bodies play a very important role as larval breeding sites for malaria mosquitoes and identification of water body sites is a direct indicator for malaria risk occurrences. The Euclidian distance of 60m to a water body is a determinant of the malaria risk incidence (Joao et al. 2018).	(i)	Open Waterbody	4
		(ii)	Swamps	4
		(iii)	Other land areas	1
Slope	Areas with higher slopes are usually fragile, mountainous and unstable. Such areas affect mosquito breeding in two ways: they do not support varieties of vegetation and animal population which makes it unfavorable for mosquito breeding, unstable slopes do not have stagnant water which mosquitoes need for breeding or lay their eggs and progress to the next development (Clennon et al. 2020) .	(i)	0-1.26% = Level Terrain	4
		(ii)	1.27-7.8% = Moderately Level	3
		(iii)	7.29.- 14.6% = Moderate High Slope	2
		(iv)	>14.7 = Steep slope	1

The formula for deriving the acceptability of the Consistency Ratio (CR) for the acceptability of the generated weights for AHP criteria is:

$$CR = CI/RI \tag{3}$$

To obtain the Consistency Index (CI). Where:

$$CI = (\lambda_{max}-n)/(n-1) \tag{4}$$

Where: λ_{max} = eigen value = 7.63 and n = number of criteria = 7

The Eigen value was derived by dividing the total sum (53.43) obtained from consistency ratio matrix by the number of criteria (7) which is 7.63. Therefore CI = (7.63-7)/(7-1) = **0.11**
The Random Index (RI) for seven (7) criteria is **1.24** (Saaty, 2015). Therefore, to obtain the Consistency Ratio (CR):

$$CR = CI/RI$$

Where: CI = 0.11, RI = 1.24. Therefore, CR = 0.11/1.24 = 0.09

According to Saaty (2015), when the CR of AHP is equal to or less than 0.1, the weights can be used for the criteria for AHP analysis, but if the value is more than one, the weights cannot be used. The weighted outputs of all the criteria were integrated using weighted sum method of overlay in ArcGIS environment. Finally, the output map was re-classified into four: highly vulnerable, vulnerable, marginally vulnerable, and low vulnerable classes of malaria. The malaria vulnerability classes were finally discussed based on each of the three ecological zones in the state: Sahel, Sudan and Guinea.

Determination of Malaria Prevalence

Malaria prevalence per 1000 was determined using the formula ((Meyrecler et al., 2019):
Total number of reported cases per LGA/Total population per LGA multiplied by 1000

RESULTS AND DISCUSSION

Malaria Vulnerability Map

Figs. 2a-g show the spatial patterns of all the seven criteria that were integrated for assessment of malaria vulnerability in this study, while Fig. 3 shows the malaria vulnerability map.

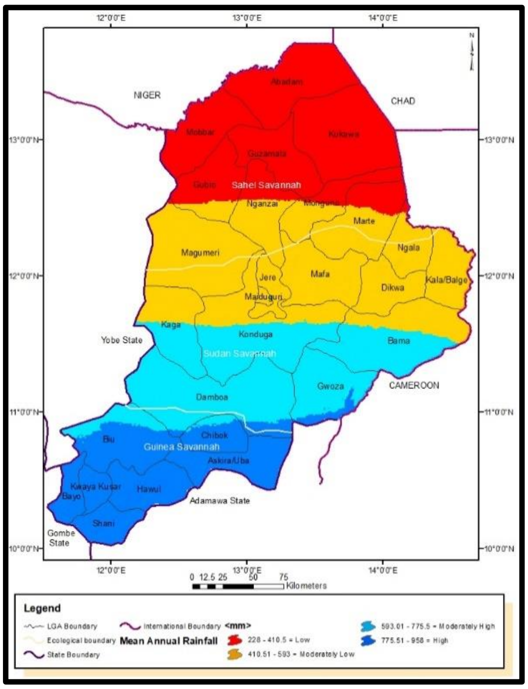

Figure 2a. Mean annual rainfall of Borno State

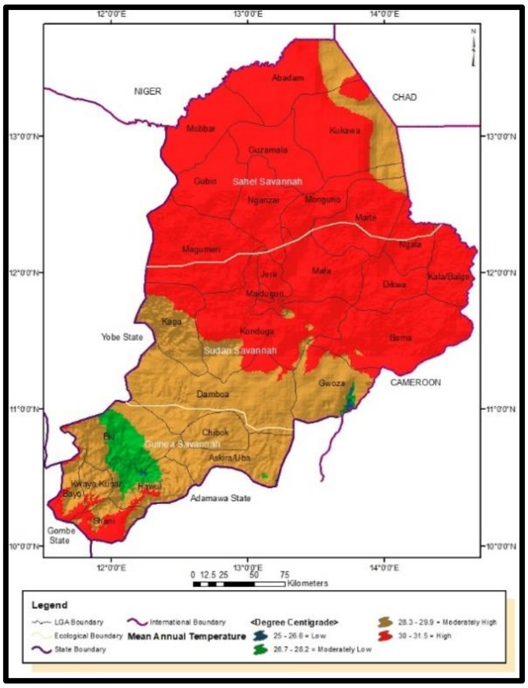

Figure 2b. Mean annual temperature of Borno

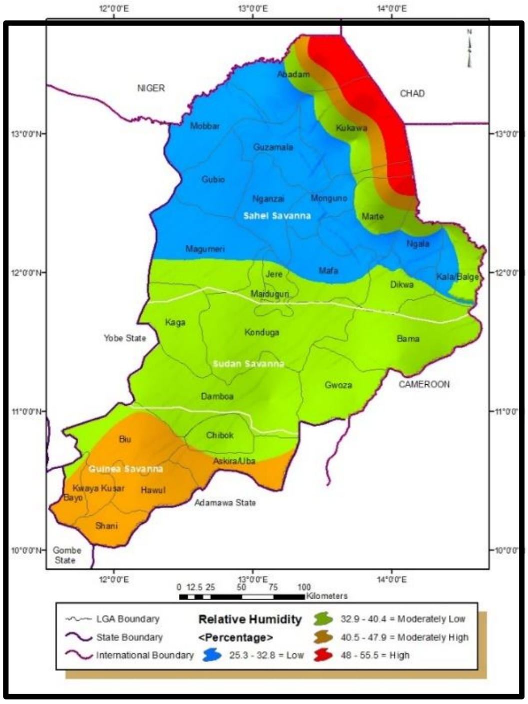

Figure 2c. Mean annual humidity of Borno **State**

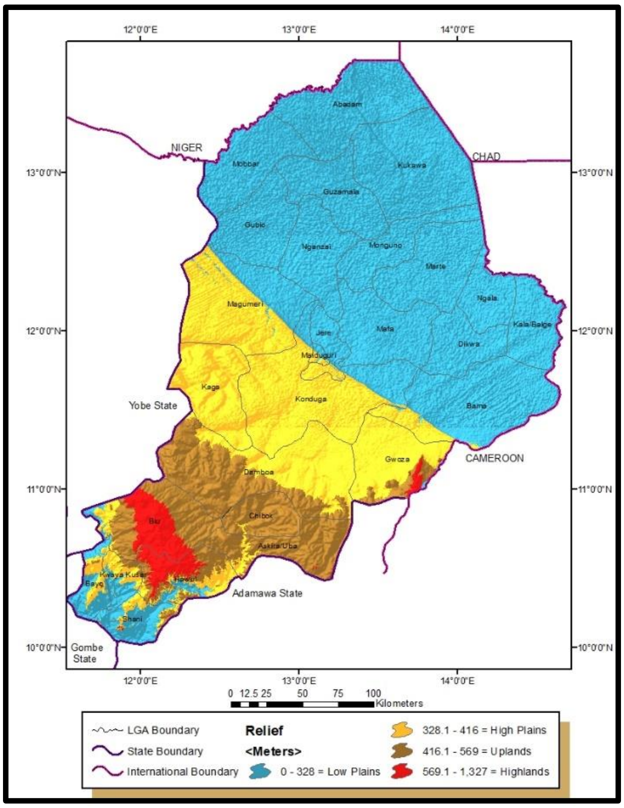

Figure 2d: Relief of Borno State

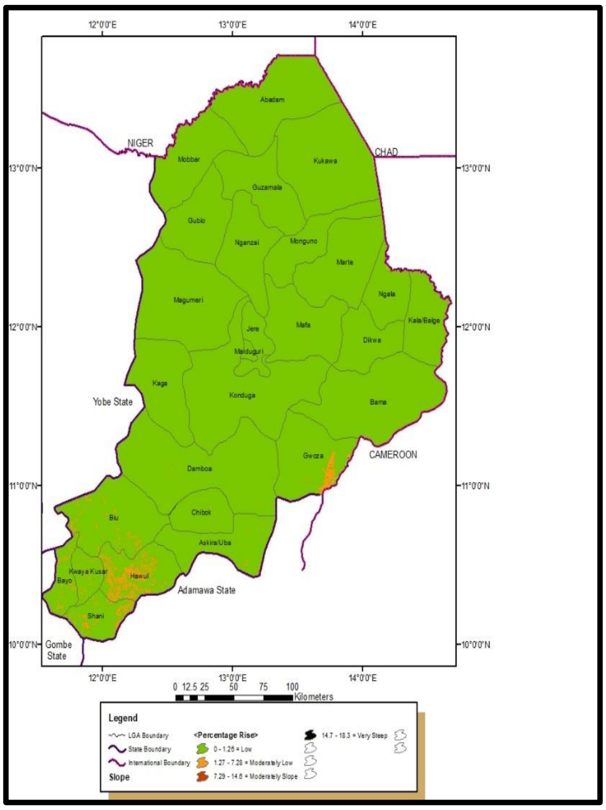

Figure 2e: Slope of Borno State

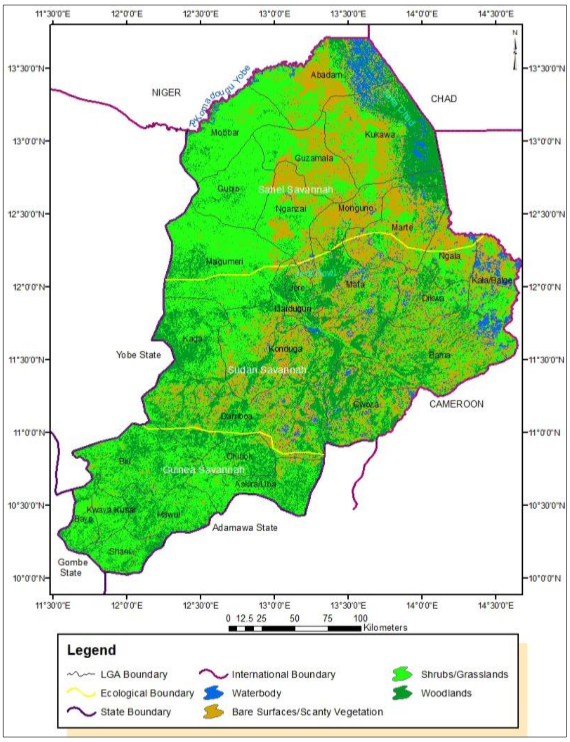

Figure 2f: Vegetation of Borno State

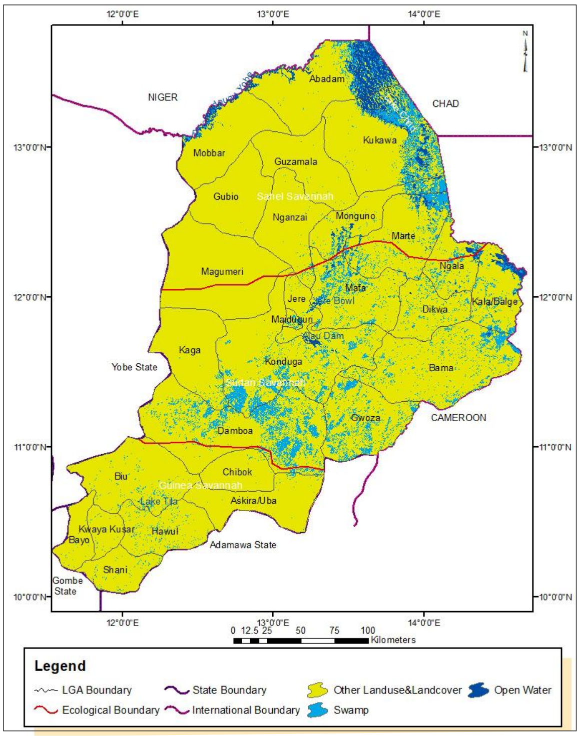

Figure 2g: Waterbody of Borno State

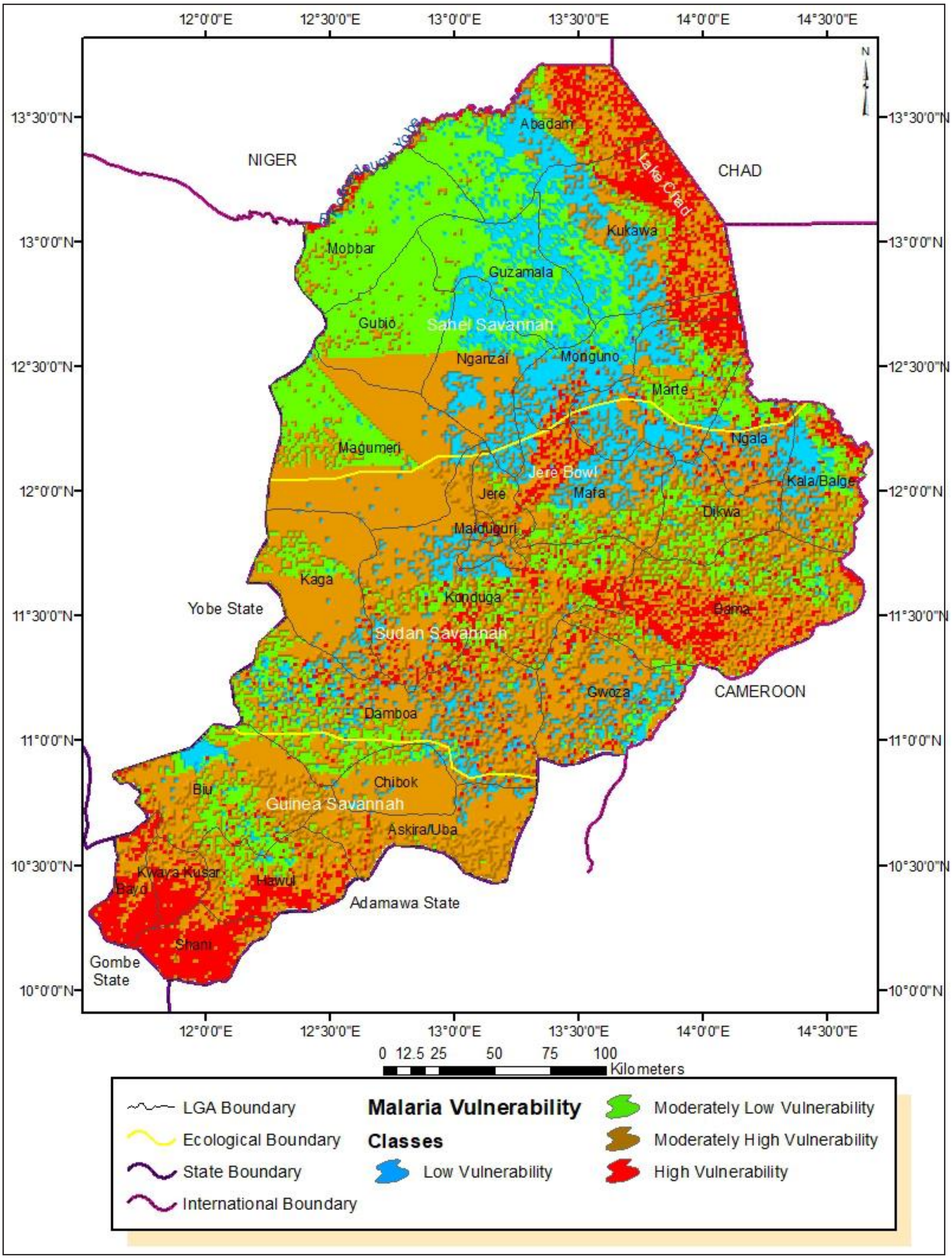

Figure 3: Malaria Vulnerability in Borno State
Source: Generated based on the overlay and AHP weighting of the seven criteria

From Figure 3, high vulnerability areas to malaria were found in the following areas: (i) Water body or swamp areas comprising of Lake Chad, Jere Bowl, the valley of River Komadougou and wetland areas in Konduga and Damboa LGAs. Water body has been reported as a catalyst for malaria prevalence (Lazarus 2015, Zhou et al., 2015; Kimbi et al., 2013, Kibret et al., 2018). (ii) The southern part of Guinea Savannah mainly in Shani, Kwaya Kusar and southern Bayo LGAs. These areas have high rainfall, high humidity, dense vegetation and low relief (Figs. 2a-g) which are all conducive for malaria vulnerability.

Areas with low malaria vulnerable areas are mainly in the hinterland of Sahel Savannah and with low rainfall, extreme temperature, low humidity and very scanty or no vegetation at all which all hinders malaria prevalence. Biu Plateau and Gwoza hills with high relief and low temperature which lower the breeding of mosquitoes and the western Sahel Savannah zone (Mobbar, Gubio and Magumeri LGAs) with scanty negetation are areas with moderately low malaria vulnerability. The generated spatial pattern of the malaria vulnerability/hazard map in this paper is very similar to that of Adigun et al., (2015) where Lake Chad, Jere Bowl and the wetlands in Konduga and Damboa LGAs were classified as more vulnerable to malaria than the other areas in the state. Based on the assessment of the impact of ecological zones on malaria vulnerability in the State, Table 2 shows the land area (Sqkm) and the percentages of each vulnerability classes in the three ecological zones.

Table 2: Malaria Vulnerability in the Ecological Zones in Borno State

Ecological Zones	High Vulnerability	Moderately High	Moderately Low	Low Vulnerability	Total Land Area	Percentages (Land Area)
Sahel	2,292.34 (8.54%)	7,725.85 (28.79%)	10,344.31 (38.55%)	6,474.10 (24.12%)	26,836.6	37.09
Sudan	2,285.94 (6.97%)	21,914.33 (66.8%)	3,687.64 (11.24%)	4918.01 (14.99%)	32,805.92	45.33
Guinea	2,609.66 (20.51%)	8,156.17 (64.12%)	1,305.44 (10.26%)	649.61 (5.12%)	12,720.88	17.58
Total	**7,187.94* (9.93%)**	**37,796.35 (52.23%)**	**15,337.39 (21.19%)**	**12,041.72 (16.64%)**	**72,363.40 100%**	**100****

***Areas are in km$^{2.}$ **Percentages were based on the total land area of each ecological zone**
Source: Calculated from the digital malaria vulnerability map in this study

Table 2 shows that more than half of the total land area of Borno State fall under moderately high vulnerable to malaria occurrence. This finding agrees with that of Onwuemene (2014) whose work on spatial pattern of malaria infections in Nigeria revealed that Borno State fell under medium level infestation of malaria. Addition of the percentages of the highly and moderately high as well as the moderately low and low vulnerability classes as presented in Table 3 shows that malaria vulnerable classes follow the same south-north decreasing pattern (decrease from Guinea through Sudan to Sahel savannah) with that of the reported cases and malaria prevalence in the state as shown in Table 3. This spatial pattern of malaria vulnerability as found in this study agrees with the work of Akpan et al., (2018) where anopheles' species (*An. gambiaes.s.* and *An. Arabiensis*) were found to decrease with the same order as found in this study.

Table 3: Malaria Vulnerability, Reported Cases and Index Cases in Borno

Ecological Zones	High Vulnerable (%)	Low Vulnerable (%)	Pop. Percentage Reported cases	Malaria Index ('000)
Sahel Savannah	37.33	62.67	4.21	9.43
Sudan Savannah	73.77	26.23	4.95	11.92
Guinea Savannah	84.63	15.38	8.03	18.24

Source: Malaria index calculated from malaria reported cases (2009-2018) from Borno State Epidemiological Center, Maiduguri

Ecological Zones and Malaria Vulnerability in Borno State

Malaria Vulnerability in Sahel Savannah

In Sahel Savannah zone, the three main areas with high malaria vulnerability are (i) Lake Chad (ii), Jere Bowl extension into Monguno LGA and (iii) the valley of Rivers Komadougou (Fig. 3). Lake Chad has high conducive environmental factors that favor malaria vulnerability such as presence of water body, vegetation cover, moderately high temperature, high relative humidity and low relief (Figs. 2a-g). Jere Bowl and the valley of River Komadougou also have water and vegetation which make the area vulnerable to malaria. The western side of the Sahel Savannah comprising Mobbar, Western Abadam, Gubio, Western Guzamala and Western Magumeri all fall under moderately low vulnerable to malaria prevalence (Fig. 3). The interior part of the Sahel Savannah comprising large parts of Guzamala, Nganzai and Monguno LGAs, Central Abadam, and the habitable region of Kukawa LGA were classified as low vulnerable areas (Fig. 3). In these interior parts, rainfall is extremely low, very high temperature, scanty vegetation, very low humidity (Figs. 2a-2g), dry lands for long period and large uninhabited land areas. These unfavorable environmental factors to mosquito breeding and malaria prevalence drastically reduce the vulnerability of the areas to malaria and therefore, collectively make the area to be very low to malaria vulnerability. Breeding of mosquitoes are more favorable in areas with high rainfall, moderate temperature, dense vegetation, high humidity and dense populated areas where slums and drainages can easily serve as abode for mosquitoes (Kimbi et al., 2013; Adigun et al., 2015; Oluyemi et al., 2019).

Malaria Vulnerability in Sudan Savannah

The following areas fell under highly vulnerable areas to malaria prevalence in Sudan Savannah; Maiduguri urban, Jere Bowl, the wetland areas in Bama, Konduga, and Damboa, and finally the fringes of the Lake Chad in Ngala and Kala Balge LGAs (Fig. 3). The high vulnerability of these areas are also due to the same factors in the high vulnerable areas in the Sahel ecological zone. Heavy agricultural practices (field work and reconnaissance 2020) including rain fed agriculture in most part of Sudan Savannah and irrigation practices especially in Jere Bowl are also contributing factors to the high malaria vulnerability in the zone. The impact of agricultural practices on malaria prevalence has been reported by Diana et al., (2017), Akawu et al., (2018) that ecological disturbances like cleared tropical forest is typically converted into grazing pastures, agricultural plots, and human settlements which allow proliferation of mosquitoes. The following areas belong to moderately low/low vulnerable areas to malaria prevalence within the Sudan Savannah ecological zone: Gwoza Hills, the peak of Gwoza hills has lower temperature (Figs. 2) than the immediate environment, which reduces vulnerability to malaria. Other low vulnerable land areas to malaria prevalence include; Western Kala Balge LGA and large land areas in Mafa and Konduga LGAs (Fig. 3).

Malaria Vulnerability in Guinea Savannah

Guinea Savannah has the largest of its geographical land area (84.63%) with high and moderately high vulnerable areas to malaria (Fig. 3, Table 2) because of its favorable conditions to malaria vulnerability such as high rainfall, dense vegetation, moderate temperature, high humidity, low relief among others. In Guinea Savannah, Shani, Kwaya Kusar, Bayo and the Southern part of Hawul LGAs are the areas with high malaria vulnerability (Fig. 3). The foot of Biu plateaus covering parts of Biu, Hawul, and Kwaya Kusar as well as major land areas of Chibok and Askira-Uba LGAs were found to belong to the moderately high vulnerable areas to malaria with similar environmental factors that are responsible for the high malaria vulnerability at the southern parts of the Guinea Savannah.

Biu Plateau and some patches of lands in Askira-Uba and Chibok LGAs belong to moderately low malaria vulnerable areas. Biu Plateau with its higher altitude makes the area to belong to moderately low temperature of between 26.7 to 28.2°C (Fig. 3) and which makes the area to be less vulnerable to malaria because low temperature cannot support malaria vulnerability. The relationships between temperature and the growth of anopheles' mosquitoes have been rated to be very high (WHO, 2020) as temperature was considered one of the factors that limits the geographical distribution of the species. Temperature affects the survival, development and life-cycle of malaria parasites in the Anopheles vectors (Bruce- Chwatt, 2011; Lazarus, 2015). Based on the findings on the comparisons of malaria vulnerability among the three agro-ecological zones, it was concluded that Guinea savannah has the highest vulnerable areas to malaria and also recorded the highest percentage of malaria prevalence in Borno State.

Table 4 shows the summary of environmental factors on malaria vulnerability in each of the agro-ecological zones in Borno State.

Table 4 Effects of Environmental Factors on Malaria Vulnerability in Borno State

Environmental Factors	Effect on the spatial pattern of malaria vulnerability
Rainfall	Guinea Savannah receives high annual rainfall ranging from 775 to 958mm (Fig. 2). The vulnerability of malaria in this zone (except Biu Plateau) is predominantly high or moderately high. The northern part of the state specifically, from latitude 12.30˚N northward, has very low rainfall of between 228-410 mm and hence, except the swampy Lake Chad region, vulnerability of malaria in this part of the state is either moderately low or low. This means that rainfall plays important role in malaria vulnerability.
Temperature	Development of malaria vectors depend on the state of temperature and which develops more quickly at higher temperatures and increases the number of mosquitoes in a given area (OU, 2019), areas with moderately high temperature in the state would be more vulnerable to malaria incidence than those with lower or extreme temperatures. Biu Plateau and Gwoza hills with lower temperature range between 25 to 28^{0}C (Fig. 2) were found to be less vulnerable to malaria. The southern Guinea savannah for instance with higher temperature was more vulnerable than the Biu hills and environs with lower temperature.
Relative Humidity	Mosquitoes survive better under conditions of high humidity and more active when humidity rises (OU, 2019). The Lake Chad area with highest relative humidity in the State (Fig. 2) was also found to be highly vulnerable areas to malaria. The western part of the Sahel savannah with low relative humidity falls within low vulnerable areas. Therefore, relative determines malaria vulnerability in Borno State.
Altitude	Very high-altitude areas are less vulnerable to malaria incidence and vice versa (DeSilva and Marshal 2015). Biu Plateau and Gwoza hills with the highest altitude in the State ranging between 569 to 1327 mm above sea level (Fig. 2) are parts of the least vulnerable areas to malaria in the State (Fig.3). The high vulnerability of malaria in southern Guinea Savannah (Fig 3) might also be connected to the low plains of area.
Slope	The plains accumulate water, create dam rainwater and increase the risk of malaria (Joao et al., 2018). Hence, steep slopes areas which cannot accumulate water or create dams are less vulnerable to malaria. Therefore, the very steep slope areas of Gwoza and Biu Plateaus (Fig. 2g) fall under low vulnerability class in (Fig. 3).
Vegetation	Areas with high vegetation in Sudan Savannah were found to be either high or moderately high vulnerable to malaria, while the interior of the Sahel with scanty vegetation fall in low or moderately low vulnerability areas. Therefore, vegetation cover is an important determinant of malaria vulnerability in the State.
Waterbody	Waterbody provides ideal breeding sites for malaria vector species (Kibret et al., 2018). In Borno State, the impact of waterbody on malaria vulnerability was clearly conspicuous in the Borno State malaria vulnerability map in Fig.3 where Lake Chad, floodplains of Jere Bowl, wetlands and the valleys of the main rivers were all found to be highly vulnerable to malaria.

Source: Fieldwork (2021)

CONCLUSION

Multi-criteria method of decision making and geospatial technique for the determination of vulnerable areas to malaria occurrence in Borno State has been demonstrated in this study. The study revealed the malaria vulnerability land areas decreases from Guinea savannah in the south through Sudan savannah at the central to Sahel Savannah in the North. The spatial pattern of the malaria vulnerability was found to be the same pattern of reported cases and malaria prevalence in the State. Environmental factors were found to play important roles in malaria vulnerability in the State as areas of water body and vegetation such as Lake Chad, Jere bowl and the valleys of major rivers like Komadougou Yobe and Hawul which are more suitable to the breeding of mosquitoes were found to be more vulnerable to malaria occurrence than the dry land areas. High relief areas like Biu Plateau and Gwoza hills with cooler temperature and scanty vegetation are less vulnerable. The importance of online climatic data was also highlighted in the study because spatial mapping of the climatic elements (rainfall, temperature and humidity) would not have been possible given the fact that the only reliable and available in-situ climatic data that are provided by NIMET are that of Maiduguri, the state capital. The capability of remotely sensed data and Geographical Information System (GIS) for data acquisition and digital mapping was also presented in this study. Manual method would have been very difficult if not impossible to generate the maps for each of the criteria and the integration of all the criteria through overlay. The use of geospatial techniques in this paper has demonstrated the ease, time saving and reliability of the applications for digital mapping and analysis. The major limitations to the use of these techniques are non-availability of data and the level of expertise of the analysts. Integration of social-economic activities for the determinants of malaria vulnerability in the state is recommended for further studies.

The following are recommendations proffered from the findings of this study:

(i) More emphasis in the control and management of malaria endemic should be placed on the towns and villages within the identified highly vulnerable areas in this study than the low vulnerable areas.

(ii) Control measures on environmental impact on malaria vulnerability such as presence of water body, vegetation and climatic factors should be put in place so as to minimize their impacts on the endemic.

(iii) The use of online climatic data should be encouraged because online data have proven to be more reliable than some of the in-situ data that might have been subjected to inaccuracies due to nonchalant attitudes of the officers in charge, inadequate expertise in data retrieval and the availability of the data in only few places; mostly the state capitals.

(iv) Digital mapping for malaria vulnerability assessment should be encouraged and embraced because of the capability of the technology to generate data/information that are captured from temporal, large and inaccessible areas, and processing the data into more accurate and reliable information through maps, tables and charts.

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