

Malaria Vulnerability Mapping of Ilorin-South, Kwara State, Nigeria

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Abstract

Malaria is a vector-borne disease (VBD) that has become a significant public health challenge in Nigeria. Despite the launch of an initiative like the Roll Back Malaria, which was aimed at halving the morbidity and mortality rate in Nigeria, there appears to have been not much success recorded. The purpose of this study is to identify areas of malaria risk and vulnerability, to effectively mitigate the consequence. To achieve this, GIS-based spatial modelling techniques was applied, taking into account factors such as climate (temperature and rainfall), land use/land cover, and topographic factors (elevation, slope and topographic wetness index (TWI) of the study area. A 30m digital elevation model (DEM) was utilized and obtained from the shuttle radar topographic mission (SRTM), Landsat 8 image from the United States geological survey, Climate data from the World climate.org platform, and the data from reported Malaria cases from the secondary health care centres. Standardized and reclassified criteria was used for the malaria risks mapping at a score range of 1 to 4, where 4 is the

highest and 1 represents the lowest malaria risk area. The Analytic Hierarchy Process (AHP) was used to determine the relative importance weight of the malaria risk criteria. The final malaria risk classes were combined using the weighted sum overlay method to produce the final vulnerability map. The spatial distribution of the malaria risk in the study was homogenous. The result shows that 12.7% (3110.04ha) of the area was at low risk of malaria, while 87.3% (21316.30ha) of the area was at high risk of malaria. An assessment was done on the map produced to evaluate the accuracy of the malaria vulnerability map produced compared to data on malaria cases collected from secondary health centres within the study area. The map produced passed the accuracy assessment which implies that the map is reliable. The study will assist in more informed decision making and policymaking in terms of planning for malaria intervention and control measures.

Keywords: Malaria risk, GIS, Mapping vulnerability, AHP, Environmental factors

1.0 INTRODUCTION

Malaria is a potentially deadly disease characterized by cyclical bouts of fever with muscle stiffness, shaking and sweating (WHO, 2000). Macleod (1988), also stated that malaria is a parasitic disease transmitted to humans through the bites of an infected female *Anopheles* mosquito. The name "malaria" is derived from the Italian words *Mal* (bad) and *aria* (air). It arose originally because the citizens of Rome thought that the disease was contracted by breathing the bad air of the Pontine Marshes (Garnham, 1966). Hornby (2007), defined malaria as a communicable disease as a result of the presence of parasitic Protozoa of the genus *Plasmodium* (*P. falciparum*, *P. malariae*, *P. ovale* or *P. vivax*) within the red blood cells. Malaria is one of the foremost prevalent diseases in the world. More than half of the world's population lives in malarious areas (WHO, 2000; Okeke, Uzochukwu & Okafor, 2006). It was estimated that clinical cases exceed 150 million with approximately 2.3 million deaths annually, most of these victims being infants and young children. About

90% of all malaria deaths in the world today happen in Africa. This is because the majority of infections are caused by *Plasmodium falciparum*, the most dangerous of the four malaria parasites and its very effective (malaria) vector (WHO, 2000).

In Nigeria, about ninety thousand (90,000) people die annually as a result of malaria infection (WHO, 2020). It was estimated that 11 percent of maternal mortality, 25 percent of infant mortality, and 30 percent of under-5 mortality were as a result of malaria infection. The disease exerts a severe social and economic burden on the nation, retarding the Gross Domestic Product (GDP) by 40 percent annually and costing approximately 480 billion naira in out-of-pocket treatments, prevention costs, and loss of man-hours (Federal Ministry of Health (FMOH) and National Malaria Elimination Programme [NMEP], 2014). Despite various malaria intervention strategies and control programmes by WHO, UNICEF, and the governments of several countries, malaria continues to be the most infectious and prevalent disease in Africa.

Since malaria is a complex disease due to its multiple interactions among parasites, vectors, human hosts, and the environment, it is important to study and model these factors together to reduce malaria risk on human health and their impact on the economy (FMOH, 2009). Climatic and topographic factors, particularly rainfall, temperature, altitude, slope, and Topographic Wetness Index (TWI) are known to have a strong influence on the biology of mosquitoes' manifestation, malaria spread and distribution (Afrane, Zhou, Lawson, Githeko, & Yan, (2007). GIS and remote sensing can be used to model these variables to ascertain the relationship between vector-borne diseases (malaria) and their associated environmental determinants/factors thereby, explaining the spatial distribution pattern, their possible causes and their implication on the community (WHO, 2010). Hence, it is advisable to develop a dynamic malaria vulnerability mapping for early warning and proactive operations in different parts of the country. Normally, the magnitude and incidence of malaria cases vary from place to place (FMOH, 2012). It is however, wise to study malaria risk factors at a high spatial resolution for better understanding and to formulate a controlling mechanism to curb and control their spread.

Earlier studies have been conducted on malaria epidemic distribution in different parts of the country. However, many of the studies did not include all the necessary factors that could affect the distribution of malaria. Oluwasogo and Adeyemi (2017), studied "Risk-based Assessment and Mapping of Malaria Distribution in Rural Kwara State". However, the GIS-based Multi-Criteria Evaluation (MCE) approach was not used in their research. GIS methods integrated with MCE decision techniques are effective tools which help to determine the weight of multiple environmental and social data to generate optimum malaria risk maps (Ahmed, 2014). Therefore, malaria susceptibility and manifestation areas can be generated easily for possible intervention work (Rai, Nathawat & Rai (2013). Therefore, this study aims to map malaria vulnerability and its prevalence by employing a GIS-based multi-criteria decision modelling approach in the study area

2.0 MATERIALS AND METHODS

2.1 The Study Area

Ilorin South Local Government Area of Kwara State, Nigeria is located between longitude $4^{\circ} 32' E$ and $4^{\circ} 40' E$ and latitude $8^{\circ} 19' N$ and $8^{\circ} 32' N$ (Figure 1). It has a landmass of about $174 km^2$ and a population of 282,500 (National Population Commission (NPC), 2016). The local government is made up of eleven (11) electoral wards with its headquarters at Fufu town.

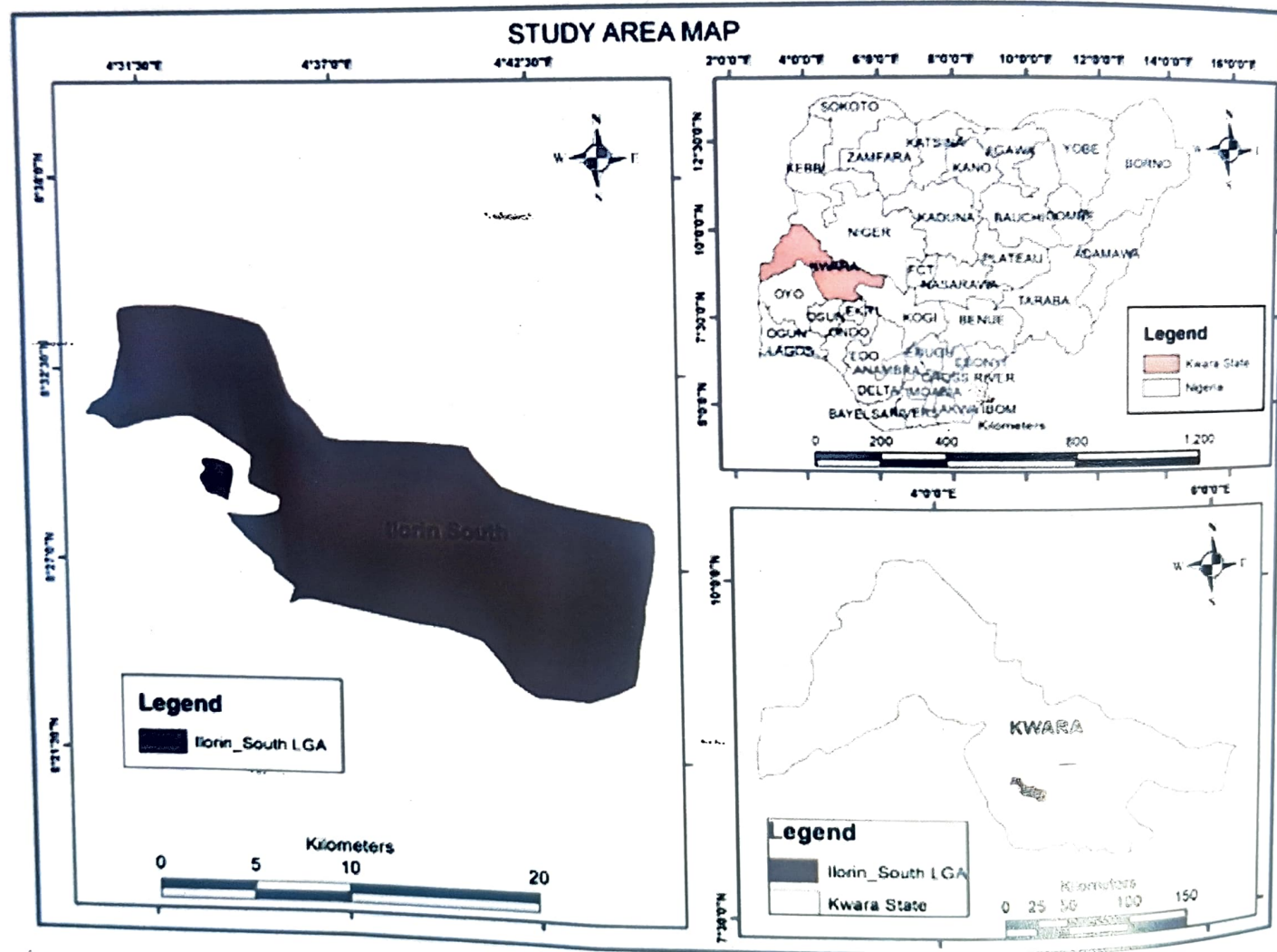


Figure 1: Study Area (Ilorin-South Local Government Area)

2.2 Data Acquisition and Sources

Different types of data sets are used for the malaria risk mapping. Reported malaria cases within the secondary healthcare centres alongside various environmental factors were used for this purpose. These are topography (Elevation, slope & TWI), climate (temperature and precipitation) and remote sensing (land-use/land-cover & NDVI).

One of the most widely used DEM data sources is the elevation data provided by SRTM (Coltelli, Fornaro, Franceschetti, Lanari, Migiaccio, Moreira, Papathanassaou,

Puglisi, Riccio, & Schwabisch, 1996), but like most other DEM sources, the SRTM data requires significant levels of pre-processing to ensure that there are no spurious artefacts in the data that would cause problems in later analysis such as pits, spikes and patches of no data (Dowding, Kuuskivi, and LI (2004). In the case of the SRTM data, these patches of no data were filled, and then slope, elevation and topographic wetness index (TWI) were derived. Precipitation and Temperature maps are derived from Worldclimate. World climate is a set of global climate layers (Gridded climate data in GeoTiff format), which is used for mapping and spatial modelling. This dataset contains nine climate variables, namely; precipitation, daily mean temperature, monthly average daily minimum temperature, monthly average daily maximum temperature, diurnal temperature range, vapour pressure, cloud cover, wet day frequency and frost day frequency. Raster Calculator in ArcGIS 10.7 was used to get the average of monthly temperature and precipitation variables for this study. Land use/cover map was utilized to distinguish different features on the land surface that are recorded by the Landsat 8 sensor. Optical bands with standard false colour combinations of Landsat-8 and TM satellite images were used to determine the land-use/land-cover classes within the study area. The land use/cover thematic map was generated by stacking band 5, 4 and 3. Composite banding toolset in the data management tool of ArcGIS 10.7 software was used to show false colour composite, which was classified using an unsupervised classification method.

Table 1: Data and their Sources

S/N	Name	Format	Date	Source	Relevance
1.	Map of Nigeria, Kwara State, Ilorin South.	Digital	2019	Nigeria Shapefile	For Demarcation of Study Area
2.	DEM data (30m)	Digital	2014	Shuttle Radar Topographic Mission	For Elevation & Slope, & TWI of the Area
3.	Temperature and Rainfall	Digital	2014	World Climate.Org	For Climatic factor maps
4.	Landsat 8 imagery	Digital	2020	USGS (United State Geological Surveys) explorer home	For land use/cover & NDVI of the area.
5.	Malaria data	Analogue	2019	Secondary healthcare centres (questionnaire)	For malaria prevalence study
6.	GPS Coordinates of Secondary healthcare centres	Digital	2019	Field book	Gives spatial reference to malaria prevalence

Source: Compiled by the Authors

2.3 Methods

Data on reported malaria cases obtained from the secondary healthcare centre within the study area were used to validate the vulnerability map produced. A conceptual model to unravel spatial problems was used to create Ilorin-South malaria vulnerability map. The

method involved the following steps:

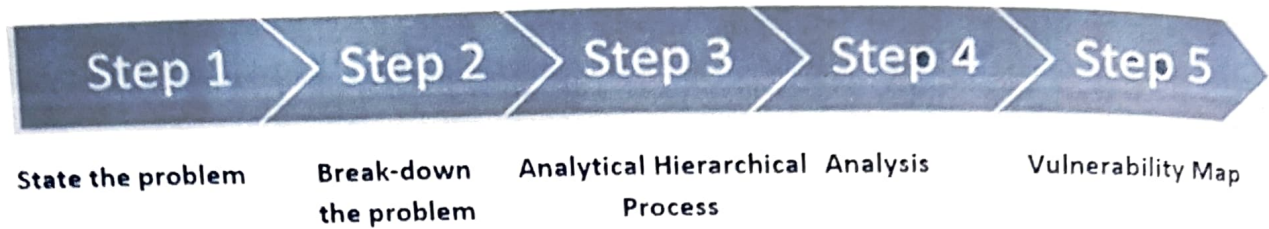


Figure 2: Methodology Flowchart

Step 1: Problem Definition

In this stage, the problem was stated as “Malaria Vulnerability Mapping of Ilorin-South Local Government Area.”

Step 2: Breaking down the Problem

The problem was broken into component malaria risk factors and was classified. The rationale for their classification was adapted from studies on malaria risk mapping by Chikodzi (2013), Alimi, Fuller, Herrera, Herrera and Qinone (2016) and Hagenlocher and Castro(2015). In this stage, the input dataset malaria risk factors were as follows: temperature, rainfall, altitude, slope, Topographic Wetness Index (TWI), land-use and land-cover (LULC), and Normalized Difference Vegetative Index.

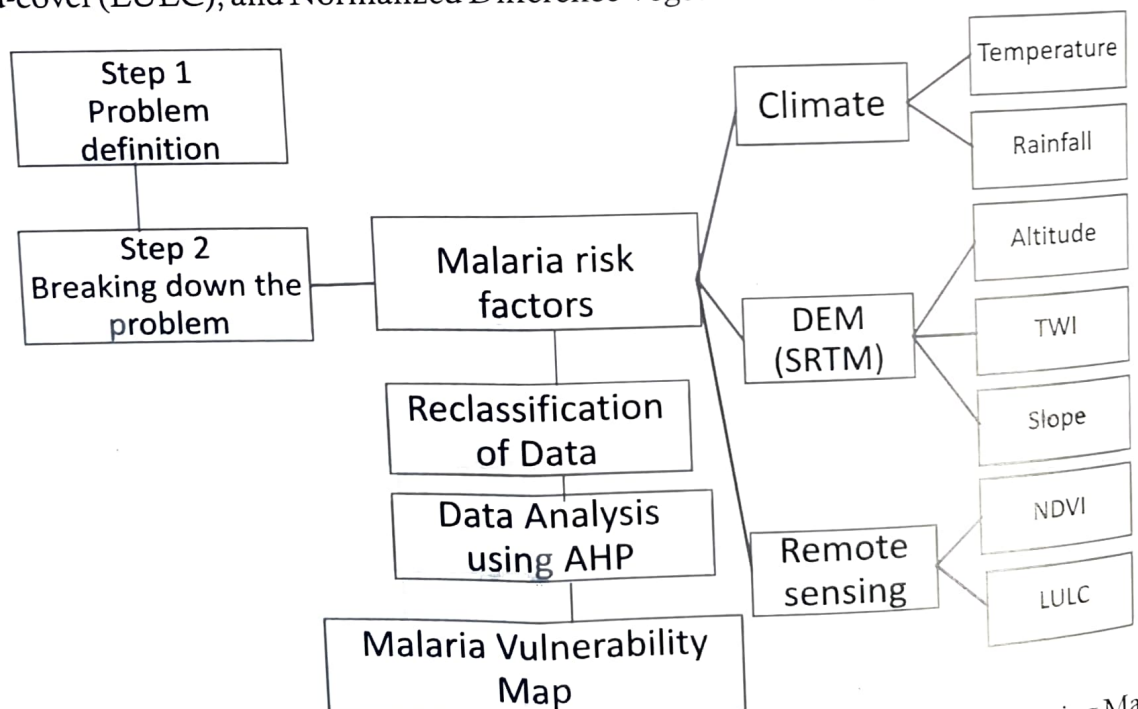


Figure 3: Schematic Representation of the Data Flow and Analysis for Generating Malaria Vulnerability Map for Ilorin-South LGA.

(DEM/SRTM = Digital Elevation Model/Shuttle Radar Topography Mission, NDVI = Normalized Difference Vegetative Index, LULC = Land-use and land-cover, TWI = Topographic Wetness Index).

Precipitation and Temperature map are derived from World Climate (www.worldclim.org). World climate is a set of global climate layers (gridded climate data in GeoTiff format) that can be used for mapping and spatial modelling. This data set contains nine climate variables, namely precipitation, daily mean temperature, monthly average daily minimum temperature, monthly average daily maximum temperature, diurnal temperature range, vapour pressure, cloud cover, wet day frequency and frost day frequency. Raster Calculator in ArcGIS 10.7, was used to get the average of monthly average temperature and precipitation variables for this study. The average temperature of the study area ranges between 25°C and 26°C which favours malaria vectors, as the highest proportion of vectors surviving the incubation period is observed at a temperature ranging from 22°C to 28°C. This is ideal for incubation of malaria vectors (Alemu, Abebe, Tsegaye & Lemu, 2011; Gebreslasie, 2015).

Rainfall is a key player in malaria occurrence and increased rainfall provides more breeding sites for mosquitoes (Matzarakis, Oguntoke & Adeofun, 2011; Nkurunziza, Gebhardt & Pilz, 2010). In this study, areas that received rainfall less than 1100mm were classified as very low risk, those that received rainfall between 1100-1150mm and 1151-1200mm were classified as low and high risk respectively, while those that received rainfall over 1200mm were classified as very high risk.

Altitude can indirectly influence the spread of malaria via its effect on temperature as there is a 1°C decrease in temperature for every 200 m increase in altitude (Pagot, 1992). In places with high altitudes, there is a low risk of malaria vector survival while places with low altitudes are high-risk areas that support malaria vector (Kazembe, Hleinschmid, Holtz & Sharp, 2006). Areas with elevation less than 300m were classified as very high risk while areas with an elevation between 300-350m and 351-400m were classified as high and low risk, respectively while areas with an elevation greater than 400m were classified as very low risk.

Malaria risk is negatively associated with slope, where breeding sites of vectors are more likely to be on gentle slopes and planes (Balls, Bodker, Christopher, William, Msangeni & Steve, 2004). The slope was derived from the 30m digital elevation model, which was extracted using the spatial analysis tool from ArcGIS. In this study, areas ranging from 0-9%, 9-15%, 15-30%, and 30-35% were classified as very high risk, high risk, low and very low risk respectively (Joao, Sergio, Jorge, & Marco, 2018).

TWI is a useful model to estimate where water will accumulate in an area with elevation difference, as a high index value indicates a high potential for water accumulation (Beven, and Kirkby, 1979). This model will help to determine potential breeding sites for malaria vectors as places with high TWI are high-risk malaria areas. In this study, areas ranging from 3-8, 8-12, 12-16 and 16-22 (radian) were classified as very low risk, low risk,

high and very high risk respectively.

Land use and land-cover is a component of the criteria used to determine the vulnerability map for malaria. Dense vegetation and water bodies are suitable for mosquitoes' proliferation. Areas with dense vegetation and water bodies were classified as having a very high risk of malaria; built-up areas were classified as having a high risk of malaria; while areas with grass/sparse vegetation and barren land were classified as having the low and very low risk of malaria respectively (Chikodzi, 2013). Variation of the photosynthetic productivity of vegetation is strongly associated with variation in malaria transmission as high NDVI is related to a high amount of green vegetation suitable for mosquito proliferation. Areas with NDVI values ranging between 0-0.5 were classified as having high malaria risk while areas with NDVI between 0.6-1.0 were classified as having very high risk (Chikodzi, 2013).

Step 3: Analytical Hierarchical Process

This step involved identifying weight for various malaria risk factors as they do not equally contribute to malaria incidence. For this purpose, the Multi-Criteria Evaluation (MCE) technique was performed using Analytic Hierarchy Process (AHP). AHP is simply a way to assign relative weights to various factors by applying pairwise comparisons. The pair-wise comparison matrix (PWCM) is a rating of the relative importance of two factors regarding the environmental malaria risk determinant. An AHP template worksheet was used to establish the relative weight of each input variable (Bernard, 2016) consistent with other studies on malaria risk mapping (Joao, et al., 2018). For determining the relative weight of risk classes, the PWCM was applied using a scale with values from 1 to 9 introduced by Saaty (1980), while the malaria risk class was ranked on a scale of 1 (very low risk) to 4 (very high risk). As a result of the pairwise comparisons and evaluation process, a reciprocal matrix was produced, where each element within the matrix represents the dominance of a particular factor over another in terms of their contribution to malaria risk. Thereafter, each element within the produced reciprocal matrix was divided by the sum of its column. Finally, the weight of each factor was calculated by averaging across the rows. After estimating weights for all considered determinants, the consistency of the estimated weights was assessed using the Consistency Ratio (CR). As a rule of thumb, a CR value of 10% (0.1) or less is considered as acceptable according to Mustafa et al., (2011).

$$CI = (\lambda - n) / (n - 1) \dots \dots \dots (1)$$

$$CR = CI / RI \dots \dots \dots (2)$$

Where:

λ : The average of consistency vector

CI: Consistency Index

CR: Consistency Ratio

RI: Random Index

n: The numbers of criteria or sub-criteria in each pairwise comparison matrix.

Step 4: Performing the Analysis

The final malaria risk classes were analysed using Weighted Sum Overlay in the ArcGIS environment, by combining all raster layers produced using overlay weighted sum to produce the final malaria vulnerability map. The index overlay method was used, within which each of the input maps was allocated a weight and every class and spatial unit existed in each factor map; therefore, different classes on a single map had different weights and each variable map also had its own weight. The final risk map was produced by summing all of the input variable maps after each had been multiplied by its overall weight, as presented in Equation 3.

$$S = \frac{\sum W_i S_{ij}}{\sum W_i} \dots \dots \dots (3)$$

Where:

W_i = is the weight of the i -th factor map

S_{ij} = is the i -th spatial class weight of the j -th map, and;

S = is the spatial unit value in the output map.

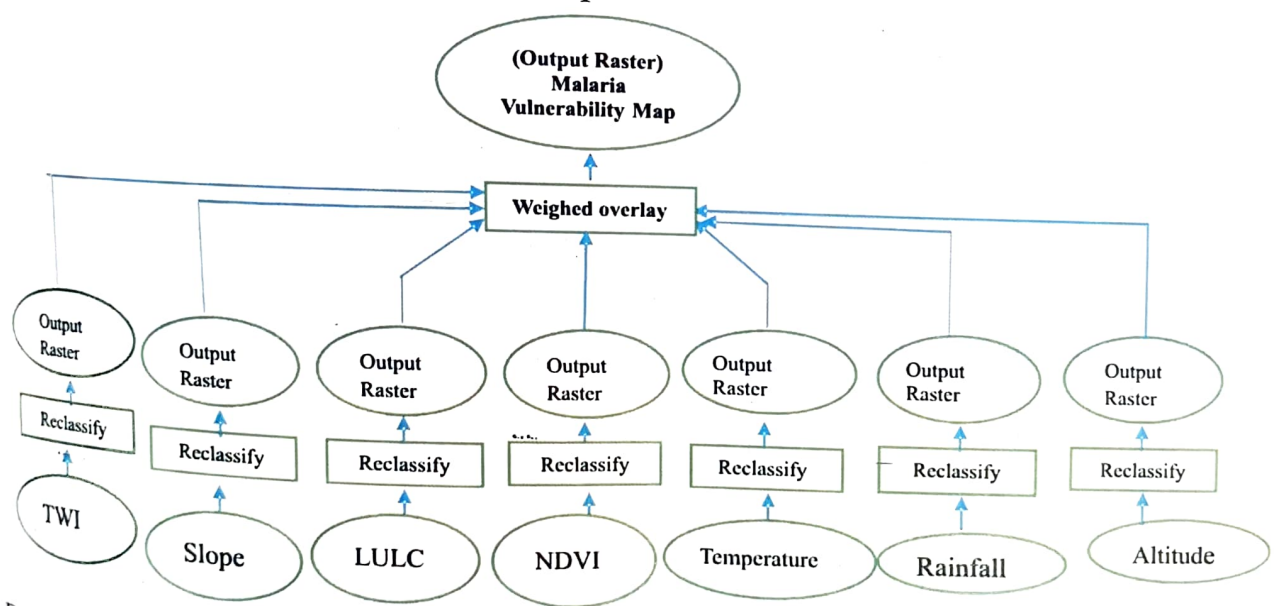


Figure 4: Analysis of the Criteria

Step 5: Assessing Accuracy of Produced Risk Map

This step evaluates the accuracy of the malaria risk map produced, compared to data on the reported malaria cases gotten from the secondary healthcare centres for the year 2019.

3.0 RESULTS AND DISCUSSION

Table 2 shows the comparison matrix of the malaria risk factors used in the study. A value of 1 means that the factors under comparison have the same weight and that they equally affect the malaria occurrence, while a value of four means the factor in the column is four

times more important in malaria risk occurrence than the comparison in the row. The weights of each factor used for the spatial model to produce the malaria vulnerability map are also presented in Table 2. The temperature and rainfall presented the highest weight (28.3%), followed by elevation (16.3%), land use/landcover and TWI (6.9%), while slope and NDVI presented the lowest weight (6.6%). The consistency index for the pair-wise matrix was 1.7% indicating a satisfactory consistency level of the estimated weights as it did not exceed 10% level.

Table 2. Pairwise Comparison Matrix of the Risk Factors used in this study

Variables	Temperature	Rainfall	Elevation	Slope	LULC	NDVI	TWI
Temperature	1	1	3	4	4	4	3
Rainfall	1	1	3	4	3	4	4
Elevation	0.33	0.33	1	3	3	3	3
Slope	0.25	0.25	0.33	1	1	1	1
LULC	0.25	0.33	0.33	1	1	1	1
NDVI	0.25	0.25	0.33	1	1	1	1
TWI	0.33	0.25	0.33	1	1	1	1
Sum	3.41	3.41	8.32	15	14	15	14
Weight (%)	28.3	28.3	16.3	6.6	6.9	6.6	6.9

The model used to produce the malaria vulnerability map was: $[(Temp. \times 0.283) + (rainfall \times 0.283) + (altitude \times 0.163) + (TWI \times 0.069) + (LULC \times 0.069) + (slope \times 0.066) + (NDVI \times 0.066)]$.

Figure 6 presents the maps of elevation, slope, Topographic Wetness Index (TWI), rainfall, temperature, land-use/land-cover (LULC) and Normalized Difference Vegetative Index (NDVI). In terms of elevation, 19.3% of the study area presented a very low risk, 28.3% a low risk, 32.8% a high risk and 19.6% a very high risk as places with high altitude has a low risk of malaria vector survival while places of low altitude are high-risk area that supports malaria vector. For the slope, 99.41% of the study area presented a very low risk, 0.52% a low risk, 0.05% a high risk and 0.01% a very high risk as flat areas on the ground are more prone to accumulate water, creating rainwater dams, increasing the risk of malaria. For TWI, 73.98% of the study area presented a very low risk, 23.43% a low risk, 2.44% a high risk and 0.15 very high risk. For temperature, 100% of the study area presented a very high malaria risk, since the highest proportion of vectors surviving the incubation period is observed at temperatures between 22°C and 28°C and this explains why the entire Ilorin-South is at a high malaria risk. For rainfall, 31.5% of the study area presented a very low risk, 44.9% a low risk, 19.3% a high risk and 4.3% a very high risk. For LULC, 15.8% of the study area presented a very low risk, 25.4% a low risk, 35.9% a high risk and 22.9% a very high risk. For NDVI, 12.8% of the study area presented a high risk and 87.2% a very high risk.

risk as the variation of the photosynthetic productivity of vegetation is strongly related to variation in malaria transmission.

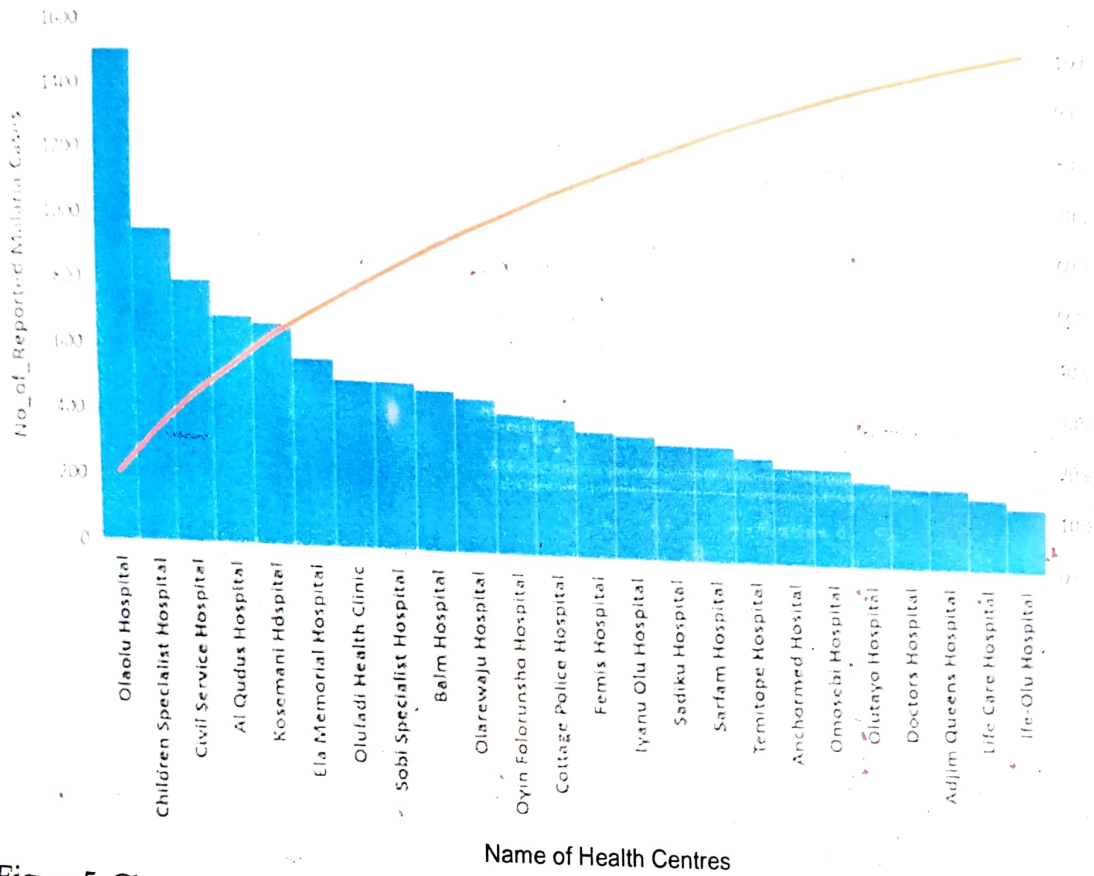


Figure 5: Chart Showing Malaria Cases Across the Health Centres

Mapping malaria risk means delineating areas that are vulnerable to host breeding sites of malaria vectors and parasites. Such delineation, which was carried out as a function of several remote sensing, climatic and topographic factors of malaria incidence was combined using weighted overlay in the spatial analysis toolbox. Figure 7 depicts the malaria vulnerability map. The result shows that there is no significant area with very low and very high malaria risk, while low and high malaria risk area covers 12.7% (3110.04ha) and 87.3% (21316.30ha) respectively. In assessing the accuracy of the malaria vulnerability map produced, data on malaria cases collected from secondary health centres were plotted using a Pareto chart as presented in figure 5 to identify the risk level across the health centres. The spatial distribution map of the health centres was overlaid on the risk map produced as presented in figure 7, and centres at high and low malaria risk were identified. The result of the risk level across the health centre was then compared to the risk map produced. The result shows that Olaolu hospital, Children specialist hospital and Civil service hospital are the top three health centres with the highest number of malaria cases which is about 95%, 58% and 49% respectively of the total malaria cases reported. These three centres are within the high-risk area as shown in the vulnerability map produced.

Three of the health centres (Olutayo hospital, Ifeolu hospital and Lifecare hospital) fall within the low-risk area and the least malaria cases were reported at these centres. This implies that the malaria vulnerability map produced is reliable.

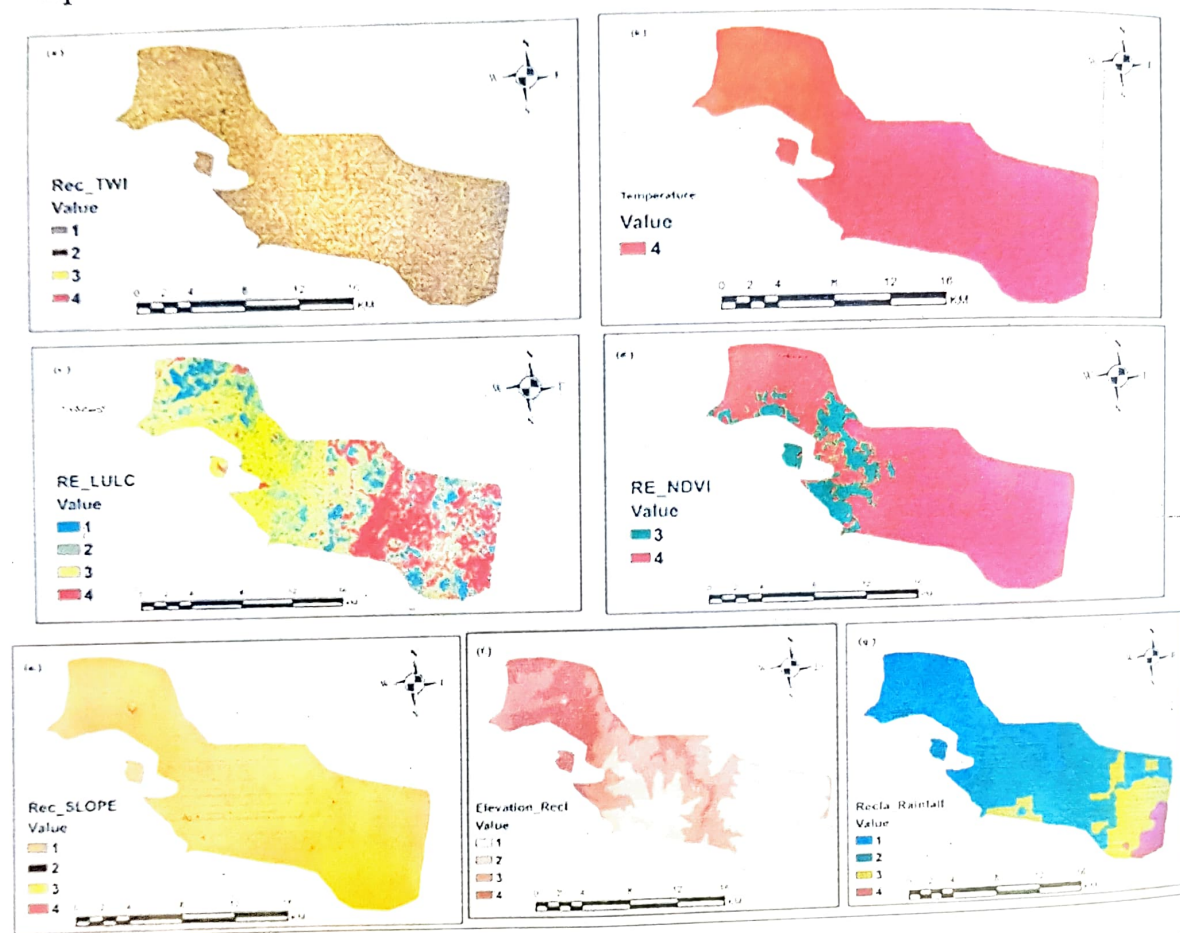


Figure 6. Criteria Reclassification of (a) Topographic Wetness Index (b) Temperature (c) Landuse & Landcover (d) Normalized Difference Vegetative Index (e) Slope (f) Elevation (g) Rainfall; for malaria vulnerability mapping ranked on a scale of 1 (indicating very low risk) to 4 (indicating very high risk).

4.0 CONCLUSION AND RECOMMENDATIONS

This study demonstrated the importance of the use of GIS and remote sensing in mapping the malaria vulnerability in Ilorin-South LGA. The entire population of Ilorin-South is at risk of contracting malaria as only 12.7% of the study area has a low risk, and the high-risk area covers 87.3%. The estimation of malaria risk has important implications on public health and the planning of effective control measures, such as the right time and place to spray to combat vectors, distribution of bed nets, correct site to build a water body, correct time and place for drainage and other relevant activities for malaria control and eradication. The study recommended that a series of Integrated Vector Management

approaches for malaria control (IVM) should be adopted. This should include the use of personal protective measures such as Long-Lasting Insecticidal nets (LLINs), wearing of protective clothing, use of repellents and chemical control such as Indoor Residual Spraying Spray (IRS), Larviciding and Outdoor spraying amongst others.

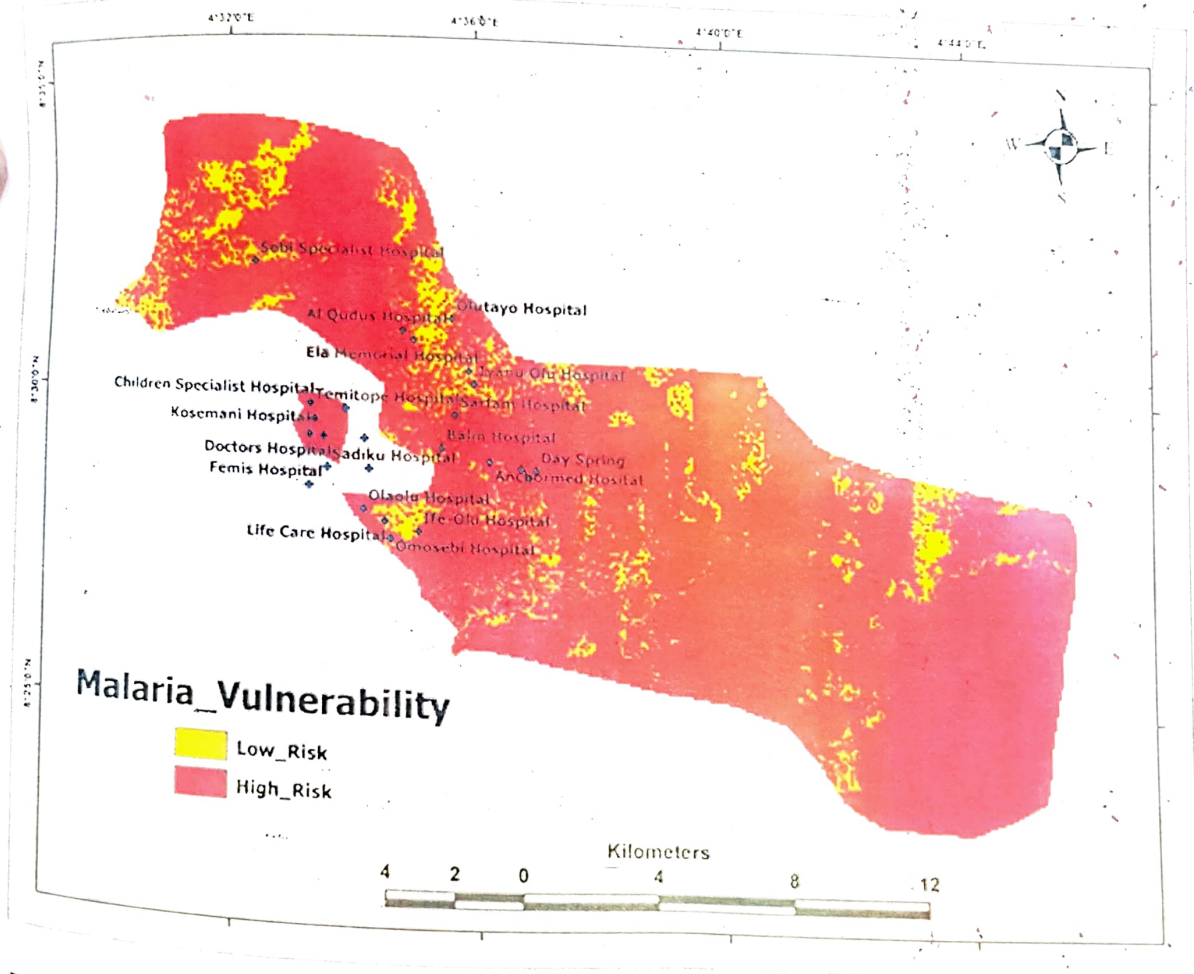


Figure 7. Malaria Vulnerability Map of Ilorin-South LGA.

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