Malaria Risk Mapping in Abuja Using Environmental and Anthropogenic Factors

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Abstract:

Malaria has long been a cause of human suffering and mortality in Sub- Saharan Africa, particularly in Nigeria. This study identifies environmental factors responsible for malaria risk transmission and identify areas with the highest malaria risk exposure to support malaria decision-making. Also, this study analyzes and generate a composite malaria risk map factors influencing the risk distribution of malaria was considered. The environmental and anthropogenic factors such as rainfall, slope, distance from the river, population density, distance from health facilities, elevation, road network, and land use land cover factors were selected to produce a malaria risk map of the Abuja district area. GIS-based multi-criteria evaluation method applied using weighted overlay analysis; an optimum malaria risk map was produced. The malaria risk map of the study area result showed that Bwari and Gwagwalada regions have very high and high-risk levels predominate with 4.56% and 1.4% accordingly. The very low and low malaria risk areas can be found in Kwali and municipal area council with 8.2% and 14.4% respectively. While the Kuje region is seen to be moderate with 71.4%. My findings show that significant environmental factors and socioeconomic factors have a strong influence on malaria and that these factors play an important role in the occurrence of this vector-borne disease, either directly or indirectly. According to the findings of this analysis, there are high malaria risk locations in the district. This indicates that the communities residing in certain regions are susceptible to the diseases. As a result, there is an urgent need to prevent and gradually reduce malaria disease distribution through policy development and healthcare delivery in priority locations. This work can be used as a guideline for future research on malaria spread, particularly in developing nations.

Keywords — Malaria, GIS, AHP, Risk-Mapping, Abuja, Nigeria.

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I. INTRODUCTION

Malaria is caused by a Plasmodium micro parasite that infects the red blood cells, about 156 of Plasmodium species that infect various types of animals have been identified; however, only P. falciparum, P. vivax, P. ovale, P. malariae, and P. knowles are known to infect humans (CDC, 2013). Mosquitoes are the primary vectors of infectious diseases such as malaria, dengue fever, yellow fever, and filariasis; the Anopheles genus is the primary vector for malaria parasites in Sub-Saharan Africa (Menger et al., 2014). Malaria is a potentially fatal disease caused by parasites that are transmitted to humans through the bites of infected Anopheles mosquitos. It can be prevented by using treated bed nets, insecticide spray, and proper sanitation. These are the preventive measures that should be identified. When symptoms have been identified, the person or patient sick must seek medical attention (WHO, 2016). Malaria fever is a major cause of infant mortality, threatening the lives of over 3 billion people. Approximately 46 percent of the world's total population lives in developing countries, and the disease is responsible for over one million deaths (Cutler et al., 2010)

Malaria is a vector-borne sickness that affects hundreds of thousands of the global population. Malaria disease affected an estimated 243 million people globally. The overwhelming majority of common cases remained at 85 percent, with 10 percent in South-East Asia and 4 percent in the African region's Eastern Mediterranean areas (Lev, 2007). In low-income countries, malaria is the fifth biggest cause of mortality. It remains a major cause of human mortality in many developing countries located in diverse ecological regions of the world, and controlling it necessitates not only diagnosis and treatment, but also control of mosquito vectors and their habitats (Dhiman, 2000). Malaria control resources are frequently finite and limited; in developing countries, the lack of epidemiological data makes it difficult to quantify disease incidence, complicating basic public health planning (Brooker et al. 2002). Malaria is the most ruthless killing disease, according to records available in Lagos State, Nigeria. Malaria care accounts for 15% of hospital admissions in Lagos State and more than 50% of ambulatory patients. The threat of malaria has continued to rise because of the prevalent climate change scenario, which provides an effective breeding ground for the vector. Malaria parasites are present in infected people's red blood cells. Malaria can also be transmitted by blood transfusion, organ transplant, or the shared use of blood-contaminated needles or syringes. Malaria can also be passed from a mother to her unborn child (congenital malaria). Malaria is not transmitted from person to person in the same way that a cold or the flu, and it is not sexually transmitted. Malaria cannot be contracted by casual contact with malaria-

The aim of this study is to determine the spatial distribution of malaria risk in the Abuja district of Nigeria's north western region. A GIS-based approach will be used to build an optimal spatial malaria risk map by considering various factors (e.g. temperature, rainfall, health centre, distance from the river, population density, and land use land cover). GIS aids in reducing these difficulties by connecting area observations and statistical methods to certify the outcomes and produce useful information. The emergence of accurate and pre-emptive disease intelligence can help supplement more natural survey techniques of disease as well as promote decision-making. Geographical information system is able to estimate variables that are, from a practical position, nearly unfeasible to obtain from field studies." Thus, traditional syndromic surveillance methods are still beneficial but are improved when the central point is shifted from disease outcomes and population analysis to liability and risk. The use of remote sensing technology and GIS can promote the accuracy and quality of risk value required to plan for disease epidemics before they transform into global human health hazards infected persons, such as sitting next to someone who has the disease (CDC, 2021).

Malaria Economic Challenges

Malaria is expected to cost Africa $12 billion a year in economic costs. This statistic considers the costs of health care, absenteeism from work, school days missed, reduced productivity due to brain damage caused by cerebral malaria, no tourism and lost from investment (John, 2021)

Malaria has also been shown to account for more than 40% of overall monthly curative healthcare costs borne by households in Nigeria as compared to a mix of other illnesses; the cost of treating malaria and other diseases drained 7.03 percent of the monthly average family income, with treatment of malaria cases alone accounting for 2.91 percent of these costs (Onwujekwe et al, 2000). Malaria spending in the home can be divided into two categories: prevention and care. Individual or household direct costs of malaria care include direct payments for medications, consulting, laboratory tests, and transportation expenses to and from the hospital, while indirect costs include lost productivity due to malaria. Malaria puts most poor children and women in rural areas at risk of death or severe debility, reducing household savings. In

Africa, households can lose up to 25% of their income due to disease. (Asenso et al, 1997)

Malaria is bad for business; the disease causes employee absenteeism, higher healthcare costs, and lower productivity, all of which can damage a company's image. Malaria can put a strain on national economies, reducing GDP in some countries by as much as 5–6 percent. In a survey in 2004, nearly three-quarters of African companies indicated that malaria was having a negative impact on their operations. According to a 2011 Roll Back Malaria survey, 72 percent of companies in Sub-Saharan Africa recorded a negative malaria effect, with 39 percent believing the impact was serious. According to leading economists, malaria causes an annual "economic growth tax" of up to 1.3 percent in malaria-endemic African countries. Malaria discourages investment and tourism, alters land use patterns and crop production, resulting in suboptimal agricultural production and decreases productivity levels. (John, 2021)

Malaria accounts for 15% of health-related absenteeism from school in some countries. Malaria is predicted to affect up to 60% of the learning capacity of schoolchildren in endemic regions. (John, 2021)

Study Area

This research is carried out in Abuja. Abuja is Nigeria's capital city, situated in the Federal Capital Territory (FCT) in the country's center. Nigeria's administrative and political capital is Abuja. Because of Nigeria's geopolitical presence in regional affairs, it is also a central city on the African continent. In the early twentieth century, Abuja was the name of a neighboring town now known as Suleja. (NCC, 2021). The population comprises the Gwari, Koro, Ganagana, Gwandara, Afo, and Bassa ethnic groups, predominantly dairy farmers. Abuja consists of six (6) local area council, which includes Abaji, Bwari, Kuje, AMAC, Gwagwalada and Kwali. The state has a total land area of 7,315m2 (Square meters) and a population of approximately 3,464,123 people (World population, 2021). The city is bordered by the State of Nasarawa to the east and south, Kaduna State to the northeast, Niger State to the west and northwest, Kogi State to the southeast. Abuja city lies on latitude 9.°4 N, and longitude 7.°29 E (NCC, 2021).

II. MATERIALS AND METHOD

Malaria infection in humans is caused by the Plasmodium protozoa parasite being transmitted from a mosquito vector to a vertebrate host. There are various Plasmodium parasite species, but only a few are capable of infecting people with malaria. The most frequent and prevalent human malaria species is vivax, which is carried to people by infected female mosquitos, the only gender that bites, of the Anopheles genus (CDC 2007). Malaria is one of the world's leading causes of death, especially among children under the age of five. Malaria has remained a major threat to public health and economic growth, especially in Sub-Saharan Africa, particularly in Nigeria. Attempts to contain or eliminate the disease have largely failed due to a variety of environmental factors. Kumin-Boateng et al. (2015) created a malaria predictive model utilizing GIS and multi-criteria decision analysis, incorporating eight risk factors ranging from environmental to anthropogenic. Each risk factor was divided into three malaria risk classes based on how it affects malaria prevalence. The categorized risk variables were eventually superimposed using weighted overlay after weights were calculated using the Analytical Hierarchy Process (AHP). According to the findings, high risk areas are located in the country's center and west-southern regions, primarily in the Ashanti, Brong Ahafo, Eastern, Central, and Western Regions. There were no areas classed as low risk, with 53.51 percent classed as medium risk and 46.49 percent categorized as high risk. The risk map developed can be utilized not only as a forecast tool, but also to gain a thorough understanding of the dynamics of malaria transmission.

The study by Ali et al (2019) focused on linking environmental parameters that provide optimal breeding locations and vulnerability mapping of mosquito-borne diseases using geospatial techniques and decision-making approaches. The analytical hierarchy process (AHP) was used as a decision-making methodology, and it was used with a geographic information system to map mosquito-borne diseases in the Kolkata Municipal Corporation. The choice factor consistency ratio was computed as 0.0470, which is 0.1 and regarded consistent and acceptable. According to the findings of the study, proximity to bodies of water is a big influence, and moisture content, water index, availability of shadow area, and presence of vegetation are all important factors in the prevalence of mosquito-borne diseases. The current research demonstrates the wide application of satellite data and spatial techniques in the zonation of epidemic diseases.

Elma et al (2019) conducted research to predict the spatial distribution of the vector and reservoir(s) of ZCL using a decision-making tool and to prepare a risk map of the disease using integrative GIS, RS, and AHP methods in endemic foci in Shush (plain area) and Khorramshahr (coastal area) counties of Khuzestan Province, southern Iran with the period of March 2012 to Jan 2013. The presence probability maps of the disease's vector and reservoir were created using the AHP method and Arc GIS 9.3. According to the maps obtained from the AHP model, the Gharb Karoon rural district has the highest chance of ZCL in the Khorramshahr study area. ZCL was found in high concentrations in the northeastern Sush rural areas of Hossein Abad and Benmoala.

Sintayehu et al., (2020) applied MCE to examine the geographic distribution of malaria risk. To study and create a map of the spatial distribution of malaria risk levels. The factors that influence the geographic hazard and risk distribution of malaria were investigated. Temperature, rainfall, altitude, slope, distance from the river, population density, and land usage are few examples of factors selected to produce a malaria risk map of the Didessa district area. An ideal malaria risk map is developed utilizing a GIS-based multi-criteria evaluation method that uses weighted overlay analysis and three map layer components (i.e. vulnerability map layer, element at risk map layer, and malaria hazard map layer). The malaria risk map revealed that 0.68 percent, 36.2 percent, 30.1 percent, and 27.52 percent were at risk. 5.5 percent of the study region was classified as having very high, high, moderate, low, or very low spatial malaria risk categories. The findings suggested that malaria is significantly influenced by main environmental parameters and socioeconomic factors, and that these factors play an important role in the disease's prevalence, either directly or indirectly. Phaisarn et al. (2008) used the AHP approach in conjunction with GIS to map the malaria risk zone in Kanchanaburi, Thailand. In this study, AHP was introduced and used to assess the risk of Malaria. The result is a Malaria risk map. Several parameters and information were included in spatial modeling. Socioeconomic factors are extremely beneficial in the prevention of malaria. Finally, the model may be used as a monitoring and early warning system to increase illness knowledge and preparedness.

Environmental and Social Data Analysis

The rainfall map for the study area was created from global climate data. The generated rainfall data was reclassified on a standardized measuring scale of 1 to 5 by 1, where 1 denotes a very low level and 5 denotes a very high level. Although an increase in rainfall enhances mosquito breeding, it should be noted that this is only up to a certain point beyond which the relationship can be reversed. High rainfall also kills mosquito larvae by destroying their stable habitats. The types of land cover and land use in an area are key risk factors for malaria transmission. High-risk zones included places with tree cover, croplands, shrub cover, and grasslands. Built-up areas, grassland, and barren regions were assessed to be of moderate risk, while wetland and barren regions were assessed to be of low risk. The Land Use / Land Cover (LULC) layer was reclassified into five classes based on their suitability for mosquito breeding sites, food sources, and utility as a refuge from climatic conditions for the vector mosquito. As a result, the new values of 1, 2, 3, 4, and 5 were assigned to each based on the malaria risk. These levels were labelled very high, high, moderate, low, and very low respectively. To determine the number of people per square kilometer, the population density calculation method is utilized. The reclassification of population density is based on the idea that the denser the population, the greater the danger of malaria. In many regions of Africa, there is a confirmed association between rising altitude and decreased mosquito numbers (Ebi et al., 2005). The elevation map has been reclassified into five classes. The slope of a location, as well as the amount of rainfall received, can have an impact on the spread of malaria. Rainwater is more likely to accumulate and dam in flat areas, increasing the risk of malaria. Because stagnant water is a natural breeding ground for mosquitoes, low slopes are more likely to have a higher risk of malaria because they allow water to accumulate. It was likewise divided into five classes. Rivers are one of the different bodies of water used for mosquito breeding (Negassi, 2008). Mosquitos require stagnant or slow-moving water to lay their eggs and complete their life cycle to become adults. Unlike other bodies of water, the river is not favorable to this because the downslope movement disturbs and destroys the eggs and larvae. However, when water is redirected from rivers for various causes, such as flood inundation, its speed lowers and it becomes more conducive to mosquito egg-laying. This condition may have an impact on a specific area by boosting mosquito breeding places and malaria frequency (Ra et al., 2012). Proximity to rivers will be calculated using Euclidean distance in ArcMap's spatial analysis capabilities. Anopheles mosquitoes have a maximum flight range of 2 km, according to (Van et al., 2003). Thus, the study area was reclassified into five classes based on mosquito flight range, and these classes were assigned new values 5, 4, 3, 2, and 1. Based on malaria risk levels, these classes were labeled as very high (short distance), high, moderate, low, and very low (long-distance) river-related malaria risk levels respectively. Regions closest to health institutions are less prone to malaria danger than areas further away. After reclassifying into five classes and assigning new values 1, 2, 3, 4, and 5, these classes were labeled as very high, high, moderate, low, and very low, respectively, based on malaria risk levels. Table 1 showing data and data source.

Table 1 data and data source

S/N	DATA	DATE	SOURCE
1	DEM (Elevation,Slope)	2010	www.earthexplorer.usgs.gov
2	Rainfall	2020	www.giovanni.gsfc.nasa.gov/giovanni/
3	Abuja shape file (Population,healthcare,road)	2020	Office of the surveyor general of the federation
4	LULC	2020	https://sentinel.esa.intds.climate.Copernicus.eu

Methodology

The AHP approach uses a preference matrix to determine the requisite weights associated with the various criterion map layers, in which all relevant criteria found are compared against each other based on preference variables. GIS-based AHP has grown in popularity because of its ability to incorporate a significant amount of heterogeneous data and calculating the appropriate weights can be very simple, even for many criteria. Each malaria risk factor's weight was determined using AHP. In the modeling of the final malaria risk zones, the risk factors do not all play the same function or have the same weight. As a result, a pairwise comparison method was utilized to weight the factors, which is one of the components of AHP, in order to define the relevance of each parameter. Saaty's pairwise comparison table (Table 2) was employed in the study to aid in the weighting procedure of the pairwise matrix.

Table 2 Scales of Pair wise Comparison Source (Saaty, 1980)

Intensity of Importance	Definition of Explanation
1	Equal importance
3	Somewhat more important
5	Much More important
7	Very much important
9	Absolutely more important
2,4,6,8	Intermediate values

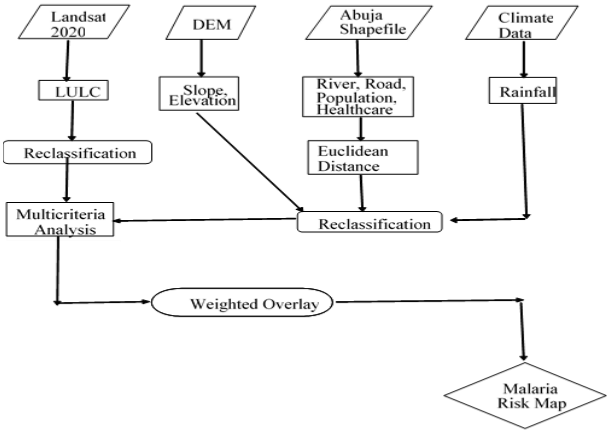


Fig. 1 Methodology Flow Chart

III. RESULT AND DISCUSSION

Figure 2. Shows proximity to healthcare facilities will reduce the threat of malaria because treatment can be easily accessed and preventive measures, such as the distribution of treated insecticide nests, can be easily accessed by residents living close to health care facilities, as the travel distance for proper medical treatment will be avoided. Healthcare delivery service in the study area varies as regions such as, Abaji, Gwagwalada and Kuje have variably few healthcare delivery service compared to Municipal, Kwali and Bwari area councils. The map shows that municipal area council have the highest numbers of healthcare facilities which limits the prevalence of malaria as when compared to Abaji and Kuje area council, thus malaria incidence predominates in this regions that have less health care centers.

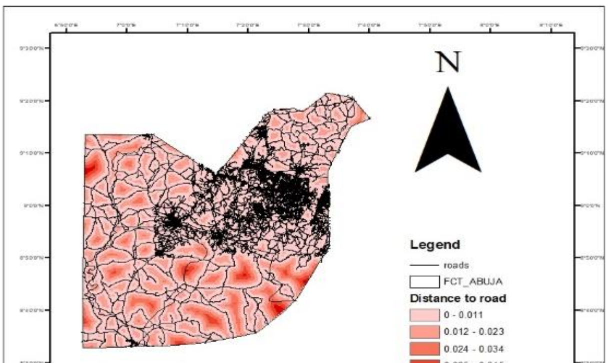


Fig. 2 Distance to health facility

Figure 3 Shows the slope is one of the land's topography; it plays a significant role in inhibiting or enhancing the malaria breeding site in a certain location. Sloped terrain provides poor mosquito breeding grounds, lowering the risk of malaria transmission. It is clearly shown on the map that Municipal, Kwali and Kuje area councils have the highest slope level as such malaria prevalence is limited comp ared to Gwagwalada, Bwari and Abaji which have the lowest slope level as such are more prone to malaria incidence.

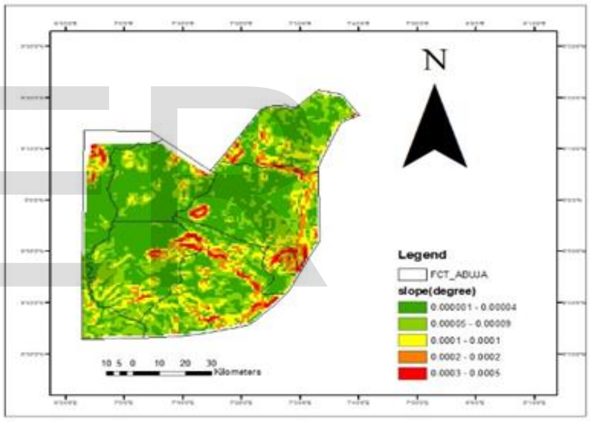


Fig. 3 Slope

Figure 4 Shows accessibility to road network makes it easier to get to healthcare facility. When the distance from road is short, the probability of finding a community is greater. Whereby there is no road network, the risk of malaria prevalence increases especial in children below 5years of age. The map clearly showed the main road path of the study region. In comparison to Kuje, Abaji and Kwali area councils, the municipal area council, Bwari and Gwagwalada area councils have an excellent road network as such malaria prevalence is limited in those areas.

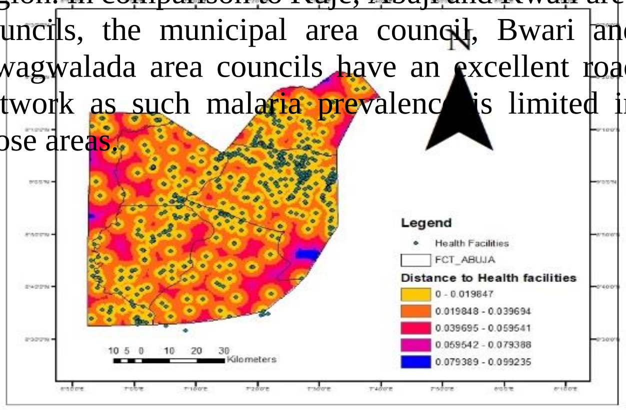


Fig. 4 Distance to road

Figure 5 According to previous research, those who live close to the rivers or bodies of water are at a higher risk of malaria incidence. Similarly, in this study, regions nearest to the river; Kuje, Kwali and Municipal area council show a high spatial distribution of malaria risk compared to Bwari, Abaji and Gwagwalada with lower risk of malaria incidence.

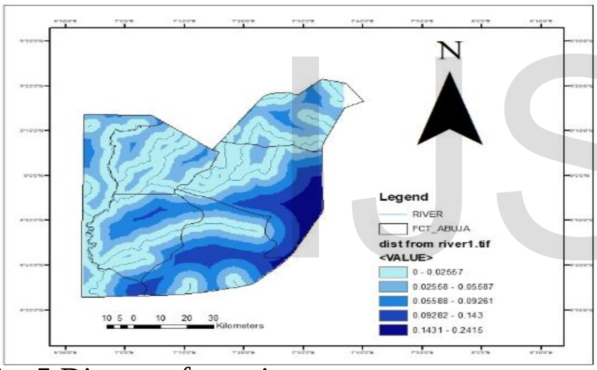


Fig. 5 Distance from river

Figure 6 Illustrates topography has a general effect on mosquito replication because greater elevations result in colder temperatures. This indicates that elevated regions have a low malaria risk level and those in lower land are more prone to malaria incidence. The elevation map clearly shows that Bwari and Municipal area Council have the highest elevation of about 467-843meter, indicating that these areas have a low malaria risk level compared to Abaji, Kwali, Kuje, and Gwagwalada area councils which have lower level ground, indicating that these areas are highly prone to malaria incidence.

Fig. 6 Elevation

Figure 7 Determination of malaria risk levels is based on the concept that a high population density is more vulnerable to malaria risk than a low population density. High population density regions that are susceptible to malaria manifestation may increase the rate of malaria risk. The study showed that municipal area council have the most population and as such are prone to malaria incidence compared to other areas

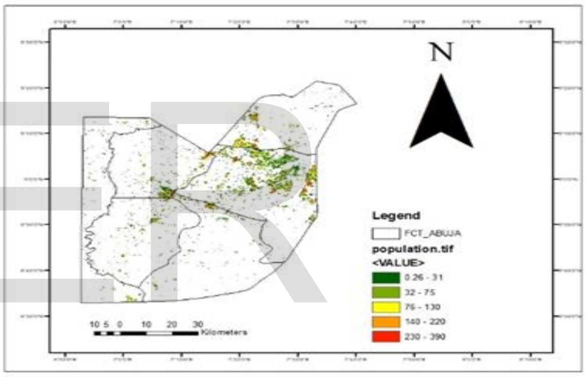


Fig. 7 Population

Figure 8 Rainfall provides anopheles mosquitoes with a habitable environment, as shown clearly on the map, rainfall increases the volume of surface water, which in most cases remains stagnant, thus housing anopheles mosquitoes, rainfall variation due to seasonality within the study area also show the dynamicity of malaria incidence. As shown clearly on the map, Municipal Area Council and Bwari experience high annual mean rainfall indicating that the areas have high malaria prevalence.

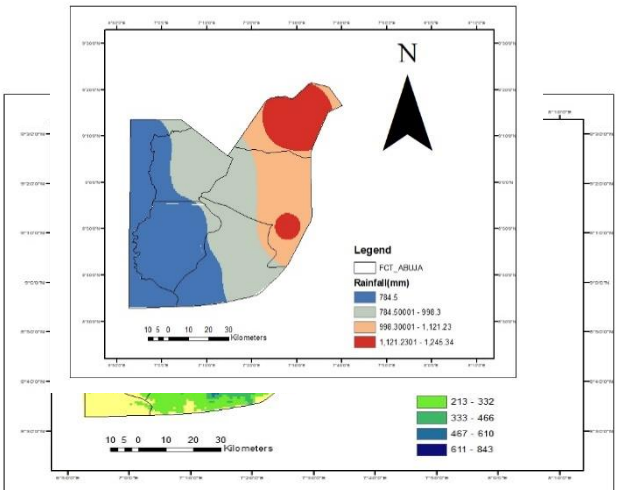


Fig. 7 Rainfall

Figure 8 Land Use / Land Cover (LULC) directly influences the temperature of larval habitats and indirectly impacts feeding conditions and other parameters. The closeness to the forest and swamps areas can be associated with increased vector density as the habitat offers a conducive environment for these organisms to reproduce. As a result, tree cover and crop land have more malaria prevalence compared to others.

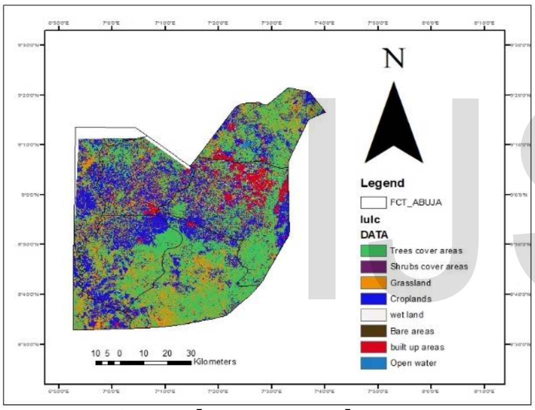


Figure 8 Land Use / Land Cover

Table 3 shows the parameters rating, were the various criteria used for this research work were rated based on their level of significance contribution on their role in terms of malaria related hazard within the study area. The parameter rating was done to determine how sensitive each criterion is in relation to malaria causative.

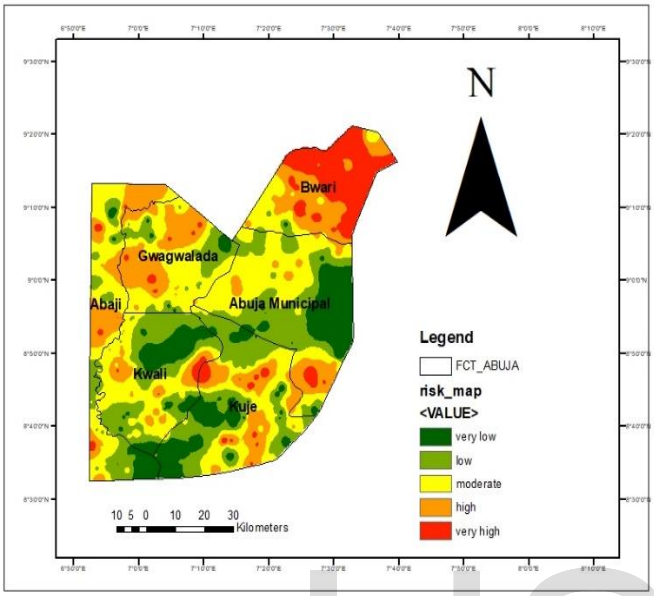
Table 3 Parameter Ratings

Factors	Criteria	Weight (%)
Rainfall	784.5 784.5 – 998.3 998.3 – 1,121.23 1,121.23 – 1,245.34	25
River	0. 02557 0.02558 – 0.05587 0.5588 – 0.09281 0.09282 – 0.143 0.1431 – 0.2415	18
Road network	0 - 0.011 0.12 – 0.023 0.024 – 0.034 0.035 – 0. 045 0.046 – 0.057	17
Healthcare	0 - 0.019847 0.019848 – 0.059541 0.039695 – 0.059541 0.59542 – 0.079388	10
Population	0.26 – 31 32 – 75 76 – 130 140 – 220 230 – 390	10
Slope	0.001 – 0.004 0.005 – 0.009 0.001 – 0.001 0.002 – 0.002 0.003 – 0.005	8
Elevation	62 – 212 213 – 332 333 – 466 467 – 610 611 -843	7
Lulc	Tree cover Shrub Grassland Cropland Wetland Bare areas Built-up areas Open water	5
TOTAL		100

Composite Risk Map

Figure 9 showing the malaria composite risk map of the study area. The map was generated using AHP. The corresponding weight assigned to each of the factor was computed based on the pair wise comparison of the eight parameters; rainfall, distance from river, distance from road and proximity to healthcare have the highest rating in terms of weight with 25%, 18%, 17% and 10% respectively while population density, slope, elevation and lulc have the lowest rating in terms of weight with 10%, 8%, 6% and 5% respectively. In the GIS system, the range numbers are labeled on the development chart as very low to very high, indicating the amount of malaria scenarios in the region. From the risk map of the study area, it can be observed that Bwari and

Gwagwalada region have very high and high risk levels predominate with 4.56% and 1.4% accordingly. The very low and low malaria risk areas can be found in Kwali and municipal area council with 8.2% and 14.4% respectively. While Kuje region is seen to be moderate with 71.4%.



Discussion

Malaria prevalence increase has become a national issue, resulting in irreparable loss of life and low rates of productivity. This research investigates the capability and integration of natural phenomena, remote detection, and climate information to effectively analyze the prevalence of malaria risk. Among other things, the study looks at malaria risk zones in Abuja that are very low, low, moderate, high, and very high. The discovered parameters have been graded and validated by experts in epidemiology and health sciences. The results indicated five primary malaria risk areas: very high-risk area, high-risk region, moderate risk zone, low-risk zone, and very low-risk zone.

IV. CONCLUSIONS AND RECOMMENDATION

CONCLUSIONS

This project work aimed to identify, evaluate, examine, and generate an operational malaria risk map of Abuja in addition to giving decision makers with a framework for proper malaria control and mitigation measures. Climate data (rainfall), topography data and environmental parameters were all utilized in this study. This data was analyzed with AHP techniques, in which each criterion was given a weight based on its relevance on malaria initiating level. Experts in the field of epidemiology studies validated the assigned weight. This data was uploaded into an Arcgis software, and a multi-criterial decision analysis methodology that allows for the combining of multi-layers was used to overlay the weights of each criterion in relation to their relative effects on the malaria threat. The findings of this study demonstrate that the climatic factor "rainfall" has a considerable influence on malaria occurrence in the studied area, while topography and environmental factors have a moderate affect.

RECOMMENDATION

The findings lead to the following recommendations: The malaria risk map from the research area shows that a huge number of Abuja areas are at high and medium risk levels. However, if one or more variables rise or fall, the situation changes to very high or other levels of risk. As a result, GIS and remote sensing should be included into malaria research to maintain data current. Health kits should be distributed to local populations as part of the overall strategy to minimize the spread of mosquitoes and malaria. This could be accomplished by providing assistance to malaria survivors, creating awareness about malaria prevention and management, and delivering the handled pesticide. In addition to the parameters utilized in this study, there are other factors that may contribute to the incidence of malaria, such as household income level, home type, temperature, and others. As a result, it is important to associate these variables with the parameters already in use for greater precision.

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