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ORIGINAL RESEARCH ARTICLE

Geospatial Assessment of Malaria Health Risk in Kaduna North Local Government Area of Kaduna State

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ABSTRACT

This paper examined malaria vulnerability using geospatial techniques in Kaduna North Local Government Area of Kaduna State. Data on malaria cases was obtained from Kaduna State Primary Healthcare Board. Satellite imageries, including Landsat 8 (OLS/TIRS) and Shuttle Radar Topography Mission (SRTM), were obtained from the United States Geological Survey Agency. Data analysis was carried out using spatial analysis on ArcGIS 10.8 and Analytical Hierarchy Process (AHP). The study revealed that Kawo, Hayin Banki, and Unguwar Rimi wards had the highest cases of malaria diagnosed using Rapid Diagnostic Testing (RDT). Using microscopy, Unguwar Sarki had the highest number of cases, with 2,591. On the other hand, Unguwar Rimi had the highest number of cases of malaria using clinical diagnosis. Among pregnant women, Unguwar Rimi had the highest number of RDT-diagnosed malaria cases, with 3,352, but Unguwar Sarki recorded the highest number of cases using microscopy. The hotspot analysis detected three malaria hotspots in the LGA with varying degrees of confidence (90% to 99%). The combination of AHP and weighted overlay in vulnerability mapping revealed that 56% of the LGA had high vulnerability, while 13% had very high vulnerability. Driving factors included proximity to water bodies, land surface temperature and elevation. The study concluded that RDT and microscopy are the most widely used malaria diagnostic methods. The study recommended that new housing projects should not be approved close to the water bodies to reduce malaria health risks in the LGA.

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INTRODUCTION

In Nigeria, like most countries in Sub-Saharan Africa, malaria is a major public health problem. The region experienced an estimated 200 million cases in 2017, contributing up to 92% of the global malaria burden (World Health Organization [WHO], 2018). Globally, there is remarkable progress in the reduction of the malaria burden, but climate change, conflicts, and humanitarian crises are still threatening global response to malaria, denying millions of people the opportunity to prevent, detect and seek cures from the disease (WHO, 2023b). This is in addition to resource constraints and biological challenges such as the resistance of malaria vectors to drugs and insecticides. With about 247 million malaria cases globally, the United Nations prioritized ending epidemics of malaria and other neglected tropical and communicable diseases in SDG 3.3.3 (United Nations, 2023).

Among other factors, climate is found to influence the occurrence of malaria globally. Shifts in the climate system and changes in the occurrence and duration of climatic extremes affect human health (Ahmed et al., 2024). Changes, no matter how little in the distribution of precipitation and temperature, can influence the spread of diseases (Chen et al., 2021). Although climate plays a critical role in the spread of diseases, other factors such as abundance of disease vectors, quality of water supply, and socioeconomic conditions of the residents are also critical (Leckebusch & Abdussalam, 2015). Thus, the fertility, lifespan, and rates of biting of mosquitoes are influenced by temperature (Mordecai et al., 2019) and humidity (Lunde et al., 2013). Furthermore, the probability of malaria transmission between mosquitoes and humans is influenced by temperature (Mordecai et al., 2019).

Apart from the climate, several studies have linked different environmental factors to malaria occurrence. For example, land use and land cover types influence the larval habitats of mosquitoes and their population (Krol et al., 2023). Thus, McMahon et al. (2021) revealed that malaria is linked to land cover greenness and surface moisture. Additionally, the pervasiveness of malaria has been linked to the abundance of surface water by providing habitats for vector breeding (Kalthof et al., 2023). Malaria cases are also found to be significantly higher around irrigation schemes, with a higher population

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density of *Anopheles* (Haileselassie et al., 2021; Hawaria & Kibret, 2023), which may enhance the transmission of *Plasmodium* (Zhou et al., 2022). Kibret et al. (2019) also revealed that dams and reservoirs escalate malaria cases in sub-Saharan Africa. Therefore, an environment's receptivity is determined by all these factors, which is defined as its ability to support the transmission cycle of malaria and its capacity to support vector mosquitoes.

The receptivity of the environment is also influenced by the populations' susceptibility to malaria, which is dependent on their exposure to mosquito bites and access to healthcare, especially concerning the prevention and treatment of malaria (McMahon et al., 2021). Thus, the socioeconomic characteristics of the local population are also found to influence the spread of malaria. Akanbi (2016) reported that malaria prevalence was highest among people with the lowest income, but other factors such as lack of education, poor housing and living conditions, and working around farmlands and irrigated lands may likely increase the risk of malaria infection (Anjorin et al., 2023; Shah et al., 2022; Taffese & Zuma, 2024). While lack of education may be equated to a lack of knowledge about malaria prevention and treatment strategies, poverty will limit populations' ability to acquire treated nets, insecticides, medications, and other healthcare-related costs.

Since the Roll Back Malaria Programme in 2000 (United Nations, 2021), Nigeria has continued to spend on malaria eradication programmes. Total spending on malaria was about US $424·4, out of which US $47.2 was out-of-pocket spending (Haakenstad et al., 2019). In recent years, the *World Bank* received 179 applications *from* 133 countries with requests for over $2.5 billion in grants (Brown et al., 2023). According to a study by Andrade et al. (2022), households in Nigeria spend an average of 8.23% of their family budgets on malaria treatment and prevention.

According to the National Malaria Elimination Programme (NMEP et al., 2022), Kaduna State has achieved 80% household ownership of insecticide-treated nets (ITNs). However, the malaria prevalence rate in Kaduna State is 36.7%, almost 10% higher than the national average (Bajoga et al., 2019). Additionally, the prevalence of malaria was found to be significantly higher in populations with low levels of education (Benjamin et al., 2018). In Kaduna, like other states in the country, the level of awareness of malaria prevention is still a little above average, with only 56% of the population aware of malaria vaccines (Musa et al., 2022).

Different methods involving Geographic Information Systems (GIS) and Remote Sensing have been employed to assess the risks and vulnerabilities associated with malaria. Ekpa et al. (2023) used the Analytical Hierarchy Process (AHP) and trend analysis to assess malaria prevalence in Ondo State. Bhattarai et al. (2023) used SatScan to assess malaria's spatial and temporal patterns in Nepal between 2005 and 2018. Abdelsattar and Hassan (2021) correlated malaria prevalence with the Normalized Difference in Vegetation Index and the population's socioeconomic status. Chen et al. (2021) produced maps for spatial variations in deaths using superposed epoch analysis and Geographic Information Systems analysis. Abdulahi et al. (2020) used the Analytical Hierarchy Process (AHP) on Idris to assess malaria risk and hazards in Eastern Ethiopia. Adeola et al. (2016) used land use land cover classification and elevation to assess the link between environmental factors and malaria in the Nkomazi community of South Africa. Xia et al. (2015) detected malaria's spatial and temporal distribution using GIS and spatial scan statistics in the Hubei province of China. It is worth noting that from the available literature, there is a paucity of research on the influence of environmental factors on malaria prevalence in Kaduna North LGA. Additionally, the study area does not have adequate records due to paucity of data at clinical levels.

A lot of studies have been conducted on malaria in Kaduna State. For example, Azua et al. (2022) used a Spatial-Oriented Decision Support System to investigate malaria incidents in Zaria. Damisa and Hassan (2021) assessed the cases of malaria in pregnant women in Lere LGA. The study revealed that malaria is linked to miscarriage and hypoglycemia in pregnancy. Suleiman et al. (2021) assessed the influence of climate parameters on the prevalence of malaria and typhoid in Kaduna South LGA. Bajoga et al. (2019) assessed the trend of malaria occurrence in Kaduna State between 2011-2015. The study used routine surveillance data and found that there is a seasonal variation in cases, but did not consider the role of environmental factors. Benjamin et al. (2018) assessed how the demographic factors of locals are influencing the prevalence of malaria in Zaria LGA of Kaduna State. However, environmental factors were not assessed. From the available literature, no study considered the combined effects of topographic, environmental and sociodemographic characteristics to map malaria risk in the region.

Despite the combined efforts made by the government and NGOs, malaria continues to be a health challenge, especially considering the sociodemographic characteristics of Kaduna's urban population. Kaduna North LGA has a population of about 620,742 as of 2023, and a population density of 8842.48/km² (Kaduna Bureau of Statistics, 2015). This increases the susceptibility of the people in the local government to malaria. This is because population density has been identified as one of the critical factors increasing the risk of malaria (Kabaria et al., 2017). Therefore, this study will fill the gap by providing an understanding of vulnerabilities and malaria risk assessment using Remote Sensing, GIS and Multi-Criteria Decision Analysis (MCDA) - Analytic Hierarchy Process in Kaduna North Local Government Area of Kaduna State.

MATERIALS AND METHODS

2.1 Study Area

Kaduna North is one of the local government area that makes up the Kaduna Metropolis. The local government lies between latitudes 10º29'16" and 10º37'8" north of the equator and between longitudes 7°24'43" and 7°29'15" east of the Greenwich Meridian. Kaduna North is bordered to the north by Igabi LGA and to the south by Kaduna South LGA. To the west and east, Kaduna North LGA is bordered by Kaduna South and Chikun LGAs, respectively (Baba et al., 2020). The local government area covers an area of 70.2 km², see Figure 1.

Kaduna is situated in a tropical wet and dry climate (Musa & Abubakar, 2024). The wet season runs for about six to seven months, mostly between April and October, with an average rainfall of 1400mm, while the dry season denotes Harmattan, having severe dust haze, with northerly winds flowing from the desert (Abubakar et al., 2024). The maximum temperature in the Kaduna metropolis can be over 30 °C, with the hottest months being March, April, and May. Relative humidity typically ranges from 25% and 90% depending on the month of the year, with the lowest humidity between December and February (Abubakar et al., 2025).

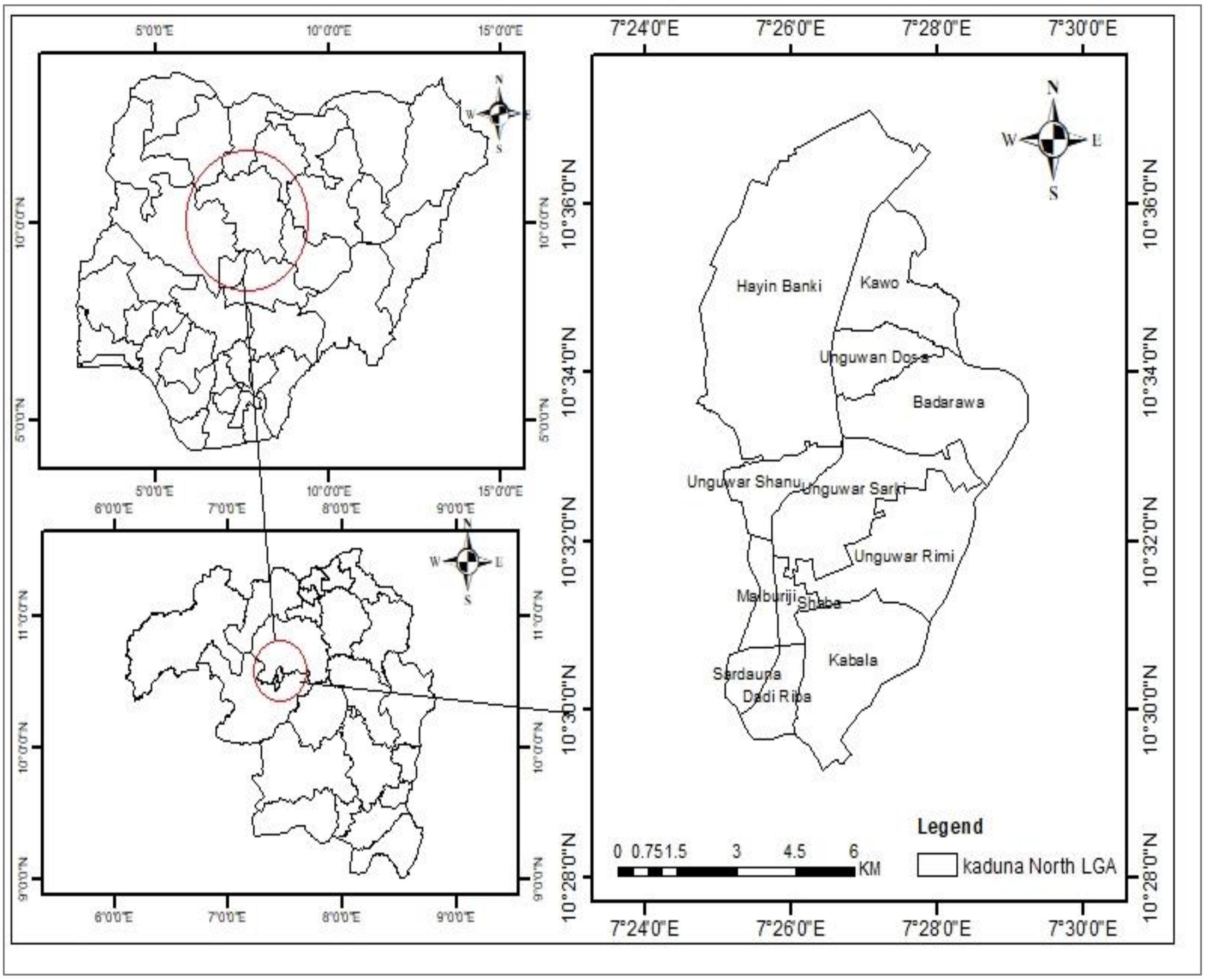


Figure 1: Kaduna North Local Government Area
Source: Adapted from GRID3 - Nigeria (2022)

The study area lies on the Kaduna Plain. It comprises extensive tracts of almost level to gently undulating lightly dissected land, broken in places by groups of rocky hills and inselbergs (Musa & Abubakar, 2024). The area's soil is characterized by a sandy surface horizon overlaid by a weakly structured clay accumulation, a typical red-brown to red-yellow tropical ferruginous soil (FAO, 2017). The area lies in the Northern Guinea savannah zone. Therefore, it has a savannah grassland type of vegetation comprising tall grasses, scattered trees, and galleries (Abubakar & Abdussalam, 2024).

From the post-colonial periods, Kaduna became the hub of textile industries in Nigeria (Bununu et al., 2015). This is because of its proximity to cotton-growing areas around Zaria. Apart from the textile, Kaduna also has plenty of commercial and manufacturing industries such as automobile, iron works, fertilizers, furniture, and cable industries among others (Saleh, 2015). Kaduna is blessed with rich agricultural lands, with many crops produced along the Kaduna River and its tributaries cutting through the metropolis (Saleh, 2015). Historically, migrating farmers were encouraged to settle in Kaduna during the colonial periods to curb food shortages (Musa & Abubakar, 2024). Furthermore, the favourable climate, fertile soil, and the Kaduna River are encouraging urban agriculture in Kaduna.

Kaduna North LGA has a tertiary healthcare facility, Barau Dikko Teaching Hospital, which Kaduna State

University manages. Additionally, the local government has a general hospital in Kawo, which is a secondary healthcare facility. There are primary healthcare centers in all the twelve wards of the LGA, with some areas having primary health clinics (GRID3 - Nigeria, 2024).

2.2 Sources of Data

Records of malaria cases and treatments were obtained from the Kaduna State Primary Healthcare Board. Landsat 8 (OLI/TIRS) imagery and the SRTM Digital Elevation Model were obtained from the United States Geological Survey Agency. Population data was obtained from the Kaduna State Bureau of Statistics. The malaria records were used to map the spatial variation and hotspot analysis. DEM was used to extract the elevation, slope, aspect, and drainage density. The Landsat imagery was used for land use and land cover analysis, surface temperature computation, and moisture and vegetation estimation. The methodological flow chart is shown in Figure 2.

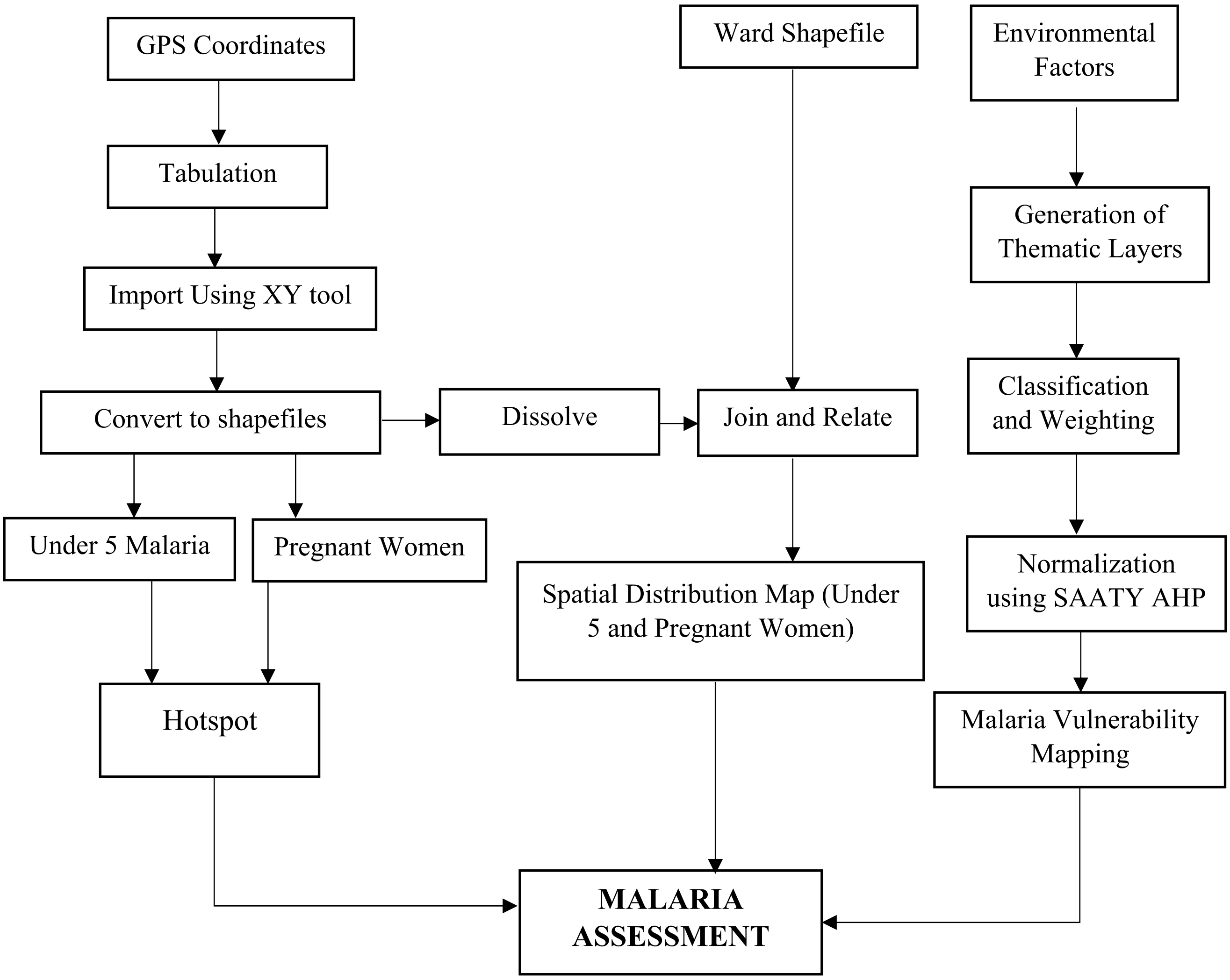


Figure 2: Methodological Flowchart

Data Analysis

Spatial Variation of Malaria Cases

To analyze the spatial variation in the occurrence of malaria cases among children under 5 and pregnant women in Kaduna North Local Government Area, locations of malaria treatment centres obtained and tabulated using Microsoft Excel, saved in Comma Delimited (.csv) format, and imported into ArcMap environment using the Add XY Data tool. The data is now converted into ESRI shapefile (.shp) format and captured and imported into a geodatabase. Additionally, the summary of cases for every ward will be imported into ArcMap, and using the Join tool, they will be added to the ward shapefiles.

Malaria hotspots

In order to identify and map malaria hotspots in Kaduna North Local Government Area, Hotspot Analysis on ArcGIS was used. This tool identifies statistically significant spatial clusters of high values (hot spots) and low values (cold spots). It automatically aggregates incident data, identifies an appropriate scale of analysis, and corrects for both multiple testing and spatial dependence.

Before the hotspot analysis, different steps were involved in data preparation. For example, the Integrate tool was used to update feature classes by assigning common coordinates for vertices that fall within the given X, Y tolerance and by adding vertices where feature vertices are within the X, Y tolerance of an edge and where line segments intersect. In this case, cases of malaria under different testing and treatment methods were integrated. Subsequently, the Collect Event tool on the Spatial Analyst toolbar was used to convert event data into weighted point data.

Analytical Hierarchy Process (AHP)

An Analytic Hierarchy Process was employed to examine the population's vulnerability to malaria health risk in Kaduna North Local Government Area. The analytic hierarchy process (AHP) is one of the several methods used in multicriteria decision-making. It was developed by Saaty (1990). This approach employs a pairwise comparison matrix to induce judgment on the relative importance of every criterion or attribute. From Table 1, the AHP has a normalized scale ranging from 1 to 9, with 1 having the least significance and 9 having the highest or maximum significance. Several studies have used the AHP technique in flood vulnerability mapping such as Samanta et al. (2018) and Shuaibu et al. (2022). The consistency index and consistency ratio were calculated as part of the AHP analysis.

For this study, based on the ranking of experts, the relative importance scale from 1 to 5 is applied. This is because of the influence of the malaria-related environmental factors considered in this study. The pairwise comparison matrix is shown in Table 2.

The output of the pairwise comparison matrix was used to assign weights to all the layers. The assigned weights were subsequently used in the weighted overlay analysis in ArcGIS. The assigned weights are shown in Table 3.

RESULTS AND DISCUSSION

3.1 Spatial Variation in the Occurrence of Under 5 Malaria Cases in Kaduna North Local Government Area

This study mapped the spatial variation of malaria cases for children under five under different kinds of tests and different treatments. These tests include Rapid Diagnostic Testing (RDT) and Microscopy. The treatments include Artemisinin-based combination therapies (ACT) and Antimalarial Drugs. Additionally, the malaria cases were categorised as patients with fever, patients who tested positive for malaria, patients with confirmed uncomplicated malaria and patients who have clinically diagnosed malaria. Under 5 children that received Long-lasting insecticidal nets (LLINs). Maps showing the spatial variation in malaria cases are shown in Figure 3.

Table 1: Saaty AHP Scale

Relative Importance	Definition
1	Equal importance
2	Equal-to-moderate importance
3	Moderate importance
4	Moderate-to-strong importance
5	Strong importance
6	Strong-to-very strong importance
7	Very strong importance
8	Very-to-extremely strong importance
9	Extreme importance

Source: Saaty (1990)

Table 2: AHP Pairwise Comparison Matrix

Matrix		Distance from Rivers 1	Slope 2	Elevation 3	NDVI 4	LULC 5	LST 6	Population Density 7	0 8	**normalized principal Eigenvector**
Distance from Rivers	1	1	3 1/3	2	3 1/9	2 2/7	2 2/7	1 5/7	0	26.28%
Slope	2	1/3	1	1/4	1 1/9	1	1/2	1/3	0	6.91%
Elevation	3	1/2	3 2/3	1	1 4/5	1 4/9	1/2	2	0	15.55%
NDVI	4	1/3	1	5/9	1	1/2	2/7	1/3	0	6.05%
LULC	5	3/7	1	2/3	2	1	1/3	1 3/5	0	10.46%
LST	6	3/7	2	2	3 5/9	3 1/3	1	2 1/2	0	22.48%
Population Density	7	3/5	3 1/9	1/2	3 1/9	5/8	2/5	1	0	12.27%

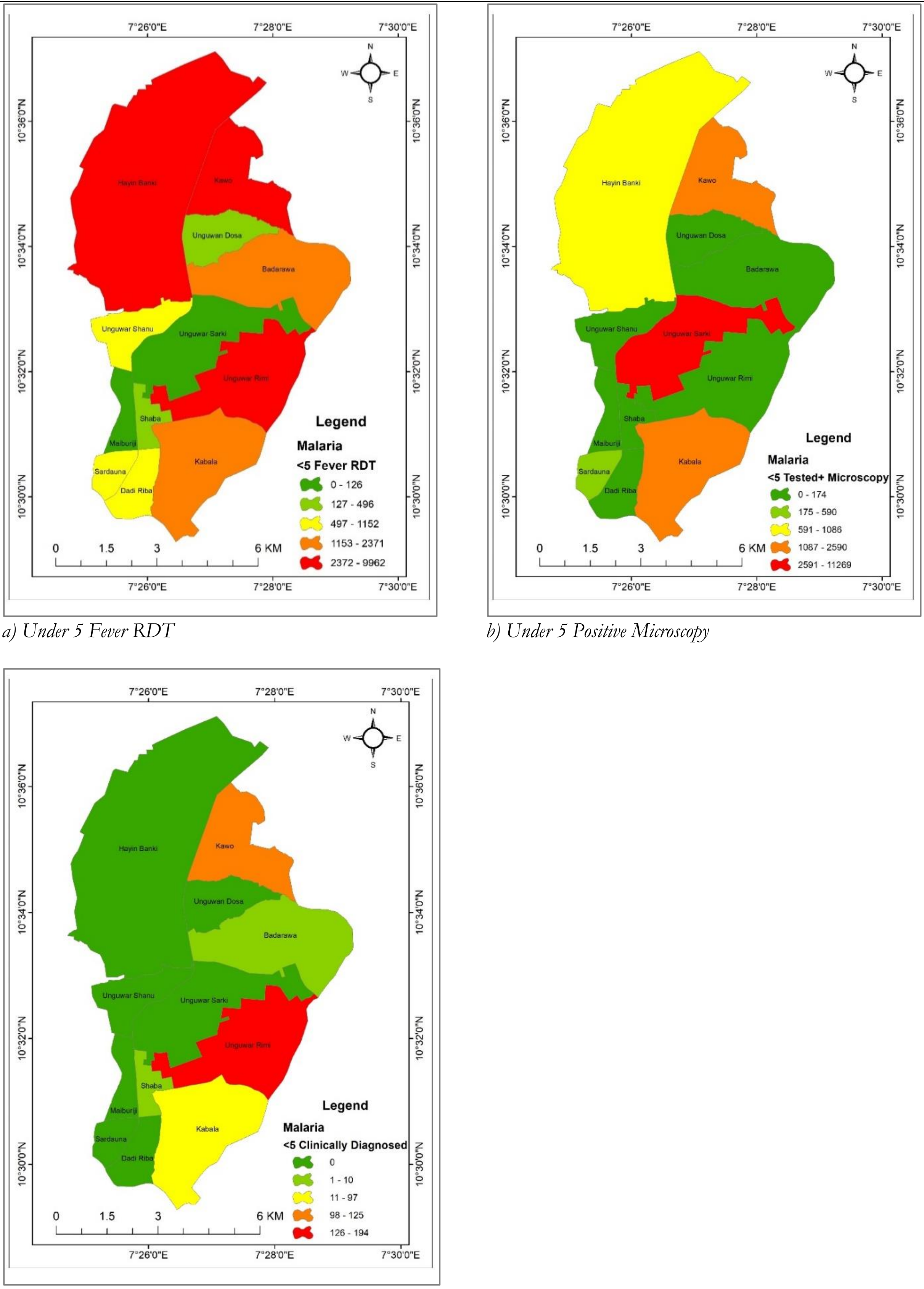
Table 3: Arrangement and weight assessment for malaria vulnerability mapping

Flood Causative Criterion	Unit	Class	Range and Ratings	Class Ratings	Weights
Elevation	m	183 - 256	Very High	5	16
		256 - 298	High	4	
		298 - 332	Moderate	3	
		332 - 368	Low	2	
		368 - 458	Very Low	1	
Slope	%	0 - 2.425	Very High	5	7
		2.425 - 4.446	High	4	
		4.447 - 7.814	Moderate	3	
		7.815 - 14.146	Low	2	
		14.147 - 34.354	Very Low	1	
Population Density	Mm/year	1092.22 - 1110.27	Very Low	1	12
		1110.28 - 1138.29	Low	2	
		1138.30 - 1171.54	Moderate	3	
		1171.54 - 1199.09	High	4	
		1199.10 - 1213.34	Very High	5	
LULC	Level	Water	Very High	5	11
		Agric	High	4	
		Settlement	Moderate	3	
		Bare	Low	2	
		Vegetation	Very Low	1	
NDVI	Level	0.033477 - 0.077367	Very High	5	6
		0.077367 - 0.097072	High	4	
		0.097072 - 0.116777	Moderate	3	
		0.116777 - 0.143649	Low	2	
		0.143649 - 0.262777	Very Low	1	
Distance River	m	0 - 356.802	Very High	5	26
		356.803 - 885.85	High	4	
		885.86 - 1353.38	Moderate	3	
		1353.39 - 1870.13	Low	2	
		1870.14 - 3137.40	Very Low	1	
Land Surface Temperature	^{o}C	0 - 0.146745	Very Low	1	23
		0.146745 - 0.381538	Low	2	
		0.381538 - 0.622201	Moderate	3	
		0.622201 - 0.898082	High	4	
		0.898082 - 1.496803	Very High	5	

Source: Author's Analysis, 2024

From Figure 3a, findings revealed that Maiburuji and Unguwar Sarki had the lowest cases of malaria tested with RDT. Shaba ward and Unguwan Dosa had between 127-496 cases, Dadi Riba, Sardauna and Unguwan Shanu had 497-112, Kabala and Badarawa wards had 1,153-2,371 cases, while Hayin Banki, Kawo and Unguwar Rimi wards had more than 2,372 cases. Figure 3b revealed that Badarawa, Dadi Riba, Maiburuji, Shaba, U/Dosa, U/Shanu and U/Rimi had the lowest cases of malaria tested with microscopy (0-174). Sardauna ward had up to 590 cases, Hayin Banki had up to 1,086 cases, while Kabala and Kawo wards had up to 2,590 cases. Unguwar Sarki recorded the highest number of cases of microscopically tested malaria up to 11,269. According to (WHO, 2023b), microscopy enables the detection of several malaria-causing parasites (*P. falciparum, P. vivax, P. malariae, P. ovale, and P. knowlesi*), and their numerous parasite stages.

Figure 3c reveals the number of clinically diagnosed malaria cases. Dadi Riba, Hayin Banki, Maiburuji, Sardauna, U/Dosa, U/Sarki and U/Shanu wards had the lowest cases of CDM. Badarawa and Shaba wards had up to 10 cases of malaria. Kabala ward had up to 97 cases, while Kawo ward recorded up to 12 cases. Unguwar Sarki had the highest cases of CDM with 194.



a) Under 5 Fever RDT

b) Under 5 Positive Microscopy

c) Under 5 Clinically Diagnosed Malaria

Figure 3: Spatial Variation of Under 5 Malaria Cases Based on Testing Methods

Previous studies have reported the number of malaria cases in Kaduna North LGA, regardless of the diagnostic method. For example, Bajoga et al. (2019) in their study reported that between 2011 and 2015, Kaduna North had a total of 24,424 cases across a population of 439,919 people. The incidence rate of malaria cases, according to their findings, was 5.5%, which is similar to the findings of Ibrahim et al. (2017) that Kaduna North LGA is one of the seven (7) local government areas with malaria prevalence above 5%.

Figure 4a shows the number of under 5 uncomplicated malaria cases treated with ACT. Dadi Riba, Maiburuji, Shaba, Unguwar Shanu, and Unguwan Dosa had less than 557 cases. Badarawa, Sardauna, and Unguwar Rimi recorded cases between 558 and 1,410, while Kabala ward had up to 2,557 cases. Hayin Banki had up to 5,273, while Unguwar Sarki and Kawo wards recorded between 5,274 and 11,162 cases of malaria treated with ACT. According to WHO (2019), Artemisinin-based combination therapies (ACTs) are recommended for the treatment of uncomplicated malaria cases. Olumese (2010) added that the treatment should include at least 3 days of treatment with an artemisinin derivative.

Figure 4b shows the distribution of uncomplicated malaria cases treated with antimalarial drugs in Kaduna North Local Government Area. Dadi Riba, Maiburuji, Shaba, U/Sarki, and U/Shanu wards had a maximum of one (1) case, Badarawa ward recorded five (5) cases, Hayin Banki and Unguwar Rimi wards recorded up to 15 cases, Kabala recorded up 22 cases, while Kawo and Sardauna wards recorded up to 147 cases of malaria treated with antimalarial drugs.

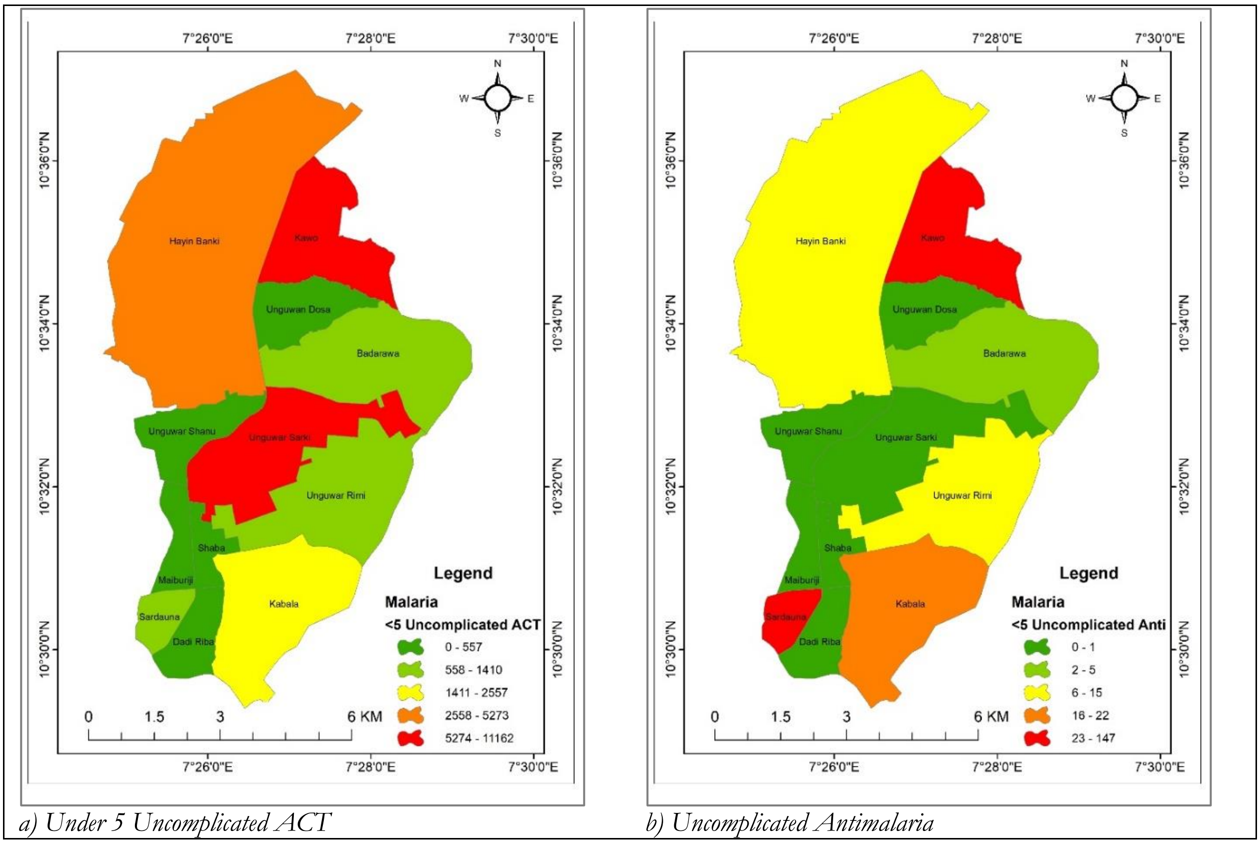


Figure 4: Spatial distribution of malaria treatments a) under 5 uncomplicated treated with ACT b) Uncomplicated treated with antimalaria

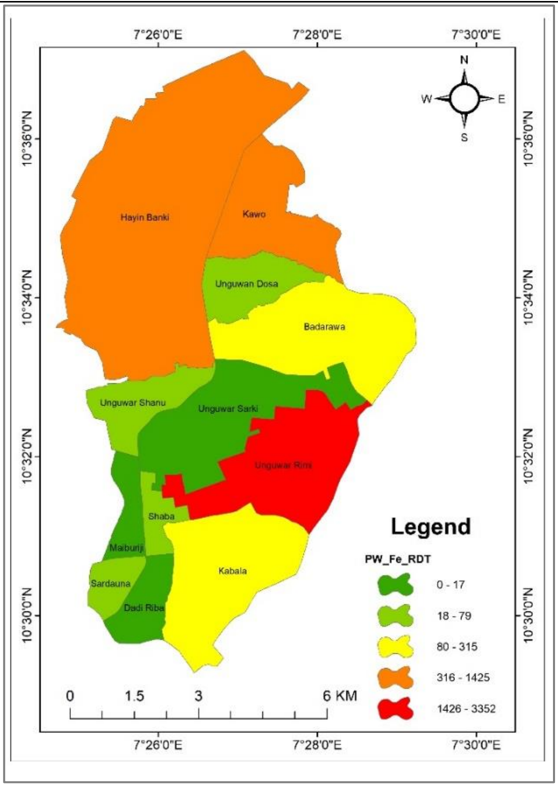
3.2 Spatial variation in the occurrence of malaria cases among pregnant women in Kaduna North Local Government Area

This study also assessed the spatial distribution of malaria cases, tests, and treatments for pregnant women according to the 12 political wards in Kaduna North Local Government Area. The results are shown in Figure 5 and Figure 6.

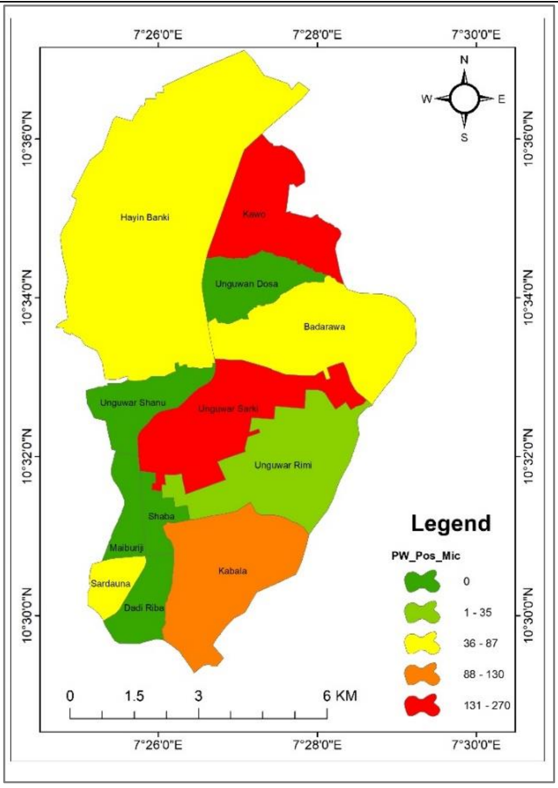
From Figure 5a, findings revealed that Dadi Riba, Maiburuji, and Unguwar Sarki had the lowest cases of malaria tested with RDT, with fewer than 17 cases. Sardauna, Unguwar Dosa, and Unguwar Shanu had between 18-79 cases; the cases in Badarawa and Kabala wards were more than 80 but less than 316. Hayin Banki and Kawo wards recorded up to 1,425 cases, while Unguwar Rimi had up to 3,352 cases of malaria diagnosed with RDT. According to Ding et al. (2023), Highly sensitive rapid diagnostic testing (HS-RDT) has a somewhat higher analytical sensitivity for detecting malaria infections in pregnancy.

Figure 5b reveals the number of malaria cases diagnosed with microscopy. The results revealed that Dadi Riba, Maiburuji, Shaba, Unguwar Dosa and Unguwar Shanu wards did not record any cases, Unguwar Rimi ward had up to 35 cases, Badarawa, Hayin Banki and Sardauna wards had between 36 and 87 cases, Kabala ward recorded 130 cases, while the highest cases were recorded in Kawo and Unguwar Sarki with up to 270. Ebong et al. (2022) reported that microscopy allows for the most accurate parasite speciation and quantification in pregnant women.

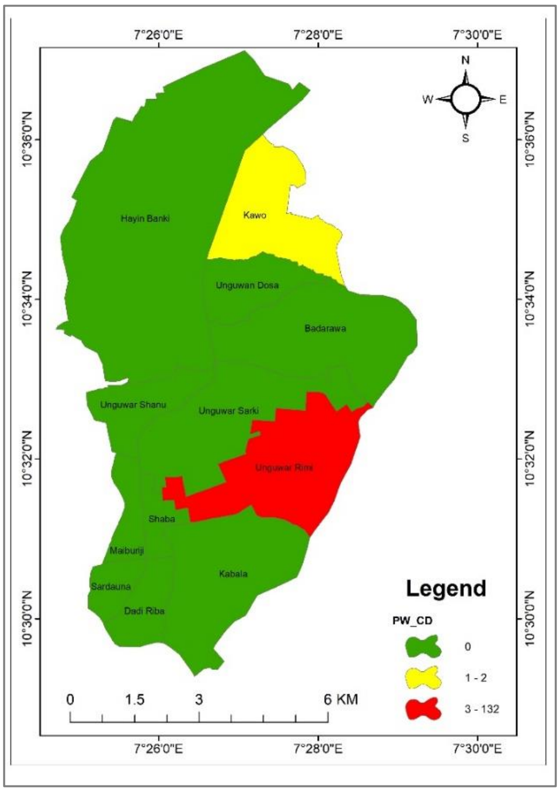
The number of clinically diagnosed malaria cases in Kaduna North LGA is shown in Figure 5c. Results revealed that the Kawo ward had only 2 cases, while the Unguwar Rimi ward had up to 132 cases of clinically diagnosed malaria. This shows that apart from the two wards, no other ward in Kaduna North LGA recorded malaria cases that were clinically diagnosed.



a) Pregnant Women Fever RDT



b) Pregnant Women Positive Microscopy

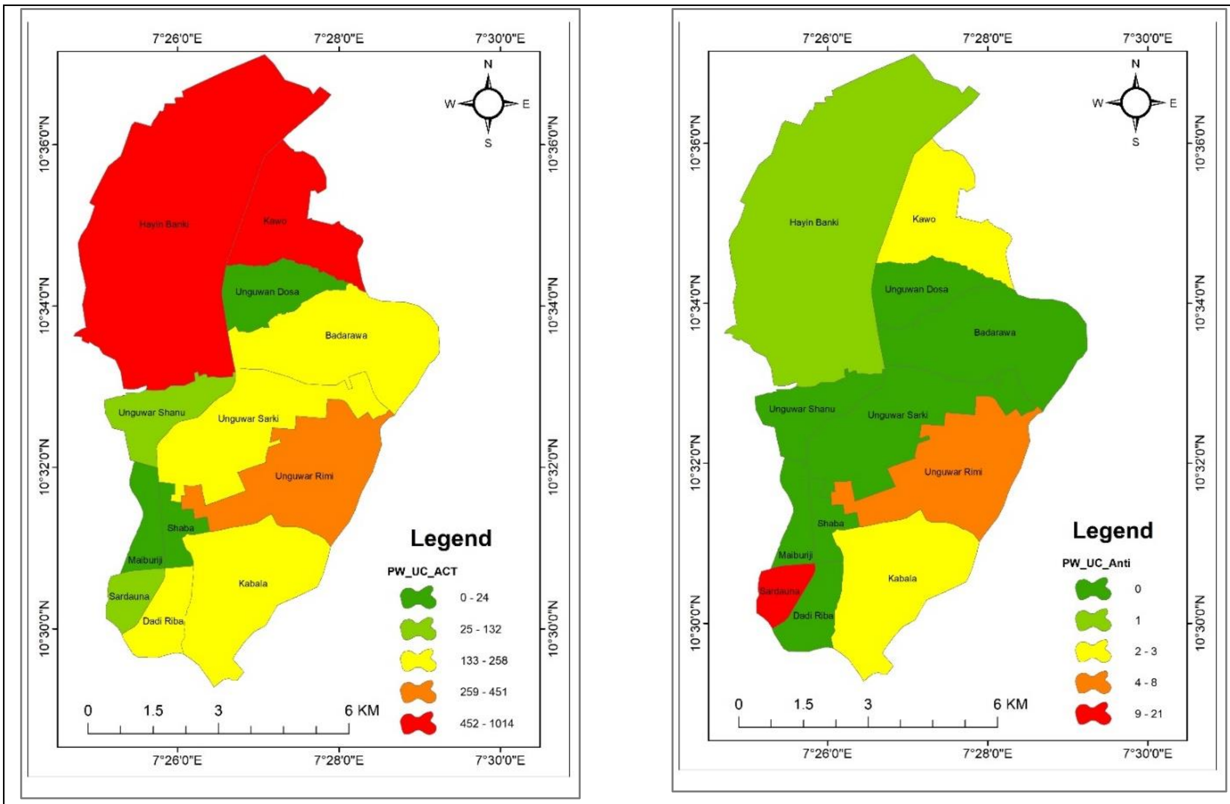


c) Pregnant Women Clinically Diagnosed with Malaria

Figure 5: Spatial Variation of Under 5 Malaria Cases Based on Testing Methods.

The number of pregnant women with malaria cases treated with Artemisinin-based combination therapies (ACT) in Kaduna North LGA is shown in Figure 6a. Results revealed that Hayin Banki and Kawo wards recorded the highest with up to 1,014. This is followed by the Unguwar Rimi ward, with up to 451 treatments. Badarawa, Dadi Riba, Kabala and Unguwar Sarki wards recorded between 133 and 258 treatments within the study period. Sardauna and Unguwar Shanu wards recorded between 25 and 132 ACT treatments, while the lowest treatments with ACT were recorded in Maiburuji, Shaba, and Unguwan Dosa wards, with a maximum of 24 treatments. According to Slutsker and Leke (2023), the WHO recommends that pregnant women with malaria in the second and third trimester of pregnancy get treatment with artemisinin-based combination treatments (ACTs), although the WHO has not recommended ACTs in the first trimester due to safety concerns. This is similar to the findings of Figueroa-Romero et al. (2022), who reported that Artemisinin-based combination therapies (ACT) are currently recommended for the treatment of uncomplicated malaria in pregnancy.

Figure 6b revealed the number of pregnant women in Kaduna North who were treated using antimalarial drugs in Kaduna North LGA. Sardauna ward had the highest with 21 treatments, followed by Unguwar Rimi with 8 treatments. Kabala and Kawo wards recorded 2 and 3 treatments, respectively, while the Hayin Banki ward had only one treatment using antimalarial drugs. Healthcare facilities in Badarawa, Dadi Riba, Maiburuji, Shaba, Unguwar Dosa, Unguwar Sarki and Unguwar Shanu wards did not record any treatment using antimalarial drugs within the study period. Some antimalarial drugs, such as artesunate, are recommended for treating complicated malaria in all trimesters of pregnancy according to international standards (Al Khaja & Sequeira, 2021; Saito et al., 2020).



a) Pregnant Women Treated With ACT   *b) Pregnant Women Treated with Antimalarial Drugs*

Figure 6: Spatial Variation of Under 5 Malaria Cases Based on Testing Methods

Malaria hotspots in Kaduna North Local Government Area

Malaria hotspots for both under (5) children and pregnant women were determined using Moran's Index and Getis-Ord Gi* statistics.

3.2.1 Malaria Hotspot for Under 5 in Kaduna North LGA

Spatial Autocorrelation for Under Five (5) Malaria Cases in Kaduna North LGA

For the hotspot analysis for children with malaria under five (5) years, the spatial autocorrelation revealed that the Moran's Index was 0.013786, and the expected index was -0.019231. Given the Z-score of 1.258291, and the p-value is 0.208287, the pattern does not appear to be significantly different than random.

To assess malaria hotspots for Under-five (U5) children in Kaduna North LGA, hot and cold spot areas were detected using the Getis-Ord Gi* statistics estimation measure. Areas with high and low-risk levels of malaria were detected. Results from the analysis revealed three hotspots, one with a 99% confidence level (Gi* $Z \geq 2.174$, Gi* $P \leq 0.05$), and two with a 90% confidence level (Gi* $Z \geq 1.669$, Gi* $P \leq 0.05$). All were located in Badarawa ward. All the remaining locations were not statistically significant (Gi* $Z \leq 1.591645$, Gi* $P \geq 0.05$); they are neither hotspots nor cold spots.

Points generated from the hotspot analysis were interpolated using the Inverse Distance Weighted (IDW) technique and shown in Figure 7.

3.2.2 Malaria Hotspot for Pregnant Women in Kaduna North LGA

Spatial Autocorrelation for Malaria Cases Among Pregnant Women in Kaduna North LGA

This study carried out hotspot analysis for pregnant women with malaria in Kaduna North Local Government

Area. Assessment of the spatial autocorrelation revealed that Moran's Index was 0.001705, and the expected index was -0.019231. Given the Z-score of 1.077305, and the p-value is 0.281344, the pattern does not appear to be significantly different than random.

For the malaria hotspots for pregnant women in Kaduna North LGA, cold spot areas were detected using the Getis-Ord Gi* statistics estimation measure, indicating areas with low-risk levels of malaria cases for pregnant women. Results from the analysis revealed one cold spot with a 90% confidence level (Gi* Z ≤ -1.669, Gi* P ≤ 0.05), which is in Unguwar Rimi ward. All the remaining locations not statistically significant (Gi* Z ≤ -1.521, Gi* P ≥ 0.05),

Points generated from the hotspot analysis were interpolated using Inverse Distance Weighted (IDW) technique and shown in Figure 8.

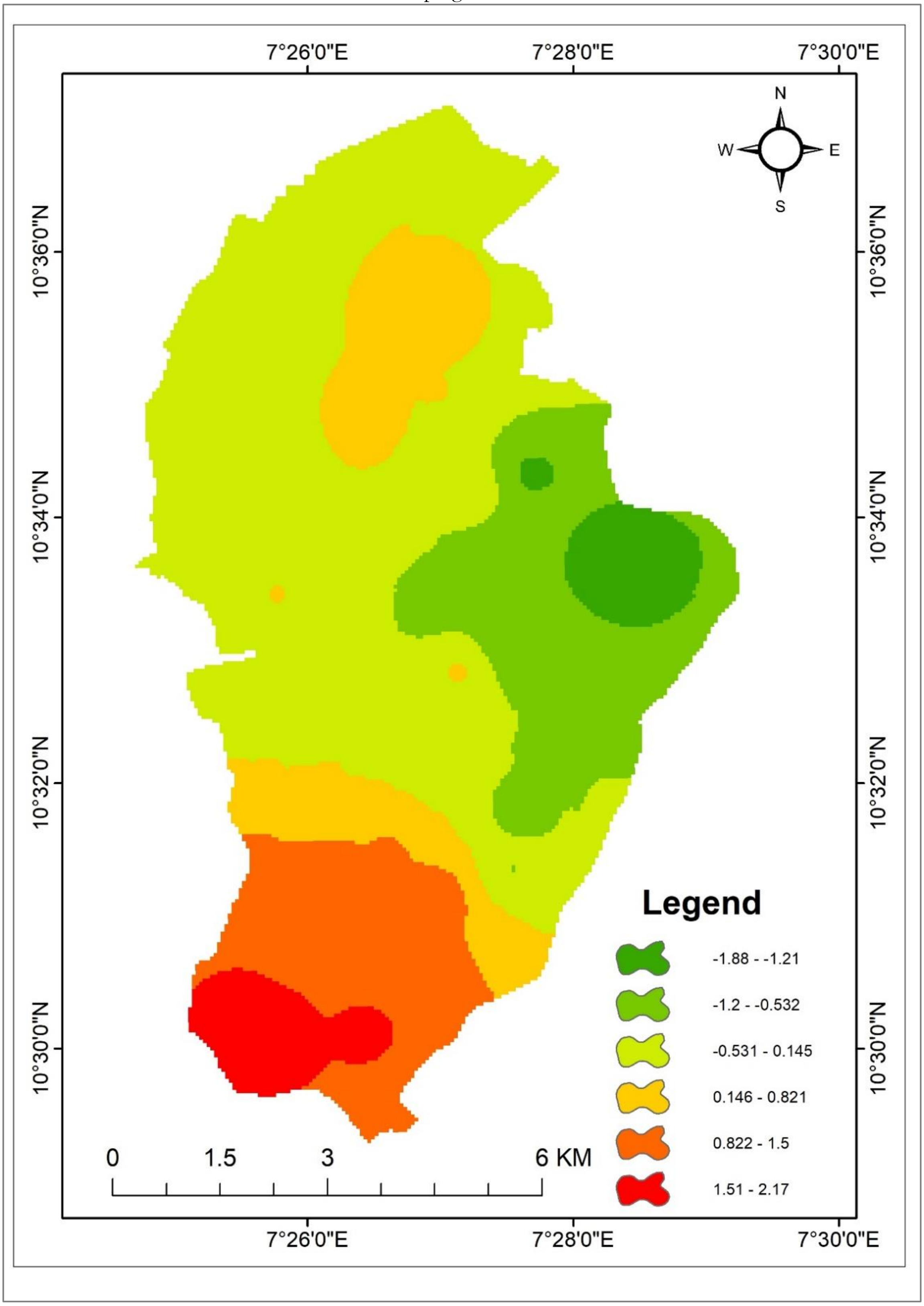


Figure 7: Malaria Hotspots for Under 5 Children in Kaduna North LGA

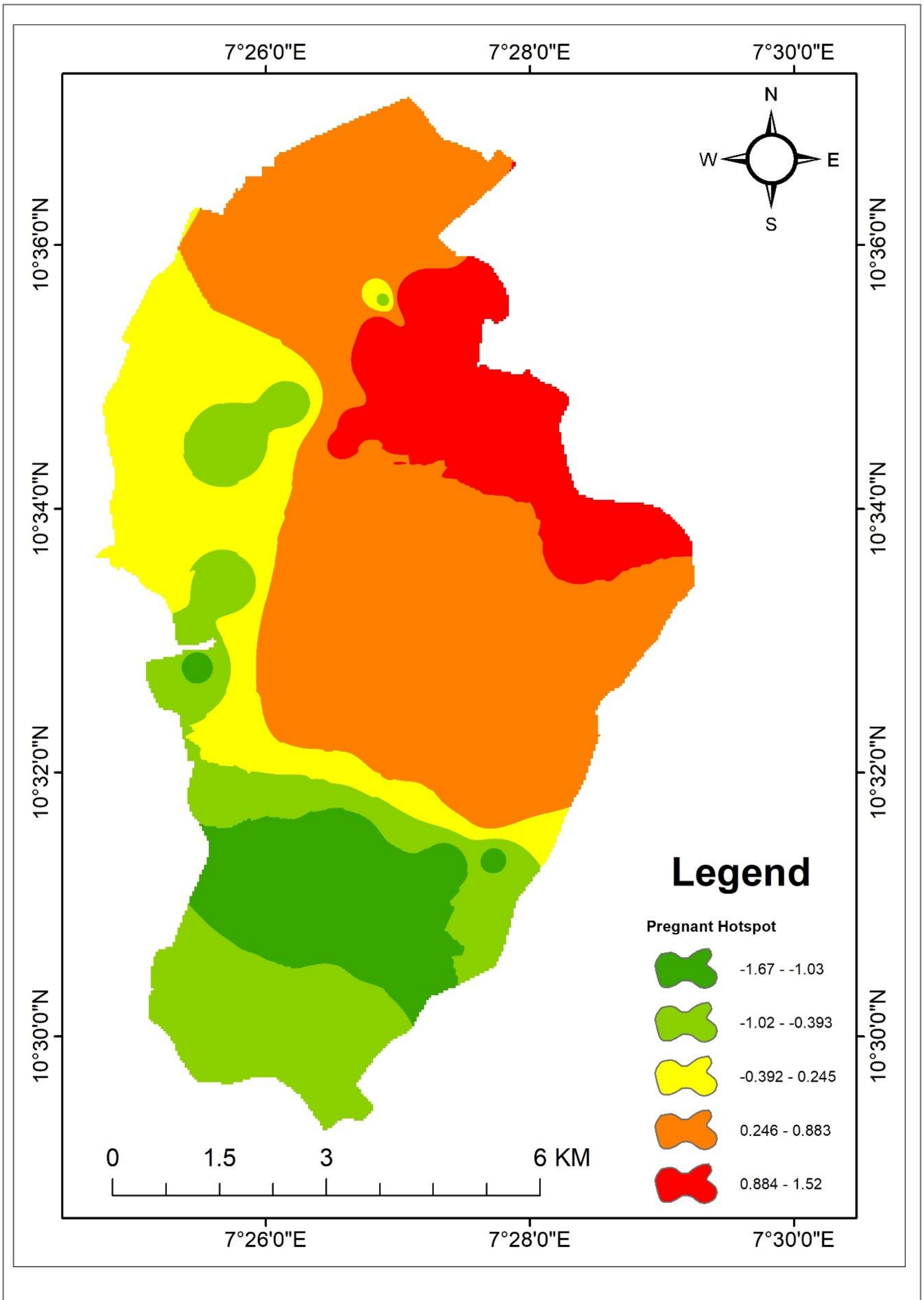


Figure 8: Malaria hotspots for Pregnant Women in Kaduna North LGA

3.3 Vulnerability of the population to malaria health risk in Kaduna North Local Government Area

3.3.1 Topographic Factors Affecting Malaria Occurrence

3.3.1.1 Elevation

The elevation of Kaduna North LGA was divided into five (5) categories. Level I 564m-590m, which covers 19% of the study area, 591m-604m covers 26.5%, 605-617m covers 23%, 618-630m covers 17.7%, and level five 631-655m which makes up 13.3%. Although malaria transmission can occur in areas with an elevation of 2,000m above mean sea level (Merga et al., 2024), studies such as Ofgeha (2023) have reported that the transmission decreases with an increase in elevation.

3.3.1.2 Distance from Streams

Rivers are good places for malaria vectors to breed. The proximity to waterways increases the danger of malaria sickness (Merga et al., 2024). Thus, this study also considered distance from streams as a factor influencing malaria transmission. Five categories were used 0-0.006 km, 0.0063-0.0114 km, 0.0115-0.0172 km, 0.0173-0.0229 km, and 0.023-0.0286 km. This classification and score of distance to rivers are made based on several literatures. This study generated distance from streams to rivers using Euclidean Distance in Spatial Analyst tools of ArcMap.

3.3.1.3 Slope

The slope has a vital influence in enhancing the malaria breeding site in a specific location. The steeper slope values are related to lesser malaria hazard and the gentler slope has high susceptibility for malaria incidence (Mwangungulu et al., 2023). Based on the suitability of the slope for mosquito breeding, the reclassified slopes map was created. Thus, areas of 1.3 km^2 (1.9%), 7.3 km^2 (10.4%), 19.2 km^2 (27.4%), 22.4 km^2 (31.9%) and 20.0 km^2 (28.5%) are very high, high, moderate, low and very low malaria risk area respectively. Areas with very high and high risks have slopes less than 1.49^o, and 1.5-2.64^o., these areas allow water stagnation, which helps in mosquito breeding. Given the association between slope and malaria cases, it appears that water is logged in regions with low-lying slopes, which increases the likelihood of water stagnation (Ofgeha, 2023).

3.3.2 Environmental Factors

Environmental variables that act as malaria causative factors were assessed in this section. These are land surface temperature, vegetation–using NDVI, and land-use land cover types.

3.3.2.2 Land Surface Temperature

Surface temperature is one of the critical factors facilitating malaria breeding because previous studies found that land surface temperature (LST) is positively associated with malaria incidence (Youssefi et al., 2022). The surface temperatures in Kaduna North were categorized into five classes, 31.8-32.6^{o}C, 32.7-33.2^{o}C, 33.3-33.7^{o}C, 33.8-34.4^{o}C, 34.5-35.5^{o}C, although the variation appears to be low. According to Yamba et al. (2023), studies have shown that 31 ^{o}C is the optimal temperature for malaria transmission. Thus, based on the findings of this study, all parts of Kaduna North LGA are susceptible to malaria occurrence.

3.3.2.3 Normalized Difference Vegetation Index

As highlighted in the literature review, changes in vegetation are directly linked to malaria prevalence (Youssefi et al., 2022). This study extracted the annual average for NDVI and categorized into five (5) levels. For level I, a range of 0.162-0.229 was used, while the ranges for level II, level III, level IV and level V were 0.23-0.27, 0.271-0.303, 0.304-0.34 and 0.341-0.388 respectively. Areas with level I-III covered 60.9% of the area, while level IV-V covered 39.1% of the local government area. Furthermore, since vegetation health varies with seasons, the influence of vegetation on malaria prevalence is different in wet and dry seasons (Asori et al., 2023).

3.3.2.4 Population Density

Population density was found to be a significant predictor of malaria risk as it provides a consistent metric to adjust for the patterns of malaria risk in densely populated areas (Merga et al., 2024). The population density of Kaduna North LGA was reclassified in the assumption that the higher the density, the greater the vulnerability of the population to malaria. Areas with 3,500 – 4,580 people per kilometre are categorized as very low-density, and low-density areas have 4,590 - 6,150. However, moderate, high, and very high-density areas are 6,160 - 7,970, 7,980 - 11,500, and 11,600-24,600, respectively. Thus, malaria incidence has a strong correlation with population size and area of the village (Ekpa et al., 2023).

3.3.2.5 Land Use Land Cover

This study classified LULC into five categories: vegetation, bare land, cultivated land, water bodies, and built-up areas. Built-up areas have the largest coverage with 34.2 km^2 (48.7%), followed by bare land with 21.5 km^2 (30.6%), cultivated lands with 9.7 km^2 (13.8%), vegetation with 4.3km^2 and water bodies with 0.5 km^2 (0.7%). Settlements are more prone to malaria diseases, as several studies also justify that increasing of more settlements can lead to an increase in malaria incidence (Mihiretie, 2022).

3.3.3 Malaria Vulnerability Mapping in Kaduna North LGA

The vulnerability of areas in Kaduna Metropolis to Malaria was assessed using the Analytical Hierarchy Process. Factors included are elevation, slope, vegetation, land surface temperature, land use, land cover, and distance to water bodies. These factors were weighted using the Analytical Hierarchy Process, and the flood vulnerability map is shown in Figure 9.

The final map was grouped into five zones: very low, low, moderate, high, and very high. Areas with high vulnerability are very close to water bodies and have very low elevation and high population density. This can be seen in the eastern part of the study area, specifically the Unguwar Sarki and Unguwar Rimi axis. Another area with high vulnerability in Kaduna North LGA is the southern and southwestern parts, covering Kabala, Dadi Riba, Shaba, and Sardauna wards. Areas with high elevation have low to medium vulnerability. Around 30% of Kaduna North LGA falls under areas with moderate to low vulnerability. Areas with high and very high vulnerability made up 56% and 13% of the area, respectively. This is an indication that vulnerability to malaria increases with increasing proximity to water bodies and high land surface temperature in Kaduna North LGA. From the AHP analysis, it can be revealed that elevation, proximity to water bodies and land surface temperature play critical roles in malaria occurrence in Kaduna North LGA.

This agrees with the findings of McMahon et al. (2021), which revealed that land surface temperature and land use type positively correlate with malaria cases. The study also agrees with the findings of Kibret et al. (2019) that distance to reservoirs are critical predictor of increased malaria incidents in Ethiopia.

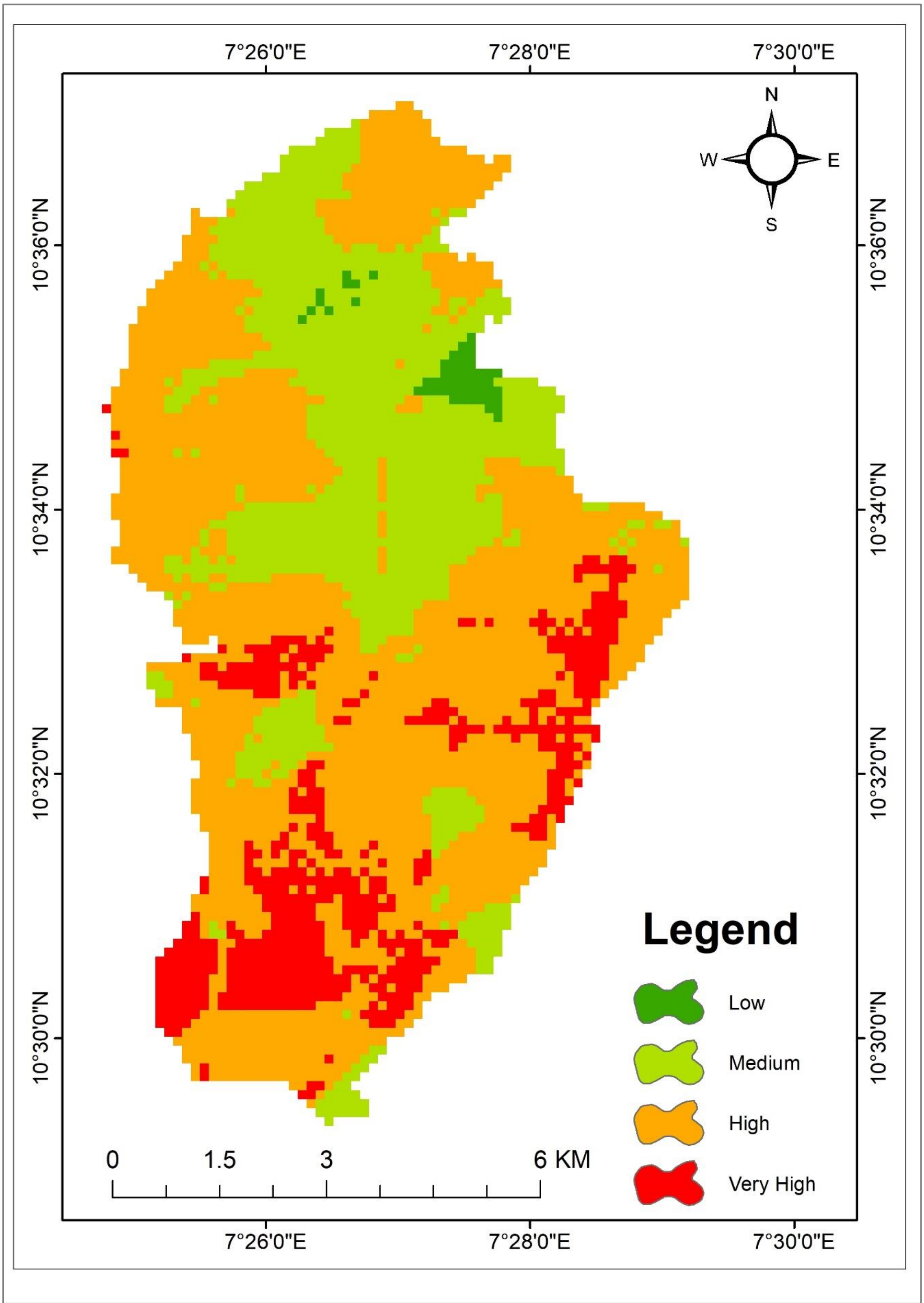


Figure 9: Malaria vulnerability map of Kaduna North LGA

CONCLUSION AND RECOMMENDATION

Based on the findings of this study, it can be concluded Rapid Diagnostic Testing (RDT) is the most common form of malaria diagnosis for both children under 5 and pregnant women in Kaduna North LGA, followed by microscopy. The number of clinically diagnosed malaria cases in Kaduna North LGA is low because it is based on the patient's symptoms and physical findings at the examination. The study also concludes that the presence of all three malaria hotspots for under 5 children in the Badarawa ward may be linked to the socioeconomic characteristics of the residents, the population density and the environmental factors. Finally, for the vulnerability assessment to malaria incidents, this study concludes that most areas in Kaduna North LGA have high vulnerability to malaria.

The study recommends that settlement expansion should be discouraged very close to the drainage systems because proximity to rivers is the dominant factor contributing to malaria prevalence. Adequate preventive measures, such as the distribution of long-lasting insecticide-treated mosquito nets should be adopted to curb malaria prevalence. Lastly, there is a need for adequate awareness of environmental sanitation to discourage the stagnation of water, which provides suitable conditions for mosquito breeding.

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