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SPATIAL DISTRIBUTION OF MALARIA AND LAND COVER PATTERNS IN OGONI LAND, RIVERS STATE, NIGERIA

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Abstract: The distribution of malaria is characterised by microgeographic variations determined by a range of factors, including the local environment. A study on the spatial distribution of malaria and land cover patterns was carried out by sampling Primary Health Centres in Ogoni Land. Nine Primary Healthcare Centres (PHCs) were selected across four local government areas (LGA) using Systematic Grid Point Sampling. Human blood samples were obtained from 318 consented individuals, and questionnaires were administered to obtain demographic data. *Plasmodium* species were identified through microscopy using thick and thin blood films. A geodatabase was created and imported into ArcGIS 10.7 to produce a thematic map of the study area. A cloud-free Landsat-8 Operational Land Imager (OLI) was employed for land cover analysis. Both supervised and unsupervised classifications of land cover were performed to generate the land cover classes. Pearson correlation was carried out to determine the significance between malaria distribution and land cover. Of the 318 individuals, 169 were infected with an overall prevalence of 53.1%.Only *P. falciparum* was identified and malaria distribution showed spatial variations. Across the PHCs sampled, the highest point prevalence was recorded in Model Primary Health Centre Koroma in Tai LGA whereas the lowest was recorded in MPHC Okwale in Khana LGA. Cumulatively, Kwawa PHC recorded the highest malaria prevalence whereas MPHC Bunu in Tai recorded the lowest prevalence. The highest prevalence was recorded in Khana LGA while the lowest was recorded in Eleme LGA. Land cover analysis revealed that Ogoni Land has a total land cover mass of 982.97km.2 Sparse vegetation dominated the study area (471.06km^2) while dense vegetation covers a total mass of 213.1km^2. Bivariate analysis showed a significant correlation between malaria prevalence and dense vegetation ($p<0.05$, 0.952). Dense vegetation played a significant role in malaria transmission in Ogoni Land. The study concludes that the presence of dense vegetation is associated with high malaria prevalence in the study area.

Keywords: *Malaria distribution, land cover, gis, remote sensing, pearson correlation*

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1. Introduction

Malaria is a parasitic disease caused by parasites of the genus *Plasmodium* (Sato, 2021) and is transmitted naturally through the bite of the female *Anopheles* mosquitoes (Bassey and Izah, 2017). In Sub-Sahara Africa, significant deaths occur annually (Bassey and Izah, 2017) due to the disease. Malaria is environmentally driven (Onyiri, 2015) and is one of the most common public health issues across Nigeria (Ayanlade *et al*., 2013). Nigeria is in tropical Africa where the best combination of adequate rainfall, humidity and temperature are characteristic, thereby providing favourable breeding conditions for malaria vectors. Malaria is holo-endemic in rural Nigeria and meso-endemic in urban areas with stable and intense transmission (Nmadu *et al*., 2015).

The distribution of malaria is characterised by microgeographic variations, regularly amongst nearby villages, households, or homes (Coleman *et al*., 2009). The local heterogeneity in malaria distribution is determined by a range of

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factors, including human factors (Ngom and Siegmund, 2015), environmental factors (Abiodun *et al*., 2016) etc. Environmental factors can influence the profusion and continued existence of both the parasites and vectors transmitting them and are therefore said to be responsible for over 70% risk (Ye *et al.,* 2007). Precise malaria and land use data are required to monitor disease risk in a changing environment. Global changes in land cover have been monitored, and data resulting from remote sensing is becoming more accessible. These data have been supplemented with new technologies that allow for the mapping of regions of interest. Since proper vector control necessitates a good understanding of the ecology of breeding, resting habitats and behaviour of the various species of mosquito (Okogun, 2005), the advent of a tool with such functionality and great efficiency is of paramount importance (Pam *et al*., 2017) in malaria studies. A more valuable approach to analysing the distribution patterns of malaria disease is achieved by the application of geospatial technology (Adeola *et al*., 2015).

Mapping malaria for effective control and elimination has become valuable since the recognition and adoption of GIS as a tool (Hay and Snow, 2006). Malaria prevalence and incidence mapping is the most basic application of GIS and has been used to visualise and classify the spatial distribution patterns of malaria over a distinct geographical location (Feng *et al.,* 2018, Weiss *et al*., 2019). Mapping and other geostatistical applications are used to link relationships between the spatial distribution of malaria and other variables like weather and climate (Kakmeni *et al*., 2018; Okunlola and Oyeyemi, 2019), vector breeding sites (Palaniyandi *et al*., 2016; Ndiaye *et al*., 2020) and land use (Ayo *et al*., 2017; Paul *et al*., 2018). This research aimed to evaluate the prevalence and spatial distribution of malaria in Ogoni Land, Rivers State, Nigeria using the GIS tool. The specific objectives are to determine the prevalence of malaria, produce prevalence maps of malaria and evaluate the impact of land cover on malaria prevalence in the study area.

2. Method

2.1 Study Area

Ogoni Land is in Rivers State on the coast of the Gulf of Guinea, east of the city of Port Harcourt. It extends across the local government areas (LGAs) of Khana, Gokana, Eleme and Tai. The map of the study area is shown in Figure 1. The study was conducted in nine primary health care (PHC) centres.

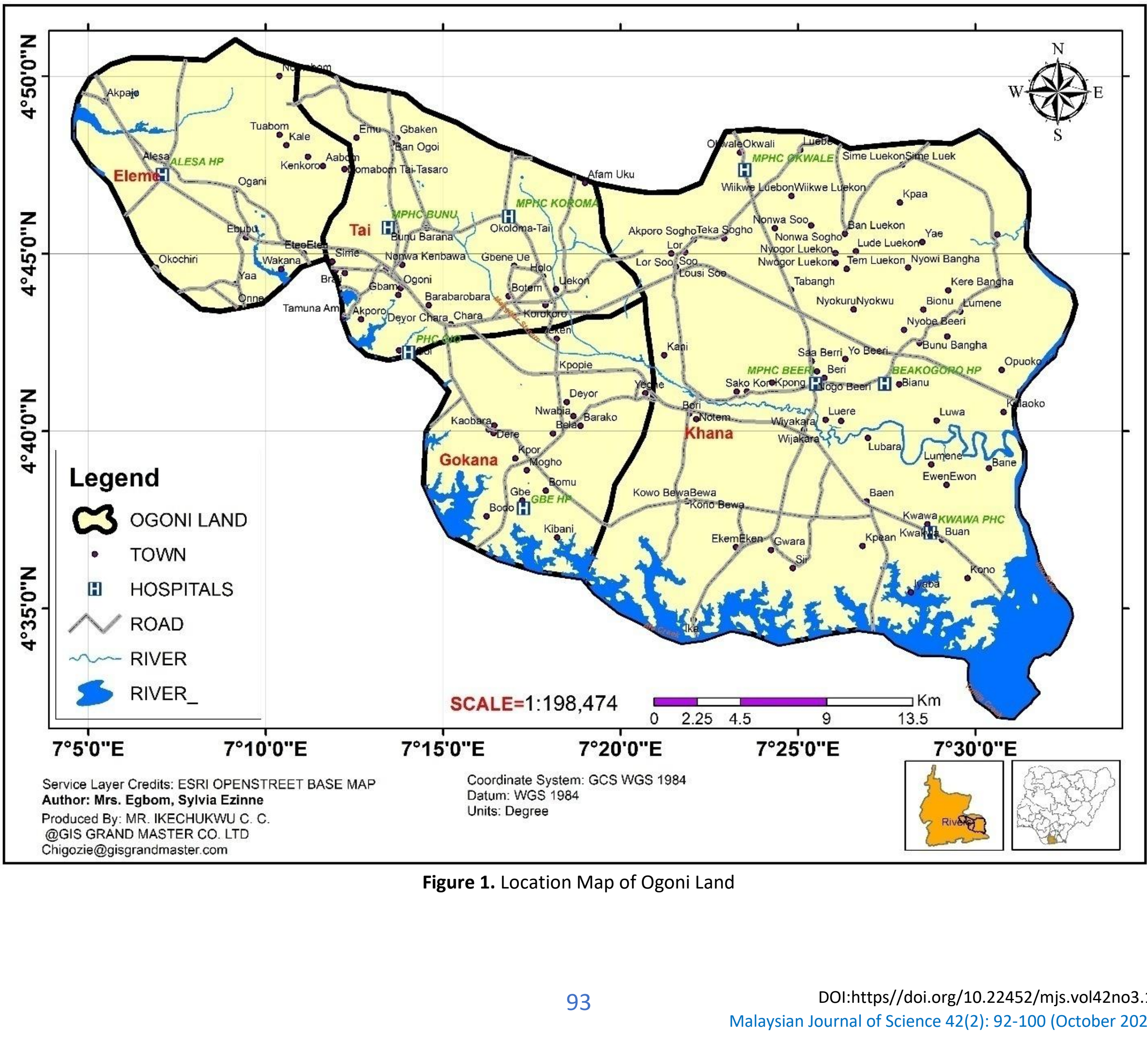

Figure 1. Location Map of Ogoni Land

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Malaysian Journal of Science 42(2): 92-100 (October 2023)

2.2 Research design and data collection

The geographic coordinates of all the PHCs in Ogoni Land were obtained using a handheld Garmin eTrex 30x Global Positioning System (GPS). A cross-sectional hospital-based study was conducted at nine selected PHCs using a systematic grid-point sampling method (Oluwole *et al.,* 2018). Blood samples were obtained through venipuncture from a total of 318 individuals using a stratified random sampling technique. This study involved 318 patients (irrespective of gender or age) seeking medical care in the selected PHCs. Ethical clearance to undertake this research was obtained from the University of Port Harcourt Health Research Ethics Committee (UPH/CEREMAD/REC/MM77/020) and Rivers State Ministry of Health (MH/PRS/391/VOL.2/438). Verbal consent was obtained from the participants and caregivers who enrolled for the study. A cloud-free Landsat-8 Operational Land Imager (OLI) was downloaded from the United States Geological Survey (USGS) Earth Explorer website. Landsat scene downloaded for the study area has path 188 and row 057 World Reference System (WRS).

2.3 Data Analysis

Data collected from the field were cleaned and datasets were developed. All data were entered into Microsoft Excel Version and analysed using IBM SPSS Version 26. Data obtained were presented in tables. Additionally, geographic coordinates and malaria prevalence data were computed into Microsoft Excel 2016 and imported into the GIS database. Spatial queries were performed using Boolean Operation in the ArcGIS environment. The Environmental System Research Institute (ESRI) ArcGIS 10.7 software was used to compute the spatial and aspatial datasets collected from the field to further display, analyse, query and model information from the results generated in the GIS software. Point prevalence and thematic maps of the study area were produced. LandSat_8 (OLI/TIRS) band 6, band 5 and band 2 were used to generate the composite band using an agricultural renderer. The composite band was used to perform unsupervised image classification. The data was further used to delineate training samples for supervised image classification into five (5) classes: waterbodies, bare soil, built-up regions, sparse vegetation and dense vegetation. The extent of these classes was extracted using the Calculate Geometry Attributes tool. The various areas occupied by the 4 LGAs were extracted and exported as an Excel file for correlation analysis. *Pearson correlation was carried out to determine the significance between malaria prevalence and land cover classes.*

3. Results

3.1 Prevalence of malaria at the various Primary Health Care facilities

Out of the 318 individuals examined, 169 (51.3%) were infected (Table 1). The highest prevalence (75%) was recorded at Model Primary Healthcare Centre Koroma in Tai LGA, followed by Kwawa PHC (62%) and Beakogoro HP (59.09%). MPHC Okwale recorded the lowest prevalence of 39.54%. However, no significant statistical relationship was found between malaria and facilities (p>0.05).

Table 1. Prevalence of malaria at the various PHCs

LGA	PHC	No examined	No infected (%)	Point Prevalence (%)	Overall prevalence (%)
Khana	Kwawa PHC	50	31	62	9.748
Khana	MPHC Beeri	39	17	43.59	5.346
Khana	Beakogoro HP	44	26	59.09	8.176
Khana	MPHC Okwale	43	17	39.54	5.346
Gokana	Gbe HP	40	22	55	6.918
Eleme	Alesa HP	23	12	52.17	3.774
Tai	MPHC Bunu	21	10	47.62	3.145
Tai	MPHC Koroma	16	12	75	3.774
Tai	PHC Gio	42	22	52.38	6.918
	Total	318	169		

($\varkappa^2$= 10.228; P=0.249)

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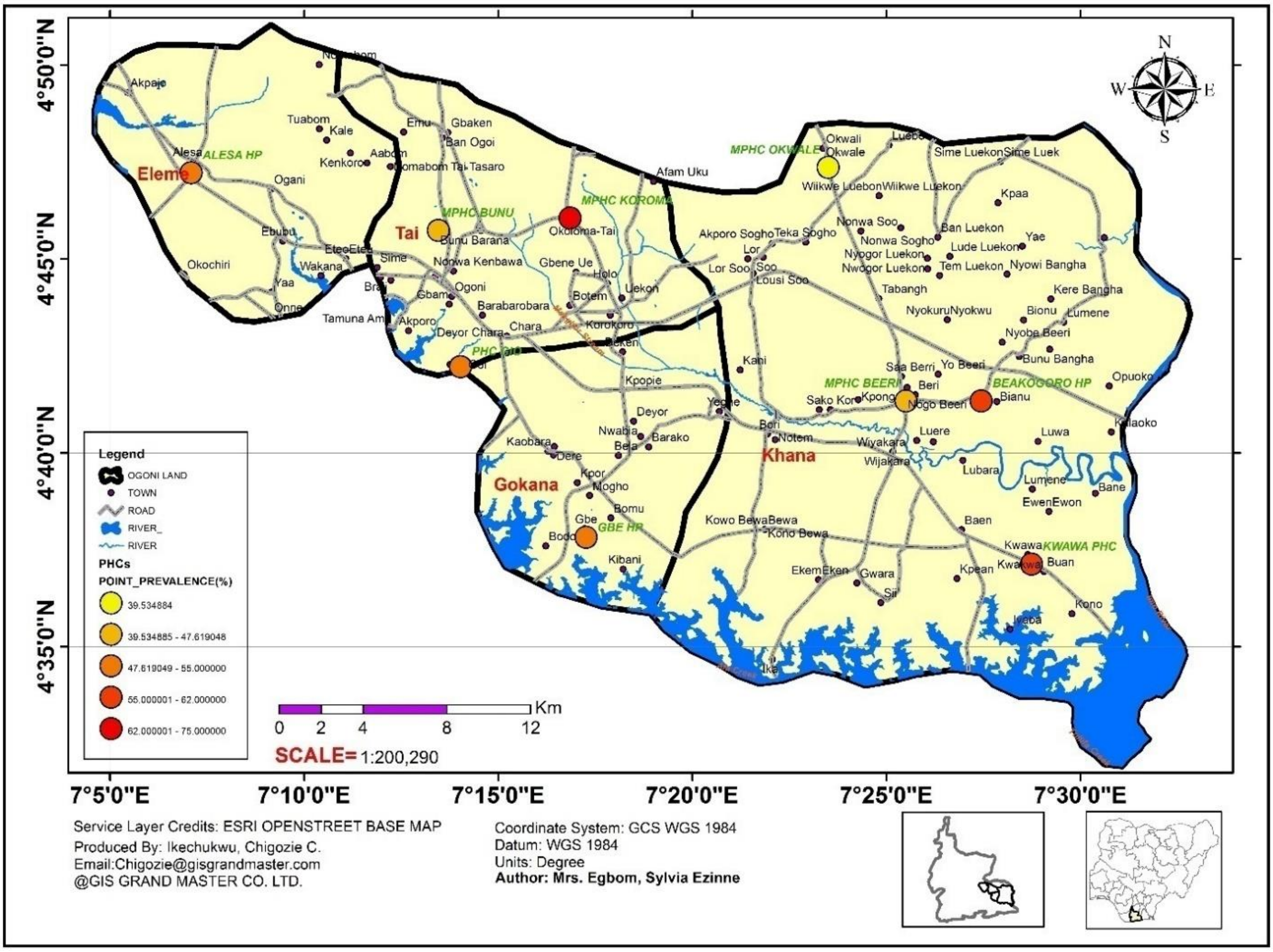

Figure 2. Point prevalence map of malaria in the study area

3.2 Prevalence of Malaria across the LGAs

Table 2 presents the prevalence of malaria across the LGAs in Ogoni Land during the study period. Khana LGA recorded the highest overall prevalence of 28.6% while Eleme LGA recorded the lowest prevalence of 3.8%. No significant statistical relationship was found between malaria and LGA (p>0.05).

Table 2. Prevalence of malaria across the LGAs in Ogoni land

LGA	No examined(%)	No infected	Overall prevalence (%)
Khana	176(55.3)	91	28.6
Gokana	40(12.6)	22	6.9
Eleme	23(7.2)	12	3.8
Tai	79(24.8)	44	13.8
Total	318	169	53.1

$\varkappa 2 = 0.417$; P=0.937

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Malaysian Journal of Science 42(2): 92-100 (October 2023)

The prevalence map of malaria distribution in Ogoni Land during the study is shown in Figure 3.

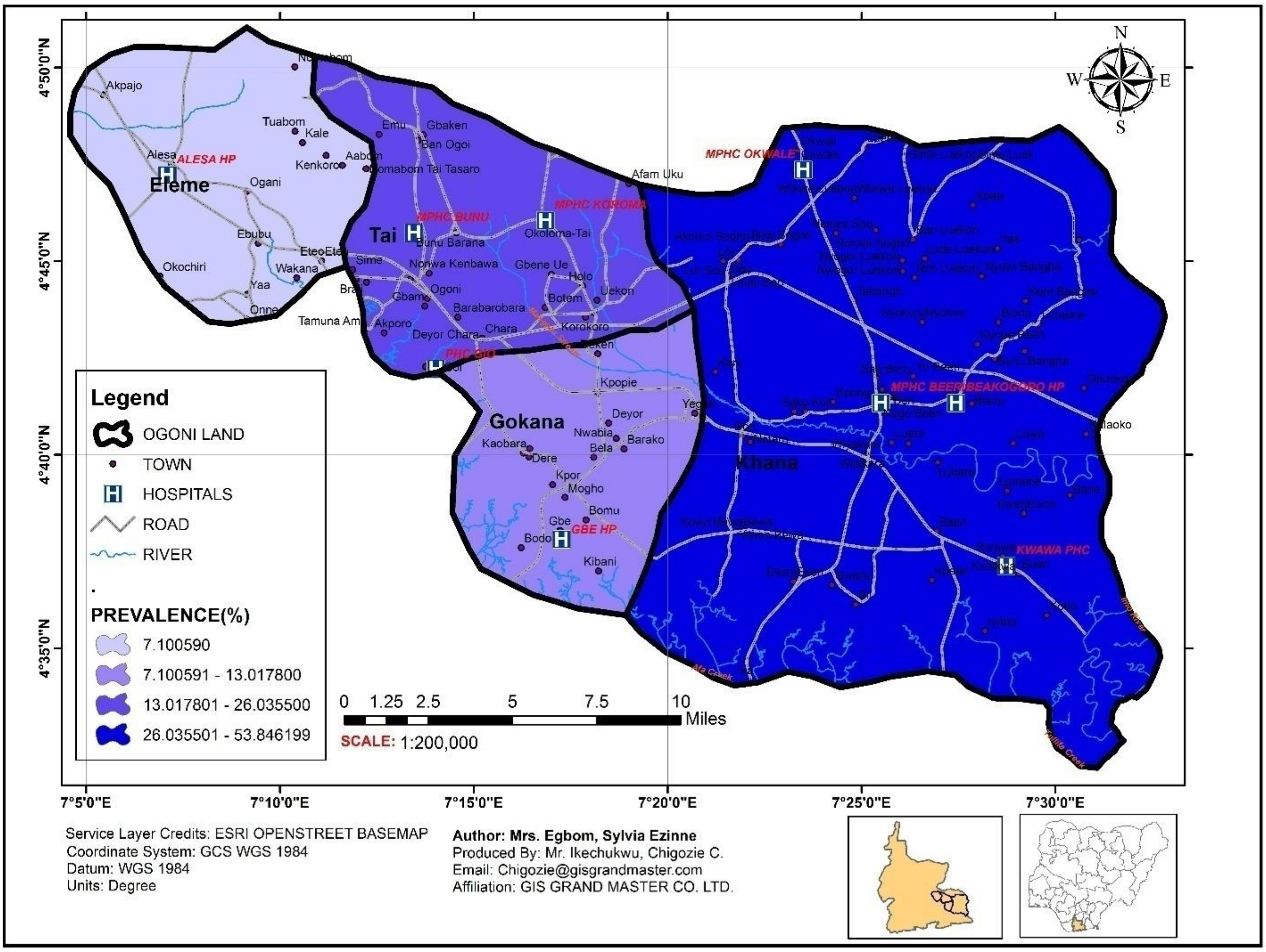

Figure 3. Map of malaria prevalence in Ogoni Land during the study

3.3 Land Cover Analysis of Ogoni Land

Table 3 illustrates the land cover analysis of the study area and Figure 4 shows the land cover map. Land cover analysis revealed that the area of Ogoni Land is 982.97km^2, which is composed of waterbodies, bare soil, sparse vegetation, dense vegetation and built-up regions with an area of 33.18km^2, 208.27km^2, 471.06km^2, 213.1km^2 and 57.33km^2 respectively. The sparse vegetation dominates the study area with 471.06km^2, followed by dense vegetation with 213.1km^2. Khana LGA covers the largest area of 560.36km^2, whereas Gokana LGA covers the least with125.94km^2. The impact of land cover on malaria prevalence during the study period was assessed using correlation analysis. Dense vegetation demonstrated a highly positive significant correlation with malaria ($p=0.048$, $R^2=0.952$). Meanwhile, sparse vegetation showed an insignificant positive correlation with malaria ($p=0.154$, $R^2=0.846$).

Table 3. Land cover analysis of Ogoniland

LGA	Waterbody (km^2)	Bare soil (km^2)	Sparse vegetation (km^2)	Dense vegetation (km^2)	Built up regions (km^2)	Total (km^2)
Khana	22.04	56.59	303.34	168.97	9.40	560.36
Gokana	8.48	45.74	44.85	18.35	8.51	125.94
Eleme	1.75	9.94	89.23	4.10	33.06	138.08
Tai	0.91	96.00	33.64	21.68	6.36	158.59
Total	33.18	208.27	471.06	213.1	57.33	982.97

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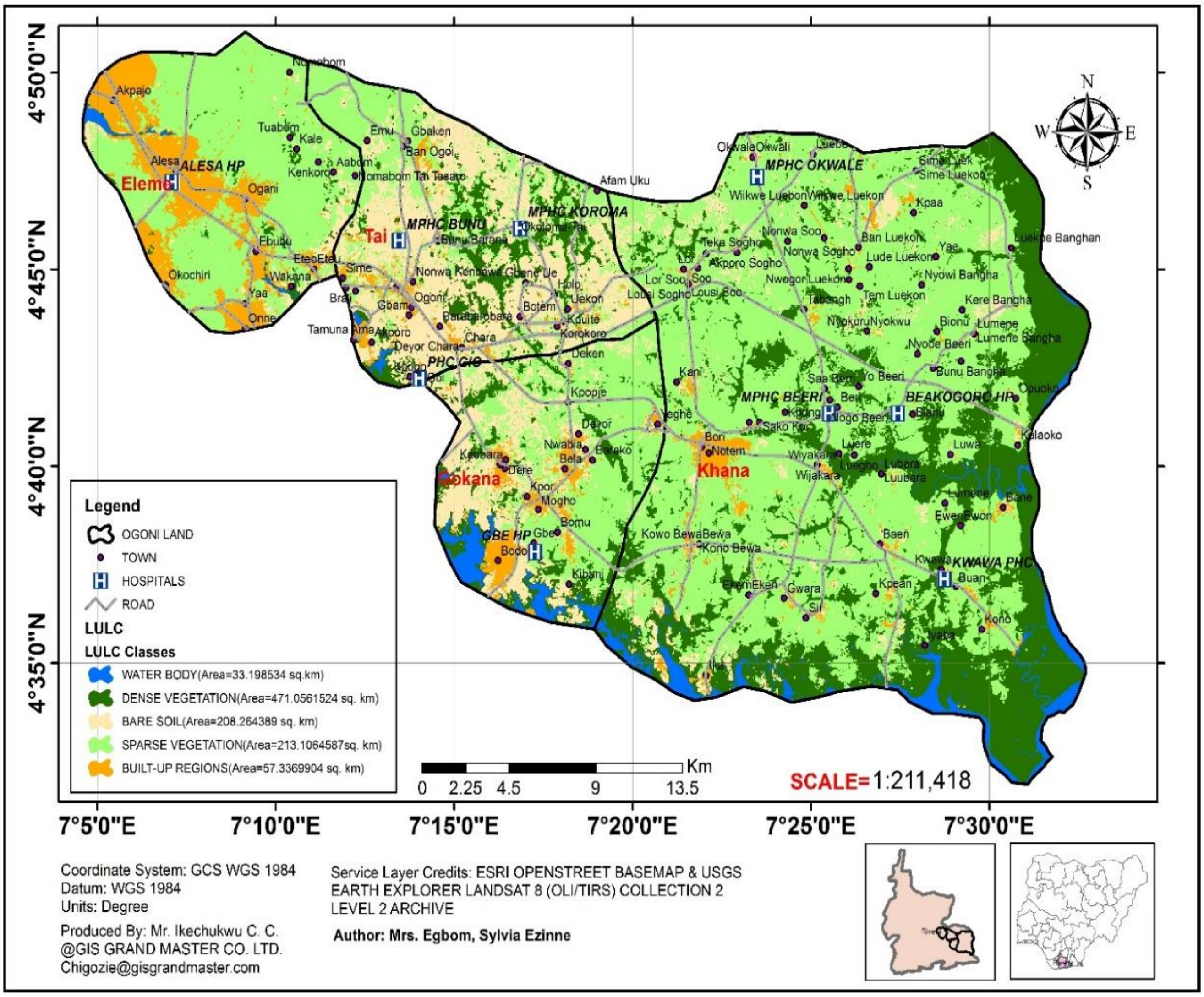

Figure 4. Land cover map of Ogoni Land

4. Discussion

An overall malaria prevalence of 51.3% was reported in the study area. This finding agrees with the numbers reported in Rivers State by Egbom and Nzeako (2017), Egbom *et al*. (2021) and Egbom *et al*. (2022), which were 52.5%, 57.4% and 56.3%, respectively. Additionally, the number was higher than that of previous reports in other parts of the State. Wogu and Nduka (2016) and Wogu *et al.* (2017) recorded a prevalence of 32% and 43.1%, respectively in Port Harcourt. However, the observed prevalence in different study areas in the State was lower than the numbers reported by Wokem *et al.* (2017) and Augustine-D'Israel and Abah (2018), which were 87% and 78%, respectively. The lower malaria prevalence obtained in this research when compared with the higher prevalence reported by Wokem *et al*. (2017) and Augustine- D'Israel and Abah (2018) could be ascribed to the increased level of awareness about malaria and its intervention strategies among the population. However, the prevalence is still high.

P. falciparum was the only species of malaria parasite recorded in this study. This finding agrees with the reports from Abah *et al*. (2017), Wogu and Onosakponome (2021), Egbom *et al*. (2021) and Egbom *et al*. (2022) who observed only *P. falciparum*. In contrast, Nzeako *et al.* (2013) reported the presence of *Plasmodium vivax* along with *P.falciparum*. The authors argued that the presence of *P. vivax* in the Delta region could be due to the presence of non-African people since the region is a hub for the petroleum industry that attracts many expatriates.

The study demonstrated spatial variations in the geographic distribution of malaria in Ogoni Land. Remote sensing of the environment in Ogoni Land used in this study provides valuable information for explaining the geographic variations of malaria. The highest prevalence was recorded in Khana LGA which has the largest area of dense vegetation. Bivariate analysis revealed that

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Malaysian Journal of Science 42(2): 92-100 (October 2023)

the disease patterns showed a positive correlation with dense vegetation, which may accountfor the observed spatial variations.

It can be concluded that spatial variation in malaria prevalence observed in the study is influenced by varying land cover classes, with a high prevalence linked with the presence of dense vegetation. The findings in this study agree with the previous reports by Adlaoui *et al.* (2011), Machault *et al*. (2012), Kabaria *et al*. (2016), Olalubi *et al*. (2020) and Awosolu *et al*. (2021) who reported a positive relationship between malaria prevalence and vegetation. However, the findings contradict the previous findings by Paul *et al*. (2018), who found no statistically significant correlation between malaria and land use patterns. The findings also disagree with Kigozi *et al.,* (2016) who reported a negative relationship between vegetation and malaria prevalence. Additionally, studies done by Adimi *et al.* (2010), Zinszer *et al*. (2012) and Ricotta *et al.* (2014) have associated vegetation with malaria incidence.

Mosquito survival and foraging are key elements in the general epidemiology of malaria (Ricotta *et al.* 2014). Vegetation provides outdoor resting locations for malaria vectors (Bassene *et al*., 2020). Plant sugars also provide sufficient energy for male mosquitoes to efficiently fertilize females thus guaranteeing species perpetuity (Stone *et al*., 2009). Research has shown that some plants provide mosquitoes with readily available meals thereby increasing their life span and decreasing contact with humans (Nikbakhtzadeh *et al.*, 2014). Therefore, vegetation plays a prominent role in the survival of mosquito vectors in their innate environment.

5. Conclusion

This study has provided prevalence statistics and spatial distribution maps of malaria in the study area. The findings confirm that malaria remains a public health burden in the study area. The observed malaria distribution patterns in this study are influenced by land cover classes with a significant positive correlation between dense vegetation and malaria prevalence. The hybrid of GIS and remote sensing has established a link between malaria and land cover, thereby explaining the observed spatial distribution patterns. These findings will aid in the deployment of appropriate malaria interventions to places most in need and in the development of an environmental management approach for malaria control to address the menace at local scales.

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