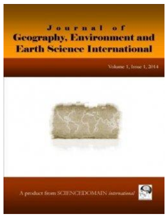

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Modelling Social Vulnerability to Malaria Risk in Katsina-Ala Local Government Area, Benue State Nigeria

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Authors' contributions

This work was carried out in collaboration between both authors. Author HTW conceived the topic and collected data from the field. Together with author BUM they designed the research outline, carried out analysis and wrote the manuscript. Both authors reviewed literature, read and consented to the final manuscript.

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ABSTRACT

Every society has certain groups of people who are more susceptible to risk due to lack of capacity to prevent it, which makes them vulnerable. Malaria is one of such infectious diseases that imposes a substantial burden on vulnerable populations. The objectives of this study is to map and analyze spatial pattern of sub-domains of social vulnerability to malaria risk in Katsina-Ala Local Government Area (LGA) of Benue State Nigeria, model and analyze areas of social vulnerability based on the sub-domains. Based on the review of related literature, a holistic risk and vulnerability framework was adopted to guide the assessment of social vulnerability to malaria risk in the study area. Stratified systematic non-aligned sampling technique was used to collect data on social vulnerability to malaria risk from three hundred and ten (310) households using structured questionnaire and GPS device. Empirical Bayesian Kriging model tool of Geostatistical analyst and Zonal statistical extension tools of ArcGis 10.2 were used for the model. Results revealed a heterogeneous spatial pattern of social vulnerability to malaria across the entire study area, Lack of capacity to anticipate

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malaria has highest influence with mean value of 0.70 on a scale of 0 to 1; social vulnerability to malaria risk in the study area is high with mean value of 2.51 on a scale of 1 to 4. The study recommends a holistic approach that focuses on the vulnerable group and a paradigm shift in attacking the anopheles mosquito that causes the disease and increasing the capacity of the victims to withstand malaria risk.

Keywords: Malaria risk; social vulnerability; GIS; Katsina-Ala LGA.

1. INTRODUCTION

In recent years efforts have been made to eradicate malaria at national, regional, continental and international levels. In spite of these efforts, Malaria remains a threat to humanity. According to estimates, there were 214 million new cases of malaria worldwide in 2015 [1]. The African Region accounted for most global cases of malaria (88%), followed by the South-East Asia Region (10%) and the Eastern Mediterranean Region (2%). In 2015, there were an estimated 438,000 malaria deaths worldwide. According to WHO [1] most of these deaths occurred in the African Region (90%), followed by the South-East Asia Region (7%) and the Eastern Mediterranean Region (2%). Children under the age of five are particularly susceptible to malaria illness, infection, and death. In 2015, malaria killed an estimated 306,000 under-fives globally, including 292,000 children in the African Region [1].

The Concept of Vulnerability is well-documented in the fields of disaster risk reduction and adaptation to climate change [2]. According UNISDR [3], vulnerability to natural hazards refers to the conditions determined by physical, socio-economic, and environmental factors that increase the susceptibility of a community to hazards. The European-funded research project MOVE (Methods for the Improvement of Vulnerability Assessment in Europe) identified key factors and dimensions that need to be addressed in line with the integrative approach towards vulnerability assessments [2]. The recognition of social vulnerability as key factor that influences the distribution of illness and health condition of communities have been intensifying in recent times. [4] asserts that social and cultural factors significantly influence the distribution of health and illness; he also added that issues of inequity affect how disease incidences are distributed and treated.

Although the application of GIS techniques in the fight against malaria has gradually gained prominence in recent years, little emphasis has been directed towards the development of quantitative methods for assessment of social vulnerability to malaria risk in a spatially explicit method that considers the socioeconomic and demographic factors that determine the vulnerability of potentially exposed populations. While few studies have been carried out to model social vulnerability to risk of malaria in some African Countries such as the works of [5] and [6] little or no attempt was made to replicate similar studies in Nigeria despite the prevalence of the disease and a large vulnerable population. Integrating data on social vulnerability to malaria risk into a Spatial Decision Support System (SDSS) through an integrative approach that takes into account socioeconomic and demographic factors that influence social vulnerability to malaria risk using GIS technique can allow decision makers make informed and timely decisions aimed at effectively reducing the risk of malaria infection on vulnerable population.

2. MATERIALS AND METHODS

2.1 The Study Area

Katsina-Ala Local Government is located in the North-Eastern part of Benue State and shares boundaries with Taraba State in the North-East, Ukum Local Government in the North, Logo in the North-West, Buruku in the West, Ushongo in the South and Kwande in the South-East. According to the 2006 national census the area has a population of 224,718 (NPC, [7] 2009). The local government geographically lies between latitude 7° 5′ 0″ and 7° 30′ 0″ north of the equator and longitudes 9° 15′ 0″ and 9° 55′ 0″ east of Greenwich Meridian Line. Politically the local government comprises of twelve (12) Council Wards (Fig. 1).

The study area falls within the Koppen's Aw (wet and dry) climatic region. The wet and dry seasons commences following the northward passage or southward retreat of the inter-tropical convergence zone (ITCZ) over the area in late March and October respectively. Temperatures are mostly high throughout the year with average diurnal range of 23°C – 28°C with the peak of 38°C. The area lies between the transition zone of the rain forest and savannah vegetation, while the northern portion consists of typical grassland savannah vegetation, with undulating hills and shrubs, the south-east is of semi-deciduous forest vegetation. The area has an elevation of 95 to 753 meters above mean sea level. It is drained by a lake, many streams and rivers; prominent among them are River Yooyo, Loko and the Katsina-Ala which is the largest (Fig. 1). The inhabitants are predominantly farmers who rely heavily on road transportation system to transport their produce to the markets. During the wet season some parts of the local government are inaccessible due to inadequate road network.

2.2 Data Sources

Both primary and secondary data were used for the study. Primary data was sourced from 310 structured questionnaires administered to randomly selected heads of house-holds, interviews and GPS readings in the field. While, secondary data was obtained from published materials and public records.

2.3 Methods

In line with the integrative assessment of social vulnerability to malaria, this study has adopted the holistic risk and vulnerability framework developed by [8] in the context of vulnerability to vector borne diseases. Fig. 2 shows the adopted and applied framework and the domains of social vulnerability to malaria and relevant indicators which considers the key elements of social vulnerability, susceptibility, and lack of resilience [5,6]. In line with the framework outlined in this study, susceptibility to malaria is determined by an individual's lack of ability to resist malaria infection. Susceptibility can be classified as generic susceptibility or biological susceptibility. Generic susceptibility refers to factors leading to the predisposition of an individual to be affected by malaria. These factors include inaccessibility or poor access to transportation, as well as poverty. Biological susceptibility refers to the effectiveness with which an infective

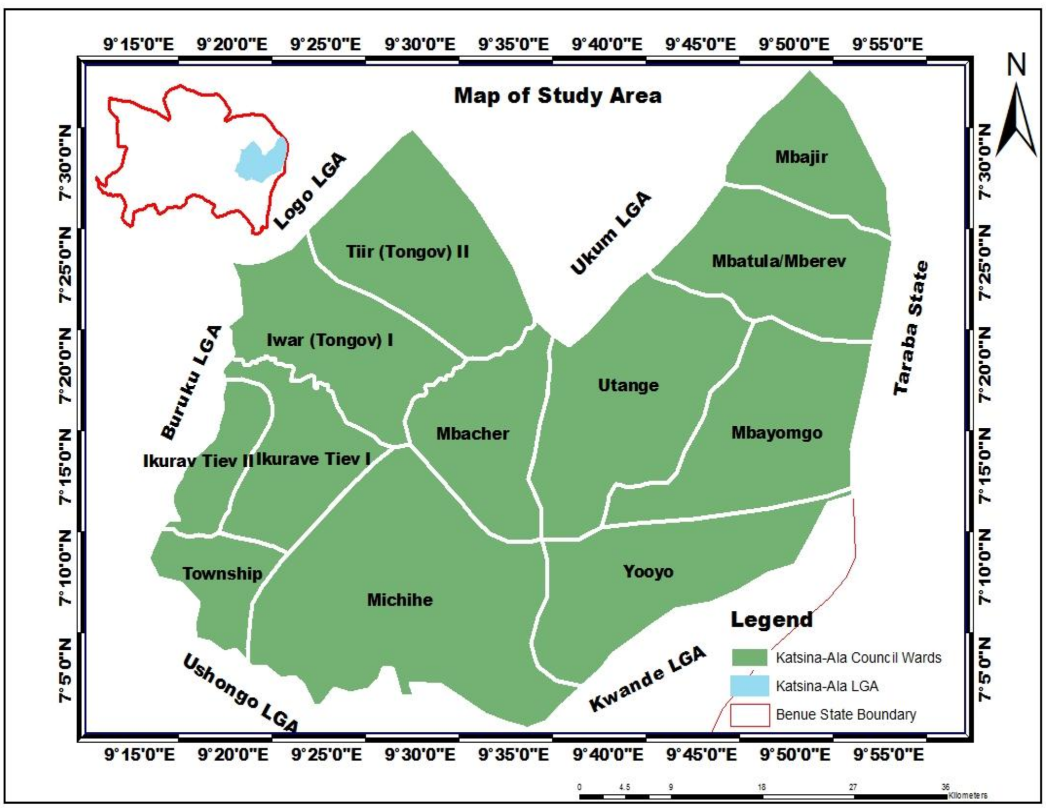

Fig. 1. The study area showing Ward Districts. At the top left is a map (inset) of Benue State showing the study area shaded in grey

Table 1. Sub-domains of social vulnerability indicators

Domain	Indicators	Source
Generic susceptibility (SUS)	✓ Travel time to closest urban center ✓ Distance to roads ✓ Number of people living on less than 2 USD per day	[8]
Biological susceptibility (BIO)	✓ Number of children under the age of 5 ✓ Number of women of childbearing age	[8]
Capacity to anticipate (C2A)	✓ No of children Under 5 sleeping under net ✓ No of pregnant women sleeping under net ✓ Level of Education ✓ No indoor residual spraying	[8]
Capacity to cope (C2C)	✓ Distance to closest hospital ✓ Number of dependents	[8]

Source: [8]

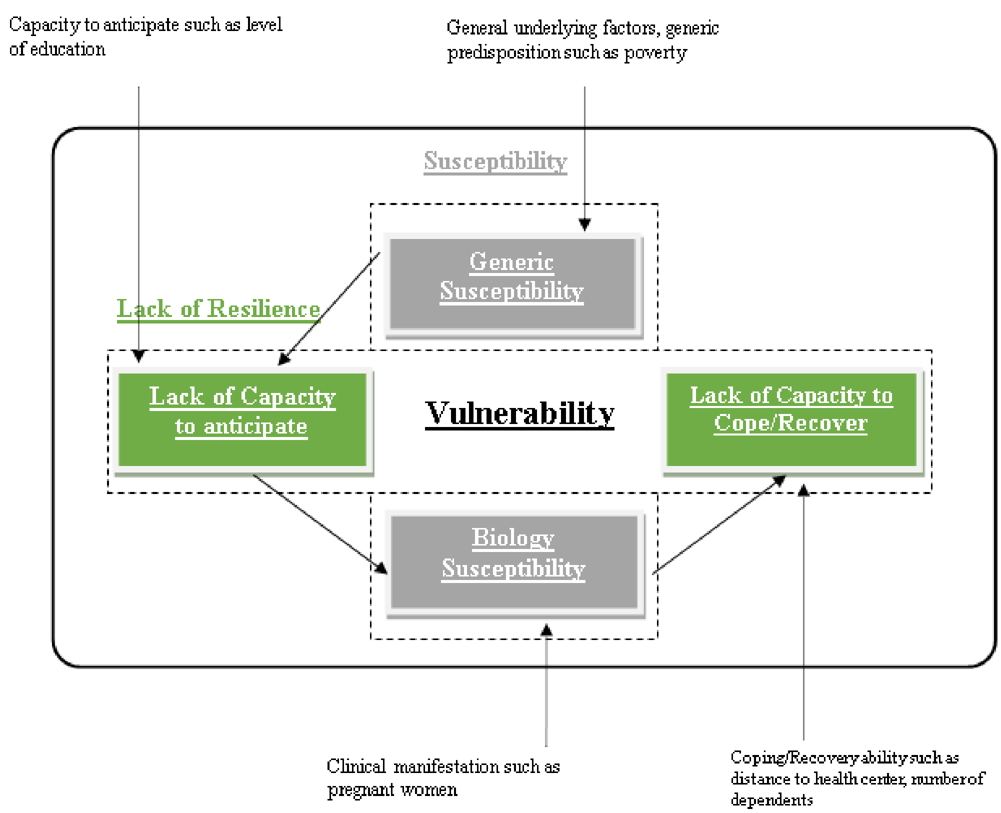

Fig. 2. Linkages between the domains of social vulnerability

mosquito infects humans which is largely a function of immunity, which depends on age, pregnancy, or co-infection with other diseases [9].

On the other hand, lack of resilience refers to the lack of capacity by societies and population groups to respond to and absorb negative impacts of malaria infection, as a result of the lack of capacity to anticipate, respond to and recover from a malaria episode [10]. The resilience of a community is determined by its capacity to anticipate the exposure to mosquito bites, which may be influenced by education, knowledge about malaria transmission, prevention, protection measures, and housing conditions [11]. A resilient community is able to cope with malaria episodes using local opportunities to cope with or recover from malaria infection. This coping and recovery capacity relates to access to health care facilities, and the ability to access appropriate, and timely medical treatment.

Both spatial and non-spatial dataset types were used in this study. Spatial dataset include Spot 5 satellite image of the study area and a geo-political map of the study area, which were used to extract the desired spatial dataset for analysis. Non-spatial data include Primary data collected through field survey at household level using a structured questionnaire that captures Social Vulnerability Indicators. ESRI ArcGis 10.2 and Microsoft Excel Software were used for geo-processing and data analysis. Stratified Systematic Non-Aligned Sampling technique was employed in selecting a sample of 310 households from a study population of 1030 household. Stratified Systematic Non-Aligned Sampling technique was used because it is one of the techniques used in spatial technology when a satellite image is available for sampling.

The technique uses a grid system to provide even distribution of randomly placed observations using a remotely sensed image [12]. In this paper, the study area was divided in to grids of 5 km by 5 km using Spot5 satellite image and a digitized topographic map of the study area.

In each household a structured questionnaire was administered to the head of the household. The head of household in this context is a decision maker of the household, in the absence of the head of household, any adult from 18 years of age deemed fit by the members of the household was administered a copy of the questionnaire and collected at spot alongside with the coordinates of the household using a Global Positioning System (GPS) with the assistance of a research assistants. The questionnaire was structured to capture information pertaining socioeconomic and demographic status of the household e.g. family size, number of women within childbearing age, number of children under the age of 5, number of pregnant women, Income level, use of Insecticide, Treated Mosquito Net, level of education etc (Table 2).

Empirical Bayesian Kriging model was used to generate the surface depicting social vulnerability to malaria risk in Katsina-Ala Local Government Area of Benue State. Empirical Bayesian kriging (EBK) is adopted for the study because it is a geostatistical interpolation method that automates the most difficult aspects of building a valid kriging model [13]. Data analysis on spatial variation in malaria risk base on social vulnerability was carried out using Microsoft Excel.

The questionnaire was structured to capture four broad factors based on the concept of vulnerability and computed as shown in Table 1 and Fig. 2: Hence the indicators captured data in different quantity, the data was standardized to make it ready for input in the model, and quartile system was used for the standardization as can be seen in Table 2.

This values were integrated into GIS and a model was developed using ESRI ArcGIS 10.2 Model builder, subsequently, used to process the data and produce social vulnerability domain maps of Katsina-Ala Local Government Area for geo-visualization as well as tabular data for geostatistical analysis.

2.4 Mathematical Preprocessing

Step I: At any given household, its social vulnerability to malaria risk is determined by its Social Vulnerability Index (SVI) value which is the sum total of its domains.

Therefore:

Step II: Vulnerability domains are determined by mean value of social vulnerability indicators or variables as follows:

Such that:

$$SVDs = \frac{variable1 + variable2 + VariableN}{number\ of\ variables} \quad (1)$$

$$SVI = SUS + BIO + C2A + C2C. \quad (2)$$

SVI = Social Vulnerability Index
SUS = Generic Susceptibility,
C2A = Capacity to Anticipate
BIO = Biological Susceptibility,
C2C = Capacity to Cope
SVDs = Set of social vulnerability domains (SUS, BIO, C2A, C2C)
Variable = factors that determine vulnerability to malaria risk
Domain = list of variable that determine social vulnerability to malaria risk

From the two equations above, values of each domain is between 0 and 1 and the sum of domain is between 1 and 4, These values were integrated into GIS database to produce Social Vulnerability Index (SVI) and the final output will be a range of values between 1 to 4 for Social Vulnerability Index (SVI) and between 0 and 1 for each vulnerability domain as shown in Table 3.

The basic spatial analysis employed in this work was done using ArcGIS 10.2. Proximity analysis using Buffering operation at specific intervals to determine the distance to Primary healthcare centres, road network and urban centres. Vulnerability surface modelling was carried out using the Geostatistical Analyst extension tool. Empirical Bayesian Kriging was used to model vulnerability source. Classification and reclassification operation was performed to classify the risk into four classes. Zonal Statistics tool was used to extract mean values for further analysis.

Table 2. Scale of measurement for social vulnerability indicators

Social vulnerability		Risk level			
Domain	**Indicators**	**Low**	**Moderate**	**High**	**V. High**
SUS	Travel distance to closest urban center	<=5km	<=10km	<20km	>20km
	Distance to roads	<=5km	<=10km	<20km	>20km
	Number of people living on less than 2 USD per day	>20$	<=20$	<=5$	<2$
(C2A)	No of children Under 5 not sleeping under net %	>=75	>=50	>=25	<25
	No of pregnant women not sleeping under net %	>=75	>=50	>=25	<25
	Level of Education	Tertiary	Secondary	Primary	None
	No. of indoor residual insecticide spraying	Daily	Weekly	irregular	None
(BIO)	Number of children under the age of 5	<=1	<=4	<=8	>8
	Number of women of childbearing age	<=1	2	<=4	>4
(C2C)	Distance to closest hospital	<=5km	<=10km	<20km	>20km
	Number of dependents	1:1	1:5	1:10	>1:10

Source: Adopted and Modified from [6] and [8]

Table 3. Standardized table for social vulnerability indicators

Social vulnerability		Risk level			
Domain	**Indicators**	**Low**	**Moderate**	**High**	**V. High**
(SUS)	Number of women	0.25	0.50	0.75	1
	Travel time to closest urban center	0.25	0.50	0.75	1
	Distance to roads	0.25	0.50	0.75	1
	Number of people living on less than 2 USD per day	0.25	0.50	0.75	1
(C2A)	No of children Under 5 not sleepinging under net %	0.25	0.50	0.75	1
	No of pregnant women not sleeping under net %	0.25	0.50	0.75	1
	Level of Education	0.25	0.50	0.75	1
	No. of indoor residual spraying	0.25	0.50	0.75	1
(BIO)	Number of children under the age of 5	0.25	0.50	0.75	1
	Number of women of childbearing age	0.25	0.50	0.75	1
(C2C)	Distance to closest hospital	0.25	0.50	0.75	1
	Number of dependents	0.25	0.50	0.75	1

Source: Adopted and Modified from [6]

3. RESULTS AND DISCUSSION

In this study, data collected as indicators were scaled, measured and weighted. These indicators were grouped into four domains, Generic susceptibility, Biological susceptibility, Lack of capacity to anticipate and lack of capacity to cope (Fig. 3). A weighted approach and quartile system was used to standardize and scale the indicators into four sub-domains and the final social vulnerability index. For each of the four sub-domains, vulnerability was classified thus: 0.25 Low, Moderate 0.50, high 0.75 and 1.00 very high such that the sum of the four domains will have a minimum value of 1 and maximum value of 4.

Thus the final social vulnerability was classified as 0 to 1.25 Low, 1.26 - 2 Moderate, 2-3 High, 3 – 4 Very high. This data was integrated and processed using GIS Techniques. From Fig. 4, Districts with Very high Generic Susceptibility to malaria risk are displayed in shades of red, High in shades of Yellow, Moderate in shades of light green, Low in share of Dark Green.

Findings revealed that based on the sub domains (Fig. 3) Generic Susceptibility to malaria risk is Very high in three (3) Districts, High in two (2) Districts, Moderate in Six (6) Districts and Low in one (1) District; Biological Susceptibility to malaria risk is Very high in three Districts, High in two (2) Districts Moderate in four (4) Districts and Low in three (3) Districts; Lack of Capacity to cope and recover from malaria risk is Very high in three, High in five (5) Districts; Moderate in three (3) Districts and Low in two (2) Districts; Lack of Capacity to Anticipate and prevent malaria risk is Very high in two (2) Districts, High in five (5) Districts, Moderate in three (3) Districts and Low in one District.

Social Vulnerability to malaria risk based on sub-domain is also very high in 25% of the districts, High in 50%, Moderate 16.67% of the districts and Low in 8.33% of the districts. This implies that about 75% of the districts of Katsina - Ala Local Government Area are at high vulnerability to the risk of malaria.

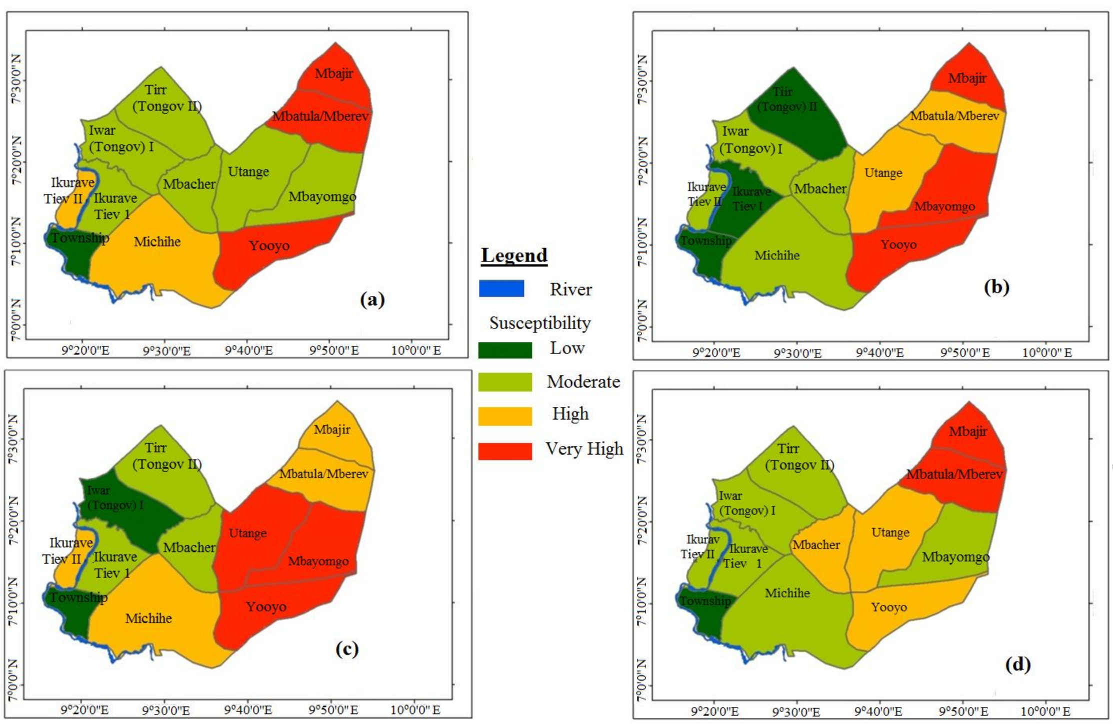

Fig. 3. Susceptibility to Malaria based on individual domains (a) Generic Susceptibility to malaria (b) Biological Susceptibility to malaria (c) Lack of capacity to cope with malaria (d) Lack of capacity to anticipate malaria in Katsina-Ala LGA

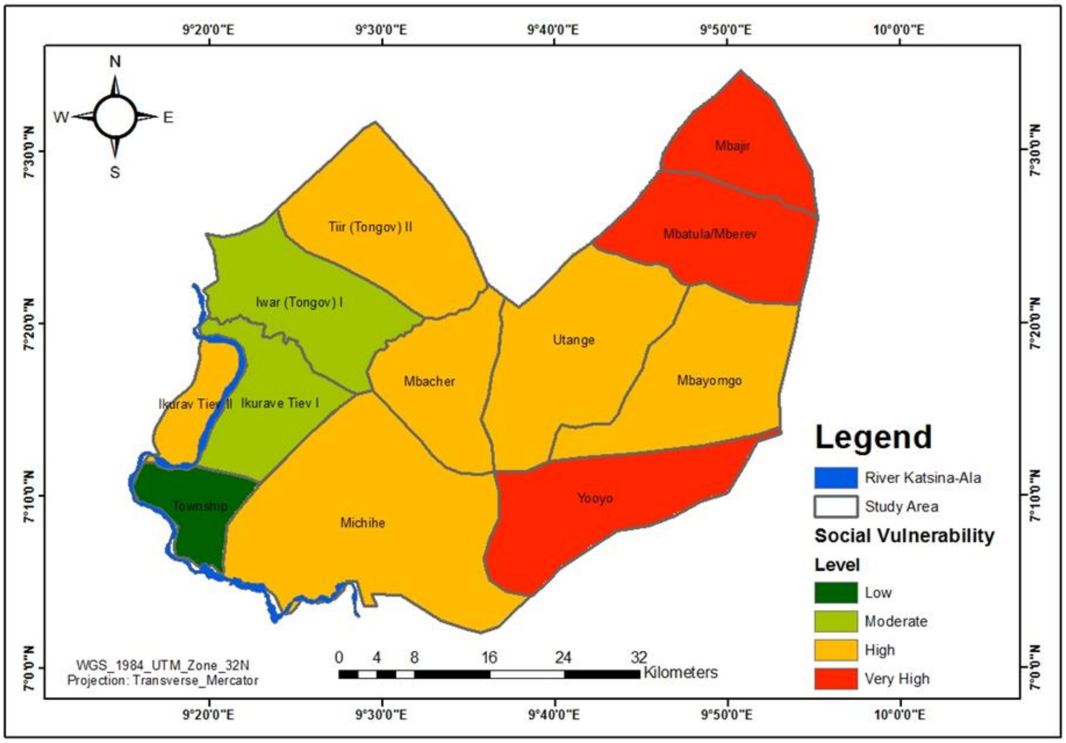

Fig. 4. Social vulnerability index

Table 4. Mean values of sub-domains of social vulnerability to malaria risk in the 11 wards in Katsina-Ala LGA

S/N	Name	SUS	BIO	C2C	C2A	SVI
1	Mbajir	0.83	0.86	0.74	1.00	3.43
2	Mbatula/Mberev	0.69	0.75	0.68	1.00	3.11
4	Mbacher	0.58	0.63	0.46	0.70	2.36
5	Michihe	0.66	0.61	0.64	0.67	2.58
6	Township	0.27	0.28	0.30	0.31	1.16
7	IkuraveTiev I	0.46	0.53	0.35	0.62	1.96
8	Tiir (Tongov) II	0.50	0.52	0.46	0.61	2.08
9	Iwar (Tongov) I	0.55	0.54	0.31	0.56	1.96
10	IkuravTiev II	0.65	0.63	0.51	0.65	2.43
11	Mbayoungo	0.54	0.79	0.86	0.66	2.85
12	Utange	0.55	0.71	0.88	0.83	2.97
	Mean values	0.59	0.64	0.58	0.70	2.51

Furthermore, the overall mean value of Social Vulnerability Index (SVI) is 2.51 on a scale of 1 to 4 indicates that inhabitants vulnerability to malaria risk in Katsina - Ala Local Government Area is high and the spatial pattern of Social Vulnerability to Malaria Risk in the area is heterogeneous implying that different factors account for vulnerability of the population at individual council wards. The results are similar to the findings by [6] and [8] in East Africa. Their findings suggest regional variations in the magnitude of subdomains.

The incorporation of spatially explicit sub-domains in social vulnerability assessments aids decision makers in identifying factors influencing social vulnerability to malaria in specific areas. This holistic approach of social vulnerability assessment can serve as a veritable tool for decision makers in targeting mitigation and adaptation efforts in areas where social vulnerability is highest, and in focusing on factors that most impact vulnerability.

4. CONCLUSION

This study applied spatially explicit modelling approach for modeling, visualizing and assessing relative levels of prevailing social vulnerability to malaria in districts of Katsina-Ala local government of Benue State. It is drawn on published works and it attempts to simplify the complex information from multisource indicators of vulnerability to malaria risk into a format that is relevant for decision-making. A holistic risk and vulnerability framework was developed and used as a pragmatic guidance tool for the identification and development of a sound indicator framework, therefore enabling transferability of results.

The results of this study provide relevant information for policymakers in identifying place-specific interventions that will reduce people's susceptibility to the disease and help to strengthen their resilience. The study shows the most vulnerable districts to sub-domains of social indicators in terms of susceptibility to malaria and lack of resilience to anticipate, to cope with or to recover from malaria risk. The decomposition of vulnerability into its sub-domains which also serve as pointers to the underlying factors that determine social vulnerability, an indication of which factors need to be addressed in each district. The developed composite indicator framework supports the prioritization of appropriate interventions in the affected district in accordance with the risk classification.

Findings from this study therefore reveals that: first priority should be given to Mbajir, Mbatyula/Mberev, Yooyo, Districts found to be at very high risk level, second priority should be given to Utange, Mbayoungo Michihe, Macher, IkuravTiev II Tir (Tongov) II, Districts found to have high risk, third priority should be given to Ikurave-Tiev I, Iwar (Tongov) I with moderate risk and the forth priority should be giving Township District found to be at low risk.

CONSENT

All respondents involved in interviews and the administration of questionnaire were duly informed and their consent was sort.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

REFERENCES

1. World Health Organization Report, Fact Sheet: World Malaria Report; 2015. Available:www.who.int/gho/publications/world_health_statistics/2015/en (Accessed 29/2/2016)
2. Birkmann J, Cardona OD, Carreño ML, Barbat AH, Pelling M, Schneiderbauer S, Welle T. Framing vulnerability, risk and societal responses: The MOVE framework. Natural Hazards. 2013;67(2):193-211.
3. UNISDR Terminology on Disaster Risk Reduction. Geneva, Switzerland: United Nations International Strategy for Disaster Reduction; 2009.
4. Heggenhougen HK. More than just “interesting!”: Anthropology, health and human rights. Social Science and Medicine. 2000;50(9):1171-1175.
5. Hagenlocher M, Castro MC. Mapping malaria risk and vulnerability in the United Republic of Tanzania: A spatial explicit model. Population Health Metrics. 2015; 13(1):1.
6. Bizimana JP, Kienberger S, Hagenlocher M. Modelling homogeneous regions of social vulnerability to malaria in Rwanda. Geospatial Health. 2016;11(1):129-146.
7. National Population Commission - NPC Official Gazette Federal Government Printers, Abuja, Nigeria. 2009;96(2).
8. Kienberger S, Hagenlocher M. Spatial-explicit modeling of social vulnerability to malaria in East Africa. International Journal of Health Geographics. 2014;13(1):1.
9. Bates I, Fenton C, Gruber J, Lalloo D, Lara AM, Squire SB, Tolhurst R. Vulnerability to malaria, tuberculosis, and HIV/AIDS infection and disease. Part II: Determinants operating at environmental and institutional level. The Lancet Infectious Diseases. 2004;4(6):368-375.
10. Hagenlocher M, Delmelle E, Casas I, Kienberger S. Assessing socioeconomic vulnerability to dengue fever in Cali, Colombia: Statistical vs expert-based modeling. International Journal of Health Geographics. 2013;12(1).

11. Ricci F. Social implications of malaria and their relationships with poverty. Mediterranean Journal of Hematology and Infectious Diseases. 2012;4(1).
12. Congalton RG, Green K. Assessing the accuracy of remotely sensed data: Principles and practices. Lewis Publishers, Boca Raton; 1999.
13. Berke O. Exploratory disease mapping: Kriging the spatial risk function from regional count data. International Journal of Health Geographics. 2004;3(1):1.

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