Mapping Malaria Risk in the New Juaben Municipality of Ghana Using GIS and Remote Sensing Techniques*

[1]B. Kumi-Boateng, [1]B. Kofi and [2]N. Mireku-Gyimah
[1]University of Mines and Technology, P. O. Box 237, Tarkwa, Ghana
[2]Dansoman Polyclinic, P. O, Box 849, Accra, Ghana

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Abstract

Malaria is a life-threatening parasitic disease which is caused by the bites of an infected female *Anopheles* mosquito and is an issue of grave public health concern. The control of malaria requires effective surveillance systems that will enable efficient malaria response in endemic regions to prevent outbreaks of the disease and to track progress. The objective of this study was to identify mosquito prone areas and develop a malaria risk map for New Juaben Municipality (NJMA) in the Eastern Region of Ghana. Geographic Information System (GIS), Satellite Remote Sensing (SRS) and Analytical Hierarchy Process (AHP) were integrated to develop the malaria risk map which would help in the identification of potential habitats for mosquitoes based on environmental factors that make a place suitable for mosquito breeding. The environmental factors considered were: vegetation, land surface temperature, distance to streams, elevation, slope and topographic wetness index. Mosquito prone areas within the study area were identified and classified into four classes (Very Low, Low, High and Very High) of which the most dominant class was "Low" (56.46 %). A malaria risk map for the study area was then developed and classified into five classes (Very Low, Low, Moderate, High, Very High) of which the most dominant class was "Moderate" (30.17 %). The "High", "Very High" and "Moderate" areas, together, constitute 56.07 % which is significant. Any efficient malaria response in NJMA should be focused in these areas. This work could be replicated in all the municipalities and districts in Ghana to help prevent outbreak and track the progress of malaria.

Keywords: Malaria, GIS, Remote Sensing, Analytical Hierarchy Process, Weighted Overlay

1 Introduction

Malaria, caused by Plasmodium parasites, is a blood-borne disease which is transmitted through the bite of an infected female Anopheles mosquito. It is a major public health issue which affects the global population at large (Kumi-Boateng *et al*., 2015; Ahmed, 2014). Malaria is typically found in warmer regions of the world, *i.e*., the tropical and subtropical countries. Vectors (female *Anopheles* mosquitoes) require specific habitats with surface water for production, humidity for adult mosquito survival and the development rate of both vector and parasite are dependent on temperature (Ahmed, 2014; Ashenafi, 2013). Although the incidences of malaria both globally and within the African Region were noted to have diminished by 21% between 2010 and 2015, and mortality rates also by 29% and 31% globally and within the African Region respectively, malaria continues to be a major cause of illness and death (Anon, 2016a). The disease was responsible for a reported mortality of 429 000 deaths in 2015, 92% of which occurred in the African Region. According to the World Health Organisation (WHO) in 2016, about 3.2 billion people (almost half of the world's population) were at risk of malaria (Anon, 2016a). Sub-Saharan Africa carries an extremely high proportion of the global malaria burden.

Malaria is one of the leading causes of morbidity in Ghana and the primary cause of mortality, accounting for over three million outpatient visits to public health facilities annually. It occurs all year round and affects a large proportion of the population. Children under five years are particularly susceptible to malaria with the disease claiming the life of one child every two minutes in the African Region. Also, pregnant women, people with immunosuppression, and travelers have been noted to have higher susceptibility of acquiring more severe forms of malaria and thus require protection from contracting the disease in 2009 reported cases attributed to malaria among children less than 5 years were 48.9 % and 11.5 % among pregnant women (Anon, 2017b).

According to WHO (2015) countries including Ghana, which have the highest malaria burden tend to have the weakest surveillance systems. Strengthening of the malaria surveillance system is imperative for the enhancement of the effectiveness of health strategies and interventions as well as their evaluations towards the reduction of the morbidity and mortality associated with malaria.

For malaria to be controlled and eventually eliminated, effective malaria surveillance systems are urgently needed to:

(i) enable efficient malaria response in endemic regions;
(ii) prevent outbreaks and resurgence, to track progress and;

(iii) hold government and the global malaria community accountable for their contribution towards the fight against malaria (Anon, 2016a; Anon, 2016b).

This study was conducted in New Juaben Municipality (NJMA), one of the 21 districts in the Eastern Region of Ghana. Within the New Juaben Municipality, malaria is the major cause of Out Patient Department (OPD) attendance in all health facilities. Statistics indicate that malaria accounts for over 47% of causes of OPD attendance increasing from 38 149 in year 2000 to 68 864 in 2005 (Anon, 2012). Geographic Information System (GIS), satellite remote sensing, spatial multi criteria decision analysis, geospatial techniques and spatial statistics have provided methodologies and solutions to analyse the epidemiological and ecological context of malaria and other infectious diseases (Saxena *et al.*, 2009; Wimberly *et al.*, 2012; Ahmed, 2014; Kumi-Boateng *et al.*, 2015; Kasera, 2016). However, certain environmental factors that can assist in identifying potential habitats for mosquito have not been integrated to map malaria risk especially in Ghana.

The objectives of this study were to use GIS, Remote Sensing and AHP to identify mosquito prone areas and develop a malaria risk map for NJMA that considers and integrate the various potential environmental factors

2 Resources and Methods Used

2.1 Materials

Landsat 8 Operational Land Imager (OLI) and Advanced Spaceborne Thermal and Reflection Radiometer (ASTER) images obtained from the United States Geological Survey (USGS); Environmental System and Research Institute (ESRI) shapefiles of NJMA obtained from the GIS and Remote Sensing Lab of the University of Mines and Technology (UMaT), Tarkwa; and the positions of public health facilities within the study area obtained from the municipal health directorate of NJMA were used for this study.

2.2 Methods

The methods used for this study are grouped into five phases as shown in Fig. 1. The first phase is the collection of data. The second phase is the development of environmental factors that support mosquito breeding. The elements at risk were determined during the third phase. The degree at which the elements at risk are vulnerable was determined in the fourth phase. Finally, a malaria risk map was developed during the fifth phase

2.2.1 Phase 1

The first phase of the study was the collection and processing of the data needed for the identification of mosquito prone areas and the eventual development of a malaria risk map for the study area.

Landsat 8 Operational Land Imager (OLI) images were downloaded and processed to remove the effects of the atmosphere on the reflectance values of the image using ENVI 5.2 from Exelis Visual Information Solutions. The processing was done by doing radiometric corrections to calibrate the image to a radiance image. The radiance image was then atmospherically corrected, resulting in a surface reflectance image. The reflectance image was then used to extract quantitative information about features on the image. The formula for converting digital numbers to radiance and reflectance are shown in Equations 1 and 2.

$$L\lambda = M_L Q_{CAL} + A_L \tag{1}$$

where:
L_λ = Spectral Radiance
ML= Radiance Mult Band x
Q_{CAL} = Digital Numbers
AL = Radiance Mult Band x
X = Band Number

$$\rho\lambda = M\rho Q_{CAL} + A\rho \tag{2}$$

where:
ρλ = Reflectance
Mρ = Reflectance Mult Band X
Q_{CAL}= Digital Numbers
Aρ = Reflectance Add Band X
X = Band Number

The extract by mask tool in the ArcMap spatial analyst tool box was used to extract the study area from the entire image using NJMA shapefile as the mask to narrow the work to only the study area.

2.2.2 Phase 2

The second phase of the study was the development of environmental factors that create enabling grounds for the breeding of mosquitoes. The factors considered were: elevation, vegetation, Land Surface Temperature (LST), slope, distance from stream and topographic wetness index.

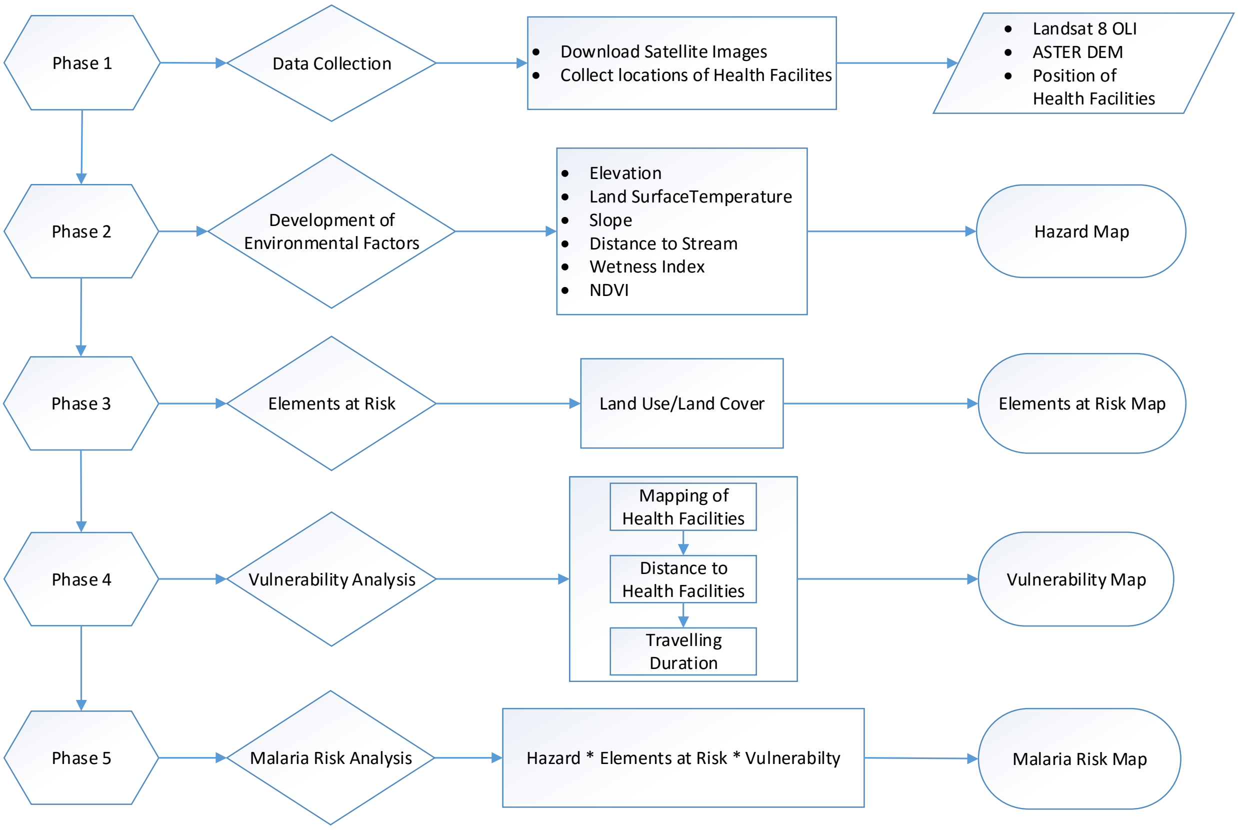

Fig. 1 Flowchart Showing a Summary of the Methods Used

Elevation

There is a proven relation between elevation and mosquito abundance (Kumi-Boateng *et al*., 2015). Due to lower temperatures at higher elevations, it becomes unfavourable for mosquitoes to breed at higher elevations since mosquitoes prefer to live at places with relatively high temperatures. Also, since it is very airy at higher altitudes, it is almost impossible for mosquitoes to fly, hence, not favourable for mosquitoes to live at higher altitudes (Denke *et al.,* 1996). Research has shown that, for small areas, large scale differences in malaria risk is defined by the topography since climate variables change very little over the limited range of elevation (Saxena *et al.,* 2009; Chikodzi, 2013; Ahmed, 2014, Adeola *et al.,* 2015). The elevation of the study area was obtained from the ASTER GDEM. Using the hydrology tool in the arc toolbox, sinks were filled and the resulting raster was then standardised using fuzzy membership function tool to obtain values ranging from 0 to 1. The fuzzified raster was then reclassified into 5 classes with class 1 indicating the highest elevation and class 5 indicating the lowest elevation. Fig. 2 and Fig. 3 are maps showing the elevation factor and the reclassified elevation factor respectively.

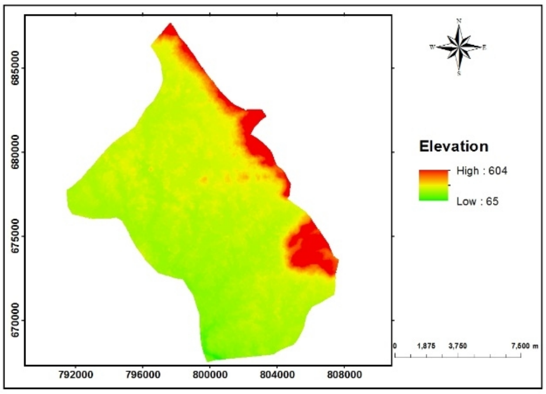

Fig. 2 Elevation Factor

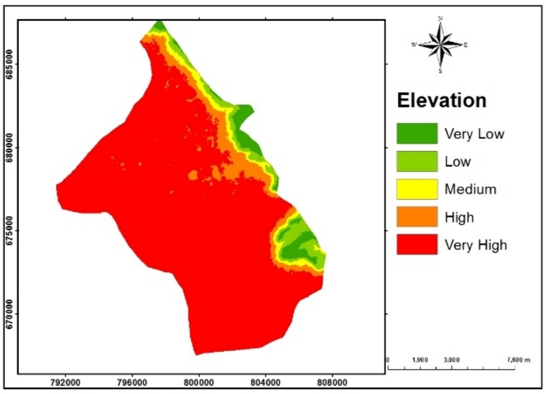

Fig. 3 Elevation Factor Reclassified

Normalised Difference Vegetation Index (NDVI)

Mosquitoes feed on the nectar of plants therefore there is a very high possibility of mosquitoes being found in vegetated areas. The presence of vegetation creates microclimatic conditions (moderate temperature and humidity) suitable for mosquito survival (Yazoume *et al*., 2008). The more the vegetation, the more the mosquitoes (Texier *et al*., 2013). Normalised Difference Vegetation Index (NDVI) was obtained from Landsat 8 images downloaded. NDVI is given by:

$$\text{NDVI} = \left(\frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}}\right) \quad (3)$$

where:

NIR = Near Infrared Band (Band 5)

Red = Red Band (Band 4)

The results generated values between -1 and +1. Higher NDVI values indicate healthy vegetation and lower NDVI values indicate unhealthy vegetation. The resulting raster was then standardised using fuzzy membership function tool to obtain values ranging from 0 to 1. The fuzzified raster was then reclassified into 5 classes with class 1 indicating the least vegetated areas and class 5 indicating most vegetated areas. Fig. 4 and Fig. 5 are maps showing the NDVI and the reclassified NDVI respectively.

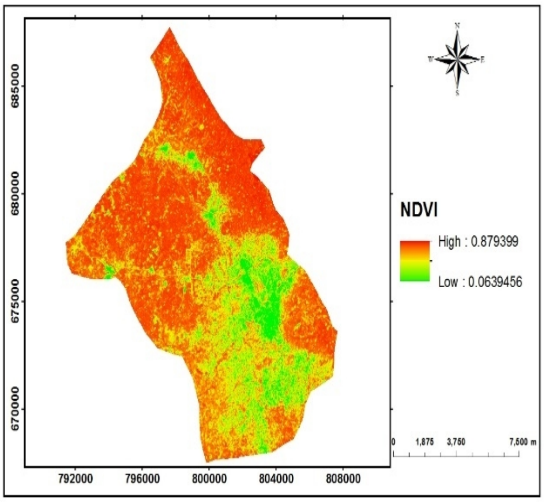

Fig. 4 Vegetation Factor

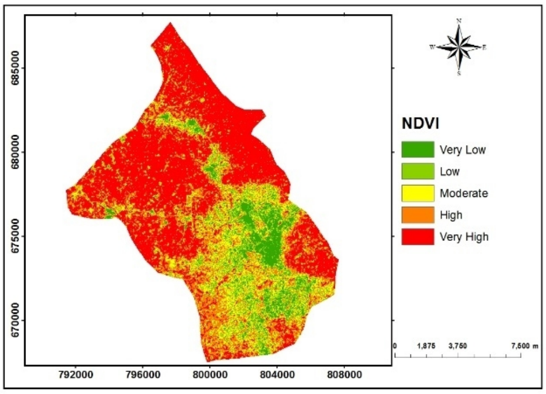

Fig. 5 Vegetation Factor Reclassified

Land Surface Temperature (LST)

Temperature is one of the key climatic variables that determine the range of malaria transmission and hence global warming is likely to result in an increase in malaria prone areas (Chirebvu *et al*., 2014). In high temperatures, the egg, larval and pupil stages of mosquito development will be shortened thereby increasing the turnover which then affects the length of the saprogenic cycle of the parasite within the mosquito host *i.e*. when temperature increase, the period of the saprogenic cycle will be shorted (Ahmed, 2014). Low temperatures have a limiting effect on the spread of malaria (Kumi-Boateng *et al.,* 2015). Usually, at temperatures below 18°C, transmission of malaria is highly unlikely to occur since the few adult mosquitoes, about 0.28 %, survive the 58 days required for sporogony at that temperature and mosquito abundance is limited by long larval duration (Chikodzi, 2013). Temperatures between 22°C and 32°C are the best to complete sporogony in less than three weeks and mosquito survival is sufficiently high (15 %) for the transmission cycle to be completed. Temperatures higher than 32 °C have been reported to cause high vector population turnover, but also cause high mortality. Thermal death for mosquitoes occurs around 41-42 °C (Kumi-Boateng *et al*., 2015; Chikodzi, 2013). LST was estimated using the thermal infrared bands (Band 10 and Band 11) from the Landsat 8 image and the calculated NDVI. The thermal infrared bands were converted from digital numbers to radiance using the formula:

$$L_\lambda = M_L Q_{CAL} + A_L \quad (4)$$

where:

L_λ = Spectral Radiance

ML= Radiance Mult Band x

Q_{CAL} = Digital Numbers

AL = Radiance Mult Band x

X = Band Number

The Radiance values were then converted to at-satellite brightness temperature using the formula:

$$T = \frac{K2}{\ln\left(\frac{K1}{L\lambda} + 1\right)} - 273.15 \qquad (5)$$

where:
T = At-satellite brightness temperature (K)
L_λ= Spectral Radiance
K_1= K1_constant_band_x, where x is the band number
K_2= K2_constant_band_x, where x is the band number

Using the radiance and at-satellite brightness temperature values obtained, LST was calculated using the formula:

$$LST = \frac{T}{1 + w \times \left(\frac{T}{p}\right) \times \ln(e)} \qquad (6)$$

where:
LST = Land surface temperature

T = At-satellite brightness temperature (K)

w = wavelength of emitted radiance

$p = h \times {}^{c}/_{s}$ (1.438 * 10-34Js)

h = Planck's constant (6.626 * 10-34 Js)

c = Velocity of light (2.998 * 108 m/s)

s = Boltzmann constant (1.38 * 10-23 J/K)

e = emissivity (0.004Pv+ 0.986)

Pv = Proportion of vegetation, calculated as,

$$Pv = \left(\left(NDVI - NDVI_{min}\right) \div \left(NDVI_{max} - NDVI_{min}\right)\right)^2$$

The average LST values obtained using band 10 and band 11 were calculated using the cell statistics tool from the spatial analyst toolbox. The resulting raster was then standardised using fuzzy membership function tool to obtain values ranging from 0 to 1. The fuzzified raster was then reclassified into 5 classes with class 1 indicating the lowest temperature and class 5 indicating the highest temperature. Fig. 6 and Fig. 7 are maps showing the LST and reclassified LST respectively.

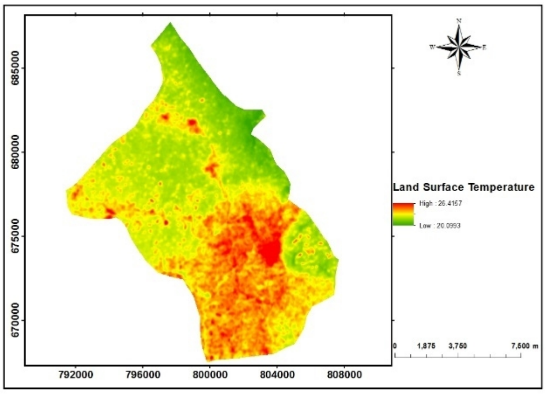

Fig. 6 Land Surface Temperature

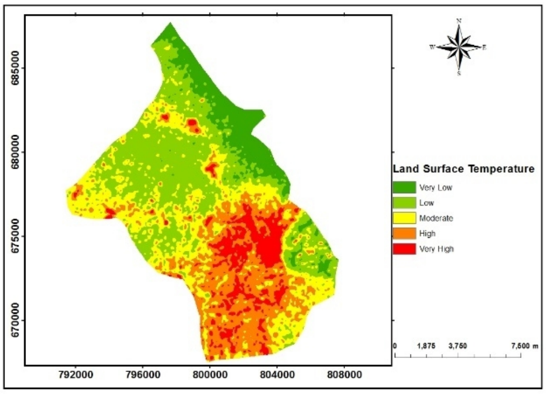

Fig. 7 Land Surface Temperature Factor Reclassified

Slope

Slope is a topographic parameter associated with the mosquito larval habitat formation since it affects the stability of an aquatic habitat. Where the slope is high the water is likely to wash the eggs away thereby preventing them from developing whereas if the slope is gentle the eggs can stay and go through all the maturity stages required. The spread of malaria could also be influenced by the slope of an area coupled with the amount of rainfall it receives. Flat areas are highly prone to accumulation of rain water and therefore increase the risk of malaria (Chikodzi, 2013; Ahmed, 2014; Kumi-Boateng *et al.*, 2015). The slope of the study area was obtained from the processed ASTER GDEM image. This was done using the slope tool from the spatial analyst tool box which identifies the slope (gradient or rate of maximum change in z-value) from each cell of a raster surface. The resulting raster was then standardised using fuzzy membership function tool to obtain values ranging from 0 to 1. The fuzzified raster was then reclassified into 5 classes with class 1 indicating the steepest slope and class 5 indicating the gentlest slope. Fig. 8 and Fig 9 are maps showing the slope factor and the reclassified slope factor.

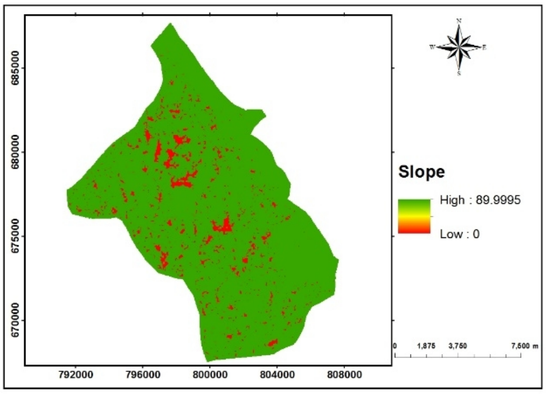

Fig. 8 Slope Factor

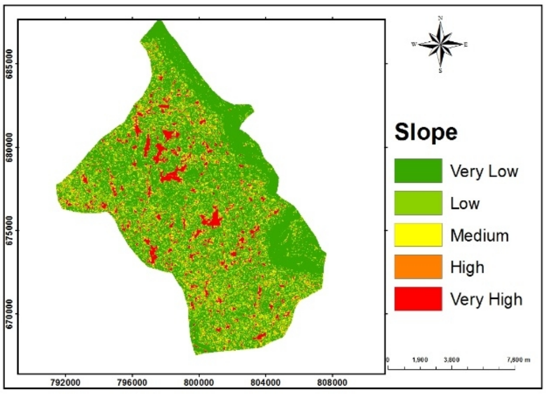

Fig. 9 Slope Factor Reclassified

Distance from stream

The occurrence and distribution of malaria to a large extent can be affected by the distribution of water bodies such as rivers and streams. Water bodies would serve as breeding grounds for the larvae of mosquitoes; this therefore makes the identification of water bodies a direct determinant for malaria risk zones (Ahmed, 2014; Kumi-Boateng *et al.*, 2015). Stream network was generated from the processed ASTER GDEM image. From the hydrology toolbox, flow direction was calculated using the flow direction tool. The resulting raster was then used to calculate the flow accumulation using the flow accumulation tool. The stream network was then simulated by using the map algebra tool to reclassify the flow accumulation raster into two classes, less than 7 000 and greater than 7 000. The stream order tool in the hydrology toolbox was used to assign numeric order to the segments of the resulting raster representing branches of a linear network (stream channels). Euclidean distance tool from the spatial analyst tool box was used to calculate the euclidean distance to the closest stream within the study area. The resulting raster was then standardised using fuzzy membership function tool to obtain values ranging from 0 to 1. The fuzzified raster was then reclassified into 5 classes with class 1 being the farthest away from the stream and class 5 being the closest to the stream. Fig. 10 and 11 are maps showing the distance to stream factor and reclassified distance to stream factor respectively.

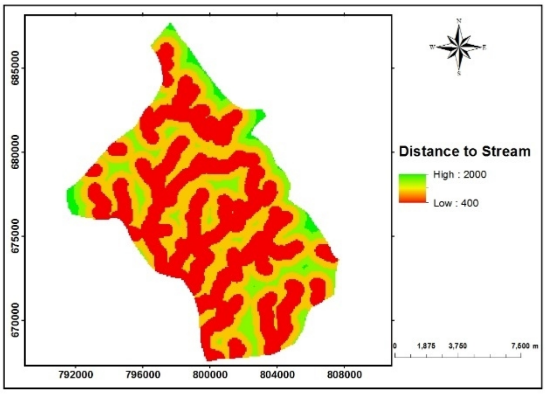

Fig. 10 Distance to Stream Factor

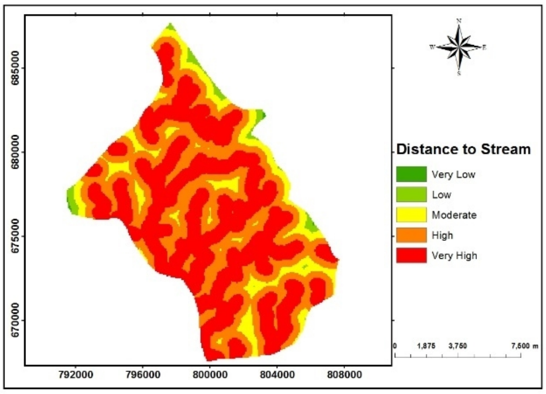

Fig. 11 Distance to Stream Reclassified

Topographic Wetness Index (TWI)

Topographic wetness index is a steady state wetness index. It is commonly used to quantify topographic control on hydrological processes (Sorensen *et al.*, 2006). The index is a function of both the slope and the upstream contributing area per unit width orthogonal to the flow direction (Moore *et al.*,1993). Wetness index can affect the availability of mosquito in an area. The wetness index factor contributes to malaria hazard. As the wetness of the land increases, the water holding capacity of the land increases and this would create a breeding site for the mosquito (Cohen *et al.*, 2008). TWI was calculated from the flow accumulation raster and slope raster using the formula:

$$TWI = \mathrm{Ln}\left(\frac{((\mathrm{FLOWACC}*30)+1)}{\tan((("\mathrm{SLOPE}")3.141593/180))}\right) \qquad (7)$$

where:

TWI = Topographic Metness Index

FLOWACC = Flow Accumulation

SLOPE = Slope

The resulting raster was then standardised using fuzzy membership function tool to obtain values ranging from 0 to 1. The fuzzified raster was then reclassified into 5 classes with class 1 representing the areas with the lowest TWI values and class 5 representing the areas with high TWI values. Fig 12 and Fig. 13 are maps showing TWI and the reclassified TWI respectively.

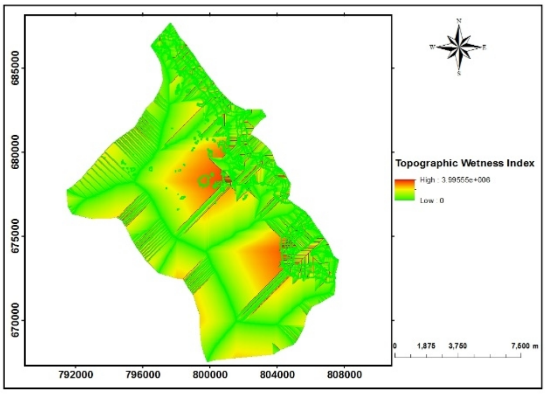

Fig. 12 Topographic Wetness Index Factor

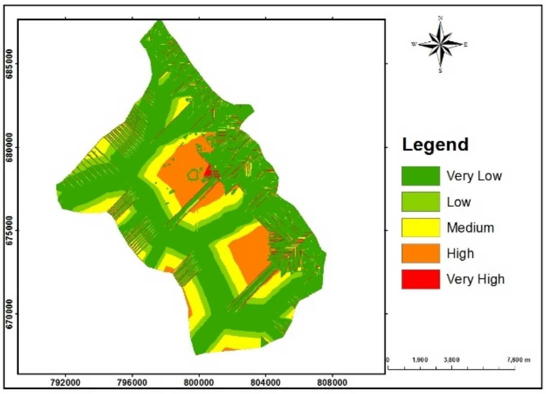

Fig. 13 Topographic Wetness Index Factor Reclassified

Hazard analysis: Hazard (H) is the probability of occurrence of a potential damaging natural phenomenon within a specified period and within a given area, hence, hazard is the probability of occurrence of mosquitoes infected with malaria parasites in each area (Hearn and Griffiths, 2011). Hazards are the external factors that affect the elements at risk (Birkman, 2007; Laurie, 2003). AHP was used to assign weights to the factor maps based on their influence in creating suitable grounds for mosquito breeding. Table 1 is the evaluation criteria (environmental factors) that were used for the analytical hierarchy process. Table 2 shows the pairwise comparison matrix and Table 3 shows the determined weights for each factor.

Table 1 Evaluation Criteria

Criteria	ID
Land Surface Temperature	F1
Normalised Difference Vegetation Index	F2
Distance from Stream	F3
Distance from Breeding Site	F4
Slope	F5
Elevation	F6

Table 2 Pairwise Comparison Matrix

	F1	F2	F3	F4	F5	F6
F1	1.00	0.25	3.00	0.17	4.00	4.00
F2	4.00	1.00	7.00	0.50	8.00	8.00
F3	0.33	0.14	1.00	0.11	2.00	3.00
F4	6.00	2.00	9.00	1.00	9.00	9.00
F5	0.25	0.13	0.50	0.11	1.00	1.00
F6	0.25	0.13	0.33	0.11	1.00	1.00
SUM	11.83	3.64	20.83	2.00	25.00	26.00

Table 3 Normalisation and Weight Determination

	F1	F2	F3	F4	F5	F6	Weight
F1	0.09	0.07	0.14	0.08	0.16	0.15	0.12
F2	0.34	0.28	0.34	0.25	0.32	0.31	0.30
F3	0.03	0.04	0.05	0.06	0.08	0.12	0.06
F4	0.51	0.55	0.43	0.50	0.36	0.35	0.45
F5	0.02	0.03	0.02	0.06	0.04	0.04	0.04
F6	0.02	0.03	0.02	0.06	0.04	0.04	0.03

Consistency ratio was calculated using the formula:

$$\text{Consistency ratio} = \frac{\text{Consistency Index (CI)}}{\text{Random Consistency Index}} \tag{8}$$

$$CI = \left(\lambda_{max} - n\right)/\,n - 1 \tag{9}$$

where:

λmax = Weight

n = Number of factors

Weighted overlay tool in the spatial analyst toolbox was used to overlay the factor maps using a common measurement scale and weights according to their importance to mosquito breeding.

2.2.3 Phase 3

The third phase is where the elements at risk were identified using the land use/land cover types. Elements at risk includes the population, economic activities, public services, utilities and infrastructures, *etc*., at risk in a given area. Random forest, a machine learning algorithm, was used in classifying the image into 4 classes (Bare Land, Water Bodies, Vegetation and Settlement) using ArcMap 10.4 as shown in Fig 14. The land use/land cover raster was further reclassified based on the effect of malaria on each class. The classes were "very low", "low", "High" and "very high". Fig 15 shows the reclassified element at risk map.

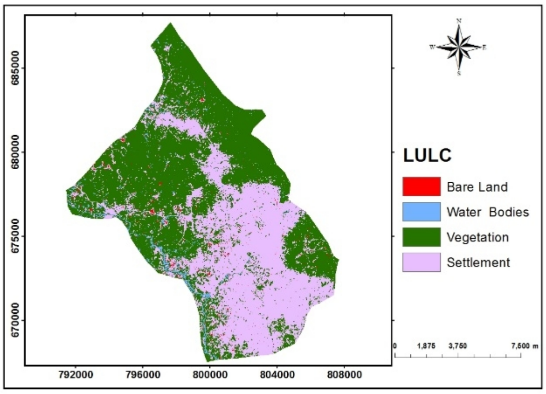

Fig. 14 Elements at Risk

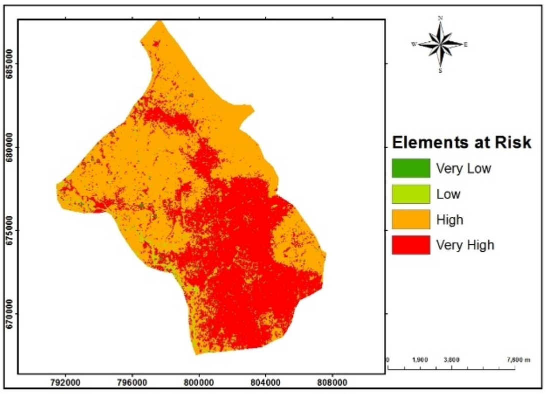

Fig. 15 Elements at Risk

2.2.4 Phase 4

The fourth phase is the vulnerability analysis. The positions of the health facilities within the study area were superimposed on the shapefile of the study area. Euclidean distance tool from the spatial analyst tool box was used to calculate the euclidean distance to the closest health facility within the study area. From the spatial analyst toolbox, a constant raster was created with a value of 20 signifying a constant speed of 20 km/hr. The raster calculator from the spatial analyst toolbox was used to generate the accessibility to the health facilities by dividing the euclidean distance raster by the speed constant raster to obtain the time it would take an individual to travel in a car with a speed of 20 km/hr to reach a nearby health facility. The resulting raster (vulnerability raster) was reclassified into 5 classes with class 1("Very Low") being the closest to a health facility and class 5 ("Very High") being the farthest away from to a health facility. Fig. 16 and Fig. 17 are the vulnerability map and reclassified vulnerability maps respectively.

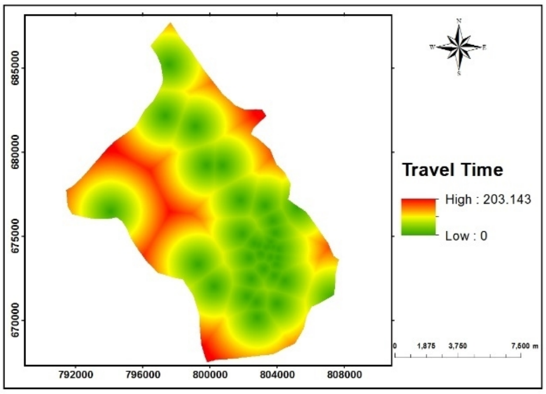

Fig. 16 Vulnerability Map

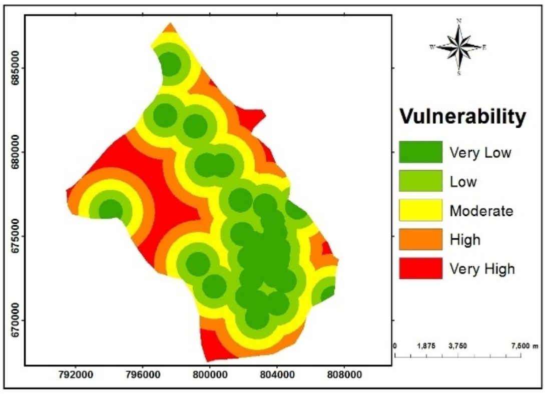

Fig. 17 Vulnerability Map Reclassified

2.2.5 Phase 5

The fifth phase is the malaria risk analysis. The development of malaria risk map of the study area was done based on the formula:

$$\text{Risk} = \text{Elements at Risk} \times \text{Hazard} \times \text{Vulnerability} \quad (10)$$

The raster calculator from the spatial analyst toolbox was used to multiply the elements at risk raster, vulnerability raster and the hazard raster to obtain the malaria risk map. The malaria risk map was then reclassified into 5 classes, in increasing order of severity of the malaria risk.

3. Results and Discussion

3.1 Mosquito Prone Areas

Mosquito prone areas within the study area were mapped based on some environmental factors that create conducive environments for mosquito breeding. For identifying mosquito prone areas, this study focused on temperature, vegetation, topographic wetness index, distance to streams, elevation and slope as factors that influence mosquito breeding. From Equations 8 and 9, a consistency ratio of 0.057511 was obtained which according to Saaty (1980), falls within the tolerable range for consistency ratio since it is less than 0.1. It is by overlaying these factors using the weights shown in Table 2.3 that the mosquito prone areas were identified and a hazard map obtained. Fig. 18 is a map showing a classification of mosquito prone areas and Table 4 also shows the classification of mosquito prone area coverage and percentage.

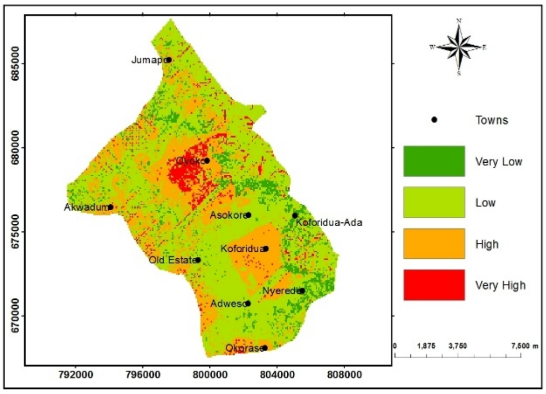

Fig. 18 Classification of Mosquito Prone Areas

Table 4 Classification of Mosquito Prone Areas Coverage and Percentage

Classification	Pixel Count	Area (km^2)	(%)
Very Low	2456	13.43	8.80
Low	15766	86.20	56.46
High	8199	44.83	29.36
Very High	1502	8.21	5.38
TOTAL	27923	152.66	100

Although the most dominant class is "Low" (56.462 %), signifying that the study area is not very prone to mosquito breeding, it was observed that all the towns except Koforidua-Ada and Jumapo are highly prone to mosquito breeding. Oyoko lies at an area extremely prone to mosquito breeding. This could be attributed to the high topographic wetness indices observed there.

The knowledge obtained about the mosquito prone areas in the New Juaben Municipality is invaluable for the development and successful implementation of health interventions and strategies towards malaria prevention and control. An ecological approach to addressing this problem may be embarked upon by deploring public health personnel to conduct a health needs assessment of the area so as to identify which interventions would be most appropriate for the identified high-risk populations and how these interventions can be culturally tailored for optimal results. Interventions or combination of interventions that may be considered include improved malaria prevention strategies *e.g*. Increased use of Insecticide Treated Nets (ITN); Improved drainage; Mosquito proofing of households; as well as improved hygiene and sanitation. Interventions may also gear towards improved access to prompt and quality health care *e.g.* early symptom recognition and antimalarial administration; Availability of basic health care for the sick; Appropriate referral protocols in place; and Improved quality of malaria treatment.

3.2 Malaria Risk Map

A malaria risk map for New Juaben Municipality was developed by multiplying the hazard map, vulnerability map and the elements at risk map. Fig. 19 is a map showing classification of malaria risk within the study area and Table 5 also shows the classification of malaria risk, area coverage and percentage.

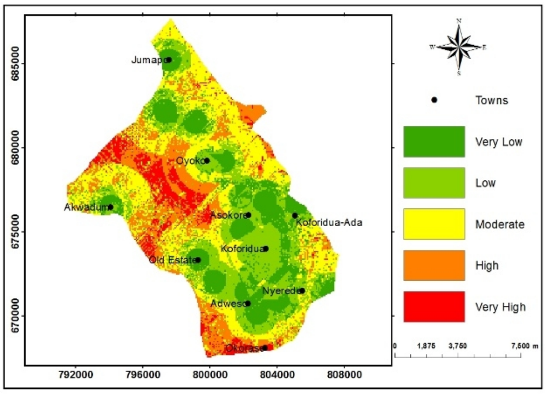

Fig. 19 Classification of Malaria Risk

Table 5 Classification of Malaria Risk, coverage and Percentage

Classification	Pixel Count	Area (km^2)	(%)
Very Low	5530	30.23	19.80
Low	6737	36.83	24.13
Moderate	8427	46.07	30.18
High	5136	28.08	18.39
Very High	2093	11.44	7.50
TOTAL	27923	152.67	100

The most dominant class is "Moderate", covering 30.18 % of the entire study area. In spite of this, it was observed that most of the towns fell at places with very low to low malaria risk except for Okorase which lies at an area with high malaria risk. This can be attributed to the minimum travel distance to a nearby health facility.

Knowledge of the positions of malaria prone areas also offers the opportunity for advocacy and policy change as per prioritisation and increased availability of resources and funds to effectively implement interventions and strategies in these settings; Increased funds for malaria research and monitoring; Periodic evaluations of drug and insecticide safety as well as evaluation of program outcomes and impacts; and building of human resource capacity to deliver malaria interventions.

4. Conclusions and Recommendations

4.1 Conclusions

4.1.1 Identification of Mosquito Prone Areas

Mosquito prone areas within the study area were identified and classified into 4 classes ("Very Low", "Low", "High" and "Very High") based on how prone the area is to creating suitable grounds for mosquito breeding. The most dominant class was "Low" (56.46 %) followed by "High" (29.36 %), "Very Low" (8.79 %) and then "Very High" (5.38 %).

4.1.2 Development of a Malaria Risk Map

Malaria risk map of the study area was developed and classified into 5 classes based on the degree of the risk posed. The classes were "Very Low", "Low", "Moderate", "High", and "Very High". The most dominant class was "Moderate" (30.17 %) followed by "Low" (24.12 %), "Very Low" (19.80 %), "High" (18.39 %) and "Very High" (7.49 %). The "High", "Very High" and "Moderate" areas, together constitute 56.07 % which is significant. Any efficient malaria response in NJMA should be focused in these areas

4.2 Recommendations

It is recommended that:

(i) a health facility is built in Okorase to reduce the vulnerability of the people living there and thereby reduce the risk posed to the people living there;

(ii) stakeholders make use of the findings in this paper in identifying appropriate strategies in response to malaria outbreak including vaccination, health promotion and vector or agent control; and

(iii) This work could be replicated in all the municipalities and districts in Ghana to help prevent outbreak and track the progress of malaria.

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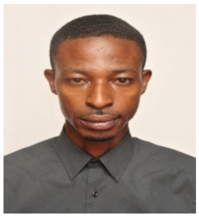
Authors

Bernard Kumi-Boateng is a Senior Lecturer at the Department of Geomatic Engineering of the University of Mines and Technology (UMaT), Tarkwa, Ghana. He holds a Bachelor of Science degree in Geomatic Engineering from the Kwame Nkrumah University of Science and Technology, Kumasi, Ghana. He obtained his Master of Science degree and Doctor of Philosophy from the International Institute for Geo-information Science and Earth Observation (ITC), Enschede-The Netherlands and UMaT respectively. His research interest includes application of Remote Sensing and GIS in Environmental Management, Spatial Statistics, Land and Compensation Surveys.

Kofi Bonsu holds BSc and MSc Degrees in the Geomatic Engineering Department of the University of Mines and Technology (UMaT). His research interest includes Application of GIS and Remote Sensing in Environmental Management and Modelling.



Nana Mireku-Gyimah is a Medical Doctor currently working with the Ghana Health Service. He holds a Bachelor of Science degree in Human Biology and a Bachelor of Medicine and Surgery both of which were obtained from the Kwame Nkrumah University of Science and Technology, Ghana. He also holds a Master of Public Health Degree from Cardiff University, U.K. His research interests include Disease Prevention and Control, HIV/AIDS and Public Health Policy and Advocacy.