Journal of Geomatics Vol 10 No. 1 April 2016

Malaria-risk assessment using geographical information system and remote sensing in Mecha district, West Gojjam, Ethiopia

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(Received: Dec 25, 2015; in final form: Feb 24, 2016)

Abstract: Malaria is a major global health problem. About 3.5 billion people are at risk of infection of malaria worldwide, with environmental factors contributing for about 70–90% of the disease-risk. Over one million cases of malaria are reported each year, out of which more than 80% is from the sub-Saharan Africa. Ethiopia is a predominantly malaria-prone country as about 75% of the landscape of the country is favorable for breeding of the malaria vector. Geographical Information System has emerged as a spatial technology, which integrates a wide range of datasets available from different sources including remote sensing and Global Positioning System. During the present study, a malaria-risk map of Mecha district of Ethiopia was prepared by establishing the relationship of various climatic and non-climatic factors related to the disease using regression analysis. Weighted overlay technique of multi-criteria evaluation was used to develop the malaria-risk map. Temperature, rainfall, altitude, distance from streams, distance from swamps and ponds, population density, health facilities and land-use/land-cover patterns were used to prepare malaria-risk areas. Malaria hazard, elements of risk and vulnerability layer were overlaid, and further verified by ground truth and village-wise reports of malaria cases to produce the final malaria-risk map. Four categories of malaria-risk ranging from very high to low were derived. Most of the study area (99.01%) was found to belong to high and moderate malaria-risk. It is suggested that effective identification and mapping of malaria-risk levels can be made using geospatial tools, to contribute for the prevention and control of this disease.

Keywords: GIS, Landsat, Malaria, Remote sensing, Regression analysis, Weighted overlay

1. Introduction

Malaria is a major health problem as it affects all age groups of the people in most parts of the world even for about 70–90% of the disease risk (Bautista et al., 2006; Erin et al., 2014). Around 300−500 million cases and more than two million deaths of malaria are reported each year, with more than 80% of these from the sub-Saharan Africa (Abdulhakim, 2013). Malaria is essentially an environmental disease, as the vectors require specific habitats with surface water for reproduction and humidity for adult mosquitoes to survive. The development rate of both the vector and the malaria parasite are influenced by temperature (Ashenafi, 2003). Approximately 4–5 million cases of malaria are reported annually in Ethiopia and malaria is prevalent in 75% of the extent of the country, putting over 50 million people at risk (Abdulhakim, 2013).

Integrated use of remote sensing (RS) and Geographical Information System **(**GIS) has been successfully demonstrated in many studies related to mapping of malaria-risk in different parts of Africa (Hay et al., 2000; Kleinschmidt et al., 2001; Sithiprasasna et al., 2005; Dongus et al., 2007). The severity of malaria is a function of the interactions between *Plasmodium*, the parasite; the *Anopheles* mosquito, the vector; the human host and the environment. Vector abundance combined with the probability of the vector feeding of susceptible human-host determines the risk of malaria infection, which is more prevalent in the tropics. It is a serious vector-borne disease. About 3.5 billion people are at risk of infection of malaria worldwide with environmental factors contributing for the disease transmission, and its seasonal patterns.

There are several factors associated with this disease and its control, such as water bodies, rainfall, temperature, population, land-use/land-cover and health facilities (Palaniyandi, 2012). Understanding the causal factors is a prerequisite to design and implement appropriate malaria-risk management. So as to mitigate the effect of this risk, effective malaria-risk management methods are required. Spatial information on malaria distribution helps to prioritize control measures.

2. The study area and methods

Mecha district lies within 11º 8'−11º39' N latitude and 36º59' 51"−37º 20' E longitude covering a total area of 149,119 km^2 (Figure 1), located in the West Gojjam Zone in the Amhara region, about 35 km from Bahir Dar, the capital town of Amhara Regional State of Ethiopia. There are 44 villages including three town administrative villages in the study area. Mecha district is situated at an altitude range of 1720 m−2800 m above sea level. The area is characterized by flat lying topography with some hilly terrain. This district has different climatic variables in different seasons. The annual rainfall pattern of the study area varies from 1000 to 2000 mm. The temperature varies from 23ºC to 27ºC. June, July and August are high rainfall months and December, January and February are low rainfall months. High temperature is recorded in March, April and May and low temperature is recorded in November, December and January.

2.1 Methodology

To develop the malaria-risk map of the study area, identification and selection of the major factors contributing for malaria breeding such as land-use/land-cover, water bodies, population, elevation, temperature, rainfall, ponds and swamps, slope and health station facilities were done. Regression analysis was applied to identify the statistical correlations between malaria cases and the above parameters. The mathematical formula applied to the explanatory variables in order to best predict the dependent variable was the following:

$$Y = \beta 0 + \beta 1x1 + \beta 2x2 \ldots . + \beta nxn + \varepsilon \qquad (1)$$

where, yis dependent variable, x1, x2, …, xn are independent variables, β0, β1, β2… βn are coefficients and ε is error term (residual).

In this study, global weighted regression (GWR) and ordinary least squares regression (OLS) were carried out to assess the spatial relationship between the parameters and malaria cases and to validate the model performance. To assess spatial model performance, values of R-squared, adjusted R-squared, Jarque-Bera p-value (JB), Akaike Information Criterion (AIC) and Variance Inflation Factor (VIF) were computed (Ehlkes et al., 2014). Independent variables greater than 7.5 VIF (strong multi-collinearity) were cut off to overlay. The dependent variable was malaria cases and the independent variables were temperature, rainfall, LU/LC, population density, slope, elevation, distance from swamps and ponds and distance from streams. Elevation variable (8.7) and slope variable (10.7) in the regression model are associated with large VIF values. To show the spatial clustering of the values associated with the geographic features in the study area, Moran's I. was also computed.

2.1.1 Moran's I: This is a tool to measure spatial autocorrelation based on both feature locations and feature values simultaneously. It evaluates whether the pattern expressed is clustered, dispersed or random (Oliveira et al., 2013). The Moran's index statistic for spatial autocorrelation is given as:

$$I = \frac{n}{So} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w\mathrm{ij} Zi Zj}{\sum_{i=1}^{n} Zi^2} \qquad (2)$$

where, Z_i = the deviation of an attribute for feature i from its mean
W_{ij}= the spatial weight between i and j,
n= total number of features and
So= the aggregates of all the spatial weights.

2.1.2 Image processing: To produce land-use/land-cover map of the study area, Landsat TM image of path 170 and row 052 of January 2015 was acquired.

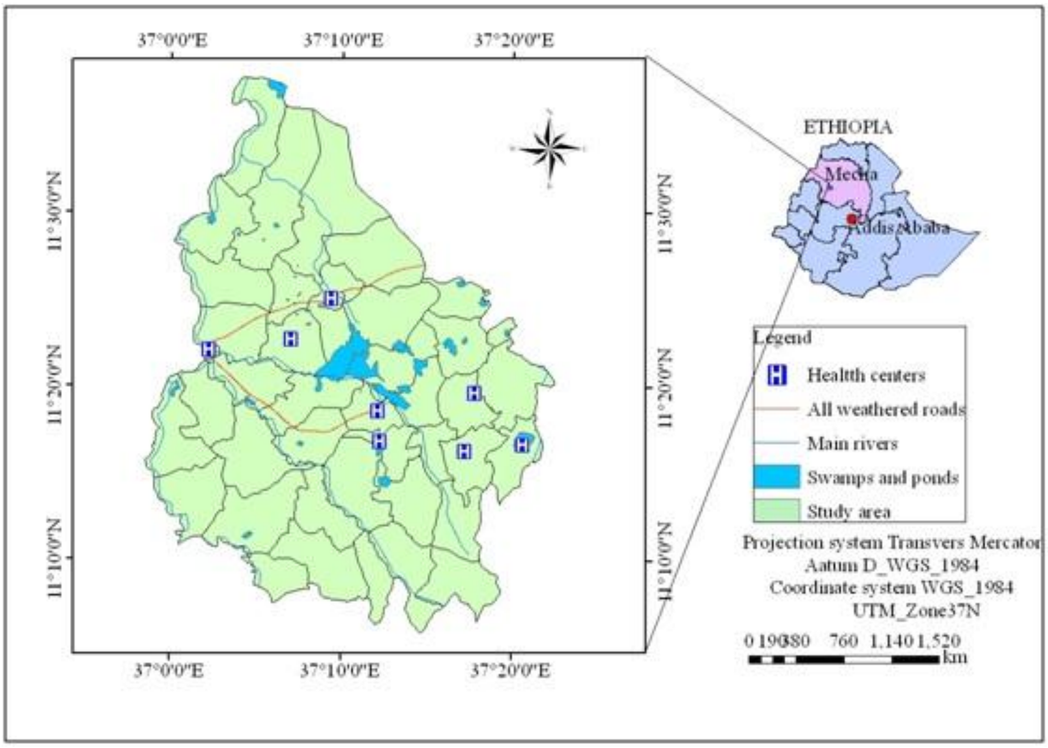

Figure 1: Location map of the study area Mecha District, Ethiopia

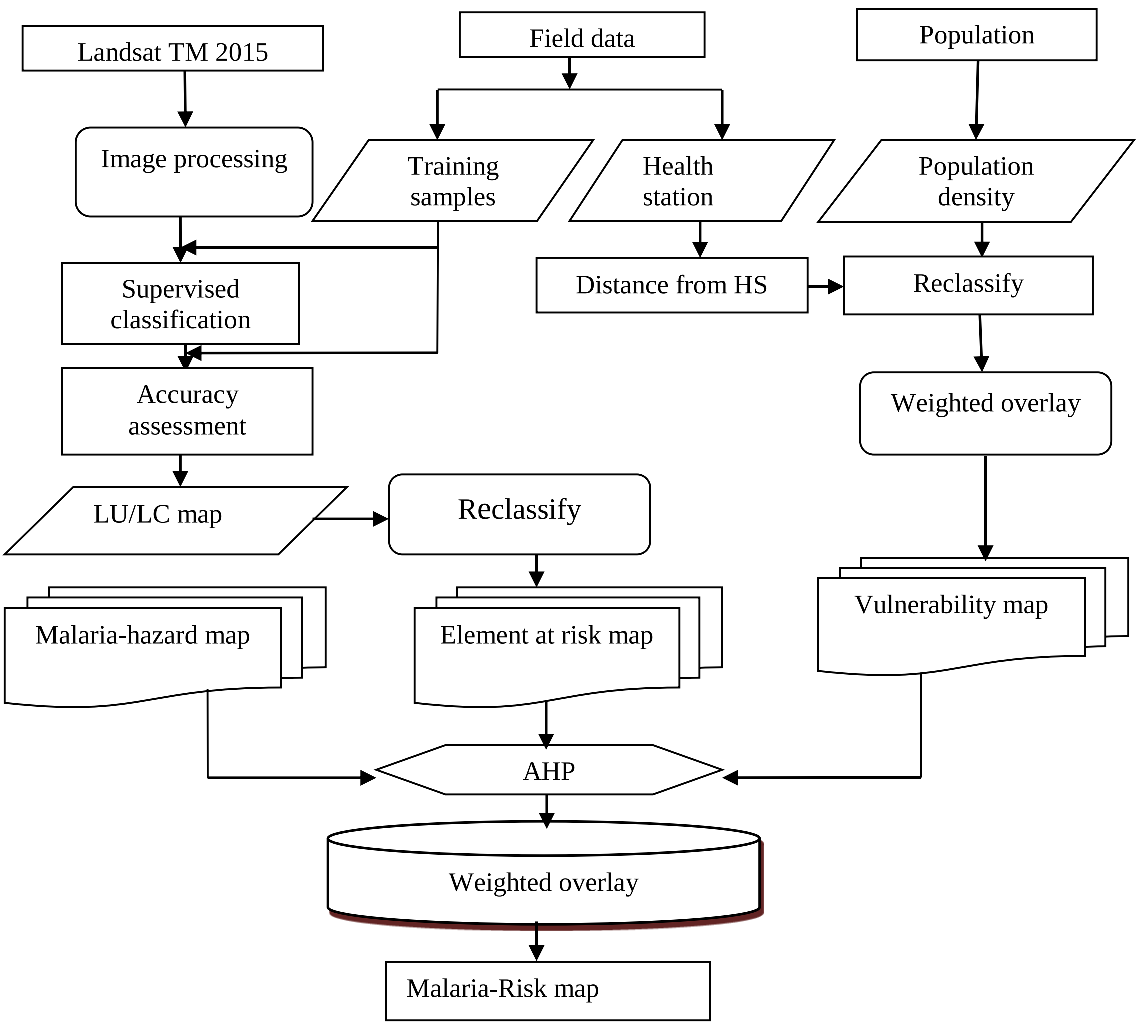

Figure 2: Malaria-risk flowchart

Image processing starting from image pre-processing (geometric and radiometric correction), layer stacking (band 2–7), image enhancement and image classification to the final accuracy assessment were done in ERDAS Imagine software. To correct the satellite image radiometrically, Operational Land Imager (OLI) band data were converted to top of atmosphere (TOA) to a planetary reflectance using reflectance rescaling coefficients provided in the product metadata file. The following equation was used to convert DN values to TOA reflectance:

$$\rho\lambda' = M\rho Qcal + A\rho \qquad (3)$$

The $\rho\lambda'$ does not contain the sun angle correction and hence the image was again converted to TOA reflectance with a correction for the sun angle as follows:

$$\rho\lambda = \frac{\rho\lambda\prime}{cos(\theta sz)} = \frac{\rho\lambda\prime}{sin(\theta SE)} \qquad (4)$$

After preparing the factors and validating the model and image processing, three malaria-risk layers were generated using their factors. The malaria-risk map was developed by combining the suitability of environmental conditions for malaria transmission based on climatic and non-climatic factors. All factor parameters compatible to hazard analysis were generated before weighted overlay. Hazard map was produced by computing and reclassifying the five parameters *viz.* meteorological (rainfall and temperature) data, distance from ponds and swamps, altitude and distance from streams layers. Each of the hazard parameters was ranked according to the importance for mosquito breeding and transmission. The process of weighting each factor was performed in IDRISI software. After assigning weight, the hazard map was computed by overlaying the five selected factors.

Vulnerability map was generated from distance from health facility map and population density map. The two layers were overlaid with 54% weight to population density map and 46% to health facility map. The weight was given by consulting health experts, who have advanced knowledge about malaria based on the regression result coefficients and available information. The element at the risk-map was computed by reclassifying the land-use/land-cover pattern of the study area. The land-use/land-cover types were ranked based on the importance from the most important to least important, and vulnerability map was developed by reclassifying land-use/land-cover types of the study area. In this study, malaria-risk was expressed as the product of malaria hazard map, vulnerability map and element at risk-map using Shook model. To produce the malaria-risk map, the influence factors were assigned for the three components of malaria-risk layers (malaria hazard, element at risk and vulnerability layer) and overlaid.

$$R=V\times H\times E \tag{5}$$

where; R=Malaria risk map; H= malaria hazard map; V= vulnerability map; E= malaria element risk map.

The methodological flowchart is presented in Figure 2.

3. Results

3.1 Malaria *vs* rainfall

Figure 3 shows the average rainfall and average malaria cases recorded in the study area during 2002–2012. Rainfall was the main climatic factor for the prevalence of malaria in the study area with 44% influence (Tables 1 and 2). The average rainfall of the study area varies from the lowest 2.056 mm to the highest 418.97 mm per month. Maximum rainfall was recorded during June−August and the minimum during December−February. A higher number of malaria cases was recorded during May−June and October−November, and lower in the months of August, March and April. There was a positive relationship between malaria cases and rainfall in the months December to February and May to July, but the relationship was negative in the months of August to November.

3.2 Malaria *vs* temperature

The present study has revealed that temperature also has influence in prevailing malaria. There was a negative relationship during the months of December−April, when the study area had lower number of recorded malaria cases, and in August when higher number of cases were registered. Although temperature favours *Plasmodium* development, lack of water prevents breeding and development of the vector. Figure 4 shows the relationship between monthly malaria incidence recorded during 2002−2012 with the data on monthly temperature variations in the study area.

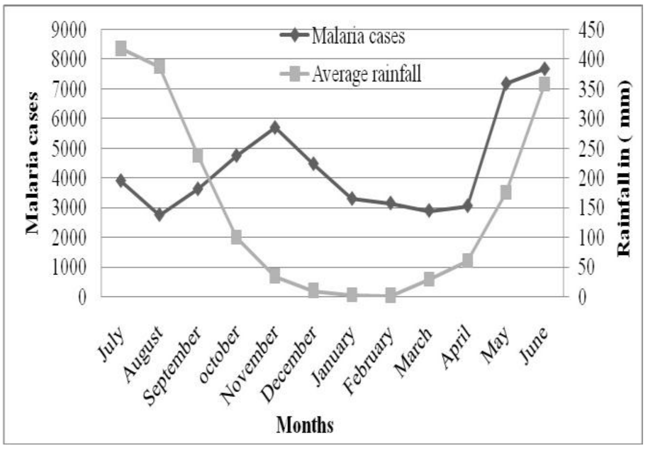

Figure 3: Malaria *vs* rainfall relationship in the study area during 2002−2012

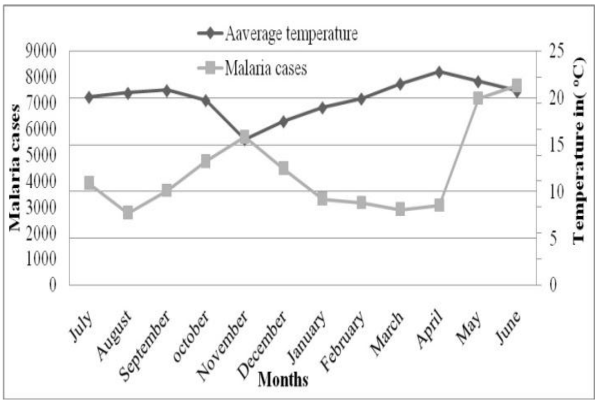

Figure 4: Malaria *vs* temperature relationship in the study area (2002−2012)

Table 1: Malaria cases and rainfall and temperature in Mecha district (2002–2012)

Months	**July**	**Aug.**	**Sep.**	**Oct.**	**Nov.**	**Dec.**	**Jan.**	**Feb.**	**Mar.**	**Apr.**	**May**	**June**
Malaria case	39164	2770	3638	4760	5705	4487	3313	3162	2909	3070	7188	7683
Rainfall	418.9	388.3	238.2	100.3	35.4	10.4	2.9	2.06	29.7	60.9	175.6	358.5
Temperature	20.07	20.5	20.78	19.72	15.52	17.45	18.94	19.89	22.5	23.78	22.76	20.69

3.3 Regression analysis for model validation

As shown in Table 2, rainfall, temperature and population density have strong positive relationship and altitude and slope have strong negative relationship with malaria incidence. These are the main factors for malaria prevalence in the study area relative to other factors analysed (Tables 2 and 3). The AIC, multiple R^2 and adjusted R^2 for this model were 657.72329, 0.8052 and 0.7566, respectively. Multiple R-squared and adjusted R-squared were both statistics derived from the regression equation to quantify model performance. In this model, R^2 was 80.5299%. Hence, 80.53% variation in the dependent variable (malaria cases) could be explained by the model.

Table 2: Result of regression analysis

Variable	Coefficient	T-stat	Probability	Robust-t	Robust-p	R^2 (%)	VIF
Intercept	-75035357	-4.74	0.000041*	-7.994938	0.000000*		
Pop. density	+69.1356	4.037	0.000319*	6.851215	0.000000*	85.54	2.0
Health station Distance	-0.031	-4.051	0.007826*	-1.130710	0.000000*	19.6	1.7
Slope	-11.04497	-0.12	0.897635	-0.191535	0.849318	16.68	10.7
Temperature	+115.4472	0.52	0.526501	0.615132	0.542817	51.04	2.4
Rainfall	+752.86	4.76	0.000039*	7.638637	0.000000*	64.02	1.9
Elevation	-114.44	-2.06	0.488905	-0.848799	0.402299	17.04	8.7
Distance from swamps	-0.04183	-4.85	0.009351*	-0.746534	0.000014*	59.00	2.2
Distance from streams	-0.08	-0.58	0.56	-0.77	0.44	12.71	1.4

* indicates a statistically significant p-value ($p < 0.01$).

Coefficients are values that represent the strength and type of relationship the explanatory variable has to the dependent variable. When the relationship is positive, the sign for the associated coefficient is also positive (+) and negative relationships have negative (−) signs. When the relationship is strong, the coefficient is large such as rainfall, temperature, altitude, elevation and population density. Weak relationships are associated with coefficients near (zero) such as distance from swamps and ponds and distance from streams. Regression analysis computed a p-value for the coefficients associated with each independent variable. P-value was used to reject the null hypothesis for statistical test that states for all purposes, the coefficient is zero and the associated explanatory variable is not useful for the model.

The regression analysis revealed small p-values. Hence, the explanatory variables were important to the model with a value different from zero (the coefficient was not zero). Table 3 shows that some of the variables are both negative and positive. The explanatory variable that showed negative and positive significance were slope, distance from streams, distance from swamps and temperature. This indicates that these variables were not statistically significant (P>0.01). However, population density, distance from health stations, rainfall and distance from swamps and ponds were significant (P<0.01).

Table 3: Results of explanatory regression analysis

Variables	Variable significance (%)	
	Negative	Positive
Population density	0.00	100
Slope	75.44	24.56
Altitude	85.44	14.56
Distance health stations	100	0.00
Distance from streams	60.18	39.82
Distance from swamps & ponds	100	0.00
Rainfall	0.00	100
Temperature	21.58	78.42

In the present model, p-value was small (0.000015), and hence the null hypothesis was rejected. There was spatial autocorrelation between the values associated with the geographic features in the study area. Moran's index value was 0.357501, and hence spatial features and their associated data values tended to be clustered (positive spatial autocorrelation) as it was greater than 0. The tool returns a Z score of 3.429816, which indicated that standard deviations were away from the mean.

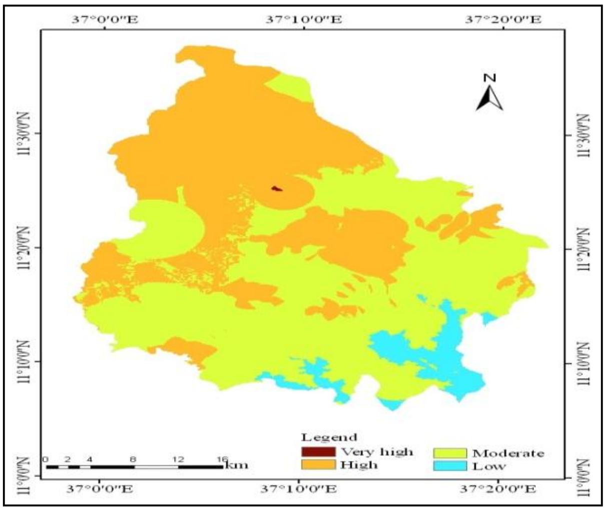

Figure 5: Malaria hazard map of the study area

3.4 Areas of malaria hazard

Rainfall, altitude, streams, temperature, swamps and ponds were the predictors of presence of malaria with percentage influence of 44%, 38%, 4%, 7% and 7%, respectively. Rainfall and altitude were the dominant factors for the existence of malaria as a hazard as compared with other selected factors, and streams showed the least percentage influence (Principal Eigenvector) for malaria prevalence. The consistency ratio for the Eigenvector of weights was within an acceptable range with the value 0.02. Table 4 shows the weight, rank and degree of vulnerability of the selected parameters of malaria hazard in the study area. Figure 5 shows the malaria hazard-risk map of the study area, which shows the level of malaria vulnerability in an extent of 46.77 km (0.31%) as very high, 64504.51 km^2 (43.25%) high, 76446.74 km^2 (51.26%) moderate and 8122.58 km^2 (5.44%) low. Thus, most of the study area is subjected to high and moderate malaria hazard-risk.

3.5 Malaria vulnerability

Figure 6 shows that in an extent of 1878.04 km^2 (1.26%) was moderately vulnerable for malaria 39794.21 km^2

(26.68%) was vulnerable for malaria at low level and 107446.73 km^2 (72%) was vulnerable for malaria at very low level. Thus, the majority of the study area is under very low malaria-risk.

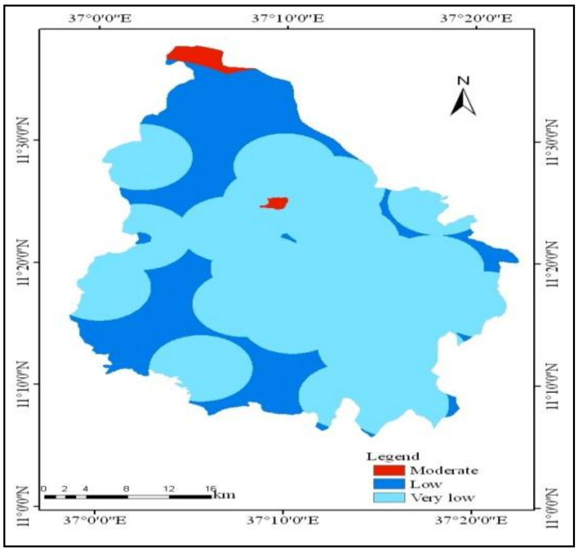

Figure 6: Malaria vulnerability

3.6 Element at risk map of malaria

The results of NDVI values ranged between -0.266708–0.569553. The lowest (negative) NDVI values indicate the water bodies. The highest NDVI values indicate plantation and bush lands. Table 5 shows the results of NDVI value for each of the LU/LC types of the area. Figure 7 illustrates that 48523.66 km^2 (32.54%) had very high, 21365.29 km^2 (14.32%) had high, 75556.48 km^2 (50.66%) had moderate and 3673.56 km^2 (2.46%) had low level of malaria vulnerability.

3.7 Identifying malaria-risk areas

As shown in Table 6, element at risk and malaria vulnerability had 63%, 31% and 6% of weight influence of hazard element at risk and vulnerability for the existence of malaria in the study area. Malaria hazard layer was the dominant factor for the final malaria-risk map. There was no area, which was free from malaria-risk. In the study district, 33.59 km^2 (0.23%) area was of very high, 69305.82 km^2 (46.47%) was high, 76830.96 km^2 (51.52%) was moderate and 2948.61 km^2 (1.97%) was of low malaria-risk. The majority of the study area was subject to high and moderate risk of malaria. The final malaria-risk model map has revealed that all parameters, analysed during the study had different weight influence for the prevalence of malaria in the Mecha district of Ethiopia. However, rainfall was the most dominant factor for the prevalence of malaria in the present study area, where as altitude had limiting effect for the prevalence of the disease as altitude has negative correlation with temperature. The total area and degree of vulnerability for malaria prevalence in the final malaria-risk map and its layers (malaria hazard map, element at risk map and vulnerability map) are presented in Table 7.

Table 4: Characteristic of factors in relation to malaria hazard area identification

Factors	Weight	Class	Rank	Degree of vulnerability
Rainfall	44	98–100 mm	5	Very low
		100–103 mm	4	Low
		103–105 mm	3	Moderate
		105–108 mm	2	High
		>108 mm	1	Very high
Altitude	38	<2000 m	1	Very high
		2000–2200 m	2	High
		2200–2400 m	3	Moderate
		2400–2600 m	4	Low
		>2600 m	5	Very low
Distance from Swamps and ponds	7	0–500 m	1	Very high
		500–2000 m	2	High
		2000–3500 m	3	Moderate
		3500–5000 m	4	Low
		>5000 m	5	Very low
Distance from Streams	4	0–500 m	1	Very high
		500–2000 m	2	High
		2000–3500 m	3	Moderate
		3500–5000 m	4	Low
		>5000 m	5	Very low
Temperature	7	<15ºC	5	Very low
		15–17ºC	4	Low
		17–19ºC	3	Moderate
		19–21ºC	2	High
		>21ºC	1	Very high

Table 5: NDVI values for each land-use/land-cover types

Land-use/land-cover types	NDVI values
Irrigation	0.143
Water bodies	-0.075
Farmland	0.144
Plantation	0.245
Grassland	0.178
Bareland	0.148
Wetlands	0.103
Settlement	0.114
Bush and shrublands	0.188

3.8 Malaria risk levels of villages in Mecha district

All villages in the study area fall within the risk of malaria prevalence. One of the villages (Merawi town) fall in the very high malaria-risk area and the other villages are in the high to low levels of malaria-risk. Figure 8 shows the villages in the study area showing the levels of malaria-risk.

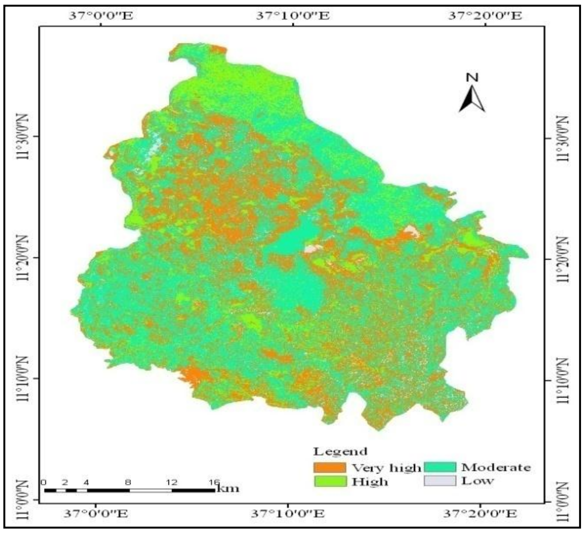

Figure 7: Element at risk map of malaria

Table 6: Characteristic of factors in relation to malaria risk area identification

Factors	**Weight**	**Rank**	**Degree of Vulnerability**
Hazard map	63	1 2 3 4	Very high High Moderate Low
Element at risk map	31	1 2 2 4	Very high High Moderate Low
Vulnerability map	6	2 3 4	Moderate Low Very low

Table 7: Summary of the results for malaria-risk and its layers

Type of area	**Area (km^2)**	**Area (%)**	**Degree of Vulnerability**
Malaria hazard map	46.77	0.31	Very high
	64504.51	43.25	High
	76446.74	51.26	Moderate
	8122.58	5.44	Low
Vulnerability map	1878.04	1.26	Moderate
	39794.21	26.68	Low
	107446.73	72	very Low
Element at risk map	48523.66	32.54	Very high
	21365.29	14.32	High
	75556.48	50.66	Moderate
	3673.56	2.46	Low
Final Malaria risk map	33.59	0.225	Very high
	69305.82	46.47	High
	76830.96	51.52	Moderate
	2948.61	1.97	Low

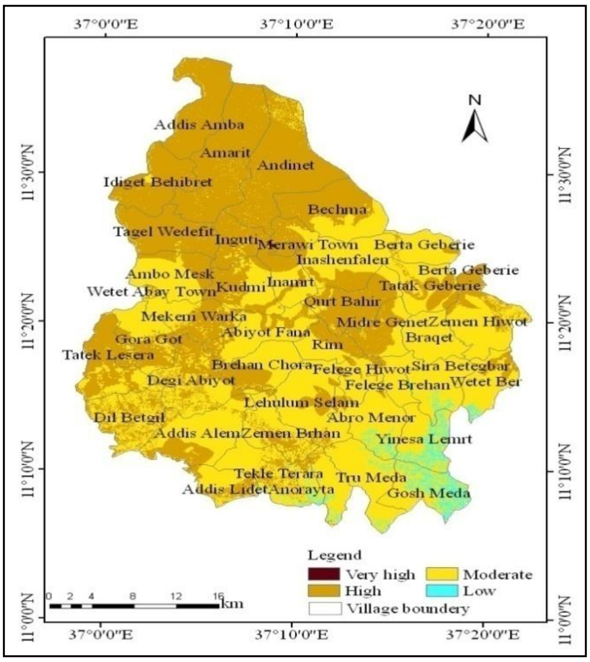

Figure 8: Malaria-risk map showing the status of villages in the study area

4. Discussion

The importance of GIS techniques is recognized in areas of disease prevalence and treatment (Carlos et al., 2010). The GIS-based malaria incidence mapping has been used for risk assessment at national, regional, and local levels in the context of resource allocation, management and to combat the disease (Saxena et al., 2009). Probability of the transmission of malaria to the present study area was determined by climatic, non-climatic and biological factors.

Areas near water bodies showed a low prevalence of malaria. There is no stagnation of water in the river. When there is heavy rain fall, mosquitoes cannot develop when the river flows fast in the absence of stagnant water bodies. However, in some areas, ponds are created close to the streams and rivers in order to store water for the dry season. Such ponds act as resourceful areas for mosquitoes to develop and contribute to increase malaria prevalence (Bautista et al., 2006). A negative association between distance from swampy areas and malaria-risk exists in the study area. It is already revealed that a strong positive association exists between malaria incidence and water bodies (Yihenew, 2007; Aster, 2010; Abdulhakim, 2013).

Higher elevation in general has long been recognized to be negatively associated with malaria due to its association with cooler temperatures that slows the development of anopheline vectors and the *Plasmodium* parasites they transmit (Patz et al., 2003). Malaria prevalence decreases with increase in altitude, particularly above 2000 m (Patz et al., 2003; Bautista et al., 2006). The present study shows higher negative correlation between monthly incidence of malaria and altitude (Yihenew, 2007; Yazoume et al., 2008).

Rainfall results in an increase in the prevalence of malaria as rains provide good breeding sites for the mosquito vectors (Stephen, 2006; Omukunda et al., 2013). The correlation coefficient for the association between monthly rainfall and monthly incidence of malaria was found greater than that for the association between other variables assessed. A rise in temperature enhances the survival chances of *Anopheles* mosquitoes and the *Plasmodium* and thus accelerates the transmission dynamics of malaria. There was a negative relationship between malaria and temperature during the months January to April and in August, when the study area had the minimum and maximum temperatures, respectively. Hence, an increase in temperatures does not mean an increase in the malaria transmission risk if this is accompanied by a decrease in rainfall. Although temperature favors *Plasmodium* to develop, lack of water prevents development of the vector.

The habitats of mosquitoes differ according to the vegetation and the nature of local environment. Land-use/land-cover types with plantation and bush lands have strong association with malaria indicating that this LU/LC may be a proxy for predictors of elevated malaria-risk (Richard and Poccard, 1998; Yasuoka and Levins, 2007; Ehlkes et al., 2014). The relationship of NDVI to Entomological Inoculation Rate (EIR) is highly correlated. The lower the NDVI value indicates the lower the vegetation level and the area is thought to be dry (Ceccato et al., 2005). The present results show high correlation between the incidence of malaria and vegetation due to the prevalence of high NDVI value as reported earlier (Oliveira et al., 2013; Ehlkes et al., 2014; Solomon et al., 2015).

In areas with low slopes, water tends to be logged, and such conditions accelerate chances for water stagnation. Absence of proper water drainage may lead to the creation of stagnant water pools, which in turn, encourages breeding and survival of mosquitoes (Thomson et al., 1999). The present study shows that slope gradient has negative influence on malaria incidence. This relationship could be attributed to the different slope types found on different geographic locations across the studied landscapes. The bottom areas characterized by flat or gentle slopes are mostly under swamps and water bodies. As slope increases from lower parts to middle and upper slopes, mosquito populations cannot sustain.

Presence of health institutions in a particular area is very important for treatment of patients, awareness creation and to implement preventive measures (Meron, 2010). These in turn influence the prevalence of disease in the locality. Absence and distant health institutions result in difficulties in accessibility and enhanced cost of treatment. Therefore, people who are near to health institutions are safer relative to those who are away from such centers. Identification of potential malaria-risk localities helps the health authorities to minimize expenditure. The present study shows negative correlation between monthly incidence of malaria and distance from health facilities. The relationship of distance from health stations and malaria incidence was statistically significant.

The high human population density has caused over-cultivation, and severe environmental manipulations leading to extensive drought and recurrent famine in many areas. This leads to more movement of people from one area to another resulting in transmission of malaria (Wakgari et al., 2006; Wiseman et al., 2006). Malaria-risk may increase in certain regions due to population movement by labor related to agriculture, mining, conflict and refugees (Martens and Hall, 2000). Work opportunities and resettlement programs in malaria endemic areas can easily attract a large number of people, making them vulnerable to the disease (Meron, 2010). Major environmental transformations like deforestation and new construction take place during resettlement, enhancing the proliferation of mosquito breeding sites, and result in malaria outbreaks (Martens et al., 1995; Kathleen, 2002; Aster, 2010). The present study shows strong positive correlation between monthly incidence of malaria and human population density.

Findings of the present study show that, a model-based malaria-risk map can be developed by establishing the relationship of various parameters using remote sensing and geographic information system. It also reveals that remote sensing and GIS techniques can be effectively used in mosquito larval habitat identification and risk area mapping. The risk area identification map indicates affected areas. The final malaria-risk map of the study area shows that the entire study area has malaria-risk factors. The study area falls under very high, high, moderate and low risk areas. The malaria-risk map developed can support decision makers to take precautions in space and time so as to control and manage malaria incidence.

Acknowledgements

The authors are grateful to the School of Earth Sciences, College of Natural and Computational Sciences, Addis Ababa University, Addis Ababa, for providing financial support to carry out this study.

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