The Impact of Meteorological Parameters on the Pattern of Malaria Incidence Rate in the Northwest, Ethiopia; Repeated Cross-sectional Study Design With Bayesian Approach

Asefa Adimasu (adimasuasefa@gmail.com)
University of Gondar College of Medicine and Health Sciences
Adhanom Gebreegziabher Baraki
University of Gondar College of Medicine and Health Sciences
Kassahun Alemu Gelaye
University of Gondar College of Medicine and Health Sciences
Dawit Wendimsigegn
University of Gondar College of Medicine and Health Sciences

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Abstract

Background: Commonly the incidence of malaria was determined by some meteorological parameters. However, updated evidences were not reported in the study area and recently malaria is reported as an epidemic disease in Ethiopia particularly in Amhara regional state. Therefore the study was aimed to estimate malaria incidence proportion linked with some meteorological parameters.

Methods: A repeated cross-sectional study design was done in 8 districts of northwest Ethiopia. All malaria patients who visited the local health institutions in the study area were the study participants. A monthly malaria surveillance data were retrieved from 8 districts of North Gondar zone health department and metrological data were obtained from west Amhara metrology agency office monthly reported databases. Data was clean and analyzed by using R2 win bugs software. The bayesian generalized negative binomial regression model was fitted for parameter estimation.

Results: The overall average cumulative annual malaria incidence rate during the study period was 29.9 per 100 populations. In this study relative humidity (IRR; 1.04 (95% BCI, 1.01-1.05), normalized difference vegetation index [IRR; 2.74(95% BCI, 1.35-5.58)], altitude [IRR; 0.97(95% BCI, 0.95 - 0.99], average maximum temperature [IRR; 1.07(95% BCI (1.05 - 1.09)] and average minimum temperature [IRR; 1.04 (95% BCI (1.02-1.07)] were the statistically significant predictors. However, monthly rainfall, length of a sunshine hour, monthly wind speed was not associated with malaria incidence.

Conclusion: The research showed a greater incidence of malaria in the study area when compared to the national statistics. Climatic variability changes the pattern of the malaria incidence in the study area.

Introduction

Malaria is a mosquito-borne infectious human disease caused by the Plasmodium genus that is introduced by the bite of the infected female anopheles mosquito into the circulatory system(1). Parasites in the human body multiply in the liver, and infecting red blood cells. The situation in the poorest nations is one of the main public health challenges(2, 3).

The total amount of malaria cases has dropped from 262 million in 2000 to 214 million in 2015 worldwide. Ninety percent of malaria cases occur in Africa, however, the magnitude of the disease has reduced by 21% from 2010 to 2015, However, in 2016, malaria has grown to 216 million globally, 81% of which happen in sub-Saharan Africa, killing roughly 655,000 individuals annually(1). Of these total deaths, 91% occurred in sub-Saharan Africa, most of which are children under the age of 5-years. This is mainly due to P. falciparum, the most hazardous disease of the four human malaria parasites, which still generates a notable global burden, even though malaria-induced morbidity and mortality have decreased over the last century, in particular among females and kids under the age of five(3).

In Ethiopia, 75% of the country is malaria's with about 60% of the total population living in areas at risk of malaria. That is, there is a malaria danger of 50,6 million individuals, and malaria affects four to five million people every year(1, 3). The number of malaria cases was decreased from 2.8 million to 621 345 in the last 25 years (4).

Amhara is one of Ethiopia's low land malaria regions. In 2011/2012, the incidence of malaria was 4.3% and the incidence rate was higher among men (4.8%) than women (3.4%) (5). P. falciparum and Plasmodium vivax are the dominant malaria species in the region. The region accounts for 31% (1.3 million cases) of Ethiopia's malaria burden(6).

In Ethiopia, malaria epidemiology is unique when compared to other African countries, both Plasmodium falciparum and Plasmodium vivax affecting the population and malaria transmission is generally unstable, with focal, seasonal outbreaks and occasional epidemics(7).

Statistical modeling offers a mathematical overview of relationships between environment and disease, identifies important environmental predictors of malaria transmission, and offers malaria risk projections based on the above relations with their accuracy. Independence from observations and variables is assumed by conventional statistical models. The occurrence of

malaria is, however, clustering because of the clustering nature of conditions that favor its occurrence (8). Ignoring this spatial correlation and assuming independence causes overestimation of the statistical significance of the covariates(9).

Due to the growth of simulation techniques such as the MCMC(10), Bayesian statistic models have become potent techniques in modeling spatial data. These methods are used for the empirical re-distribution of parameters. The Gibbs sampler algorithm(11), Metropolis-Hasting algorithm(12), and the reversible Jump MCMC (12) are significant methodologies.

Understanding the connection between the incidence of malaria and environmental / climate variables is helpful to study how climate variability can influence long-term disease transmission and distribution(13).

In the latest years, there has been no study that considers both the lowland and highland areas. In this research, we used statistical modeling from the Bayesian point of view that offers a mathematical overview of relationships between environment and disease and identifies substantial environmental malaria transmission predictors along the way.

Materials And Methods

Study design and period: A repeated cross-sectional study was conducted using all malaria cases reported and all reported average monthly metrological data from eight districts in northwest Ethiopia 2016.

Outcomes and predictors of the study

The malaria incidence rate was the primary outcome variable and Average Monthly Maximum Temperature, Average Monthly Estimated Rainfall, Average Monthly Minimum Temperature, Average Monthly Elevation (Altitude), Average Sunshine Hour, Average Monthly Relative Humidity, and Normalized Difference Vegetation Index (NDVI) was the independent variables.

Setting

The study was performed in the northern part of Ethiopia in 2016. The area is one of the 11 zones of Amhara Regional State. According to the central statistics agency report, the total population of the study area is 38,004,589 which covers 45,934.090 square kilometers and the population density is 64 persons per square kilometer. Topographically the area contains two main parts, namely the lowlands (552 meters) and highlands (2926 meters) above sea level(14).

According to National oceanic and atmospheric service (NOAAS) classification, the study area had minimum (0.2) and maximum (0.6) normalized difference vegetation index (forest, shrub, grassland and vegetation's)(15), 28.7°C and 14.1°C maximum and minimum temperatures respectively, 0 to 87.5% relative humidity and two rainy seasons: the main one from June to September, followed by a shorter one from March to May. The dry season ranges from October to February (16).

Data Source

Retrospectively, malaria data were acquired from monthly reports from the health department in northwest Ethiopia in 2016. The information was recorded in monthly surveillance forms from each district health center and subsequently reported to district health offices that are finally reported to the Zone health office. The malaria data sets were aggregated at the district level and it included data on total cases of malaria, parasite types (P. Falciparum, P. Vivax, and mixed infections), malaria cases of various age groups and times (month and year).

The climatic and environmental predictors used in this study were extracted from different web sources. Normalized difference vegetation index and Altitude were extracted from remote sensing data at 0.25 km by 0.25 km and 1 km by 1 km spatial resolution respectively from Moderate Resolution Imaging Spectro-radiometer (MODIS) **(Fig. 1).** The NDVI is a proxy measure of vegetation cover ranging from 1 to -1. Positive values indicate the presence of vegetation and negative values and values close to zero represent barren or water surfaces. Elevation (distance above the sea level) data were extracted at 1 km resolution from Digital Elevation Model (DEM). MODIS and DEM are obtained from the U.S Geological Survey (USGS) EROS Data Center. Satellite-derived daily rainfall estimates were obtained from the Ethiopia Meteorology Agency (EMA) with 1 km

by 1km resolution. Monthly accumulated rainfalls (mm) were summarized for each district from daily rainfall estimates (Table 1).

Table 1
The environmental data and the databases from which they were extracted

Factors	Resolution	Source
Normalized Difference Vegetation Index (NDVI)	2.5 km^2	Moderate Resolution Imaging Spectro-radiometer (MODIS) {http://reverb.echo.nasa.gov/reverb}
Maximum, Minimum, Temperatures	----	Ethiopia West Amhara meteorology agency (EWAMA)
Average Sunshine hour		Ethiopia West Amhara meteorology agency (EWAMA)
Estimated monthly Rainfall	----	Ethiopia West Amhara meteorology agency (EWAMA)
Relative monthly humidity	----	Ethiopia West Amhara meteorology agency (EWAMA)
Elevation (Altitude)	1 km^2	Digital Elevation Model (DEM)

Statistical Analysis

All statistical analysis has been performed by R software version 3.4.1 using packages like R2, MCTEST, ARM, CODA, MCMC, Bayes Boot and the Bayesian Tools.

Descriptive statistics such as proportion and the model parameters were estimated by using a Bayesian framework with the MCMC algorithm in the package GeoRglm in the R statistical software. MCMC methods involve the construction of a Markov chain (a mathematical representation of a random process where future values are conditionally independent of past values, and depend only on the present value), with the desired probability distribution at its equilibrium (the stationary posterior distribution which the chain will converge to following a suitable number of iterations). Samples can then be drawn from the equilibrium distribution and summarized to provide parameter estimates, Quintiles, and other measures of the distribution. Non-informative, uniform priors (in Bayesian inference a prior is a probability distribution expressing uncertainty about a parameter before taking into account data observations) were selected for each parameter to represent prior knowledge of their distributions. This allows the observed data to have the greatest influence on posterior distributions without being constrained by the choice of prior and can also improve MCMC convergence. The number of cases in each location is Poisson distribution and the natures of the data are counted, however, the variance of the parameters was overdispersed, as a result; Poisson regression was extended to the negative binomial regression model.

Colinearity among all possible pairs was done and if any couple has had a coefficient of correlation > |0.7| indicated the presence of Colinearity. Variables that have Wald $P > 0.1$ were removed and $P < 0.05$ as the entry criterion for the stepwise Poisson regression. A scatter plot and classified predictor variables were used to examine non-linear interactions.

Using the Deviance Information Criterion (DIC), the quality of each model was evaluated (17). A Bayesian ' p-value ' analog was calculated from the predictive posterior distribution to evaluate the predictive capability of the models. In particular locations, we should calculate the area of the predictive posterior distribution which is more extreme than the observed data. The model predicts the observed data well for a specific location when the observed data are close to the median of the predictive posterior distribution and therefore the ”p-value” close to 0.5. A box plot is used to summarize the “p-values” calculated from the test locations under a particular model. The box plot displays the minimum, the 25th, 50th, 75th quartile as well as the maximum of the distribution of the p-values.

Results

During the research period, the general average annual cumulative incidence of malaria was 29.90 per 100 populations at risk with 95% CI (29.89, 29.99). The research included eight districts and all districts reported events of malaria over the period of the research. In the study period, 112,282 malaria incidents were recorded. Plasmodium falciparum was the dominant species which accounts for 70.7% (95% CrI; 69.3, 71.8) and Plasmodium vivax accounts 27.1% (95% CI; 26.1, 28.1) of the total case. The highest malaria cases (71.78%) were seen in adults over 15 years, while the other 19.72% and 8.5% were in the age between 5 to 15 and under five years respectively.

The highest burden of malaria cases has been noted in the districts of Metema, Quara, and Chilga from July to October (Figure-2). An analysis of the spearman's correlation coefficient between malaria and monthly weather conditions (relative humidity, Rainfall, Sunshine hour, Maximum temperature, minimum temperature, and wind speed) was carried out (Table 2).

Table 2
The correlation coefficients' analysis of malaria and climatic variables' in northwest Ethiopia, 2016

		Monthly Relative humidity	NDVI	Monthly Rainfall	Length of Sunshine hour	Maximum Temperature	Minimum Temperature	Monthly wind speed	Altitude
number of malaria	Pearson Correlation Coefficient	0.409**	-0.12	0.07	-0.047	0.31**	0.34**	-0.19	-0.39**
	P-value	0.00	0.25	0.49	0.65	0.00	0.00	0.06	0.00

**. Correlation is significant at the 0.01 level (2-tailed)

**. Correlation is significant at the 0.05 level (2-tailed)*

Based on correlation analysis, the highest significant positive correlation was found between malaria incidence and monthly relative humidity (r = 0.41, p = 0.00), maximum temperature (r = 0.31, p = 0.01) as well as minimum temperature (r = 0.34,p = 0.01). However, the correlation between malaria incidence and monthly rainfall, length of sunshine hour and monthly wind speed were not statistically significant.

In the Bayesian generalized negative binomial regression analysis, relative humidity (IRR; 1.04 (95% BCI, 1.01–1.05), NDVI [IRR; 2.74(95% BCI, 1.35–5.58)], altitude [IRR; 0.97(95% BCI, 0.98–0.99], the average maximum temperature [IRR; 1.07(95% BCI (1.05–1.09)] and average minimum temperature[IRR; 1.04 (95% BCI (1.02–1.07)] were the significant variables in this study (Table 3).

Table 3
Estimation of malaria and its risk factor by using Bayesian generalized negative binomial regression model in north Gondar zone, northwest Ethiopia 2016

Variables	IRR	95% Bayesian Credible Interval	
		Lower	Upper
Altitude(M)	0.97*	0.95	0.99
Normalized Difference Vegetation Index(NDVI)	2.74**	1.35	5.58
Mean Maximum Temperature (C^0)	1.07***	1.05	1.09
Mean Minimum Temperature(C^0)	1.04***	1.02	1.06
Rainfall (MM)	1.01`	0.99	1.00
Relative Humidity (g/m3)	1.04*	1.01	1.05

** P-value < 0.05 ** P-value < 0.01 *** P-value < 0.001*

Discussion

This study determined the annual average incidence of malaria and identified climatic variables that affect its occurrence in highland and lowland areas of northwest Ethiopia.

The average annual malaria incidence rate was 29.9 per 100 populations. This is greater than studies conducted(9.7%) in the northwest Ethiopia(18), (4.3%) in Amhara region(5), (6.8%) in the southern nation and national states(4) and (10.4–13.5%) in Gambella; (7.6–14.1%) in Tigray, (0.9%) in Oromiya and (5.4%) in Southern Nations Nationalities People's Regions (19) and (4.5%) in Ethiopia(13). However, it is smaller than the research carried out in the Tigray region in 2011 (43%) and 2014 (33%) (20). The higher incidence of malaria in the study area might be related to a long rainy season and temperature variability(13, 20). The majority, 69.8%, of the malaria cases were due to plasmodium falciparum species. This is consistent with other studies from the southwest part of Ethiopia (19). The high burden of plasmodium falciparum and plasmodium vivax in the region was also documented in another study(13). The cause could be the temperature that favors their growth; temperatures more than 18C^0 for p. falciparum and more than15 C^0 for p. vivax is suitable for the growth of these two species. The temperature is higher than the minimum indicated in most parts of Ethiopia, particularly in Northwestern Ethiopia(18). Research in Tanzania also endorsed this idea(21).

The malaria victims that accounted for about 71.8% are adults over 15 years old. This is consistent with other researches(22, 23). However, another research has shown that malaria infection decreases in this age group(24). The high occurrence of malaria in adults could be attributed to the high mobility of people in this age group to malaria-risk areas for farming and other reasons.

In early April, the significant transmission time was noted and reaching its peak at the end of June and July. Between October and November, the second peak was noted. Other surveys have shown that there are two peak transmission periods in Ethiopia during the summer, but the incidents of the disease are variable(25). However, whatever the point of departure, everybody agreed that the first wet (summer rain) season was high in malaria transmission, with the wet season following the end(25).

Keeping the other variables constant in the model, the estimated incidence rate ratio of malaria was increased by 1.04 for a unit increment of relative humidity. It is supported by other studies conducted in Mali, Bangladesh, and Mozambique (26–28). Humidity between 55–80% is suitable for the completion of the Plasmodium falciparum and Plasmodium vivax malaria parasite life cycles (26). It seems that humidity plays an important role in the life cycle of the mosquito. In the presence of high humidity values, the parasite would complete the necessary life cycle to increase the transmission of the infection. When there is a unit increment of altitude, the rate of malaria incidence was reduced by 0.95 times. These findings are in agreement with other studies (27, 29–31).

The estimated risk of malaria incidence was increased by 1.07 times for a unit increment of average maximum temperature. This is in line with other studies (32–35). It might be the effect of temperature for the development of mosquitoes, their survival, and reproduction (36). A study in the highlands of eastern Africa disclosed that a rise of 1% in minimum temperatures over 1–2 months and a rise of 1% in peak temperatures over 2–5 months led to a rise of 80%-95% in the proportion of outpatients diagnosis of Malaria (37). However, another study conducted in Bangladesh found that temperature and numbers of malaria cases have no significant relationship(38). The development of the mosquito larvas and Plasmodium parasites is accelerated at high temperatures. A higher number of mosquito generations and greater abundance occur with enhanced growth rates. As temperatures rise, the transmission of malaria increases up to a rarely exceeded limit of 37C^0(24, 25). Higher temperature also increases the feeding rate of adult female mosquitos, which can increase the likelihood that the malaria parasite may transmit to uninfected human hosts(39, 40). The sporogenic cycle of plasmodium growth, which occurs in the mosquito, is also shortened by the fact that the temperature rises to an ideal rate (25, 41). Furthermore, insect longevity is temperature-sensitive and there are limited temperatures above which mosquito mortality increases and minimum temperatures below which insects become inactive(39).

The effect of rainfall on malaria incidence is somewhat controversial. In this study, rainfall had no significant relationship with malaria incidence. The finding is supported by other studies that studied across different countries (30, 42). But, many other studies have found a positive correlation. Studies in Angola, Mozambique, Mali, Zambia, Uganda, Botswana, and Thailand, for example, have found that greater precipitation values are linked to greater malaria incidence (26, 31, 43–46). In contrast, other studies have shown that precipitations are an important contributor to malaria reduction in some regions of India and Seri Lankas (26, 47–51).

The incidence rate of malaria was 2.75 times higher when a unit scale increment of normalized difference vegetation index. Other studies have also found a strong link between natural vegetation and malaria transmission (52–55). NDVI can serve as a surrogate variable that represents available water or conditions that are consistent with a higher likelihood of standing or pooled water. As precipitation falls to the ground and is absorbed by plant life, plants increase their biomass and therefore reflect radiation in the near-infrared region of the electromagnetic spectrum over a larger area than in times of vegetation senescence. It is therefore reasonable that if the water is widespread in order to enhance vegetation, there is a higher probability that water for mosquito reproduction will be accessible. Thereby probability of being infected, along with malarial transmission, rises as the mosquito population rises.

Conclusion

The finding of this study indicated that a greater incidence of malaria was observed in the study area when compared to the national statistics. Commonly reported metrological parameters (altitude, maximum and minimum temperature, relative humidity, and the normalized difference of vegetation index) were identified as predictors for malaria incidence. However, in surprising way wind speed, sunshine hour, and rainfall were not statistically significant predictors.

In particular, despite national monitoring programs and the Ministry of Health's attempts to eliminate this disease in our nation, the research showed that malaria is still a severe public health problem and the assessment gives additional insight into the underlying variables that specifically characterize malaria hazards in high-risk regions. Further studies at the village and the individual level would be important using primary data, including all areas of Ethiopia and explaining the local disease clustering by consideration other risk variables, such as soil temperature, air pressure, and socioeconomic factors. The communities and local authorities should implement the environmental control program and actively participate in it through campaigns aimed at clearing the bush.

Abbreviations

ADDS, Africa Data Dissemination Service BCL, Bayesian Credible Interval; CDC, Communicable Disease Control; CSA, Central Statistical Agency; DEM, Digital Elevation Survey; DIC, Deviance Information Criterion; IRR, Incidence Rate Ratio; EWAMA, Ethiopia West Amhara Metrology Agency; FMOH, Federal Minister Of Health; GIS, Geographical Information System; GLM, Generalize Linear Model

GPS, Geographical Positioning System; GTP, Growth and Transformation Plan; LST, Land Surface Temperature; MCMC, Markov Chain Mantel Carlo; MODIS, Moderate Resolution Imaging Spectro-Radiometer; NDVI, Normalized Difference Vegetation Index; NOAAS, National Oceanic And Atmospheric System; RR, Relative Risk; USG, United States Geological Survey; WHO, World Health Organization

Declarations

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Funding

No

Conflicts of interest/Competing interests

No

Ethics approval

The study was approved by the Institutional Review Board of the University of Gondar. Support letters were obtained from North Gondar health offices for retrieving retrospective malaria data from records.

Consent to participate

The research was done based on record review without contacting patients. All the information was kept confidential and no individual identifiers were collected.permission was obtained from the North Gondar zone health management information department.

Consent for publication

Not applicable

Availability of data and material

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Authors' contributions

All the authors have actively participated during conception and design, acquisition of data, or analysis and interpretation of data. All authors read and approved the final version of the manuscript.

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Figures

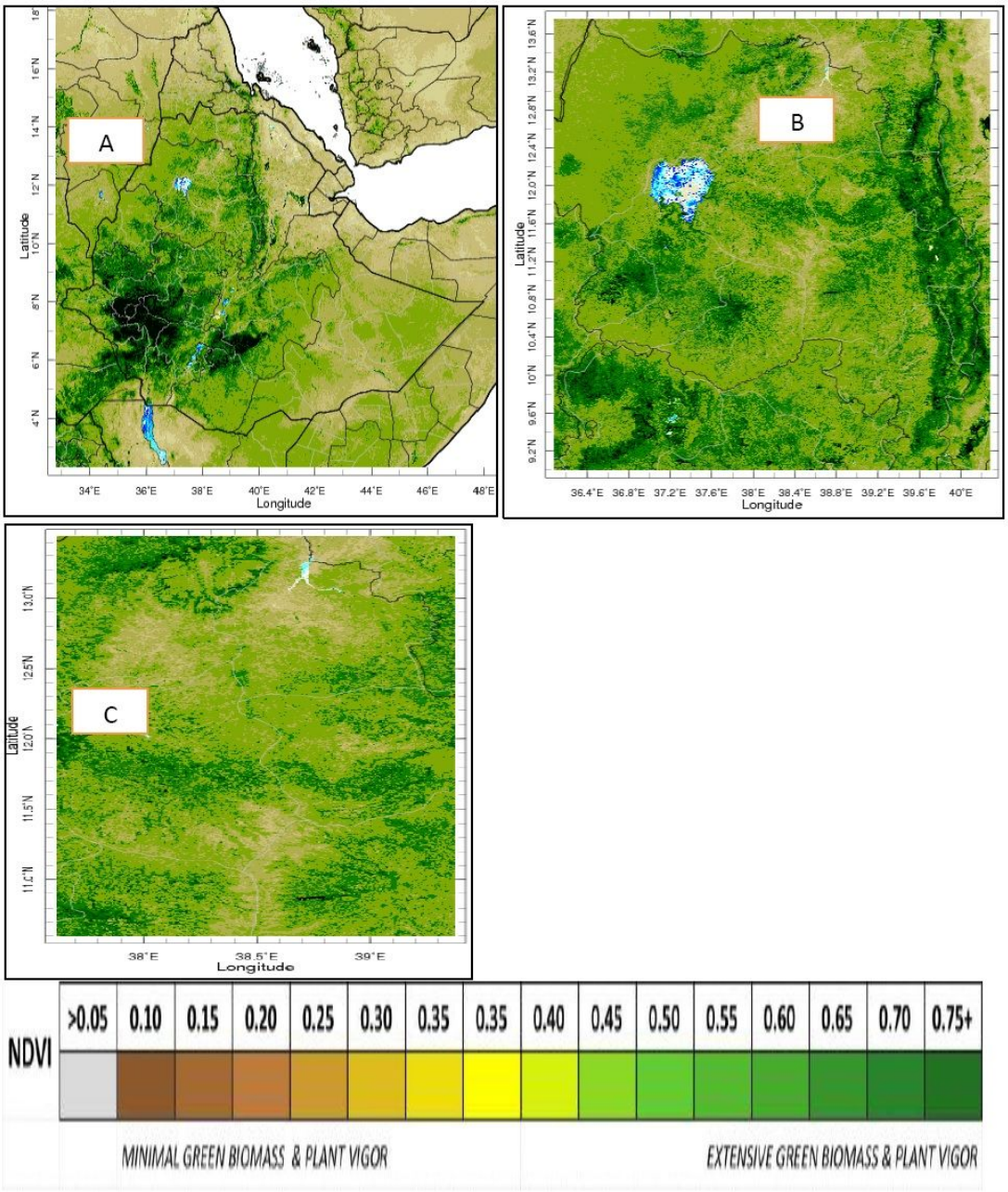

Figure 1

The NDVI maps of Ethiopia (A), Amhara regional state (B) and the study area, data extracted from Moderate Resolution Imaging Spectro-radiometer (MODIS) 2016. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

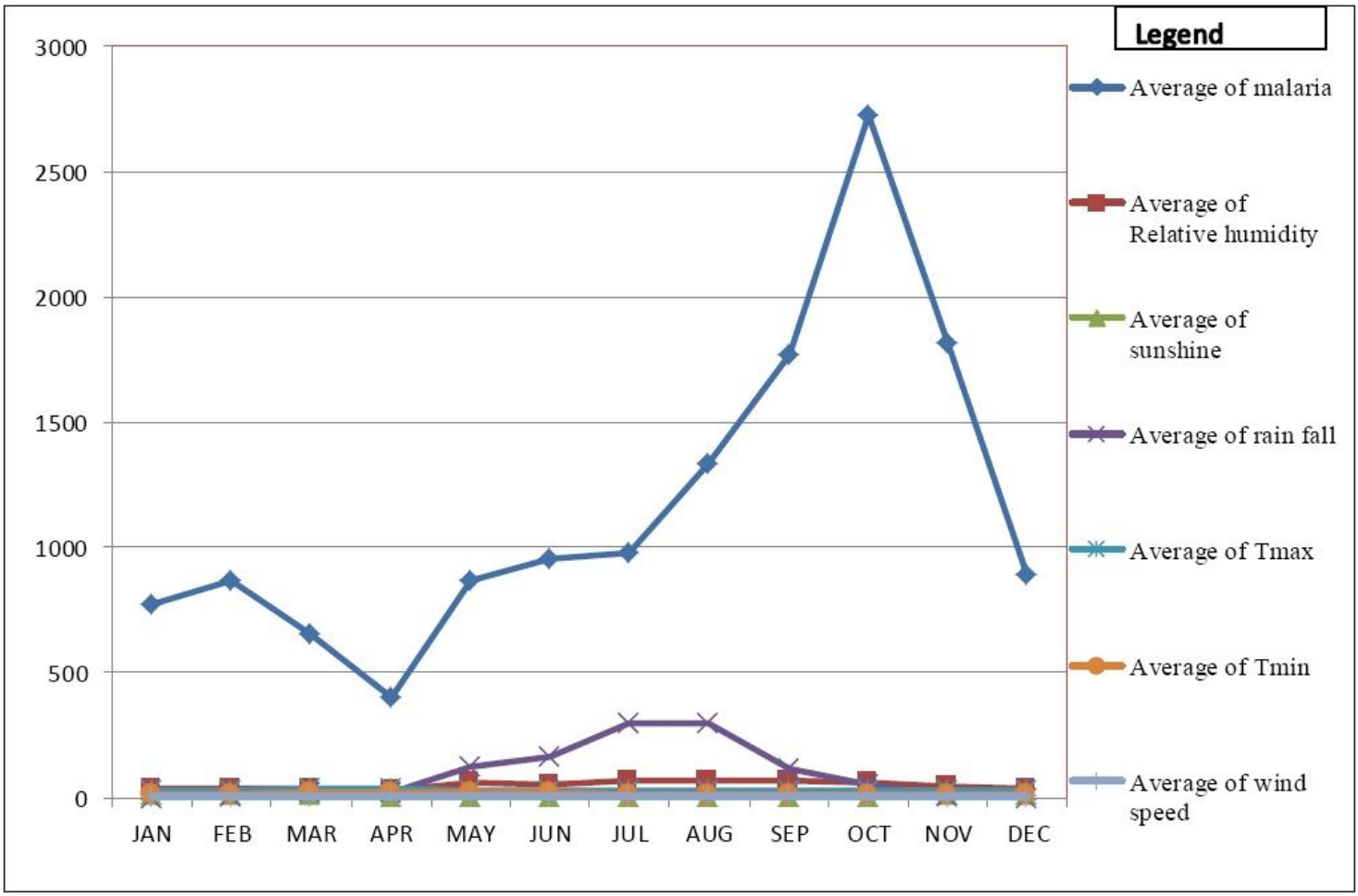

Figure 2

Average monthly recorded data of malaria and climatic variables' in North West Ethiopia 2016