Impact of Climate Variation on Malaria Incidence in Rwandan Highland

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Abstract

Fluctuations in climate variation could influence the emergence and re-emergence of vector-borne infectious diseases such as malaria in highlands. The transmission of malaria is caused by vector and arthropod that strive in area with high rainfall and they are limited by low temperatures and high altitudes. Malaria vectors for many years were found in lowlands and not found in highlands because of weather conditions. The present research sought to evaluate the possible impacts of climate variability on malaria incidence in Rwandan highlands. Using secondary data on malaria cases from medical records in sampled using multistage sampling Health Centres of highlands (26) and meteorological data collected from meteorological stations of Mubuga, Kivumu and Karambi. Regression analysis was used to determine relationship between climate variability and malaria prevalence. Analysis of data for 11 years period indicated that; maximum temperature did not have high variation; it was in the range of 23 and 25ºC, while minimum temperature varied considerably with a range of 8.02 and 14.55, average of minimum and maximum indicated linear growth as it combines the values of maximum and minimum temperature (16.34 and 19.54ºC), rainfall was increasing throughout of the period of study with high variation and extreme weathers, the monthly average was between 95.62 to 156 mm. In Karongi it varied between 87.00 to 122 mm, Muhanga it was between 80.63 to 235 mm and Rubavu it was between 81.33 to 136 mm. Relative humidity was also important, its variation was not too high since the highest value of relative humidity was 72.24% and the lowest was 66.10%. Generally relative humidity was decreasing with time. With 5% level of significance, all selected climate parameters were not correlating with malaria transmission at the same level; in Karongi malaria prevalence had a strong positive correlation with: maximum temperature and rainfall, r=0.68, a moderate positive correlation with rainfall and relative humidity, r=0.5 and a strong positive correlation with average temperature and rainfall, r=0.66. In Muhanga malaria prevalence had a strong positive correlation with minimum temperature, r=0.76, while in Rubavu malaria prevalence had a weak positive correlation with maximum temperature and relative humidity, r=0.44 and a weak positive correlation with average temperature, rainfall and relative humidity r=0.33. Results showed the evidence of the existence of relationship between climate parameters and malaria prevalence in highland areas of Rwanda. All national programs on malaria control should take into account this area of Rwandan highland, since it is highly susceptible to climate change and malaria prevalence.

Keywords*: Climate variability, Highland, malaria, incidence, prevalence*

1. INTRODUCTION

Malaria is both preventable and treatable disease (UNICEF, 2015). Yet more than 220 million cases of malaria are estimated to occur each year all over the world, and approximately 785,000 people die from the disease annually. Half of the world's population, some 3.3 billion people living in 109 countries, are at risk of malaria (Paaijmans *et al.*, 2009). Worldwide, malaria is the fifth-leading cause of death from infectious diseases (after respiratory infections, HIV/AIDS, diarrheal diseases, and tuberculosis) (WHO, 2014).

Each year, a million of people are killed by malaria in Africa, according to the World Health Organization (WHO). In 2006 more than 90 percent of deaths victims of malaria, were from African region where 45 of the 53 countries are endemic for the disease (WHO, 2014). These data render malaria the dominant tropical parasitic disease and one of the top three killers among communicable diseases (Kuhn, *et al.* 2005). Malaria also can cause morbidity through fever, weakness, malnutrition, anemia, spleen diseases, and vulnerability to other diseases (Oaks, *et al*, 1991).

Malaria is considered endemic in regions of stable *Plasmodium* transmission, but malaria outbreaks often also rise in regions of unstable transmission where altitude can be 1500-2500 meters above sea level, which are characterised by climate that is not suitable for mosquitoes (Kuhn, *et al.,* 2005). For African highlands, every 1000 meter gain in elevation is accompanied with temperature decrease of 6^{o}C (Kevin, 2009). In such regions, malaria outbreaks are considered as irregular, but sometimes higher than normal rates of malaria transmission often occur, and symptoms are exacerbated due to the low immunity of human population inhabiting these areas. In addition of that, local population may not be aware of mosquito types in their neighbourhood, what may result in reduced adoption of protection measurement (Patz *et al*., 2008).

Numerous, and in some cases conflicting, predictions have been developed regarding the frequency, severity, and duration of epidemics that may emerge. With respect to the bio geographical focus of this issue, the central question is whether pathogens and parasites that are currently restricted to lower latitudes where the world's greatest biodiversity lies move toward poles (mostly north) and upward in altitude (Chapin III *et al.*, 2012).

Rwanda had made a big achievement toward malaria eradication as it was among the pillars of MDG (UNICEF, 2015), but, recently WHO Global Malaria Program (2015) reported a tripling in confirmed malaria cases (from 483 000 to 1.6 million), and a doubling in admissions (from 5306 to 11 138) between 2012 and 2014 According to preliminary analysis conducted by the MOPDD, the vast majority of this increase is among persons over five years of age (RBC, 2017). This increase in malaria case numbers in Rwanda (according to RBC) are most likely due to resistance increase to insecticides, anti-malarial drugs, substandard LLINs and climate variability (President's Malaria Initiative, 2014).

While most of highlands of Rwanda are located in the fringes of endemic zones, where transmission is limited by rainfall or by lower temperatures, there are strong seasonal patterns and occasional major epidemics (Bizimana, 2015). In such regions, climate is a major determinant of year-to-year changes in malaria incidence. In some locations, warming trends in the past two decades might have contributed to changing the epidemiology of malaria (Paul & Dirk, 2004). But what effects will future changes in climate have on malaria in Rwandan highland?

Regarding research priorities, there is a great need to better understand the current relationships between "multiple physical phenomenon" of weather and disease, while at the same time we must begin to consider future risk estimates required by policy makers. New discoveries from field data are particularly essential in constructing credible simulation models. The present paper tried to model the effect of climate variability on malaria incidence in Rwandan Highlands for the period of 11 years.

2. METHODOLOGY

2.1. Study area

Rwanda is a small (26,338 km^2), land-locked country in the Great Lakes region of Eastern Africa, bordered by Uganda, Burundi, the Democratic Republic of the Congo, and Tanzania. It has a population of approximately 12 million people (projection from 2012 census results), making it the most densely populated country in continental Africa. Administratively, the country is made up of 30 districts, which are divided into sectors, cells (*cellules*), and 14,953 *umudugudus* (villages of 50–100 households).

Rwanda has a complex climate, with wide variations across the country and with very strong seasonality (DFID, 2009). It is primarily a mountainous country, with average altitude of 900 m in south-west, 1500 to 2000 m in the south and the centre of the country, 1800 to 3000 m in the highlands of the north and the west and 3000 to 4500 m in the regions of Congo-Nile Crest and the chain of volcanoes (President's Malaria Initiative, 2014). The equatorial climate is modified by this widely varying altitude across the country. It leads to a more temperate climate than much of the rest of East Africa. Average annual temperature in Rwanda ranges between 16ºC and 20ºC though they are much lower than this in the higher mountains (MINIRENA,2013)

2.2. Highland region of study area

Rwandan highland lies in West, North and Southern part which is one of the four categories of Rwandan relief. The study area covers 3 Districts; Karongi and Rubavu in Western province in the range of Congo-Nile divide and Muhanga district in Southern province. The study area lies in 1.505^{o} and 2.317^{o}S and 29.244^{o} and 29.813^{o}E at an altitude ranging from 1,500 to 3000 m above the sea level. Note that the districts comprise lower land relief for instance foothills, but the altitude is dominated by highland parts with altitude of 1500 m above the sea level (Figure 1).

Average temperature is between 16–21^{o}C while the lowest temperature is 6^{o}C. The rainfall patterns are characterized by four seasons, a short rainy-season from September to November and a longer rain season between March to May. Between these seasons are two dry periods, a short dry period between December to February and a long dry period from June to August. Rainfall is around 1500 mm per annum in the north and northwest volcanic highland areas.

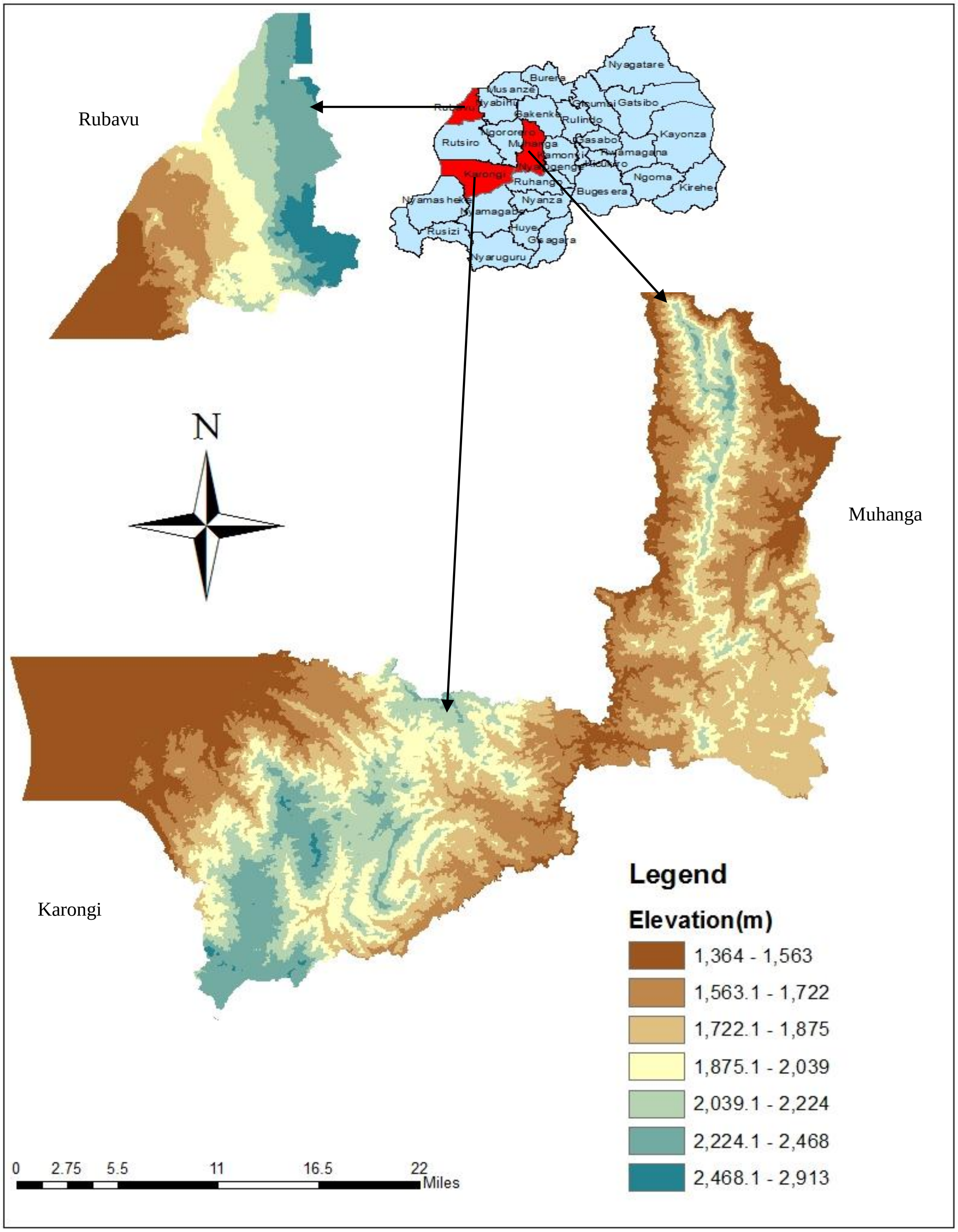

Figure 1: Topographic map of the study area (Muhanga, Karongi and Rubavu)

2.3. Data collection methods

The researcher secured the permit for accessing the secondary data form Ministry of Health and Rwanda Meteorology Agency. The permit was issued by Rwanda Biomedical Centre after being recommended by Rwanda National Ethic Committee. Preliminary visit was performed to ensure the matching of Health centres and meteorological stations.

2.3.1. Malaria cases collection

Epidemiological data collected were monthly malaria cases, between October 2004 and December 2014, collected at health centre facility level in each district for routine reporting to the HMIS. Data included parasitological confirmed cases symptomatically diagnosed as malaria by trained health workers. Data were aggregated at sector's level for all health facilities in each area. Data for 11 years were available in the three districts of study area, giving 26 units (equivalent to 26 sectors and health centres).

2.3.2. Population data

Baseline population for each of these Health Centres was obtained from National Statistics Institute of Rwanda (NSIR) using census of 2002 and 2014. Subsequent population serviced by each health centre for the years 2004 to 2014 was projected using the exponential population growth equation;

$$N_t = N_0\, e^{rt}$$

Where N_t =size of population at time t, N_0 =size of population at time zero, *e*=base of natural logarithms =2.71828, *r*=rate of population growth, *t*=time elapsed.

Malaria incidence was per 1000 population were calculated as follow:

$$Malaria\ Incidence = \frac{Number\ of\ malaria\ cases}{Population\ in\ a\ given\ period}\, x1000 \quad 2.$$

3.3. Climate data collection

Time series daily meteorological data of the period 2004–2014 composed by daily temperature, rainfall and relative humidity, were obtained from Rwanda Meteorological Agency (RMA). The parameters collected were from 3 meteorological stations located in study area; Mubuga for Karongi District, Kivumu for Rubavu District and Karambi for Muhanga District. Data were computed as mean minimum monthly temperature, mean maximum monthly temperature, average of mean maximum and minimum temperature, average monthly rainfall and average of relative humidity.

2.4. Data Analysis

2.4.1. Descriptive statistics analysis

Descriptive statistics were used for organizing, summarizing, and presenting data in an informative way using tables and figures. Average was computed for all variables and median to fill missing data. Normalization of data using natural logarithm was used to obtain a more homogeneous variance of a series to be used in multiple linear regressions and correlation.

2.4.2. Multiple Linear Regression analysis

The purpose was to model the dependence of malaria incidence on covariates including maximum temperature, minimum temperature, and average of minimum and maximum temperature, rainfall and relative humidity in Rwandan highlands. Assuming other factors hardly to control was held constant. Throughout this study adoption of the following notation for the variables: x_1 is temperature, x_2 is rainfall while x_3 is relative humidity.

E-views 7 was used in model construction with a lag period of one month, the period corresponding to the parasite cycle completion as Paaijmans, *et al*, (2009) indicated.

The model was: $y = ß_0 + ß_1X_1 + ß_2X_2 + ß_3X_3+\varepsilon$

For the final model, the variables with $P>0.05$ would be removed and rerun the model with the only variables with significance below 0.05. In the model, ε is a random error with a mean of zero and a constant standard deviation σ. The model was estimated by finding the coefficients of the x values that make the error sum of squares as small as possible.

Significance level used was 5%: which is the probability of rejecting null hypothesis when it is true.

The explanation power (squared correlation R^2) was used to measure the goodness of fit of the regression model and indicated the explanatory power of the model. The R^2 was used to measure the proportion of variations in malaria incidence that is caused by variation in climate parameters. A high R^2 represented a higher influence of climate parameter, while a low R^2 signified a weak relationship between climate variation and malaria incidence.

3. RESULTS

This study sought to analyse the relationship between climate variation (temperature, rainfall and relative humidity) and malaria incidence in Rwandan highlands. The summary of the data collected in three districts were presented in Table 1

Table 1: Average malaria incidence, temperature, rainfall and relative humidity for 2004-2014

Year	Malaria incidence	Max temp in °C	Min Temp in °C	Mean temp in °C	Av of Rainfall	Rel Hum
2004	14.44	24.44	8.24	16.34	107.44	72.23
2005	12.46	25.27	8.02	16.65	98.91	69.72
2006	14.31	24.51	11.72	18.10	120.13	69.74
2007	5.03	23.31	13.02	18.18	98.62	71.02
2008	2.88	23.58	14.54	19.07	95.61	73.67
2009	4.22	24.08	14.34	19.19	96.47	70.35
2010	1.65	24.05	13.60	19.54	113.38	68.29
2011	0.08	23.94	12.60	18.16	124.60	70.71
2012	0.26	24.35	13.55	18.99	109.12	68.86
2013	2.47	24.40	14.55	19.48	104.49	66.09
2014	5.73	24.28	13.05	18.44	156.93	66.66
Grand Total	5.14	24.18	12.78	18.53	108.11	69.58

Table 1 indicated that malaria incidence was in the range of 12/1000 and 14/1000 between 2004 and 2006, after it reduced sensibly to 5/1000 in 2007, since then the lowest value stood at 0.08/1000 in 2011. There was a linear increase from 2011 and following years as Table 1 gave detail. Climate parameters varied according to the seasons of the year; Rwanda annual weather is divided into four seasons; long dry season from June to mid-September, Short rain season in mid-September, October, and November, Short dry season in December to February, Long rain season March, April and May (MAM). These seasons affect malaria distribution in the country.

Malaria transmission occurs year-round with two peaks (May-June and November-December) in Rwanda, following distinct rainy seasons (MINISANTE, 2011). Figure 2 presented malaria incidence according to different seasons of the year from 2004 to 2014. Muhanga always presented high annual malaria incidence than others, secondly comes Karongi and lastly Rubavu. But the growth rate was higher in Karongi

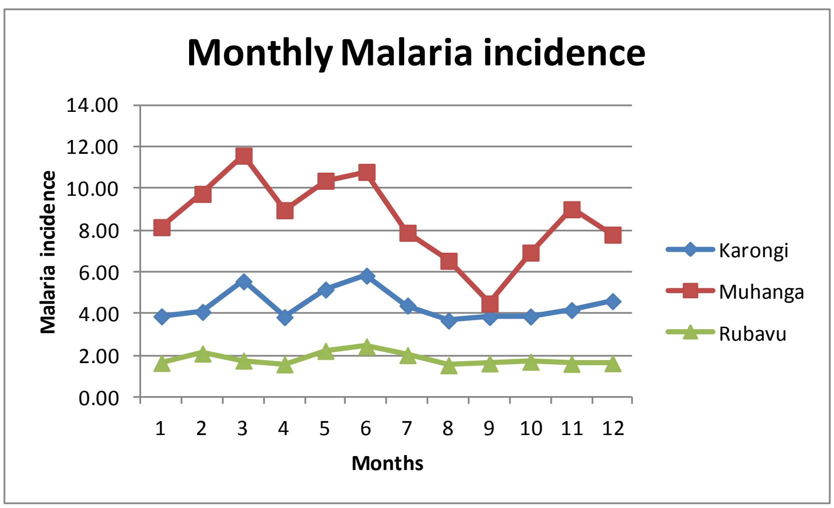

Figure 2: Monthly malaria incidence in study area for 11 years.

From the Figure 2, the month of March proved important peaks of transmission in Karongi and Muhanga, while in Rubavu additional peak was observed in February. In December, except Karongi other curves indicated reduction. Annual May/June's peaks of transmission remained throughout the area of study.

3.1. Analysis using multiple linear regressions

Multiple linear regression analysis was used to predict malaria incidence using climate variables (temperature, precipitation and relative humidity), temperature was presented in 3 levels; Maximum temperature, Minimum temperature and mean temperature for each district. Table 2 summarize the result of analysis:

Table 2: Summary of multiple linear regressions

	Temperature	*Regression equation*	*R-square*	*Corelation coefficient*	*Valid parameters at 5%*	*Model equation*
Karongi	**Max Temp**	$\hat{y}$=148.18-50.35x_1+0.12x_2+2.74x_3+0.34	0.47	0.68	Max Temp, Prec	$\hat{y}$=146.63-46.23x_1+0.132x_2+0.345
	Mini Temp	$\hat{y}$=55.35+1.12x_1+0.18x_2-14.22x_3+0.39	0.28	0.5	Prec, Relat hum	$\hat{y}$=58.83+0.18x_2-14.33x_3+0.39
	Aver Temp	$\hat{y}$=226.69-73.43x_1+0.14x_2-2.16x_3+0.41	0.44	0.66	Av temp, prec	$\hat{y}$=232.69-78.34x_1+0.14x_2+0.41
Muhanga	**Max Temp**	$\hat{y}$=3.18-1.6x_1-0.0083x_2+0.36x_3+0.77	0.59	0.76	None	Absent
	Mini Temp	$\hat{y}$=-13.44+4.10x_1-0.038x_2+0.5x_3+0.76	0.59	0.76	Minimum temp	$\hat{y}$=-8.33+2.91x_1+0.76
	Aver Temp	$\hat{y}$=0.32+0.49x_1+0.01x_2-0.58x_3+0.77	0.59	0.76	none	Absent
Rubavu	**Max Temp**	$\hat{y}$=-50.60+10.13x_1+0.050x_2+3.74x_3+0.20	0.2	0.44	Max Temp, Rel Hum	$\hat{y}$=-52.31+9.99x_1+4.3x_3+0.20
	Mini Temp	$\hat{y}$=-50.60+10.13x_1+0.050x_2+3.74x_3+0.20	0.04	0.2	None	Absent
	Aver Temp	$\hat{y}$=-50.60+10.13x_1+0.050x_2+3.74x_3+0.20	0.11	0.33	Av temp, prec, hum	$\hat{y}$=-31+3.75x_1-0.004x_2+4.35x_3+0.21

Table 2 summarizes the results of analysis using multiple linear regressions; three equations were presented for every district according to maximum, minimum and average temperature. Considering the level of significance, a parameter with P > 0.05 was removed from the equation and final model was presented using valid parameters at 5%. Some models at 5% were absents, others one or two parameters were valid.

The hypothesis stated that H_o: $b_1 = b_2 = b_3 = 0$, against H_1: $b_1 \neq b_2 \neq b_3 \neq 0$, not all the b_s are zero and excluding mutually. *There is an influence of temperature, rainfall, relative humidity on malaria incidence in Rwandan highland*. Regression coefficients are b_1, b_2, b_3 ($\hat{y}= b_0 + b_1x_1 + b_2x_2 + b_3x_3$ are valid).
From the Table 2, regression equations indicated the values of b_s different from 0, what validate alternative hypothesis and rejection of null hypothesis at 5%.

4. DISCUSSION

Data analysis revealed that incidence of malaria was influenced by the seasons. According to Greek physician Hippocrates (about 400 BC) epidemics are related to seasonal weather changes, he uttered that physicians should have "*due regard to the seasons of the year, and the diseases which they produce, and to the states of the wind peculiar to each country and the qualities of its waters*" (McMichael *et al.*, 2003)

Generally the fluctuation of climate variables were quite different from what was normally expected, according to Chemonics International Inc, (2003) average temperature should not go beyond 16-17ºC while annual rainfall should be 1300-2000 mm or 108-166 mm per month, relative humidity 70% 95%. Table 1 indicated that temperature and rainfall rose while relative humidity reduced significantly.

Data collected indicated high spatial and time variation of climate parameters; generally, maximum temperature ranged between 23 and 25ºC with lower variation, while minimum temperature ranged between 8.02 and 14.55ºC with considerable variation, average of minimum (16.34ºC) and maximum (19.54ºC) indicated linear growth. Rainfall was increasing; the monthly average ranged between 95.62 to 156 mm, while relative humidity, its variation was not too high; the highest value was 72.24% and the lowest was 66.10%.

Malaria transmission occurs year-round with two distinct peaks (May-June, November-December) in the endemic zones following distinct rainy seasons (MINISANTE, 2011).

Figure 1, indicated slight difference where March shows another important peak of transmission in Karongi and Muhanga, while in Rubavu another peak was observed in February. December shows a decrease instead of showing a peak. May/June's transmission peak remains throughout the area of study.

Since geographical and seasonal distributions of many infectious diseases are linked to climate, the possibility of using climate parameters as predictive indicators in disease EWS has long been a focus of interest (Kuhn *et al.*, 2005). The geographical distribution and population dynamics of insect vectors are closely related to patterns of temperature, rainfall and humidity.

Seasonal analysis of malaria incidence indicated how climate variation influenced the variation of malaria prevalence in Rwandan highlands. It was confirmed that rainfall plays an important role in the creation of breeding sites for vectors as it can flush away the mosquitoes' breeding sites (Wilson, 2001). Though relative humidity and temperature play an important role in the survival and longevity of the mosquito vector, it is rainfall that regulates the development rate of both mosquito and parasite to complete lifecycle. When relative humidity drops below 50% to 60%, it is believed that malaria transmission cannot occur because of the reduced lifespan of mosquitoes (Mohammed *et al*., 2012, Eldridge, 2009). The mean relative humidity throughout the year was between 63.28% and 73.87%, which means relative humidity is not a limiting factor for malaria transmission in the highlands of Rwanda.

Regression analysis of malaria incidence and maximum temperature, rainfall and relative humidity in Karongi, showed a significant result with *F-statistic* = 95.134, $p < 0.001$, and Adjusted R squared = 0.47 or 47%. Except relative humidity, other predictors had significant zero-order correlation with malaria incidence at 5% significance level.

Regression analysis using minimum temperature, rainfall and relative humidity yielded a significant equation with *F-statistic* = 41.98, $p < 0.001$, adjusted R squared = 0.27 or 27%. Except minimum temperature, other predictors had significant zero-order correlation with malaria incidence at 5% significance level. Minimum temperature did not have a significant partial effect in the full model but rainfall and relative humidity had significant partial effects.

Regression analysis using mean temperature, rainfall and relative humidity showed a significant equation with *F-statistic* = 86.46, $p < 0.001$, adjusted R^2= 0.44 or 44%. Except relative humidity, other predictors had significant zero-order correlation with malaria incidence at 5% significance level.

Regression analysis using maximum temperature, rainfall and relative humidity in Muhanga, yielded a significant result with *F-statistic* = 155.46, $p < .001$, and adjusted R squared = 0.59 or 59%. All predictors did not have significant effect in the full model at 5% significance level. When other predictors were ignored, maximum temperature and rainfall were negatively correlated with malaria incidence.

Maximum temperature in Muhanga ranged between 25.6°C and 27.26°C, and rainfall had the highest value among other Districts of study in 2014 with 235.21mm. Malaria in that period was not significant. Whoever, Muhanga and other districts of southern and western provinces, malaria incidence remained relatively high during malaria post intervention period (Karema *et al*., 2012), but negatively correlating with heavy rainfall.

Regression analysis results using minimum temperature, rainfall and relative humidity yielded a significant equation with *F-statistic* = 158.64, $p < 0.001$, and adjusted R squared = 0.58 or 58%. It was observed that only prediction with minimum temperature was possible at 5% significant level. Other predictors did not have significant effect on the full model at 5% significance level.

Significant reduction of minimum temperature remained above the threshold for *Anopheles gambiae* mosquito vector (the main mosquito species found in the East African highlands) whose biological activity is between 8°C to 10°C (Dekens *et al.,* 2013), This value of minimum temperature stood between 14.6.6°C and 15.2°C. While the minimum temperature threshold for transmission of the *Plasmodium falciparum* parasite (the main parasite species found in the East African highlands) is 16°C to 19°C, temperature is lower at night than day time. According to Githeko (2010), due to the influence of diurnal maximum temperature (27°C), maturity of malaria parasite may take almost 8 days only which is less than its lifespan of 23-days average of Anopheles *gambiae mosquitoes.*

Regression analysis using mean temperature, rainfall and relative humidity yielded, a significant equation with *F-statistic* = 155.12, $p < .001$. $R^2 = 0.59$ or 59%. As shown in Table 2 all predictors did not have a significant effect on a full model at 5% significance level. When other predictors were ignored, relative humidity was negatively correlating with malaria incidence.

The average temperature was within the minimum conditions of malaria transmission (19.2°C and 20°C) but again malaria transmission depended on season and altitude. Githeko & Ndegwa (2001) argued that *"if the mean annual temperature is superior, or equal, to 18°C; anomalies superior or equal to 3°C would be expected to precipitate malaria outbreaks as long as the mean monthly rainfall is greater than 150 mm."* Here mean temperature was higher than 18°C, long term anomalies was higher than 3°C but rainfall was below 150 mm, so malaria outbreak was expected despite the absence of significant effect in the full model at 5% significance level.

Regression analysis using maximum temperature, rainfall and relative humidity in Rubavu, showed a significant result with *F-statistic* = 20.96, $p < 0.001$, adjusted R squared = 0.19 or 19%, except rainfall, other predictors had significant zero-order correlation with malaria incidence at 5% significance level.

The increase of maximum temperature in

Rubavu between 2011- 2014 with 4 units, exposed this area to high risk of malaria. Compared with malaria parasite and parasite survivorship, maximum temperature was higher than 18^{o}C, this implied that parasite development was too fast despite the low incidence of malaria on Figure 1.

Minimum temperature was too low to allow malaria transmission. No where minimum temperature reached the threshold of neither parasite nor vector development. The range was between 7.56^{o}C in 2011 and 13.94^{o}C in 2013. With these values, malaria transmission was not possible. The same was observed for combination with rainfall and relative humidity. Model equation was not possible at 5% significance level.

Regression analysis using mean temperature, rainfall and relative humidity gave significant equation with *F-statistic* = 10.98, p <0 .001, and adjusted R squared = 0.10 or 10%, all predictor had a significant zero-order correlation with malaria incidence at 5% significance level and had significant partial effect in the full model, but rainfall was negatively correlating with malaria incidence, while other predictors were positively correlating with malaria incidence.

5. CONCLUSION AND RECOMMENDATION

5.1. Introduction

This study has used available real monthly data on malaria cases, rainfall, temperature and humidity over 11 years (2004-2014) from the highlands of Rwanda to analyse the possible impact of climate variability on malaria incidence. Data analysis indicated that minimum temperature remained above the threshold for *Anopheles gambiae* mosquito vector (the main mosquito species found in the East African highlands) for its biological activity (8^{o}C to 10^{o}C). The minimum temperature in study area was between 8.03^{o}C to 14.55^{o}C. While the threshold of minimum temperature for transmission of the *Plasmodium falciparum* parasite (the main parasite species found in the East African highlands) was 16^{o}C to 19^{o}C.

Multiple linear regression analysis using malaria prevalence as dependent variable, with lag period of 1 month, and climate parameters as independent variable (maximum, minimum and average temperature, rainfall and relative humidity), showed that all predictors had different impacts at 5% of significance level. All the selected climate parameters were not correlating with malaria transmission at the same level; in Karongi malaria prevalence had a strong positive correlation with: maximum temperature and rainfall, r=0.68, a moderate positive correlation with rainfall and relative humidity, r=0.5 and a strong positive correlation with average temperature and rainfall, r=0.66. In Muhanga malaria prevalence had a positive strong correlation with minimum temperature r=0.76, while in Rubavu malaria prevalence had a weak positive correlation with maximum temperature and relative humidity, r=0.44 and a weak positive correlation with average temperature, rainfall and relative humidity r=0.33. Regression equation indicated the values of coefficient b_s different from 0, what validate alternative hypothesis and rejection of null hypothesis at 5%.

5.2. Recommendations

Meteorological variables are among the factors that precipitate malaria epidemic; rainfall provides the breeding sites for mosquitoes, and higher temperature and relative humidity increase mosquito survival and parasite development.

Malaria is invading new areas including highlands that used to be shelters against malaria, but the altitude above 2600 m above the sea level, Malaria is still rare and its adaptation is still impossible.

In prediction using climate variability, it is highly commendable to use seasonal input so that effort can put where it is needed: Example preparation of medication and other malaria control measures just after rain season because it is the time when malaria can be on high rise

Facilitation and motivation of more research on communicable diseases in relation to climate change especially in the highlands of Rwanda is needed, as climate change is shifting diseases' ecology.

There is a need for a better understanding of the global forces such as global heating and extreme weather events with diseases (e,g Eli Niño) and their impact on increase and/or transmission of malaria.

6. Acknowledgment

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