Global Journal of Environmental Science and Technology: ISSN-2360-7955, Vol. 2(6): pp 339-348, July, 2015.

Full Length Research

Modelling climate induced relative malaria incidence in the major sub climatic zones of Uganda

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Accepted 19th June, 2015

Malaria is widespread in Africa and causes untold mortality and morbidity. It's sensitive to climate and this has raised considerable concern over the implications of climate change on future disease risk. The problem of malaria vectors (*Anopheles mosquitoes*) shifting from their known locations to invade new zones is of important concern. The objectives of this paper were to; i) established relationship between climate and malaria incidence, ii) develop climate induced malaria incidence zonal models, and iii) project malaria incidence occurrence in the major sub climatic zones of Uganda. Correlation and regression analysis was used to determine the climate drivers of malaria incidence and built models using GenStat 14th edition. Climate data were downscaled using Statistical Downscaling Model (SDSM v 5.1.1) and HadCM3 B1 scenarios, and using the zonal models. Malaria incidence was projected. The results show that relative malaria incidence was most correlated with minimum temperature in Western and Northern regions (r=0.818 and r=0.651; respectively), and with relative humidity at 06:00 (r=0.692) in the Central region. Relative malaria incidence for the different zones can be modeled and predicted as;$\mathbf{0.969 Minimum\ Temperature - 10.806} + \mathcal{E}$ (R^2_{adj}=0.656) ,$\mathbf{0.739 Minimum\ Temperature + 0.168 Relative\ Humidity\ at\ 6\ O'Clock - 23.606} + \mathcal{E}$($R^2_{adj}$=0.581), $\mathbf{1.019 Minimum\ Temperature + 0.025 Mean\ Relative\ Humidity + 0.305 Maximum\ Temperatre - 0.002 Rainfall - 22.184} + \mathcal{E}$ (R^2_{adj} = 0.404); for the Western, Central and Northern regions; respectively. The projected malaria incidence is likely to gradually decrease from 2020s to 2040s, and then increase until 2090s across the three major sub climatic zones of Uganda with the western and northern regions experiencing the highest and lowest incidence respectively, in the business as usual scenario. However, these projected incidences will present similarities in terms of periodicity and the peaks that will be lagged from the cold/wet seasons with different regions presenting relatively different patterns and trends with peak malaria incidences.

Keywords: Climate change and malaria, models, malaria projections, and East Africa

INTRODUCTION

Malaria is a mosquito-borne disease that has afflicted humans globally for thousands of years, killing over 2.7 million people annually (Pattanayak *et al*., 2003). The disease is most prevalent in tropical and subtropical regions of the world, especially in Sub-Saharan Africa (SSA), South and Latin America, Southeast and Central Asia (Prothero, 1995). It continues to be the single largest threat to child survival in SSA (WHO, 2008). Malaria can cause lasting side-effects, which affect individual development, mainly through anemia, neurological and physiological sequel, as well as the risk of infection with the human immune-deficiency virus (HIV) following blood transfusion (Snow *et al*., 1999a). Sachs and Malaney (2002) also noted that malaria retards economic and social development through effects such as reduced working hours due to sickness or attending to the sick, income spent on financing health care, which in turn lead to impacts at national level because of massive health care budgets, reduced productivity of the work force but even reducing over 5% of the economic growth of endemic countries in SSA.

In Uganda, clinically diagnosed malaria is the leading cause of illness and death, accounting for 25-40% of outpatient visits at health facilities, 15-20% of all hospital admissions, and 9-14% of all hospital deaths (MOH, 2001, 2012a; Moses, 2012; Namanya, 2000). During the last decade, for example; the number of malaria cases in government health centers countrywide rose by 13% from 2,923,620 in 1999 to 3,311,088 in 2000. Since 1995, the number of malaria cases has been rising every year (Kiwanuka, 2003; MOH, 2012b). On average, a person in Apac district near Lake Kyoga would receive more than 1,500 infectious bites per year (Lynch *et al*., 2005). The major causes of malaria are linked to the environment, weather and climatic factors, mainly precipitation, temperature and humidity (Gagnon *et al*., 2002; Norris, 2004; Patz and Lindsay, 1999; Vittor *et al*., 2006). Previous research has shown that climate is the key factor in explaining RMI in different regions (Campbell-Lendrum and Woodruff, 2006; Craig *et al*., 1999; Mantilla *et al*., 2009). An association between climate variability and the epidemics of malaria has been declared in seven cities of the East African highlands in Ethiopia and Kenya (Wandiga *et al*., 2006). Mantilla *et al*. (2009) noted that there is an association between the incidence of malaria and certain climatic variables, especially temperature and rainfall. An increased temperature of just 0.5^{O}C can significantly increase the abundance of mosquitoes, sometimes up to 100%. The increase in temperatures shortens the larval development, decreasing the amount of time required for the adult mosquitoes to spread malaria and allowing for the development of more mosquitoes (Patz and Olson, 2006; Renate, 2009).

The relationship between different vectors of malaria and their environment vary greatly around the world, but due to the severe health and economic cost of malaria epidemics, there is still a growing need for methods that will help to understand the influencing factors, allow forecasting, early warning, so that more effective control measures may be implemented (Alemu *et al*., 2011). Although both climate and weather variables were liable such as to play a major role in initiating epidemics, there is limited analysis of their association with the epidemic transmission parameters has been undertaken in Uganda (Anyamba *et al*., 2006). Mathematical models would provide powerful tools for appropriate interventions and eradication strategies in the future, but these require realistic modeling of the malaria transmission dynamics and its response to climatic variables. This paper was intended to establish the relationship between climate variables and RMI in the three major sub climatic zones of Uganda; develop a climate induced RMI models for major sub climatic zones of Uganda; and project future RMI trends for the periods of 2020-2039, 2040-2059, 2060-2079, 2080 and 2099 in the major sub climatic zones of Uganda.

MATERIALS AND METHODS

Description of the study area

This study was conducted in three climatic zones of Uganda. Uganda lies astride the equator, between latitudes 4^{o} 12´ N and 1^{o} 29´ S and longitudes 29^{o} 34´ W, and 35^{o} 0´ E with an area of 241,550.7km^{2} and an estimated current population of 34.1 million in July 2012 (UBOS, 2012). Temperatures are in the range of 15^{o} - 31^{o} C. More than two-thirds of the country is a plateau, lying between 1000 – 2500 meters Above Sea Level (ASL) but with a minimum and maximum altitude being 620 and 5110m ASL respectively (UBOS, 2012). Uganda's climate is tropical, moderated by its high altitude with little annual variations in temperature. The seasonal rainfall is driven mainly by the migration of the Inter-Tropical Convergence Zone (ITCZ), a relatively narrow belt of very low pressure and heavy precipitation that forms near the Earth's equator. The exact position of the ITCZ changes over the course of the year, migrating southwards through Uganda in October to December, and returning northwards in March, April and May causing two distinct wet periods – the 'short' rains in October to December and the 'long' rains in March to May. Climate data from Kabale, Entebbe and Gulu towns are representative of the three regions (Basalirwa, 1995; Mwesigwa and Mathenge, 2007; UCE, 2004) figure 1 and table 1.

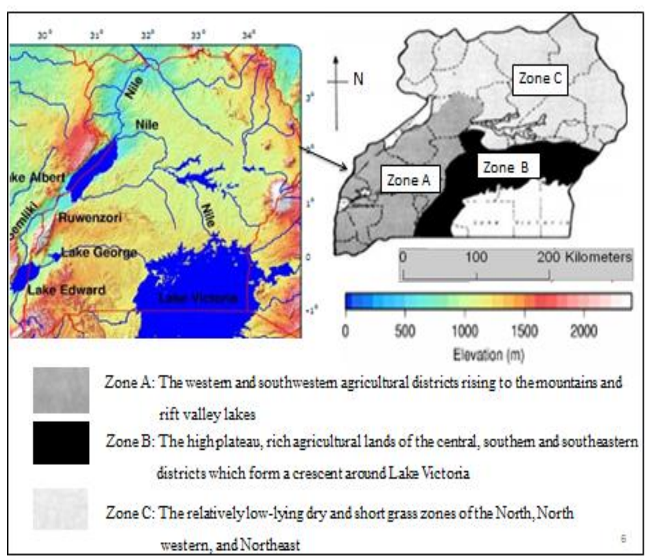

Figure 1: Location of Uganda and the three sub climatic zonal regions under study

Table 1 Description of sub climatic zonal representative towns in Uganda

Sub climatic zones	Towns	Latitude (°)	Longitude (°)	Elevation (m)	Rainfall (mm/year)	Geographic Description
High plateau Central, S &SE	Entebbe (B)	0.058	32.467	1140	1575-1728	Lake Region
Southern &SW highlands	Mbarara (A)	-0.617	30.65	1400	946-1242	Southern Highlands
Northern Savanna/ North, NE &NW	Arua (C)	3.017	30.917	1180	1425-1603	Northern Savanna

Establishing the relationship between climate variables and RMI in the three major sub climatic zones of Uganda

Laboratory confirmed aggregated malaria cases from the hospitals in each of the three major sub climatic zonal representative towns from 1987 to 2012 were obtained from the regional hospitals. The estimated population for each of the zonal representative towns was obtained in the same period from the Uganda Bureau of Statistics (UBOS). The corresponding missing annual population data were obtained using the equation; $P_n= P_O(1+r)^n$, where; P_O is current annual population, P_n is missing annual population for the n^{th} year, r is the population growth rate, and n is the number of years from the referenced year 2013 (UBOS, 2012). The number of annual malaria cases for each zonal town was divided by the corresponding annual population and finally expressed as a percentage to get RMI.

Daily cumulative precipitation (Rainfall), maximum temperature (Max Temp), mean temperature (Mean Temp), and minimum temperature (Min Temp), relative humidity at 12:00 (RH: 12:00) and 06:00 (RH: 06:00) O'clock, and mean relative humidity (Mean RH) were obtained from the nearest meteorological stations for each of the towns for the period; January 1987 to December 2012, and their monthly averages were computed. The missing and inconsistent data was filled and corrected using advanced spatial interpolation techniques as described by Grieser (2006). Thus in Arua, Mbarara, and Entebbe towns; Shepards method, Modified Inverse Distance Weighted Average (IDWA), and Thin-Plate Spline methods were used due to the low land plateau and sparsely distant stations, high altitude variations, and localized Lake Victoria crescent conditions; respectively.

The relationship between RMI and weather variables was determined using regression technique in GenStat 14th edition. Pearson's correlations were computed to determine the type and strength of the relationships between climate parameters and RMI after performing normality tests and checks on each of the variables. One month lag effect for RMI, rainfall, mean temperature and relative humidity was also computed and included in modeling. The long term annual variations and seasonal effects/changes in RMI were also included. Linear multivariate regression analysis was employed to develop independent climate induced RMI regional models for each sub climatic zone. To avoid multicollinearity and autocorrelations among and between the climatic variables, collinearity diagnostic tests were computed, and the climate parameters that significantly influenced RMI with poor collinearity among them were used to generate the RMI models for the different major sub climatic zones (Alemu *et al*., 2011). To independently validate the developed zonal models, both spatially and temporally, it was convenient that these RMI predictive models be tested using independent data sets for the same spatial and temporal resolution in other towns different from the ones used for model development in the same sub climatic zones. Therefore, malaria and climatic data from 2000 to 2010 were collected in the second sub climatic zonal representative towns of Kabale, Kampala and Gulu for zones A, B and C; respectively.

Projection of future RMI trends for the periods of 2020-2039, 2040-2059, 2060-2079, 2080 and 2099 in the major sub climatic zones of Uganda

The zonal climate projections used for the RMI simulations were downscaled using Statistical Downscaling Model (SDSM v.5.1.1) and the UK Hadley Centre model (HadCM3) runs with high (A2) and low (B) emission scenarios for Arua, Mbarara and Entebbe towns. The HadCM3 comprises of projected 20 year averages of monthly temperature and precipitation data (IPCC, 2001; New *et al*., 1999).

In addition to the regression techniques used to model the relationship between climate and RMI, the Average Absolute Error (AAE) between the simulated and the observed was computed for each of the zonal representative town using: $\mathrm{AAE} = \frac{\Sigma|O-E|}{n}$, (Diriba, 2006; Vandermeer, 2010). Where; O is observed RMI. E is predicted RMI, n is the number of observations. This was to avoid changes in the direction of the difference between observed and simulated.

RESULTS

Relationship between climate and relative malaria incidence in Uganda

Figure 2 shows the relative malaria incidence trend for the different years in the three study regions of Uganda.

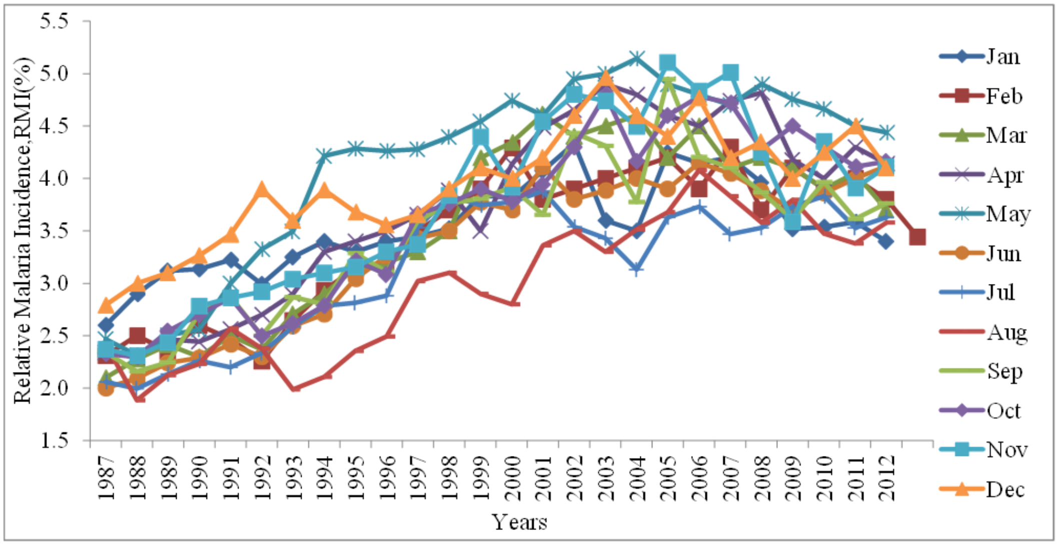

Figure 2: Inter-annual variations of relative malaria incidence trends in Uganda, 1987-2012

Table 2: Long term seasonal effects on mean relative malaria incidence in Uganda

Seasonal effects on mean RMI (±0.05)	**Zone A**	**Zone B**	**Zone C**
Long dry period (December to February)	3.63	3.97	4.29
Long rains (March to May)	3.76	4.10	4.49
Short dry period (June to August)	3.16	3.49	3.93
Short rains (September to November)	3.63	3.97	4.50
p-value	0.036	0.043	0.035

Table 3: General correlation between climatic variables and significance of the linear relationship with monthly relative malaria incidences in each of Uganda's sub climatic zonal towns, 1987-2012

Towns (Climatic zones)	**Mbarara (Zone A)**		**Entebbe (Zone B)**		**Arua (Zone C)**	
Correlation Coefficient	Pearson r	P-value	Pearson r	P-value	Pearson r	P-value
Max Temp (^{O}C)	0.282	0.081	0.135	0.255	0.286	0.079
Min Temp (^{o}C)	0.818	0.000	0.648	0.000	0.651	0.000
Mean Temp (^{o}C)	0.730	0.000	0.482	0.006	0.568	0.001
Rainfall (mm)	0.095	0.322	-0.368	0.203	-0.286	0.078
Mean RH (%)	0.228	0.132	0.576	0.001	0.085	0.341
RH: 06:00 (%)	0.087	0.337	0.646	0.000	0.112	0.293
RH: 12:00 (%)	0.406	0.020	0.300	0.068	0.048	0.407

RMI in Uganda followed a seasonal pattern between the wet and dry months with RMI peaks in the months after the rainy seasons, and a long term inter annual trend that was not climatic in nature. In addition, it has been increasing over the year since 1987 for all the months. For the last twenty five years, RMI has doubled. February tended to have the lowest RMI. Higher values of RMI were observed in May and June for first five years and the late five years of 1990s; respectively.

RMI varied from year to year ($p<0.001$) and so was for the season. Although RMI has been increasing over the year, the general inter-seasonal trend has been decreasing instead since 1987. However, there was a statistically significant ($p=0.00$) negative lag effect between the wet and dry periods with peak RMI occurring just after the peak rainfall. The inter-seasonal variations in the mean RMI was also significant in all the zones (Table 2).

Table 3 shows the correlation between climate variables and the significance of their relationships with RMI. In Climatic Zone A, all the climatic variables were positively correlated with RMI. Mean and minimum

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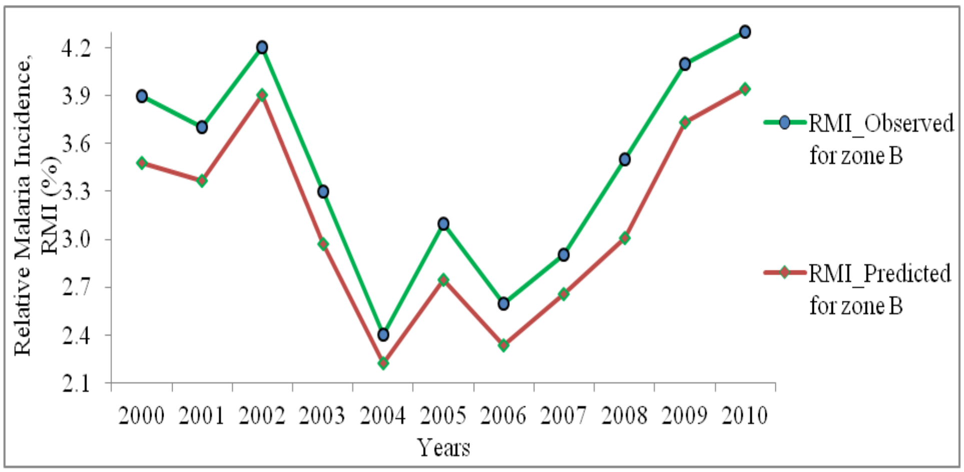


Figure 4: provide table legend???

temperature was strongly (p=0. 000), and significantly linearly related to RMI. There was weak and statistically insignificant relationship between Max Temp, rainfall, Mean RH and RH: 06:00 with RMI. RH: 12:00 showed moderate and statistically significantly (p=0.020) correlated with RMI.

In Climatic zone B, all the climatic variables were positively correlated except rainfall that was negative and not significantly linearly related (p=0.203) with RMI. There was a strong correlation and significant relationship between Min Temp (p<0.001), and RMI. Similarly mean RH (p=0.001), and RH: 06:00 (p<0.001) were strongly related with RMI. However, there was a moderate correlation but statistically significant relationship (p=0.006) between Mean Temp and RMI. RH: 12:00 was weakly and not significantly linearly related (p=0.068) with RMI.

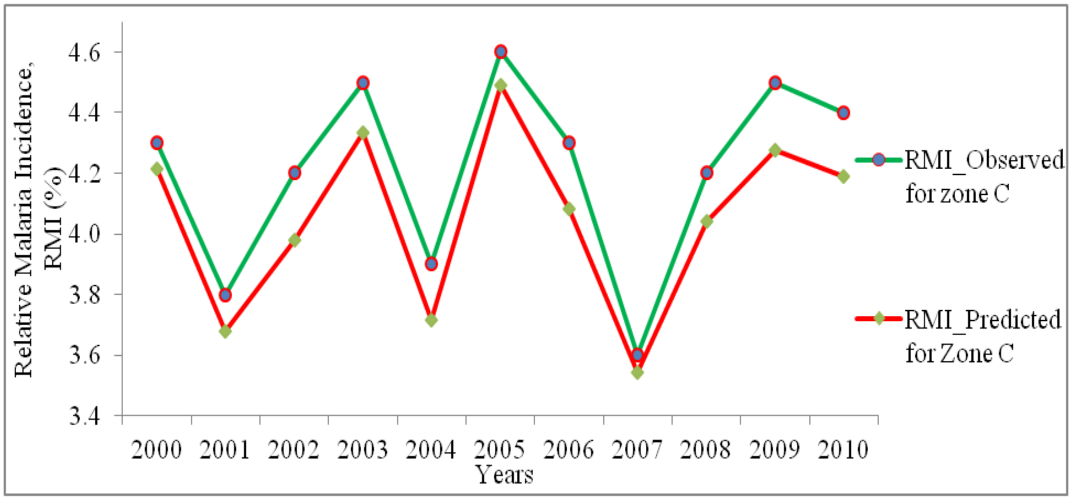
In Climatic Zone C, Min Temp and Mean Temp were strongly correlated with RMI with (p=0.000) and (p=0.001); respectively. Other climate variables were statistically insignificantly (p>0.005) related and weakly correlated with RMI, except rainfall that was not correlated (p=0.078) with RMI.

Climate induced relative malaria incidence models for the selected climatic zones of Uganda

RMI can be modelled using the equations below:

For Zone A (R^2_{adj} = 0.656); $\mathrm{RMI} = 0.969\mathrm{Min\ Temp} - 10.806 + \mathcal{E}$ .The model validation results showed a strong correlation and significant relationship between the observed and simulated RMI with Average Absolut Error (AAE) and R^2_{adj} of 0.362 and 0.996; respectively. RMI_Observed =0.9042RMI_Predicted + 0.6384 (Figure 3).

For Zone B (R^2_{adj} = 0.581); $\mathrm{RMI} = 0.739\mathrm{Min\ Temp} + 0.168\mathrm{RH\ at\ 06{:}00} - 23.606 + \mathcal{E}$ .The model validation results also showed a strong correlation and significant relationship between the observed and simulated RMI with AAE and R^2_{adj} of 0.331 and 0.980; respectively. RMI_Observed = 0.924RMI_Predicted + 0.3901 (Figure 4).



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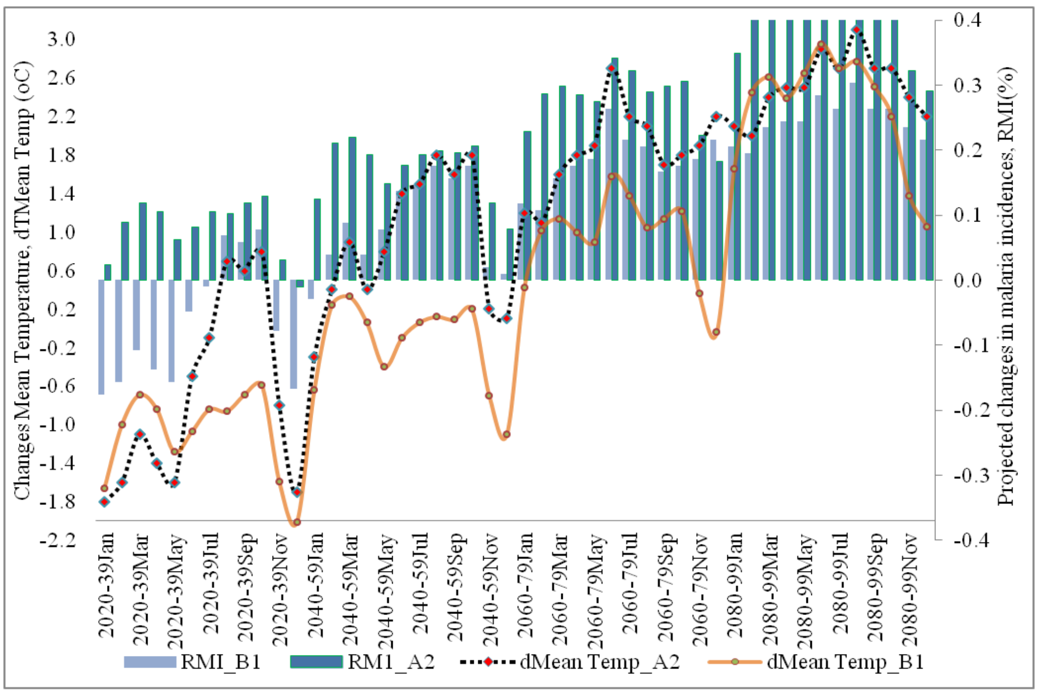

Figure 6: Projected changes in RMI in zone A (Mbarara town), Uganda

For Zone C (R^2_{adj} =0.404); $RMI = 1.019 Min\ Temp - 0.002 Rainfall + 0.025 Mean\ RH + 0.305 Max\ Temp - 22.184 + \varepsilon$ .The model validation results showed moderate correlation but convincingly good relationship between the observed and simulated RMI with AAE and R^2_{adj} of 0.160 and 0.968; respectively. RMI_Observed =1.047RMI_Predicted - 0.0306 (Figure 5)

Projected climate change induced relative malaria incidence for the major sub climatic zones of Uganda

The projected RMI will increase gradually from 2060 to 2099 with relatively high inter annual and seasonal variability in zone A. The projected RMI presents a temporal periodicity, and a lag period that coincide with the peak temperature anomalies. For every degree rise in the projected mean temperature in zone A, RMI increases by 0.11% and vice versa (Figure 6).

The projected RMI in zone B is likely to behave similarly to the trend observed in zone A with relatively more pronounced fluctuations. Mean Temp was the only significant climate variable in predicting RMI with a percentage increase of 0.29 per degree rise in mean temperature and vice versa. From 2020 to 2040, the RMI peaks will decrease with the lowest incidence in June and December. From 2040 to 2099, RMI will increase gradually in seasonal cyclic and annual trend

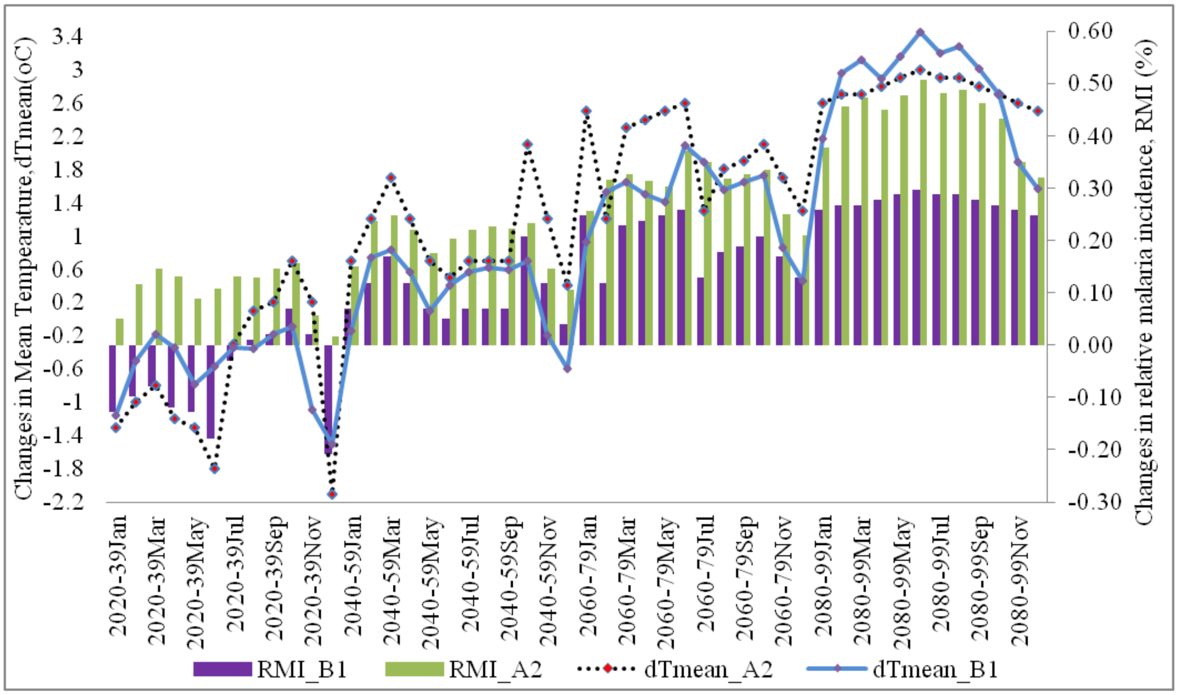

Figure 7: Projected changes in RMI in zone B (Entebbe town), Uganda

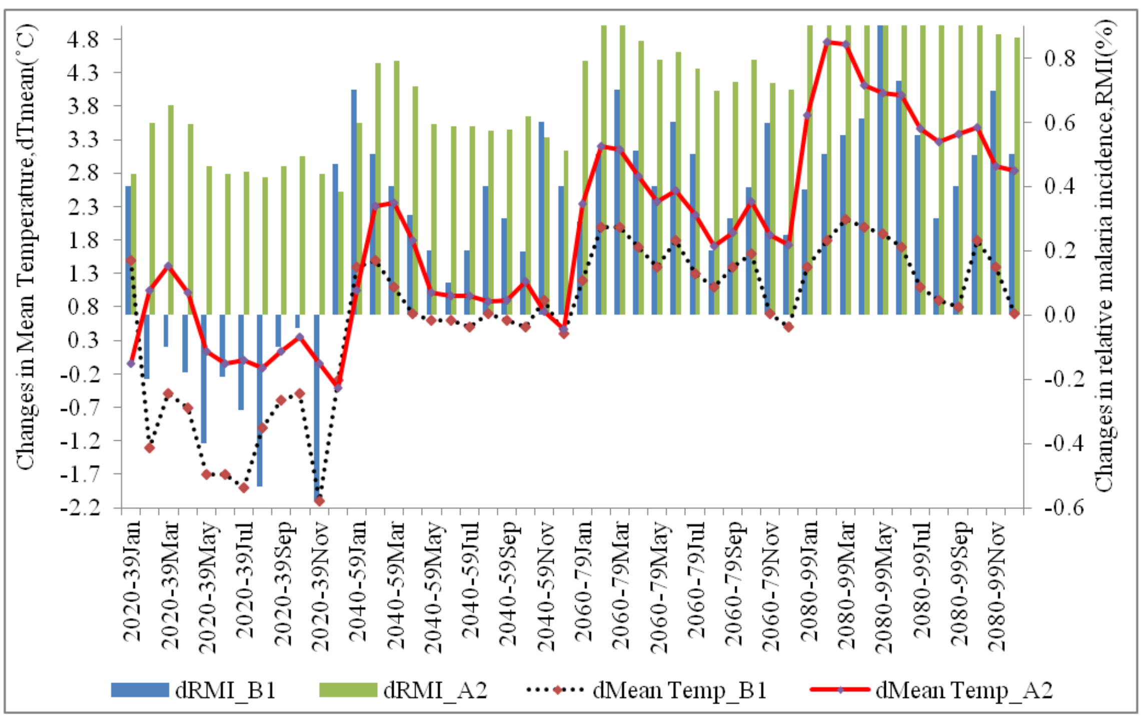

Figure 8: Projected RMI in zone C (Arua town), Uganda

fluctuations (Figure 7).

For Zone C, the projected RMI will have similarities in terms of periodicity, and small lag between cold period and RMI peaks. This is projected to increase significantly from the long term averages from 2040 to 2099 but also exhibiting seasonal cyclic and annual trend fluctuations throughout under high and low emission scenarios (Figure 8).

DISCUSSION

There was correlation between RMI and climate variables in all the climatic zones with minimum temperature being the strongest correlated among the climatic variables. This is consistent with results of similar studies conducted in Ethiopia by Alemu *et al*. (2011), Ghana by Tay *et al*. (2012), and Burundi by Loevinsohn (1994) which suggest that minimum temperature is the most important factor for malaria transmission in high altitude regions while in low altitude regions its rainfall, relative humidity, mean and maximum temperatures that greatly influence malaria over other climatic factors.

The influence of climate on RMI was highest in zones A and B, and lowest in zone C. This is partly attributed to the climatic differences in the annual rainy seasons leading to the different transmission levels between the zones with zones A and B having a more favorable climate for mosquito development and malaria transmission throughout the year than C, that has one long favorable season annually. This is in agreement with the research findings in Ghana by Tay *et al*. (2012), West Africa by Usher (2010), East Africa by Omumbo (2004) and Nigeria by Ayanlade *et al*. (2010) which conclude that malaria transmission season is highly dependent on the frequency and duration, annual rainy seasonal cycles with longer seasons, allowing more intense transmissions while short seasons favor more frequent infections and higher incidence for any given locality.

Secondly, the results can also be explained by the uneven distribution of non-climatic factors that also contribute to malaria transmission besides climate. The long term civil by the Lord's Resistance Army (LRA) from the late 1980s until of recent in the Northern part of Uganda which retarded delivery of drugs, hospitals, infrastructure and the related malaria prevention and control programs partly explains the high RMI threat in Arua than in Entebbe and Mbarara. Similar observations were made by AFM (2007) that conclude that Uganda's brutal dictatorships inhibited post-colonial development and retarded infrastructure development in most parts leading to the arising of malaria and other vector-borne diseases over the past decades. This was aggravated by the inadequate planning, lack of malaria early warning systems, and failure by the ministry of health to take climate change into account as the key threat to malaria transmission has worsened the malaria situation to reach epidemic levels in more than 95% country (AFM, 2007; Kiwanuka, 2003; Namanya, 2000; Yeka *et al*., 2005).

For the three zones, projected RMI will present a similarity in terms of periodicity and the peaks that will be lagged from the wet season. Different regions present different patterns and trend with peak RMI in zone A shifting from March and October to May and November in the period of 2020 to 2040, and 2060 to 2099 respectively whereas in the zone B, the RMI peak will occur in April and November for the period of 2020 to 204. In the zone C, the peak RMI is projected to occur in May for the period of January 2020 to December 2099. However, zones A and B will have the same pattern and trend deviating in terms of peaks while no significant deviations from historical RMI is likely to be observed in the Northern region from January 2020 to September 2060, with a steady increase from October 2060 to December 2099.

These projections are supported by the results of Tanser *et al*. (2003) and Huynen *et al*. (2013) which suggest a general increase in the projected malaria transmission and incidence in Africa from 2000 to 2100 due to global warming and climate change effects.

The projected RMI in the zone A will be relatively higher than that of zones B and C. This is partly because of the higher projected increase in minimum temperature and more adverse climate change effects due to global warming affecting mostly zones A and B than zone C which is expected to have least effects in contrast. This is consistent with the observations in Uganda made by NEMA (2009) and Huynen *et al*. (2013) which suggest that because of climate change, some disease vectors like *Anopheles* mosquitoes move to higher altitudes, thus spreading malaria in areas of Kabale and Mbarara (zone A) than before. Elsewhere, similar observations were made in Africa by Tanser *et al*. (2003), East Africa by Omumbo (2004), Germany byHoly *et al*. (2010), and Ethiopia by Alemu *et al*. (2011) which suggest that global warming is responsible for malaria epidemiological shifts from the lowland to the highland regions that are now becoming warmer and more favorable for mosquito breeding.

CONCLUSION

In light of the above results and discussions, it is concluded that a correlation exists between RMI and climate parameters in all the three regions; particularly the mean and minimum temperature in the Western; minimum temperature, mean relative humidity and relative humidity at 06:00 in the Central region, and minimum and mean temperature in the Northern region. Key determinants of RMI were; minimum temperature in the Western region, minimum temperature and relative humidity at 06:00 in the central region, and rainfall, mean relative humidity, minimum and maximum temperature in the northern region. All affect RMI positively except rainfall. RMI is projected to increase gradually from 2020s to 2070s and double by 2090s across the three major climatic zones of Uganda with the Western and Northern regions experiencing the highest and lowest

RMI; respectively in the business as usual scenario. This projected RMI will present a similarity in terms of periodicity and the peaks that will be lagged from the wet season with different regions presenting different patterns and trends with peak RMI. There will also be a shift in the projected RMI from their traditional lowland regions of the northern and north eastern to highland regions of the south and south western parts. This will be as a result of anthropogenic climate change associated with increase in temperature (highest S&SW highlands), heavy rains and flooding providing more conducive conditions for the breeding and spread of malaria vectors especially the mosquitoes that will cause epidemiological shifts from low land to highland areas.

It is therefore recommended to establish a strong collaboration between the Ministry of Health and climate scientists for the development of strong systems of surveillance and early warning in order to manage the current and future malaria epidemics not only in Uganda but also in East Africa. There is also need to develop higher resolution validated models and digitized GIS stratification maps linking climate and RMI at the village scale so as to identify more accurately those populations at RMI risk for effective and timely malaria management.

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