Original article

Modeling effect of climate variability on malaria in Ethiopia

Girma Taye[1], Mirgissa Kaba[1], Adugna Woyessa[3], Wakgari Deressa[1], Belay Simane[2], Abera Kumie[1], Getachew Berhane[4]

Abstract

Background: Temperature in Ethiopia has increased at about 0.2°C per decade. This coupled with global evidences on relationship between weather and disease outcome suggest that climate variability facilitates and exacerbates the transmission of several infectious diseases. Despite wide recognition of the impact of climate variability on health, there is scanty information on climate variability and its implication on specific disease outcome in Ethiopia. Statistical methods are available for studying the relationship between climate variability and disease outcome but use of such methods to forecast future disease burden has not been widely considered.

Objective: The study aims to model climate variability and its impact on burden of malaria.

Methods: Twenty one year weather data, from National Metrology Agency of Ethiopia (NMAE) and 11 years Malaria prevalence data, from Federal Ministry of Health (FMoH) was used in the analysis. Box plot, time series plot, time series based models (ARIMA with different parameters and smoothing methods) and poison regression were employed to identify pattern of climate variability over a period of 21 years; determine vulnerability of disease to climate change and forecast future burden of the disease. Data were organized by region and analyzed using SPSS and findings are presented by region.

Results: The result shows that average maximum and minimum temperatures and total annual rainfall are characterized by high inter-annual variability for all regions during the last 21 years. Minimum temperature was associated with high malaria prevalence in Tigray (p=0.01), Gambella (p=0.01), Dire Dawa (p=0.025) and Afar regions (p=0.03). Conversely maximum temperature was associated with high malaria prevalence in SNNP (p=0.05), Oromia (p=0.01), Benishangul-Gumuz (p=0.01), Amhara (p=0.01), and Afar regions (p=0.01). Malaria prevalence, projected until 2020, showed increasing trend over years for all regions indicating that climate change exacerbate malaria cases if no intervention is in place.

Conclusion: Effect of climate variability is felt on malaria cases through changing magnitude and seasonality of rainfall and temperature. Forecasts of standardized malaria cases showed wide confidence interval and increasing trend in the coming five years for all regions and require intervention in the years to come Poison regression is useful to study relationship between weather and disease prevalence, while selection of appropriate time series model is important to forecast future disease burden. In view of this, it is recommended to choose appropriate model parameters to obtain accurate disease burden forecasts. [*Ethiop. J. Health Dev.* 2015;29(3):183-196]

Key words: Modeling climate variability, Health, Malaria, Ethiopia

Introduction

The current health sector development in Ethiopia stems from the implementation of a sector wide approach since 1997/98 through the Health Sector Development Program (HSDP), four of which are already in place. The health facilities serving the population have grown tremendously over the years such that primary health care (PHC) unit now serves about 25,000 people. However, the country faces internal problem related mainly to human resources and finance; and external problems related to the effect of climate change. As a response to the second problem, Ethiopia among other policies, has adopted environmental policies and Ethiopia's Program of Adaptation to Climate Change (EPACC) (1).

The Intergovernmental Panel on Climate Change (IPCC) forecasts that some parts of Africa will become warmer and wetter, whereas others will become drier, and there will be higher frequencies of storms and floods (2). Although climate change is high on the agenda of public health worldwide, and that Ethiopia experiences variable weather conditions, and endemic to various climate-sensitive diseases, there is limited information in Ethiopia on association between health outcomes such as malaria and weather variables. Little is known about trends of climate change impacts on malaria prevalence. Such information might be very important for the country as Ethiopia is developing its five-year (July 2015-June 2020) Health Sector Transformation Plan (HSTP), and will soon start implementing it. However, climate change is identified as one of the major threats in achieving HSTP. Therefore, this calls for generating information in key health components affected by climate variability and change.

Global climate change has emerged as a challenge to the global and national socio-economic developments. Hence, Ethiopia is among many nations vulnerable to health impacts of climate change (3, 4). Over the last

[1]School of Public Health, AAU;
[2]College of Development Studies, AAU;
[3]Ethiopian Public Health Institute;
[4]College of Natural and Computational Sciences, AAU

decades, temperature in Ethiopia has increased at about 0.2°C per decade (5). The increase in minimum temperatures is more pronounced with about 0.4°C per decade with an alarming increasing trend since the 1990's. The mean annual temperature in the country will increase in the range of 1.7-2.1°C by 2050 and in the range of 2.7-3.4°C by 2080 (6). Forecasts indicate that the amount of annual rainfall and number of rainy days will decrease in some parts of the country by the 2080 (7).

Climate change is currently adversely impacting the health and lives of people around the world, particularly in low-income countries (8-10). There are several mechanisms in which climate change impacts on health (11)). However, two main climatic impacts on health are evident from literatures: direct effect due to heat stress and weather related extreme events, and an indirect effect is climate-mediated change in the incidence of infectious diseases and deaths.

Extreme climate events include heavy precipitation that results in flooding, low precipitation combined with changes in temperature resulting in drought, heat waves due to unusual increase in daily temperature, and flooding due to excessive rainfall. Flooding is strongly associated with malaria and other vector-borne diseases transmission and could destroy the existing health infrastructure (12-13). Describing data or fitting standard models may not enable one to track how extreme events occur and how they are related to health.

The common direct effect of climate change on human health in Ethiopia is not well documented (14). However, anecdotal evidence reveal high burden of morbidity and mortality linked to climate change and consequent water-, food- and vector-borne diseases are common (13). Appropriate models should however be used to verify whether these evidences are acceptable. Evidences of widespread vector-borne infectious diseases like malaria, schistosomiasis and leishmaniasis are available. The recent (2013) phenomenon of yellow fever and dengue fever outbreak are good examples of climate change induced public health challenges in the country (25). Malaria is expected to have substantial link with climate change. An increase in temperature and rainfall variability is believed to host the breeding of mosquitoes and early maturation of the parasite, hence increasing probability to sustain the transmission of malaria. In general, statistical methods appropriate for different scenarios have not been properly selected and applied. The methods are often limited to descriptive aspect and common tests. Particularly forecasting future impacts depends on the appropriateness of the model and correct data size. The objective of this study is therefore to assess relationship between malaria cases and climate variability and determine level of vulnerability of population to be exposed to malaria during the next five years development plan.

Methods

Source of Data: Health and climate data were obtained from Federal Ministry of Health (FMoH) and the National Meteorological Agency of Ethiopia (NMAE). Formal request was written to these institutions to obtain relevant data. Accordingly, NMAE has provided monthly mean weather data (maximum and minimum temperature, relative humidity and rainfall) for 21 years (1994-2014) while FMoH provided malaria related data for 11 years (2004–2014). Data cleaning was carried out to ensure the quality.

Methods of data analysis: Descriptive methods such as frequency, tables, boxplot and time series plots were used to examine consistency of the data and observe trends to help identify appropriate models for the actual analysis. Autocorrelation Function (ACF) was fitted to weather data 1994-2014 (252 months) to assess effect of Climate Variability on occurrence of weather variables. Autocorrelation is a tool that helps to identify if there is possible relationship between two time points in a time series data that are ***n months*** apart. Time Series Model fitting was done in SPSS version 20. Family of time series models were used to forecast the status of malaria for the coming five years, 2015-2020, based on observed data. The Generalized Linear Model (GLM) was fitted to malaria prevalence, taken as response, and weather variables, as predictors using poison link function. This model is also referred to as poison regression to shorten the name. Rainfall, relative humidity, minimum and maximum temperature were used as predictors for each region to forecast disease outcome in the near future. Several poison regression models with different groups of predicators were fitted; for example, model with single predictor, two predictors, etc. in different combinations. Model fit test was checked to select a more stable model that explains relationship between weather variable and disease prevalence. Any model with uncertainties due to incomplete iteration was dropped. These models were compared using Akaike's information criteria and that model with the smallest criteria was considered.

Malaria cases were standardized against the corresponding population of each region. Various times series models such as ARIMA with such parameters as different AR, Differencing and MA values and a number of smoothing methods were fitted and the best fitting models selected based on results of model diagnostics. Predictions may not be reliable unless the existing series (2004-2014) is sufficiently smoothed. For this reason the observed time series was smoothed using best chosen model so that forecasts can easily be made in to the future.

Ethical considerations*:* Formal request was written to FMoH and NMAE by School of Public Health (SPH) of Addis Ababa University explaining about the objective of the study so as to access both weather and malaria related data. Both institutions provided the required data after receiving confirmation from SPH that the data will not be used for any other purpose other than answering questions stated in the objectives.

Results

Climate outcome: In order to observe average variability in rainfall for one cycle (year), monthly average rainfall (averaged over 21 years) was computed and this was plotted in a graph. It was found that seasonality of rainfall varies from region to region (Figure 1). The amount of rainfall reaches its pick for different regions at slightly different months. Somali region seem to receive lowest rainfall amount compared to other regions included in the figure at all seasons. During Ethiopian main rainfall season, between June and September, all regions (including those not included in this figure), except Somali region, received above 100 mm of rain. There are considerable differences in the amount of rainfall between the regions even during the main rainy season. Amhara region received less rainfall during off season and exceptionally lots of rain during main season, while Oromia received higher rainfall amount than other regions during offseason.

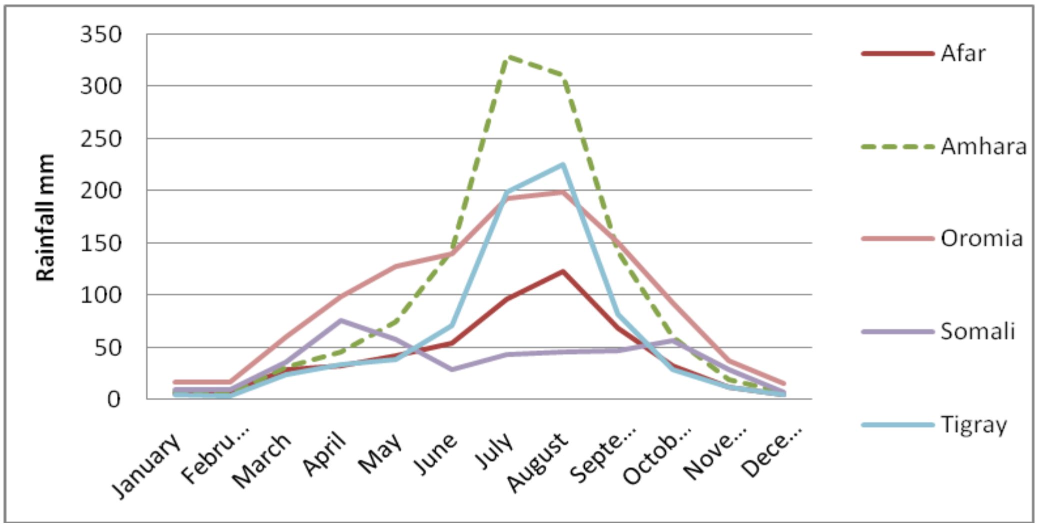


Figure 1: **Monthly average rainfall distribution for selected regions (1994-2014)**

Along with such varying rainfall, increasing temperature trend over years (presented further below) shows that Ethiopia has become warmer over the past century and the looming Climate Variability is believed to contribute to further warming over the next century at unprecedented rates.

Boxplot clearly depicts existence of within and between regions variability for the three weather variables: rainfall, minimum and maximum temperature, although extent of the variability differs from region to region. The plot shows that Gambella have high variability in rainfall with large inter-quartile range, whereas Afar has very consistently the same amount of rain from year to year, although amount is smaller as compared to other regions. Benishangul-Gumz has the highest monthly average rainfall over a period of one decade. The finding shows that rainfall was not normally distributed over the 21 years period for all regions but the non-normality is sever for Addis, Amhara, Benishangul-Gumz, Dire, Tigray and Gambella which is an indication of gradual shift in pick periods of rainfall hinting impact of Climate Variability on these regions. Addis, Afar, Amhara and Tigray regions experience heavy rainfall conditions which were much more than their corresponding median rainfall amount in some years. Inspection of the three plots (Fig 2-4) show that Gambella tends to have high variability in all the three weather variables.

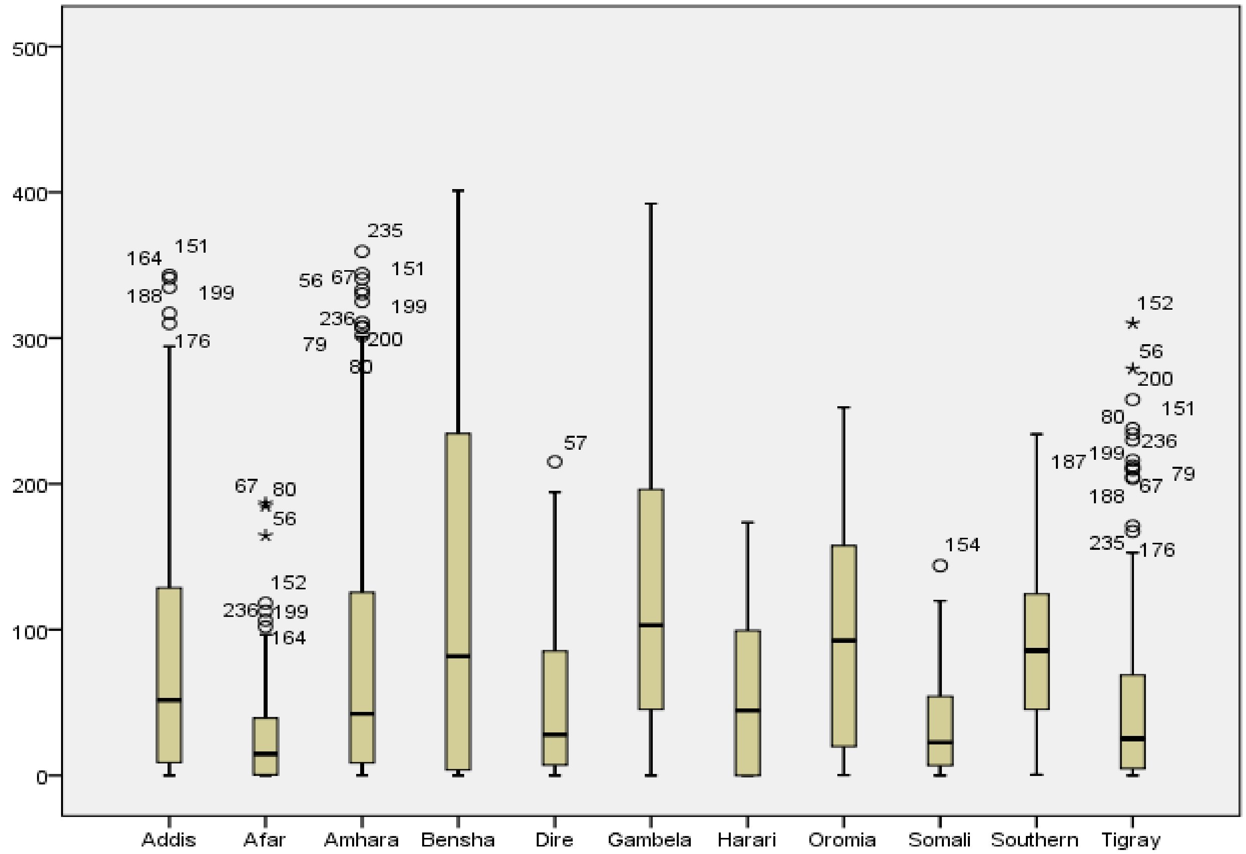


Figure 2**: Box Plot for mean monthly rainfall (1994 – 2014) by region**

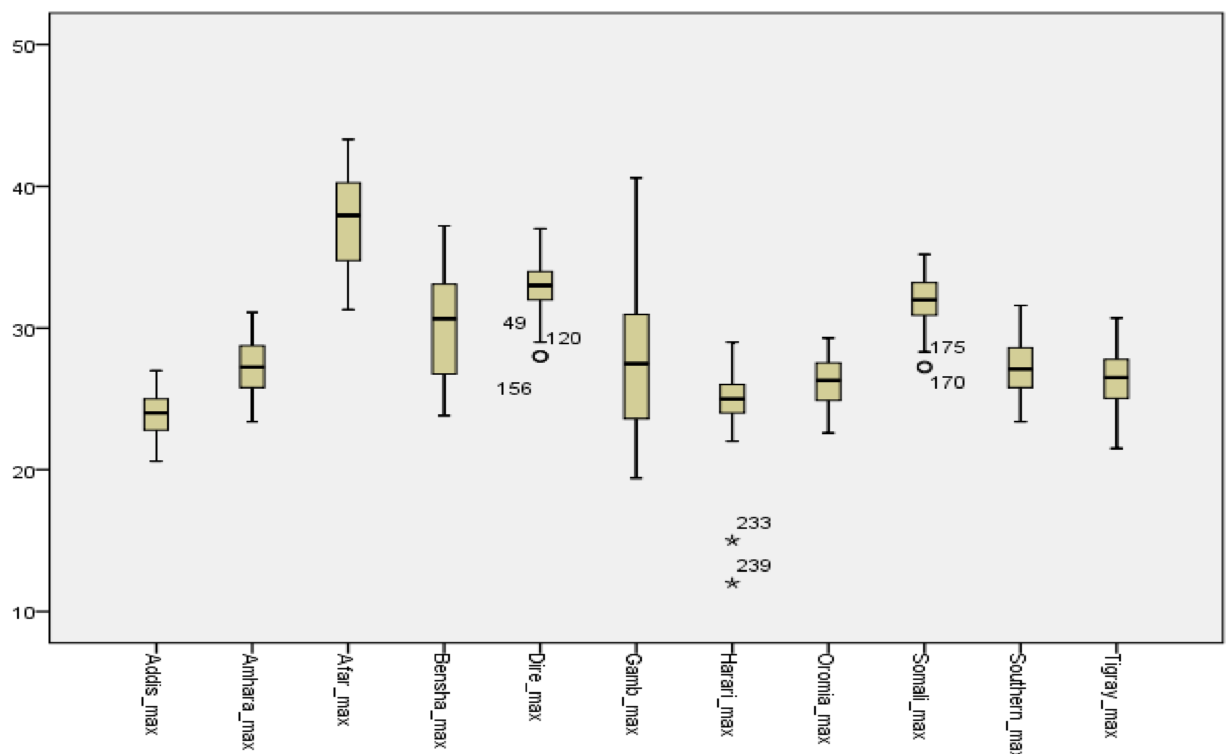


Figure 3: **Box Plot for mean monthly Max temp (1994 – 2014) by region**

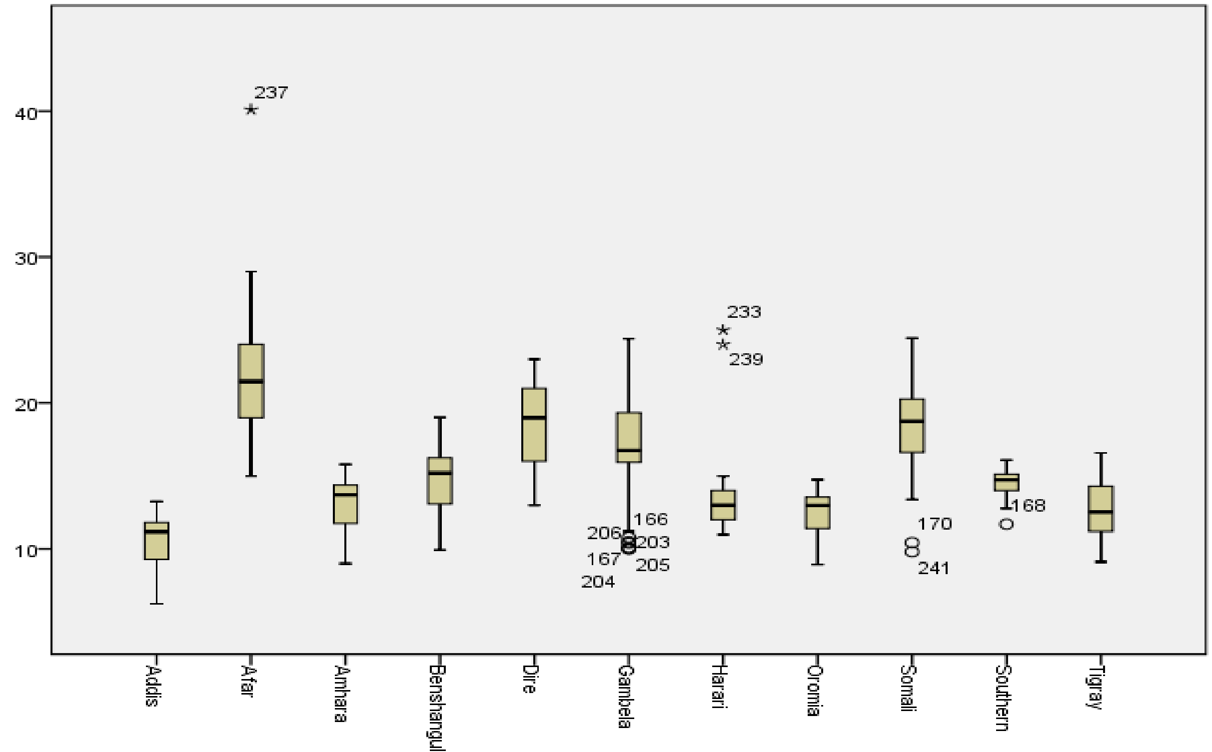
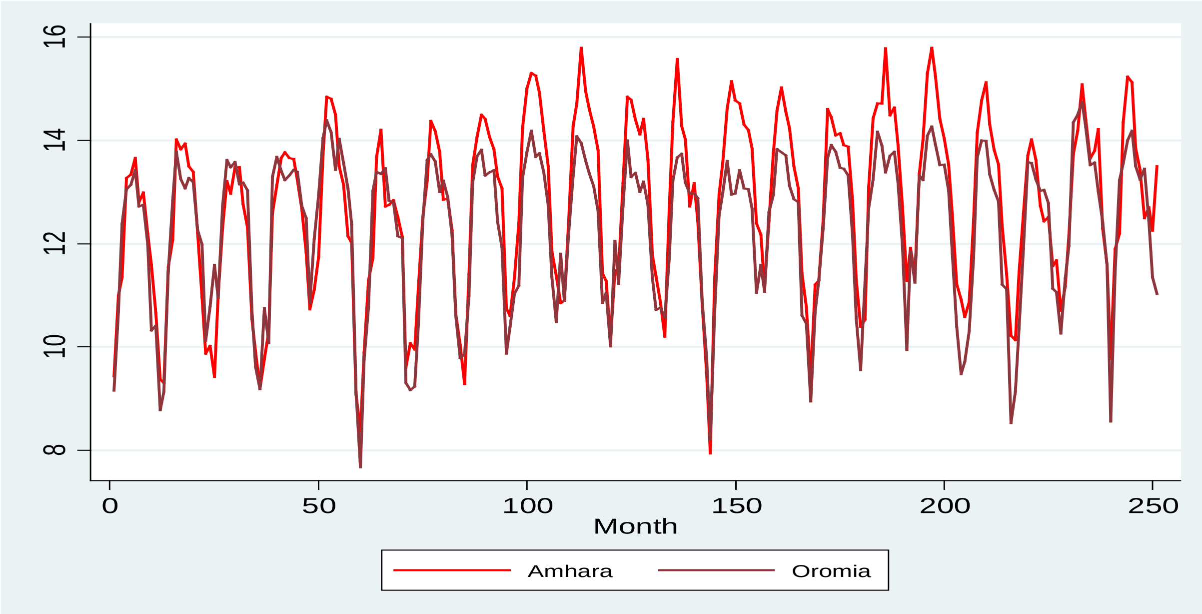


Figure 4: **Box plot for Monthly Mean Minimum Temperature (1994 – 2014) by Region**

Long term trend for monthly weather Data: Weather data obtained from NMA span 21 years (252 months), hence time series plots for rainfall, minimum temperature and maximum temperature was produced. A plot, which compare Amhara and Oromia regions for thier minimum temperature, is given in Figure 5; only the two are shown to make the graph simple and readable.

From thses plots the following is evident:*i) periodic occurence of the weather variables, ii) over all trend (for 252 months) of the weather variables, and iii) comparison among various regions in terms of trend of weather variables.* From this result, it is evident that Amhara tend to have higher minimum temeprature throughout than Oromia, but both regions depicted an increasing trend in temerature. The other plot (can be obtained on request) compares the four emerging regions interms of monthly average maximum temperature trends. Except for Gambela region, which showed different pattern, the plots for the other three emerging regions (Assosa, Benishangul, and Afar) show similar periodic occurence of high/low temperature for which the periodic effect seems to coincide. It is therefore expected that these regions would be subjected to similar impacts of climare change.

Gambela depicted slightly different pattern which is hard to cohmprehend due to highly undulating nature with no obvious cycle or seasnal effect. Particularly, Gambela recorded minimum temerature which is lower than that of Benishangul until about 2006, then took over since then. The rate at which the minimum temerature is increasing for Gambela region require special attention. Afar, on the other hand, is mostly on the top of the three regions in producing high minimum temperature throughout the decades. The graph shows observed periodic occurence which should be verified through proper statistical analysis. Different plots are presented in annex that comapre regions in terms of pick points, seasonality and overall trend.



Figur 5: **Time series plots of Minimum Temperature for Amhara and Oromia**

Measuring relationship among records of consecutive months for each of the three weather variables: In this section Auto Correlation Function (ACF) is fitted to rainfall (Table 2), to Maximum Temp (Table 3), and to Minimum Temp (Table 4) for each region to determine relationship among consecutive records of each variable so that periodic occurrence of key phenomenon such as rainfall onset or hottest period in a year can be identified. There were 252 months in the data which provide a range of lag distances (lag distance, a technical term for time series analysis, is defined as number of months between two time periods. For example, the lag distance between September and November of 2000 is 2). For each region ACF tables and graphs (Annex 4) were produced, but the results are summarized in tables 1-3 for lag distances showing highly significant ACF values (out of the total 16 lag distances initially fitted). The tables provide estimated correlation coefficients between months that are ***x*** lag distance away from each other (known as autocorrelation coefficient) and the graph is meant to depict possible periodic occurrence over the period of two decades. In Table 1, for example, autocorrelation coefficient for rainfall between consecutive months (lag 1) for Benishangul is 0.78, highest compared to other regions and shows the fact that rainfall persists for several consecutive months; whereas in Afar this value is just 0.28 showing rainfall is observed only for few months in sequence.

Table 1: **Summary of Autocorrelation values for Rainfall, for selected lags by region**

	Lag Distances				
Region	**1**	**2**	**11**	**12**	**13**
AA	0.62	0.22	0.59	0.76	0.60
Afar	0.28	0.11	0.59	0.76	0.60
Amhara	0.69	0.20	0.2	0.64	0.90
Benshangul	0.78	0.41	0.74	0.88	0.72
Dire Dawa	0.25	0.06	0.21	0.40	0.23
Gambela	0.66	0.43	0.46	0.55	0.56
Harari	0.41	0.15	0.29	0.40	0.30
Oromia	0.74	0.38	0.71	0.86	0.70
Somalia	0.33	0.11	0.21	0.54	0.21
Southern	0.41	0.02	0.29	0.56	0.27
Tigray	0.58	0.08	0.53	0.81	0.52

Table 2: **Summary of Autocorrelation values for Min Temp, for selected lags by region**

	Lag Distances				
Region	**1**	**2**	**11**	**12**	**13**
AA	0.70	0.35	0.61	0.73	0.57
Afar	0.62	0.31	0.20	0.25	0.18
Amhara	0.79	0.46	0.68	0.78	0.64
Benshangul	0.73	0.36	0.62	0.77	0.63
Dire	0.78	0.38	0.69	0.83	0.68
Gambela	0.79	0.73	0.47	0.47	0.63
Harari	0.32	0.14	0.22	0.24	0.15
Oromia	0.74	0.38	0.65	0.74	0.58
Somalia	0.70	0.49	0.30	0.32	0.32
Southern	0.60	0.28	0.43	0.51	0.38
Tigray	0.80	0.47	0.74	0.84	0.71

Table 3: **Summary of Autocorrelation values for Max Temp, for selected lags by region**

	Lag Distances				
Region	**1**	**2**	**11**	**12**	**13**
AA	0.65	0.28	0.58	0.75	0.60
Afar	0.73	0.37	0.64	0.76	0.63
Amhara	0.70	0.30	0.57	0.74	0.56
Benshangul	0.80	0.42	0.72	0.86	0.71
Dire	0.65	0.27	0.62	0.79	0.60
Gambela	0.77	0.65	0.35	0.37	0.29
Harari	0.33	0.10	0.17	0.22	0.11
Oromia	0.72	0.37	0.61	0.78	0.62
Somalia	0.75	0.58	0.33	0.39	0.34
Southern	0.76	0.39	0.64	0.77	0.63
Tigray	0.66	0.27	0.56	0.78	0.57

When the regions are compared for their ACF values of the weather variables, the result shows that very similar trend is observed for all regions regarding rainfall pattern. Firstly, the entire 16 lag ACFs show highly significant autocorrelations in all regions (but lag distances with highly significant ACF values were presented in summary tables as indicated earlier). Secondly, the magnitude of lag1 and lag 2 ACFs are often very similar and highest. This shows that the amount of rain for consecutive months (lag 1) and for periods two months apart (lag 2) is highly related. For the main rainy season, for example, rain starts in June and stays until August or latter in most part of the country. Thus amount of rainfall between June and July is very similar for most regions giving highest autocorrelation value (lag 1). Similarly, rainfall amount in June is also somehow similar to rainfall in August (lag 2) producing second highest autocorrelation values once again. For this reason the magnitude of AC values for lag 1 and lag 2 are both high and similar. But, the amount of rainfall in June and November (lag 5), for example, are very different in their magnitude, therefore they have small autocorrelation value showing that the periods, 5 months apart, are not related in terms of amount of rainfall. The high autocorrelation values, ranging from 0.4 for Harrari to 0.88 for Benishangul regions, shows presence of strong seasonal effect of rainfall every 12 months (lag12). This coincides with the commonly known onset of rainy season mostly every June which is an evidence for periodicity of rainfall in all regions.

Nevertheless, there is a striking phenomenon in the ACF values of rainfall in all regions. The ACF estimates for lags 11, 12 and 13 are positive and high for the entire regions which are assumed to be related to Climate Variability. This, somehow, contradicts the perception that rain begins always in the same month (possibly June) every year in the country. The result rather shows that rainfall may not occur every 12 months as we perceived, but may start every 11 months (that is in a period less than a year) or may even start after 13th months. That means some years rain may come in June and the following year in May, i.e., in less than a year period; alternatively, rain may start in June in a given year followed by an onset in July the next year, spaced 13 months apart.

The 5th, 6th and 7th lags also show relatively high rainfall ACF for the entire regions but with negative values. This is an indication of the presence of sub-periodic occurrence of rain or related phenomenon within one full rainfall cycle contrasting rainy and dry months. It is evident that, a periods 5 to 7 months apart shows negative relationship. This is because periods that are six months apart experience rainfall in the first month and dry situation after sixth months. Significance of 5th, 6th and 7th lag distances are probably related to changes in the duration of rainfall. Once again, this phenomenon is a warning sign for regional health offices commissioned to control malaria that occurrence of rainy and dry seasons be clearly identified and closely monitored within the framework of Climate Variability to halt spread of mosquitoes.

A periodogram and results from *spectra analysis* using *Fourier frequencies* is presented to help in determining the periodic effect or the cycle in the occurrence of rainfall as compared to the ACF. The periodogram is a useful graphical statistics for uncovering the important frequencies in a time series data. We used Oromia rainfall data for demonstration as it does not have missing values. Frequencies are plotted from 0 to 0.5. The cycles are determined by the picks in the graph and determined by 1/F (where F is frequency). Consequently, the result shows that the first pick occurs at about 0.08 frequency on the periodogram, hence the periodic cycle occurs at about 12 months (1/0.08). This agrees with results from ACF. The second pick occurs at about 0.17, giving the second cycle of 6 months. This approach basically confirms results obtained from ACF. Periodogram for other regions were fitted but since the results agree with results from ACF it was not presented.

The ACF for minimum and maximum temperature shows similar pattern with that of rainfall. Lags 1 and lags 11-13 are relatively very high and positive, indicating shifting periodic occurrence of high/low temperature; the first two lags are often relatively high and positive for most regions indicating that occurrence of high/low temperature stays for two or more months consistently.

The ACF values for lags 1, 2, 11, 12 and 13 are summarized into three tables, each for rainfall, min temp and max temp, to show the significant ACF for ease of interpretation. Annex1 shows the Autocorrelation values, corresponding standard errors and significance levels for each lag. The graphs very often shows the long (12th lag) and the short (6th lag) period occurrence of rainfall.

Climate Variability and its implication on health

Malaria Prevalence: In order to study impact of Climate Variability on burden of malaria, it is important to assess magnitude and distribution of malaria prevalence over both space and time. Therefore, mean and Standard Deviation was computed for Malaria incidence data per 1000 population and the result shows that malaria prevalence highly fluctuate from year to as evidenced by large SD throughout. These fluctuations take place due to periodic occurrence of malaria infection which coincides with seasonal occurrence of weather variables (Table 4). Therefore, there is an indication that malaria prevalence is related to the weather variables. Except Dire and Tigray, malaria prevalence reached its minimum in 2009 due to nationwide intervention but increased rapidly afterwards.

Table 4: **Mean and SD for 11 years (2004-2014) Malaria incidence by region (per 1000 population**)

Region	Mean	SD[1]
Addis Ababa	0.771268	0.317823
Afar	39.08745	23.84352
Amhara	23.51261	16.15571
Benishangul	168.5863	132.0971
Dire Dawa	3.994276	4.894654
Gambela	146.1917	111.8262
Harari	19.38148	19.2638
Oromia	11.56308	7.502907
Southern	44.40289	28.66824
Somalia	4.151803	4.434802
Tigray	42.81922	26.74605

[1] Standard deviation

Based on this indicative result, the next section is devoted to assessing relationship between weather variables and malaria to find out if Climate Variability is accountable for such oscillation.

Association of Climate Variability and malaria incidence in Ethiopia: Relationship between Climate Variability and malaria cases was assessed for seven regional states and two city administrations and results from best performing models were summarized and presented in Table 4. The finding shows that a minimum temperature and malaria cases showed statistically significant association in Tigray, Gambella, Dire Dawa and Afar. The relationship was strongest in Tigray. Similarly, maximum temperature showed association with malaria case in SNNP, Oromia, Benishangul-Gumuz, Amhara, Afar and Addis Ababa. From this finding the extent of relationship between malaria cases and rainfall, min temp and max temp showed high variability among regional states indicating differential impact of Climate Variability to the regions (Table 4).

The direct output from Poisson regression contains estimated parameter, B (regression coefficient), STD of the parameter, 95% C.I. for the estimate and its corresponding significance probability (p-value). The importance of the weather variable in explaining malaria prevalence is judged by the magnitude of B, of course given that the parameter is significantly different from zero. Weather variables associated with large B contribute more in increasing/decreasing (depending on the sign) the burden of the disease. The B may not be directly interpreted, but changed to a different scale, as presented in Table 4. For example, considering Malaria cases in Amhara region, B was 0.028 for rainfall and it is highly significantly larger than zero (p=0.01). Hence exponentiating this (exp [0.028]) gives 1.029. This value is known as Rate Ration (RR). It is interpreted as: estimated percentage change in Malaria cases is 2.9% for a 1 mm increase in the rainfall; which shows that high rainfall increases Malaria infection. But association of Burden of Malaria and maximum Temperature is reverse, as B value is negative. For a one Degree celiac increase in maximum temperature, Malaria infection decreases by about 1.7%.

Table 5: **Regression using GLM for malaria cases, May 2015**.

Regional States	**Variables**	**RR**	**95%CI**
Addis Ababa	Rainfall	0.991	0.990-0.992
	Tmax	1.291	1.248-1.336
	Tmin	0.836	0.809-0.863
Afar	Rainfall	0.862	0.860-0.863
	Tmax	1.121	1.110-1.132
	Tmin	1.506	1.501-1.511
Amhara	Rainfall	1.038	1.038-1.038
	Tmax	1.746	1.741-1.750
	Tmin.	0.293	0.292-0.294
Benishangul-G.	Rainfall	1.006	1.006-1.006
	Tmax	1.399	1.392-1.407
	Tmin	0.731	0.729-0.733
Dire Dawa	Rainfall	0.951	0.949-0.953
	Tmax	0.266	0.254-0.279
	Tmin	2.165	2.052-2.285
Gambella	Rainfall	0.996	0.996- 0.996
	Tmax	0.878	0.876-0.881
	Tmin	1.239	1.236-1.243
Oromia	Rainfall	0.971	0.970-0.971
	Tmax	1.851	1.844-1.859
	Tmin	0. 653	0.651-0.655
SNNP	Rainfall	1.042	1.042-1.042
	Tmax	2.099	2.093-2.102
	Tmin	0.722	0.720-0.724
Tigray	Rainfall	1.032	1.032-1.032
	Tmax	0.858	0.848-0.869
	Tmin	3.036	2.999-3.074

Somali with three year missing and not included in the analysis

Forecasting vulnerability to malaria by Region: Various time series based models were fitted [that is with different parameters, like AR(1), AR(2), ARMA, ARIMA, etc.,] and those judged better than others were used to estimate past trends in malaria cases and projected future malaria burden. Forecasts are presented in terms of graphs so that future projected trends can easily be recognized visually (numerical forecasts can also obtained from the same software output). In figure 6, the graph is divided into two compartments, the left compartment contain estimated trend using 11 years data and compartment on the right hand side contain trend representing future forecast. The right hand side contains red and blue graphs representing observed and fitted trend respectively, with their corresponding CI. The right hand side of the graph shows trend for the forecasted malaria cases with corresponding CI. Looking through the observed malaria data in figure 6, two pick points may be observed, lowest and highest malaria cases in 2009 and 2013 respectively in considerable number of regions. These years may be attributed to interventions (2009) and normalization of cases for some reason (2013). In Amhara region, the fitted (blue line) curve shows a rapid overall increasing trend in malaria cases from year to year (Figure 6). The forecast values followed similar pattern. For example, malaria cases are projected to be about 833,586 by 2015 (or from 48 persons to 75 persons per 1000 people based on the C.I.) and expected to reach over one million by 2020 (or approximately 55 to 120 persons per 1000 people using the C.I) if things continue the way they are today. Therefore, there is strong evidence that Climate Variability exacerbate malaria cases if no action is taken.

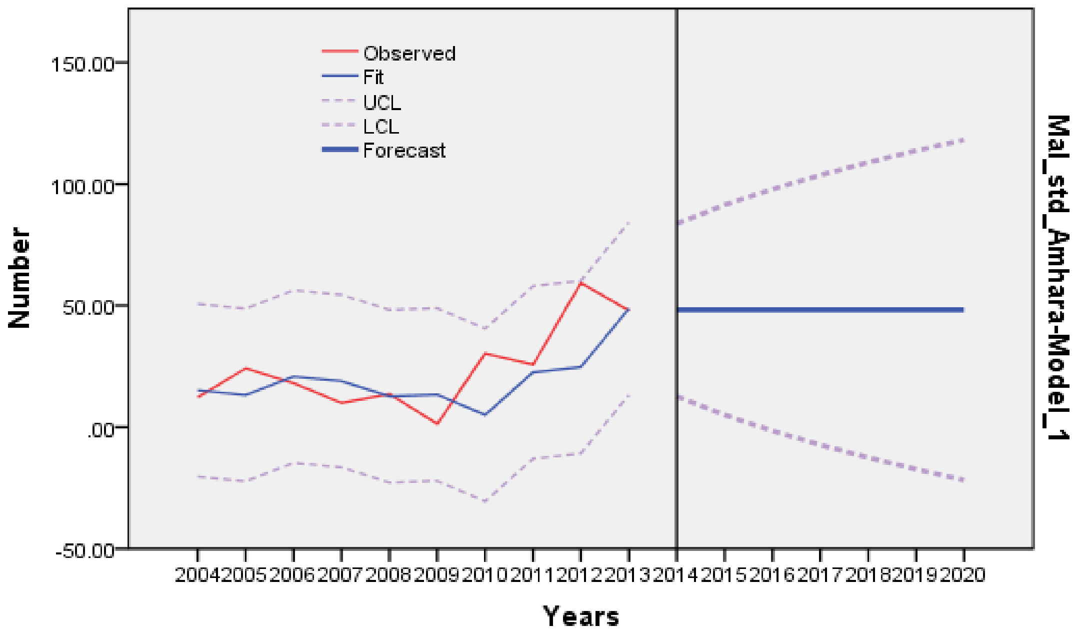


Figure 6: **Current trend of Malaria (persons per 1000 people)in the left panel (with its observed in red, estimated in blue and 95% Confidence interval) and predicted values in the right panel (again with estimated value in blue and 95% C.I) for Amhara region**

In Oromia region, malaria cases showed a small but gradual decrease from 2004 up to 2009, and then sharp increase during the following year reaching the maximum by 2013 and started to decline again. Due to short fluctuations in the annual data, the estimated line could not be smoothed as that for Amhara region. Although there is a general increasing trend through the decade, the fitted curve is a bit undulating. Because of lack of smoothens in the fitted line contributed to a constant forecast of about 359,941 (approximately 17 cases per 1000 people which may reach 45 cases per 1000 people by 2020 from C.I.) throughout. The 95% Confidence Interval on the other hand is very wide, even getting wider and becoming a parabola, which is an indication of difficulty of projecting in the future due to lack of clear pattern from present and past observations. Oromia and SNNP regions showed similar pattern in malaria cases.

Discussion

Ethiopia is a country characterized by undulating land escape, ranging from lowest point (Dallol) to over 4000m high mountain (Ras dashen). Synthesis of results from analysis of weather variables presented earlier shows that regions dominated by higher elevations such as Amhara region receive more rainfall and tend to be less warm than those regions in low arid areas, such as Somali region. On the other hand, Oromia and SNNP regions seem to have more consistent rainfall amount on average over these years and probably less affected by Climate Variability. Minimum temperature is not normally distributed in all regions, while maximum temperature is distributed approximately normally in all regions, which indicate the fact that, it is the minimum temperature which is important in the study of Climate Variability. These findings agree with studies made by (5), who documented an alarming increase in minimum temperature since 1990; and (11), who pointed out mechanisms in which Climate Variability impacts on health. Such increasing trend in temperature over years shows Climate Variability may bring even more warming and less rain in the coming future.

Results obtained from ACF, where rain onset showed tri-annual situation in a year, provide an idea that rain onset and offset may change from time to time and the length of stay may as well vary, which could be ascribed to CC. For Addis Ababa, for example, the ACF values of lag11, lag12 and lag13 are 0.59, 0.76 and 0.61 respectively, indicating presence of 3 possible seasonal periods for onset of rainfall; an indication of a possible shift in the rainfall patterns in the last two decades. Gambela and Benishangul regions show slightly different ACF patterns. Here, Lag1 and lag2 ACF values are positive and relatively high showing longer rainy periods over the past two decades. The periodic occurrence of rain also spread over longer period, from 10th lag to 14th lag. This shows that rain often stay longer mostly up to 5 months with some shift in the onset. Rainfall in Afar seems more erratic as the largest positive ACF is at 13th lag. This could be due to Climate Variability over the last two decades and surely these changes affect occurrence and magnitude of disease outcome. It is therefore important to understand the changes taking place in the onset of rain due to impact of Climate Variability so that interventions introduced to control malaria coincide with breeding period for anopheles mosquitoes; prevention and control strategies may also need to be different for these regions in the future.

The ACF for minimum and maximum temperature have similar pattern with that of rainfall. Except for Gambela and Somali regions, the remaining regions have similar pattern of ACF for min and max temp. The ACF for the two regions is unique in the sense that all ACF values are positive. This shows that high maximum temperature prevails throughout the year, a process that was evolving over the decades probably inducing Climate Variability. More spread of high positive ACF values over 2010 to 2014 was observed indicating a gradual reduction of the lag length (increased frequency) for occurrence of high maximum temperature.

Weather variability and Climate Variability are drivers of several infectious and non-infectious diseases that are of great public health concerns in Ethiopia. Malaria, yellow fever, dengue fever, meningitis, and leishmaniosis are the most common climate sensitive disease (3-4). Malaria is one of the widely studied climate-sensitive diseases in Ethiopia. In Ethiopia, 75% of the total landmass (or <2000 m) is malarias or potentially malarias (11). However, the occurrence of endemic malaria is documented during non-epidemic years beyond the threshold elevation for transmission (15-16). From description of malaria prevalence in the result section of this article, it was found that burden of malaria fluctuates from season to season which coincides with seasonality of the weather variables; which is in line with the findings of (15).

Yellow fever and dengue fever are also climate sensitive vector-borne diseases (11). For instance, WHO report showed the re-emergence of yellow fever in southwestern during 2013 and newly emerging of dengue fever in eastern part of Ethiopia. Climate Variability have the potential to increase the risk of transmission by increasing the distribution and abundance of vectors, and duration of mosquito and seasons (17). Another important issue is that it is likely that some areas will have increased in activity and human infection with predicted Climate Variability, but risk of increased transmission will vary with locality, vector, host and human factors (17).

This study found that there is considerable association between weather variables and malaria incidence in the country, but the relationship varies from region to region. Although not specifically about highlands, this finding is in line with similar results from other studies which concluded that malaria transmission in highland areas is critically influenced by night time temperature. The role of temperature in determining malaria endemicity and intensity is more pronounced at areas boundary to upper limits of malaria endemicity (18). Consequently, the abrupt rise in night time temperature mainly due to warming is expected to push the elevation known to be the upper limit boundary, which is 2000 m in Ethiopia. Because there is an increase in the minimum temperature even in the highlands, this finding is in line with that of (18).

Results from poison regression showed that malaria prevalence is positively associated with increased rainfall and minimum temperature but negatively associated with maximum temperature. Particularly, increase in maximum temperature led to decrease in malaria infections. This agrees with findings of (19) that temperature fluctuations around low mean temperatures facilitating to speed up rate processes, whereas fluctuations around high mean temperatures act to slow down the processes. On the basis of basic biology of malaria vectors, studies showed absence of vectors in geographic zones with very cool ones to survive (20-22).

This result provides a general framework of relationship between malaria and weather variables that can be generalized to other diseases as well. Such significant relationship between the weather and disease burden indicate importance of considering weather variables to accommodate issues of Climate Variability in future planning of interventions. This study agrees with several other studies done here and elsewhere as follows: Temperature is reported to affect sporogonic development of *P. falciparum*by altering the kinetics of ookinete maturation (23). It was found that as temperatures decrease from 27 to 21°C ookinete development and blood meal digestion takes longer duration. However, high temperatures of 30 and 32°C appeared to significantly affect parasite densities and infection rates by interfering with developmental processes occurring between parasite fertilization and ookinete formation, especially during zygote and early ookinete maturation (24).

On the same note emerging and remerging vector-borne diseases were also reported in recent years. For instance, WHO report showed the reemergence of Yellow Fever in southwestern during 2013 and Dengue Fever in eastern part of Ethiopia (25). Climate Variability has the potential to increase the risk of transmission by increasing the distribution and abundance of vectors, and duration of mosquito and seasons (17).

Data collected for this study witnessed that dengue fever was observed in 2013 in Dire Dawa in considerable amount; but few number was captured in 2014 in Afar and Somalia regions. A similar recent study also indicated that dengue was present in Ethiopia (Dire Dawa and Harrar), Somalia (Mogadishu), Madagascar (Diego Suarez) and in the Comoros Islands (Mayotte) and in other parts of Somalia (Kismayu, Berberaand Hargeisa) and Mauritius (22). It has been described that the disease is well adapted to the urban environment but also occurs in rural areas. The vector breeds in containers where water is allowed to accumulate. *Aedes* mosquitoes thrive in warmer environments, but not in dry environments. Higher ambient temperatures favor rapid development of the vector, increase the frequency of blood meals, and reduce the extrinsic incubation period (EIP). Dengue fever is among climate sensitive diseases believed to aggravate with rise of temperature and environmental changes.

A study has shown, if the ambient temperature is too low, mosquitoes are unlikely to survive long enough to become infectious and pass on dengue (26). The Comoros, Ethiopia, Kenya, the Seychelles, Somalia, Tanzania, Réunion, Mauritius, and Mozambique were considered to be endemic from 1975 to1996 (27). Dengue occurs sporadically in Kenya and Somalia in which four major outbreaks occurred between 1982 and 1993 in various regions of Somalia. Therefore, the findings in malaria which mostly agreed with findings of other researchers support earlier findings on dengue.

Projections of malaria cases using time series models provided some insight about the past and future malaria incidence trends for regions of Ethiopia. Forecasting using standardized malaria cases showed steady state but with wide C.I which fits to the expected rise of malaria in the coming five years. These findings agree with similar study done in the continent. According to projections done in the past the highland areas of Ethiopia and Zimbabwe are among those with expected rise of malaria incidence in higher altitudes. A climate forecast related to future distribution of malaria in relationship with Climate Variability or temperature rise demonstrated both Ethiopia and Zimbabwe will be the most affected (28) . The Highlands of Zimbabwe become more suitable for transmission (29).

In a similar study (22) composite of vector-borne diseases demonstrated increase in geographical areas of the diseases beyond their endemicity limit. They assessed the potential impacts of anthropogenically-induced Climate Variability on vector-borne diseases globally and suggested an increase in extent of the geographical areas susceptible to transmission of malarial Plasmodium parasites, dengue Flavivirus and Schistosoma worms. Those diseases are highly sensitive to Climate Variability on the periphery of the currently endemic areas and at higher altitudes within such areas. The study indicated that compared to the present endemic areas the increase in the epidemic potential of malaria and dengue transmission may be estimated at 12-27% and 31-47%, respectively, while in contrast, schistosomiasis transmission potential may be expected to exhibit a 11-17% decrease (20,21,30).

Regarding related diseases, it was reported that some areas will have increased human infection from dengue with predicted Climate Variability, but risk of increased transmission will vary with locality, vector, host and human factors (17). A literature has shown that dengue was relatively uncommon in East Africa before 1952. However, outbreaks were documented in several countries between 1924 and 1950; Mozambique, Madagascar, Ethiopia, Somalia, and the Comoros.

Conclusion:

Results from analysis of data showed that seasonality of rainfall varies from region to region; the amount reaches its pick for different regions at different months; hence interventions for the regions should be designed accordingly. The weather variables show periodic occurrence with differential trend for regions. It is concluded that rainfall, min temp and max temp did not always occur every 12 months for the last two decades as expected, but also occur every 11 months or even 13 months apart possibly due to Climate Variability with some level of variability among regions. Relationship between weather variables and malaria cases was found to depend on regions, implying that the level of Climate Variability impact also differ from region to regions which should be considered during planning of interventions. Forecasts of standardized malaria cases showed wide confidence interval and increasing trend for all regions with different magnitude. It is therefore concluded that this result fits to the expected rise of malaria in the coming five years and require intervention in the years to come.

From statistical point of view, it is concluded that data description methods such as trends and boxplots are found to be suitable to indicate presence/absence of shifts in pick periods of weather variable; and provide suggestions as to whether Climate Variability may exist or not for a given time span. If forecasting future disease case is thought, it is necessary to first fit Poisson regression and select weather variables that show significant relationship with climate-sensitive diseases. Such variables with significant importance will be used in time series models to forecast future burden of disease. In addition, the length of time period of data used in modeling weather and disease related variables affects the quality of forecasts; if possible, longer period of observed data is advised for better results. Once forecast is done, it is advisable to use forecasted values provided by the confidence interval for planning interventions, rather than using the point estimate of forecasted values; the former gives a better estimate of the true trend.

Limitation

Data on health sector interventions such as bed net distribution, insecticide spraying and environmental control could not be obtained for the years for which malaria cases were observed. Readers are expected to recognize this in interpreting the finding.

Acknowledgement

We thank World Health Organization (WHO) for funding this study. The FMoH, regional health bureaus, EPHI and ENMA are acknowledged for providing data used in this study.

References

1. Federal Democratic Republic Of Ethiopia. Environmental Policy of Ethiopia. The Resource base and the need for a policy 1997.
2. IPCC 2014. Climate Variability: Synthesis Report; Summary for Policymakers 2014.
3. UNDP. Framework for UNDP Ethiopia's Climate change, Environment and Disaster Risk Management Portfolio 2011.
4. César E. Ethiopia Environmental and Climate Change Policy Brief.Sida's Helpdesk for Environment and Climate Change 2013.
5. Tadege A. Climate Change National Adaptation Programme of Action (NAPA) of Ethiopia. Addis Ababa, Ethiopia: The Federal Democratic Republic of Ethiopia Ministry of Water Resources and National Meteorology Agency 2007b.
6. Tadege A. Climate Change National Adaptation Programme of Action (NAPA) of Ethiopia. Addis Ababa, Ethiopia: The Federal Democratic Republic of Ethiopia Ministry of Water Resources and National Meteorology Agency 2007a.
7. Ayalew D, Tesfaye K, Mamo G, Yitaferu B, Bayu W. Outlook of future climate in northwestern Ethiopia *Agricultural Sciences* 2012; 3**,** 608-624.
8. Patz Ja, Campbell-Lendrum D, Holloway T, Ja F. Impact of regional climate change on human health. *Nature* 2005; 310-317.
9. Portier C. J, Thigpen T. K, Carter S, Dilworth C, Grambsch A, Gohlke J, Hess J, Howard S, Luber G, Lutz J. A Human Health Perspective On Climate Change: A Report Outlining the Research Needs on the Human Health Effects of Climate Change. *Environmental Health Perspectives* 2010.
10. Mcmichael Aj. Globalization, climate change and human health. The New England *Journal of Medicine* 2013; 1335-1343.
11. World Health Organization (WHO). Health impacts of climate extremes: in Climate change and human health: Risks and Responses 2003.
12. World Health Organization Ethiopia. A review and analysis of the trends of household drinking water and sanitation coverages using EDHS data in relation to diarrheal disease morbidity- the perspective in Ethiopia 2006.
13. World Health Organization, UNICEF. *Joint Monitoring for Water Supply and Sanitation* [Online] 2014. Available: http://www.wssinfo.org/.
14. Ghebreyesus T, Tadese Z, Jima D, Bekele E, Mihretie A, Yihdego Y, Dinku T, Connor S, Rogers, D. Public health and weather services–climate information for the health sector. *WMO Bulletin* 2008; 57**,** 258-261.
15. Tesfaye S, Belyhun Y, Teklu T. Malaria prevalence pattern observed in the highland fringe of Butajira, Southern Ethiopia: a longitudinal study from parasitological and entomological survey. *Malar J* 2011; 10.
16. Graves P, Richards F, Ngondi J. Individual, household and environmental risk factors for malaria infection in Amhara, Oromia and SNNP regions of Ethiopia. *Trans R Soc Trop Med Hyg* 2009; 103**,** 1121-1120.
17. Russell P. World-wide malariadistribution, prevalence and control.AmJTrop MedHyg.1956; 5:937–56. Russell RC "Mosquito-borne es in Australia: the current scene and implications of climate change for human health. . *International Journal for Parasitology* 1998; 28**,** 955-969.
18. Molineaux L. The epidemiology of malaria as an explanation of its distribution, including some implications for its control. In: Wernsdorfer W, editor. Malaria Principles and practice of malariology Great Britain, Churchill Livingstone: Sir McGregor Eds 1988; 913-918.
19. Paaijmans K, Blanford S, Bella S, Blanford J. Read, A. & Thomas, M.. Influence of climate on malaria transmission depends on daily temperature variation. *PNAS* 2010; 107**,** 15135–15139.
20. Martin M, Lefebvre G. Malaria and climate sensitivity of malaria potential transmission to climate. *Ambio* 1995; 24**,** 200-207.
21. Martens P, Kovats R., Nijhof S, De Vries P, Livermore M, Mcmichael A. Climate change and future populations at risk of malaria. *Global Environ Change* 1999; 9**,** S89-107.
22. Martens, W., Theo, H. J. & Focks, D.. "Sensitivity of malaria, schistosomiasis and dengue to global warming". *Climatic Change* 1997; 35**,** 145-56.
23. Noden B, Kent M, Beier J. The impact of variations in temperatur eo nearly Plasmodium falciparum developmentin Anophelesstephensi. *Parasitolog* 1995; 111**,** 539-545.
24. Olson S, Gangnon R E, E, Durieux L, Guégan J, Foley J, Patzj A. Linksbetween climate, malaria, andwetlands inthe Amazon Basin. *Emerging Infectious Diseases* 2009; 15**,** 659-662.
25. World Health Organization, UNICEF. Progress on sanitation and drinking-water - 2014 JMP update. Geneva 2013.
26. Patz J, Graczyk T, Geller N, Vittor A. Effects of environmental change on emerging parasitic

diseases. *International Journal of Parasitology* 2000; 30**,** 395-1405.

27. Van Kleef E, H B, Hales S. The geographic distribution of dengue fever and the potential influence of global climate change. TropIKA 1–18 2010.
28. Tanser F. C, Sharp B, Sueur D. L. Potential effect of climate change on malaria transmission in Africa. *THE LANCET* 2003; 362.
29. Craig M, Snow R D, L. S. A climate-based distribution model of malaria transmission in Sub-Saharan Africa. *Parasitology Today* 1999; 15**,** 105-111.
30. Lysenko A, Semashko I. Geographyof malaria. A medico-geographic profileo f an ancient disease. In: Lebedew AW, editor. ItogiNauki: Medicinskaja Geografija. Academy of Sciences, USSR; Moscow 1968; .25-146.