Long-run relative importance of temperature as the main driver to malaria transmission in Limpopo Province, South Africa – a simple econometric approach

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Abstract

Malaria in Limpopo Province of South Africa is shifting and now observed in originally *non-malaria* districts and it is unclear whether climate change drives this shift. This study examines the distribution of malaria at district level in the province; determines direction and strength of the linear relationship and causality between malaria with the meteorological variables (rainfall and temperature) and ascertains their short and long run variations. Spatio-temporal method, Correlation analysis and econometric methods are applied. Time series monthly meteorological data (1998-2007) were obtained from South Africa Weather Services while clinical malaria data came from Malaria Control Centre in Tzaneen (Limpopo Province) and South African Department of Health. We find that malaria changes and pressures vary in different districts with a strong positive correlation between temperature with malaria, $r = 0.5212$, and a weak positive relationship for rainfall, $r = 0.2810$. Strong *unidirectional* causality runs from rainfall and temperature to malaria cases (*and not vice versa*): F (1, 117) = 3.89, $\rho = 0.0232$ and F (1, 117) = 20.08, $\rho < 0.001$ and a *bi-directional* causality exists between rainfall and temperature and temperature to rainfall and from rainfall to temperature, F (1, 117) = 19.80; F (1,117) = 17.14 with $\rho < 0.001$ respectively in both cases. Results show evidence of strong existence of a long-run relationship between climate variables and malaria, with temperature maintaining very high level of significance than rainfall. Temperature, therefore, is more important in influencing malaria transmission in Limpopo Province.

Key words: Malaria, Climate change, Limpopo Province, Spatio-temporal, Causality, ARDL Model

INTRODUCTION AND PURPOSE

Malaria is the most nagging parasitic infection affecting humans, accounting for an estimated 300–500 million cases of malaria worldwide with 90% of annual cases reported in sub-Saharan Africa (Reiter, 2008). A recent resurgence of malaria in the East African highlands involves multiple factors, ranging from climate and land use change, to drug resistance, variable disease control efforts, and other socio-demographic factors (Patz et al., 2002; Pascual et al., 2006). Malaria epidemics have long been reported to occur among vulnerable populations where immunity is often non-existent or poorly developed. It is estimated that epidemic malaria causes between 12% and 25% of estimated annual worldwide malaria deaths, including up to 50% of mortality in persons less than 15 years of age (Thomson et al., 2005).

Malaria is an extremely climate-sensitive disease (Rogers and Randolph, 2000) common in the tropics, (Patz and Olson, 2006), but also reported in mild-to-cold climates (Hulden, 2009). Rainfall and temperature anomalies are widely considered to be a major driver of inter-annual variability of malaria incidence in the semi-arid areas of Africa (Connor et al., 1999), and Thomson et al. (2005), recently recorded a warming trend in the East African highlands that corresponded with concomitant increases in malaria incidences (Pascual et al., 2006). Further, Siraj et al., (2014) provides evidence that an increase in the altitude of malaria distribution in warmer years will increases malaria burden in the densely populated highlands of Africa and South America. Ebi et al., 2005) studies on malaria in Zimbabwe assert that by 2050, the projected warming would make Zimbabwe's entire highland area climatologically more favourable to malaria. Large epidemics of malaria elsewhere have been associated with climate anomalies, such as in Colombia, the Indian subcontinent, and Uganda (Bouma and van der Kaay, 1996). Recently, it has been shown that in Botswana, indices of El Niño-related climate variability can serve as the basis of malaria risk prediction and early warning (Lindblade et al., 1999).

Empirical studies have reported rainfall (Githeko and Ndegwa, 2001; Thomson et al., 2005; Nkomo et al., 2006) and temperature (Paaijmans, 2010; Ngomane and de Jager, 2012) as the main climate factors that influence malaria transmission; however, other studies have included other variables such as humidity and vegetation (Haque et al., 2010;; Alemu et al., 2011). Recent sensitivity analysis by Lunde et al., (2013) of some malaria-transmitting anopheline mosquitoes of the Afrotropical region shows that relative humidity can be very important for malaria transmission. Rainfall provides condusive site conditions for mosquito breeding, and humidity and temperature together affects mosquito survival (Poveda et al., 2001).

Warmer temperatures shorten the mosquito life cycle, thereby increasing its population (Patz et al., 2005; Patz and Olson, 2006). High temperature shortens the development time of vector-borne pathogens; and combined with favourable climate conditions, the population of carrier-mosquitoes increases (Atul and Nettleman, 2005; Naqvi, 2009). Alongside drug resistance and land-use patterns, this increases the incidence of malaria (Harrus and Baneth, 2005; Pascual et al., 2006; IOM, 2008; Relman et al., 2008). Mordecai et al., (2013) concludes that as temperatures increase due to climate change, vector control will likely become more important, difficult and expensive in temperate areas but some warm areas may simply become too hot to support malaria. Studies report the most efficient and optimal transmission to occur at $25°C$ *(*Lunde et al., 2013, Mordecai et al., (2013), but at extreme high or low temperatures (above 28˚C or below 16˚C), the cycle cannot be completed and transmission decreases dramatically or cannot occur ((Mordecai et al., 2013, Zucker, 1996; Williams et al., 1999)

In both theory and literature, variation in rainfall and temperature will affect observed malaria cases. Apart from climatic influence in malaria transmission, social and economic factors—e.g., population and migration—also play a significant role (Haines et al., 2000; van Lieshout et al., 2004). Moreover, a combination of mutating malaria parasites, resource constrains, and weak health systems, implies low adaptive capacity (Kovats and Haines, 2005).

South Africa has a warm climate, and much of the country experiences average annual temperatures of above 17°C (DST, 2010). M Malaria transmission is distinctly seasonal and limited to warm and rainy summer months. Case notifications generally increase from November, peak in late March to May, and then decline by the end of June. Craig et al. (2004) report that, in South Africa, the average seasonal pattern in malaria incidence follows periodicity in rainfall and temperature with a three to four month lag. Although we find this lag time rather long, elsewhere, the response time is not uniform. In the East African Highlands for example, Zhou et al. (2004) finds a one to two and two to five month lag for minimum and maximum temperature respectively, while Briet (2008) and Hashizume et al. (2009) report rainfall lag time of zero to three months and two to three months for Sri Lanka and Kenya, respectively.

Malaria is endemic in the low-altitude areas of South Africa at the border with Mozambique and Zimbabwe. Specifically, transmission is prevalent in three provinces: KwaZulu-Natal, Limpopo, and Mpumalanga province (Sharp et al., 1988; Gerritsen et al., 2008; Ngomane and de Jager, 2012; Kondo et al., 2002). Limpopo Province (Approximately 22-25ºS, 27-32ºE) lies in the low altitude area pre-disposed to malaria due to warm conditions. The occurrence of malaria cases in the province has been reported to be highly dependent on seasons (Bouma and van der Kaay, 1996). Interventions through the malaria control program in South Africa rely heavily on the intermittent use of indoor residual spraying in periods shortly after heavy rains when malaria cases tend to rise. This program continues despite no empirical evidence that rainfall drives malaria in the province. Therefore, there is a need to establish the relative importance of rainfall and temperature in malaria transmission for effective malaria control. It is important to understand the relative importance, strengths, and direction of causality of climate-malaria drivers, as well as the role of rainfall and temperature as it relates to malaria dynamics in the short and long run. This is central in enhancing malaria control policy measures and informing the design of malaria early warning systems. Due to the fact that climate change by itself will increase vulnerability (Bohle et al., 1994;; van Lieshout et al., 2004), target planning is necessitated by careful consideration of all factors.

Despite reported reduction in malaria trends in South Africa through a combination of various social, economic, and policy efforts (Blumberg and Frean, 2007); the impact of recent climate change on malaria incidence remains poorly understood. Little is written about climate impacts on malaria in Limpopo Province. While Shewmake (2008) does not mention malaria in a study of household vulnerability to climate change, Gerritsen et al.

(2008), on the other hand, provide only an overview of seasonal malaria incidence and mortality, and detect trends over time and places in the province.

This study uses Spatio-temporal, correlation, and econometric approaches (unit root tests and causality tests) to achieve the above aims. The spatial method examines the distribution of malaria at the district level within the province, while Pearson Correlation determines the direction and strength of the linear relationship between malaria with the meteorological variables. The econometric approach is applied to 1) validate and examine the intrinsic characteristics (stationarity) of malaria cases, rainfall, and temperature; 2) test the direction and relative strength of causation; and 3) ascertain the short run and long run equilibrium relationship of the variables. The strength of econometric methods lies in their ability to distinctively separate the effects of correlation from those that are related to causality, thereby eliminating the common fallacy that correlation implies causation. Causality is tested using the standard Granger Causality Test.

Conceptual framework

The conceptual framework for this study advances a multiple-factor explanation for malaria, ranging from climate and land use change, to drug resistance, variable disease control efforts, and other socio-demographic factors. Figure 1 below illustrates a simplified, non-detailed interrelationship. This study looks at the climate-malaria inter-relationship.

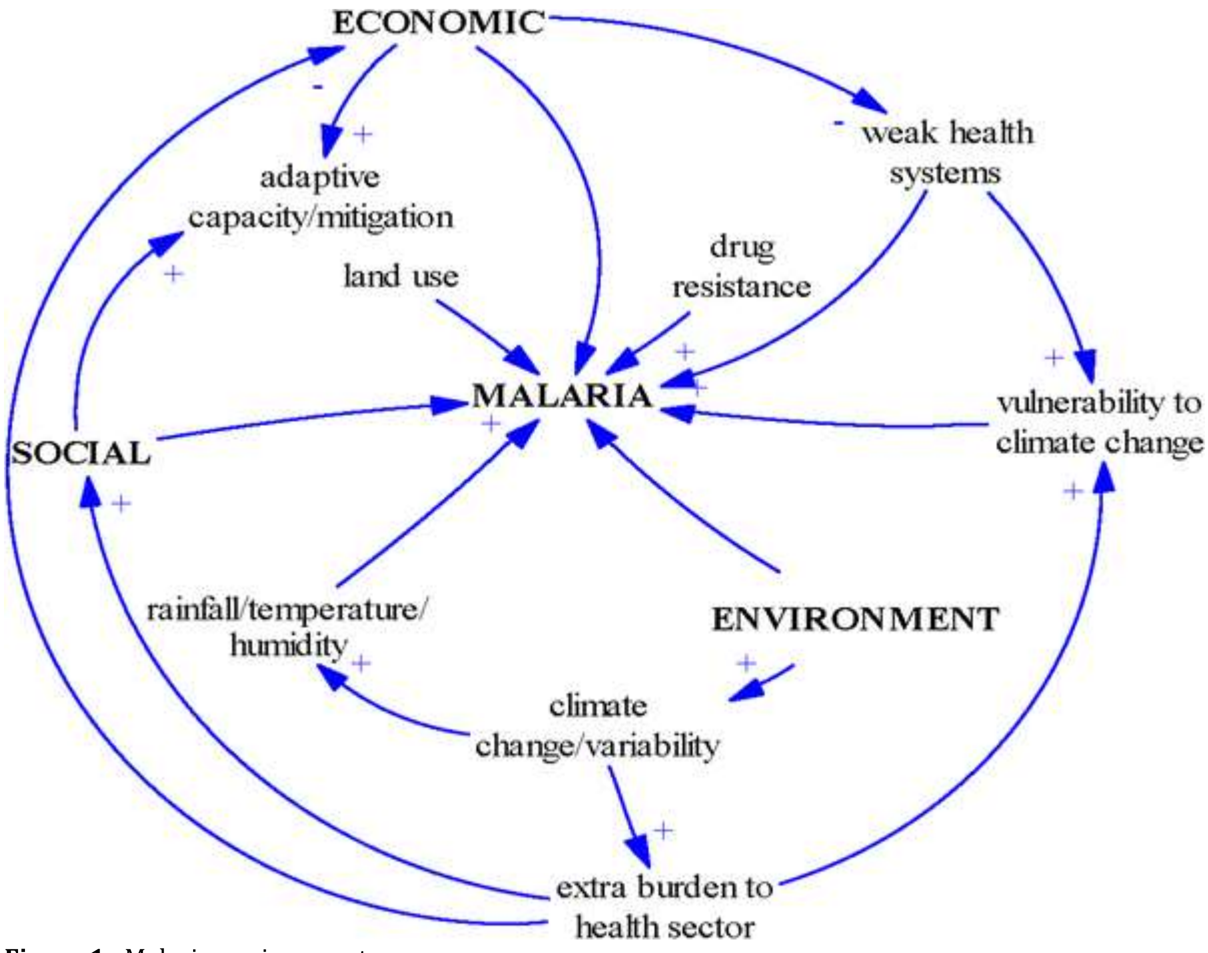

Figure 1 : Malaria-environment nexus

METHODS

Data and sources

Monthly average rainfall and temperature along with the number of malaria cases from January 1998 to July 2007 are used. Climate data was obtained from the South Africa Weather Services, while malaria data were obtained from South African Department of Health and Malaria control Centre in Tzaneen, captured through passive and active surveillance systems. Details of the methods on how this data was collected can be obtained from Gerritsen et al. (2008).

Description of the methods

a. *Spatio-temporal and correlation*

The spatial distribution of malaria at municipality and district levels were mapped ArcGIS. Changes in the distribution were obtained using the Inverse distance weighted (IDW) interpolation method. IDW routine assumes that each measured point has a local influence that diminishes with distance. It gives greater weights to points closest to the prediction location, and the weights diminish as a function of distance. Malaria records for the various municipalities were spatially weighted and aggregated at the district level. Weighted points at the centroid of each district were then interpolated using the Inverse Distance Weighting model (Jorgensen et al., 2010; Messina et al., 2011; Hanafi-Bojd et al., 2012). The model assumes that the mapped variable decreases in influence with distance from its weighted location (Baltas, 2007). Given seasonalised climate variables, a linear relationship between temperature, rainfall, and malaria cases, can be derived from the Pearson Correlation coefficients as reported by Wilks (1995). The linear relationship between temperature and malaria cases with the influence of precipitation can be determined as a partial correlation Panofsky and Brier (1968) and Mardia et al. (1979).

b. *Econometric approaches*

Causality

In order to determine causality, Granger (1969) proposed a time series data-based approach. Intuitively, the standard Granger-causality test examines whether past changes in one variable, *y*, help to explain current changes in another variable, *x*, over and above the information provided by the lagged values of *x*. If not, then one concludes that "*y* does not Granger-cause *x*"." To determine whether causality runs in the opposite direction, from *x* to *y*, one basically repeats the experiment, but with the variables interchanged. The null hypothesis that *y* does not Granger-cause *x* is rejected if the coefficients in the equation are jointly significant based on the standard F-test.

There are three different types of situations in which a Granger-causality test can be applied and four possible feasible outcomes. The situations are: (i) a simple Granger-causality test with two variables and their lags; (ii) a multivariate Granger-causality test with more than two variables and; (iii) Granger-causality in a VAR framework. For the purposes of this study, we focus on the second situation (multivariate Granger-causality) since we have three variables: malaria cases, rainfall, and temperature. The four feasible outcomes are: 1) *independence;* here, neither malaria cases, rainfall, nor temperature, *Granger-cause* each other; 2) *unidirectional Granger-causality* where rainfall *or* temperature independently *Granger-causes* malaria cases, but not the other way round; 3) *unidirectional Granger-causality* where malaria cases cause rainfall or temperature independently, but not vice versa; and 4) *bi-directional (or feedback) causality* where malaria cases, rainfall, and temperature *Granger-cause* each other. Theoretically, it is expected that rainfall and temperature influence malaria cases. A bi-directional causality is expected between rainfall and temperature. We do not expect malaria cases to cause rainfall or temperature.

Stationarity (unit root) test

As a requirement for time series analysis, this paper first studies the univariate characteristics (stationarity) of rainfall, temperature, and malaria cases in this study using the standard Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1981) and Kwiatkowski, Phillips, Schmidt and Shin (KPSS) tests (Kwiatkowski et al., 1992). Stationarity is a process where the parameters of the process do not change with time; i.e., the mean, variance, and autocorrelations are constant in time, while the non-stationary variable is otherwise. A non-stationary variable can be transformed into a stationary process by either adjusting for trends or including a time index as an independent variable in the regression. Sometimes de-trending and inclusion of a time index may not be sufficient to make the series stationary due to the possibility that statistics for changes in the series between periods and seasons are constant, in which case, the data is *differenced*. Differencing implies transforming the variables into a series of period to period and/or season to season differences. A stationary series is denoted as I (0) but when the series is differenced once, it is said to be integrated to order one, i.e. I (1) and a twice difference is I (2).

In econometrics, testing for stationarity is an indispensable requirement for two main reasons. First, without stationarity tests, it is not possible to obtain any meaningful sample statistics such as means, variances, and correlations with other variables. Secondly, stationarity tests provide important clues in the search for an appropriate methodology and forecasting model. Although it is known from the literature that combining stationary variables with non-stationary variables in a regression model yields spurious (non-sensical) results and, therefore, an unreliable outcome (Komen and Kapunda, 2006; Gupta and Komen, 2009), models now exist that regresses both stationary and non-stationary data. The recourse lies in the recently developed Autoregressive Distributed Lag (ARDL)-Wald (Bounds) test framework by Pesaran and Shin (1995, 1999), Pesaran et al. (1996), and Pesaran (1997).

Autoregressive Distributed Lag (ARDL)-Bounds Test Model

The ARDL methodology is applicable in testing causation and long relationship in cases where not all variables are integrated to the same order. Cointegration (long-run relationship) is a situation where two or more series are non-stationary, but a linear combination of them is stationary. The advantage of using the ARDL–Bounds test in testing cointegration is that while the conventional cointegration method estimates the long-run relationships within the context of a system of equations, the ARDL method employs only a single reduced form equation (Pesaran and Shin, 1995). Most importantly, the ARDL framework avoids the larger number of specifications to be made in the standard cointegration test, such as decisions regarding the number of endogenous and exogenous variables to be included, the treatment of deterministic elements, as well as the optimal number of lags to be specified (Duasa, 2007). The procedure can be applied irrespective of whether the regressors are stationary or non-stationary, or mutually cointegrated (Pesaran et al., 2001).

Model specification
The ARDL specification takes the following form:

$$\Delta \ln mala_t = \gamma + \sum_{i=0}^{\eta} \alpha_i \Delta \ln rain_{t-i} + \sum_{i=0}^{\eta} \delta_i \Delta \ln temp_{t-i} + \sum_{i=1}^{\eta} \varpi_i \Delta \ln mala_{t-i} + \beta_1 \ln rain_{t-1} + \beta_2 \ln temp_{t-1} + \beta_3 \ln mala_{t-1} + \varepsilon_{t-1} \quad (1)$$

Where $\ln mala, \ln rain$ and $\ln temp$ are natural logarithms of malaria cases, rainfall and temperature respectively; Δ denotes first difference operator; and η is the optimal lag length.
The ARDL estimation proceeds in two steps. First is estimation of equation (1) by Ordinary Least Squares (OLS) in order to establish the existence of a long-run linear relationship. Once cointegration is confirmed, the second step is to estimate the long run coefficients (equation 2).

$$\ln mala_t = \gamma_1 + \sum_{i=0}^{\eta} \alpha_{1i} \ln rain_{t-i} + \sum_{i=0}^{\eta} \delta_{1i} \ln temp_{t-i} + \sum_{i=0}^{\eta} \varpi_{1i} \ln mala_{t-i} + \varepsilon_{t-1} \quad (2)$$

The investigation of the long-run relationship using the ARDL approach involves the estimation of equation 2, through an Unrestricted Error Correction Model (UECM). Since specification assumes that the disturbances are serially uncorrelated, the choice of appropriate lag order is important (Sultan, 2010). The appropriate lag length in the ARDL model is selected by either Akaike Information Criterion (AIC) or the Schwarz Bayesian Criterion (SBC). The lag length that minimises SBC is selected. The unrestricted model is then estimated and progressively reduced, eliminating the statistically insignificant coefficients, and reformulating the lag structure where appropriate, to achieve orthogonality. The unrestricted ECM minimises the possibility of estimating spurious relations, while retaining the long-run information, suitable for economic interpretation (Greenidge et al., 2001). A battery of diagnostic tests can then be used to check the performance of the UECM (Akinboade et al., 2008; Hendry et al., 1984 in Sultan, 2010).

The short run dynamics is derived from the ARDL specification, equation (3), by constructing and Error Correction model (ECM), equation (4).

$$\Delta \ln mala_t = \gamma_2 + \sum_{i=1}^{\eta} \alpha_{2i} \Delta \ln rain_{t-i} + \sum_{i=0}^{\eta} \delta_{2i} \Delta \ln temp_{t-i} + \sum_{i=1}^{\eta} \varpi_{2i} \Delta \ln mala_{t-i} + \sigma ECM_{t-1} + \varepsilon_{t-1} (3)$$

Where ECM is the error correction term, defined as:

$$ECM_t = \ln mala_t - \gamma_1 - \sum_{i=0}^{\eta} \alpha_{1i} \ln rain_{t-i} - \sum_{i=0}^{\eta} \delta_{1i} \ln temp_{t-i} - \sum_{i=0}^{\eta} \varpi_{1i} \ln mala_{t-i} (4)$$

All coefficients of the short-run equation are coefficients relating to the short-run dynamics of the model's convergence to equilibrium, and σ represents the speed of adjustment.

The F test is used to test the existence of long-run relationship. The null hypothesis (H_0) of no cointegration among variables in equation (1) is tested against an alternative hypothesis (H_1), presented below.

$$H_0 = \beta_1 = \beta_2 = \beta_3 = 0$$
$$H_1 = \beta_1 \neq \beta_2 \neq \beta_3 \neq 0$$

The asymptotic distribution of the obtained *F-statistic* is nonstandard regardless of the degree of integration of the variables. This however, depends on whether (1) the variables included in the ARDL model are *I (0)* or I (1); (2) the number of regressors; (3) the model contains an intercept and/or a trend; and (4) the sample size. Two sets of critical *F-values*, representing the lower bound and the upper bound, have been provided by Pesaran and Shin (1999) for large samples. Narayan (2004) presents the critical *F-values* for sample size ranging 30–80. If the computed *F-statistic* for a chosen level of significance lies outside the critical bounds, a conclusive decision can be made regarding the cointegration of the regressors. If the statistic is higher than the upper bound, the null hypothesis of no cointegration can be rejected and the next step is to estimate the ARDL ECM where the short-run and long-run elasticities may be determined (Narayan 2004; Pesaran and Shin, 1999 in Sultan, 2010).

Computed and critical bounds of the *F-Statistic* are provided by (Pesaran et al., 2001). The *F-statistics* should lie outside the bounds for a long-run relationship to exist, but for short-run, the coefficient of the error correction model (ECM) should be negative and statistically significant.

RESULTS

In this section, we report spatial, correlation, time series, and short- and long-run results respectively.

Spatio-temporal and correlation results

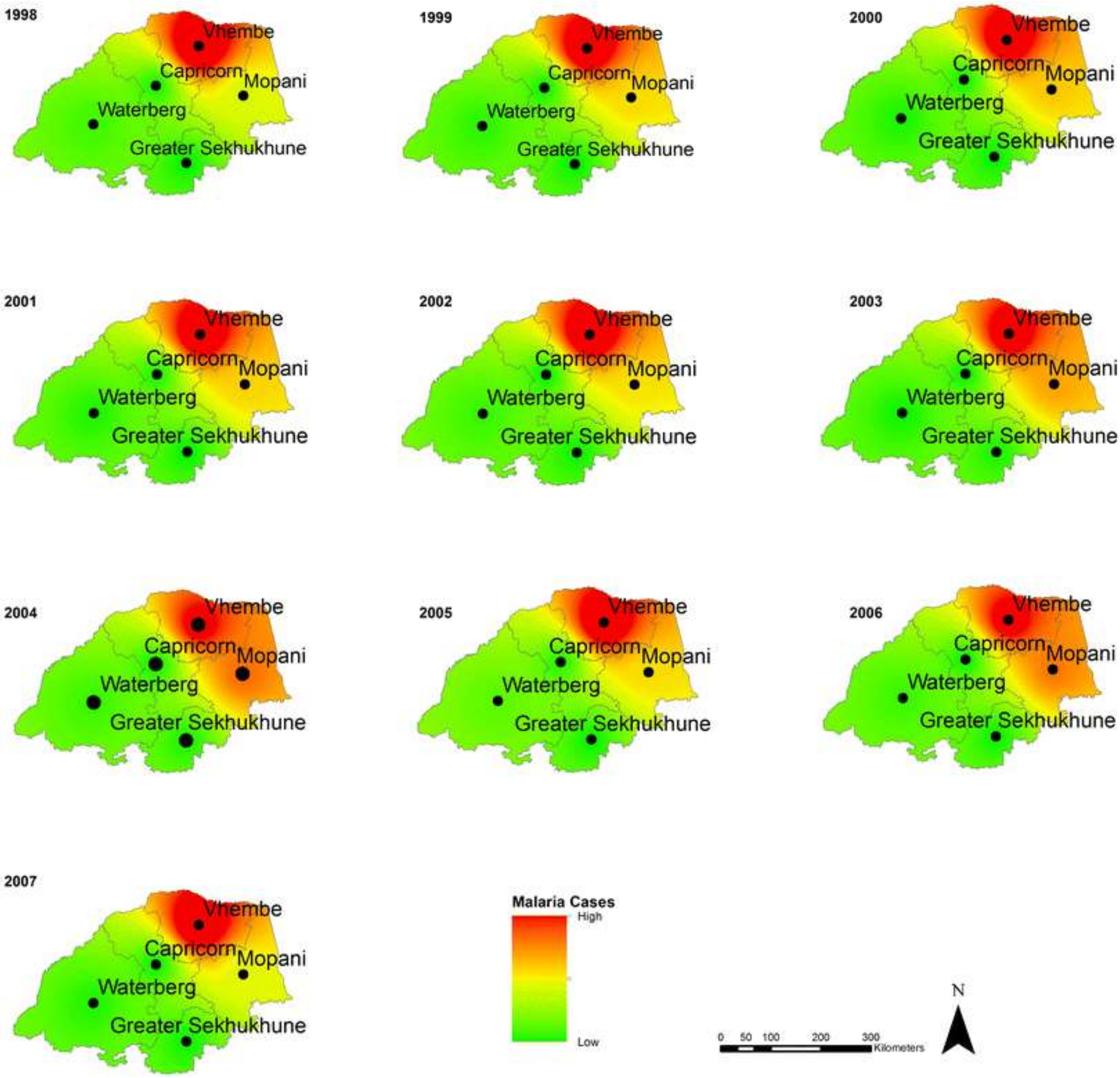

Figure 2 : Ten-year municipal and district spatial distribution of malaria in Limpopo Province

The number of malaria cases at the district level show that malaria is high in the Mopani and Vhembe districts throughout the study period of analysis, 1998 to 2007. The Vhembe district consistently shows more malaria cases. In the Mopani district on the other hand, malaria cases appear to be erratic, as shown on the maps. The overall trend shows that, whereas there were fewer cases in 1998, this was followed by a slight increase from 1999 to 2006. Very few cases were reported in Capricorn, Waterberg, and Greater Sekhukhune.

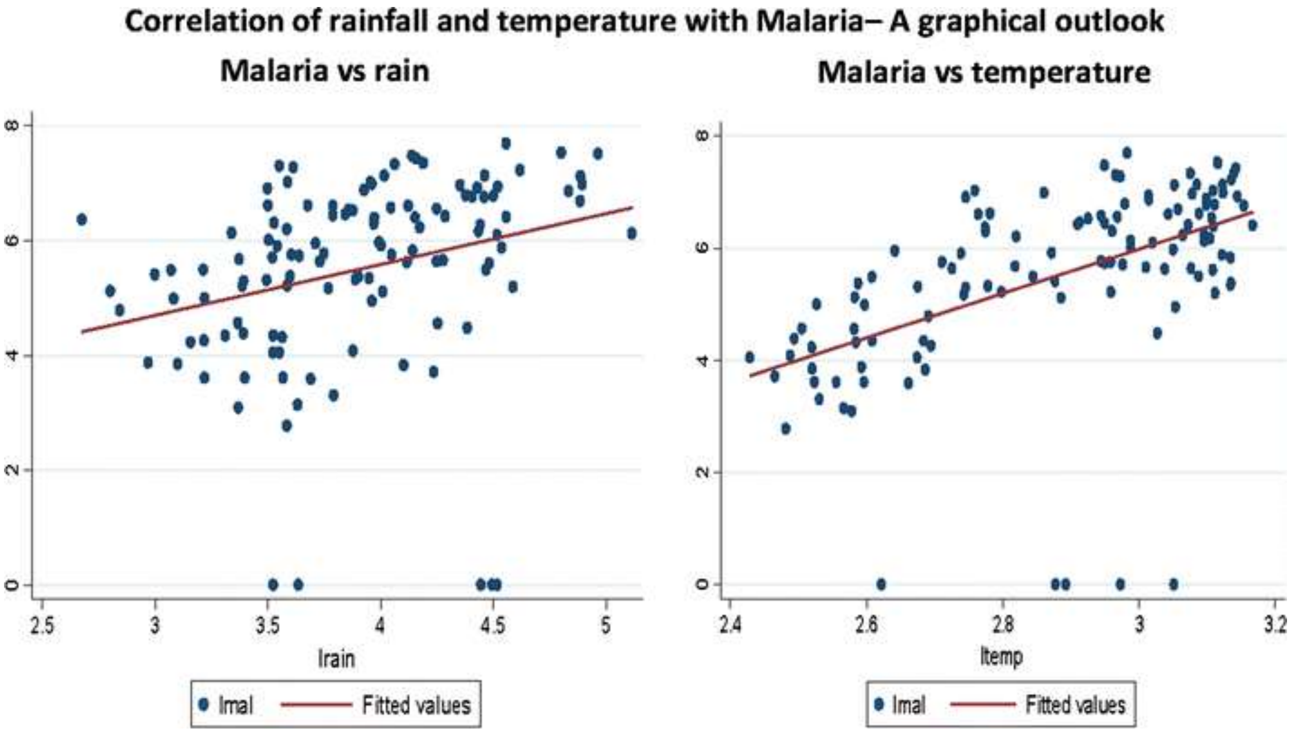

Figure 3 : Correlation of rainfall and temperature with malaria—a graphical outlook

Figure 3shows a scatter plot for rainfall and temperature with malaria cases. More observations are scattered away from the fitted line in the first panel (rainfall) than in the second panel (temperature). This indicates a high positive correlation with temperature than rainfall with an R-squared of 57.8%.

Figure 4 illustrates the trend relationship between average rainfall and average temperature in relation to malaria cases.

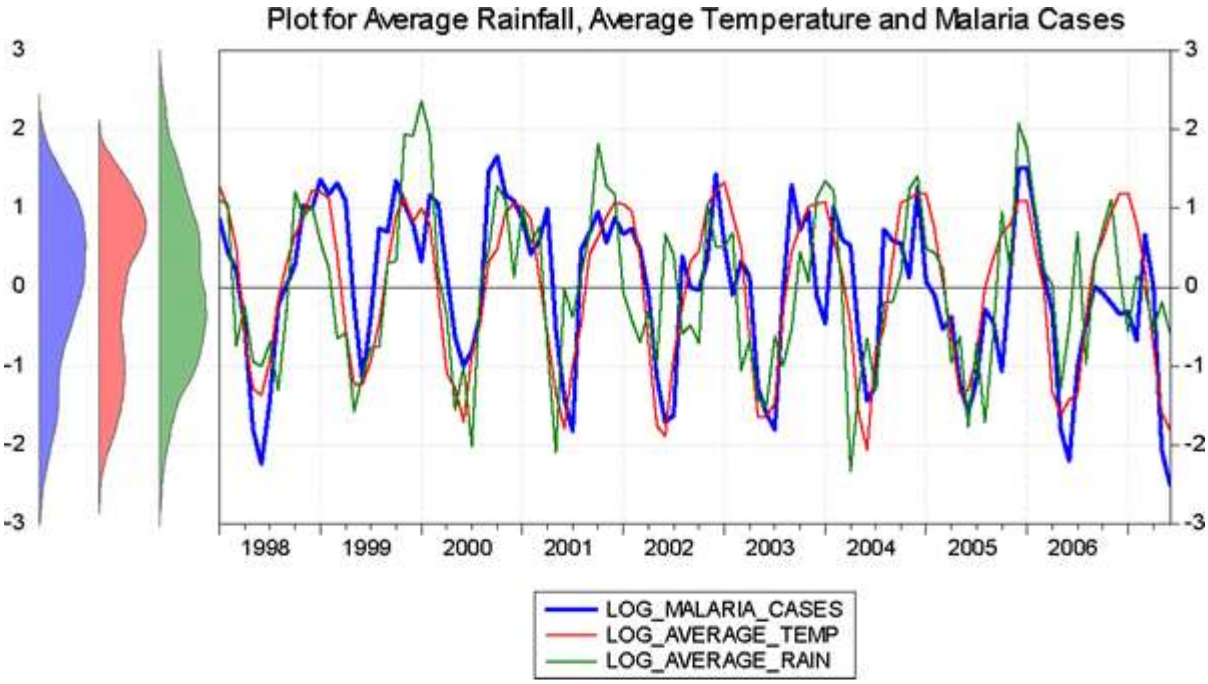

Figure 4 : Plot for average rainfall, average temperature, and malaria cases

This reveals a very strong positive correlation between rainfall and temperature with malaria cases, although higher rainfall does not increase malaria cases significantly (e.g. 1999, 2001 and 2005). An increase in temperature is, however, consistent with an increase in malaria cases. The actual influence is further validated by statistics using the cross correlation method. This study finds a strong positive correlation of climate variables to malaria cases, with temperature exhibiting a stronger influence as compared to rainfall. The coefficient for temperature and rainfall is found to be 0.5212 and 0.2810 respectively.

Results for causal relationships

Table I presents Granger causality test results.

Table I : Causal Relationships.

	Pairwise granger causality tests Date: 06/23/13 time: 23:50 Sample: 1998M01 2007M12 Lags: 2			
	Null hypothesis	**Obs**	**F statistic**	**Prob.**
(a)	RAINFALL does not Granger-cause Malaria	117	3.89071	0.0232
	MALARIA does not Granger-cause RAINFALL		1.44730	0.2396
(b)	TEMPERATURE does not Granger-cause MALARIA	117	20.0805	4.E−08
	MALARIA does not Granger-cause TEMPERATURE		0.07211	0.9305
(c)	TEMPERATURE does not Granger-cause RAINFALL	117	19.7996	4.E−08
	RAINFALL does not Granger-cause TEMPERATURE		17.1410	3.E−07

a. Rainfall versus malaria cases

We find a *unidirectional* causality from rainfall to malaria cases. For 117 observations, at a 5% significance level, the computed F-statistic is equal to 3.89071 with $\rho = 0.0232$ implies that the null hypothesis that rainfall does not *granger-cause* malaria is rejected. Rainfall, therefore, influences malaria but reverse is not true. We do not reject the null hypothesis that malaria *granger-causes* rainfall since the F-statistic equal to 1.44730 with $\rho = 0.2396$.

b. Temperature versus malaria cases

We also find a *unidirectional* causality from temperature to malaria cases. The computed F-statistic is 20.0805 with $\rho < 0.001$ implying that reject the null hypothesis that temperature does not *granger-cause* malaria cases while from malaria cases to temperature, the-statistic is 0.07211 with $\rho > 0.001$, implying malaria cases does not granger-cause temperature.

c. Temperature versus rainfall

This study finds a *bi-directional causality* between temperature and rainfall at a 1% level of significance. The F-statistic for the causation from temperature to rainfall and from rainfall to temperature is 19.80 and 17.14 respectively with $\rho < 0.001$in both cases meaning that rainfall influences temperature and vice versa.

Stationarity (unit root) results

Table II is a summary of the stationarity test.

Table II : Unit Root Test Results.

Test	**Log of malaria**		**Log of rainfall**		**Log of temperature**	
	Levels	**First difference**	**Levels**	**First difference**	**Levels**	**First difference**
ADF_{μ}			−7.926***		−2.252	−11.029***
ADF_{τ}	−4.283***					
$KPSS_{\mu}$	0.620		0.033***		0.021***	
$KPSS_{\tau}$						
Conclusion	Stationary at levels: I(0)		Stationary at levels: I(0)		Non-stationary	Stationary at first difference: I(1)

Computed ADF Augmented Dickey–Fuller (Dickey and Fuller 1981), KPSS Kwiatkowski, Phillips, Schmidst and Shin tests (Kwiatkowski et al. 1992).

*, **, and *** Means significance at 10%, 5%, and 1%, respectively.

The results indicate that malaria and rainfall follow an autoregressive process with a unit root as the null hypothesis is rejected for these variables, while for temperature, the null hypothesis for existence of a unit root could not be rejected, implying that rainfall and malaria cases are stationary, while temperature is non-stationary.

ARDL **results**

Short-run and long-run results

These are results of estimating equation (1). This stationarity test result pointed to ARDL -Bounds Test as the appropriate methodology for analysis of the analysis of the short-run (in this case, variation within months) and long-run (variation in years) dynamics of rainfall and temperature as they relate to malaria. UECM results are summarised in Table III, following similar procedure by Hendry et al., (1984), and Akinboade et al., (2008).

Table III : Unrestricted Error Correction Model.

Variables	Coefficient	Standard error
Constant	−3.158603	2.156372
D(LMALA(-2))	−0.473095	0.123357***
D(LRAIN(-1))	0.745233	0.248330***
D(LTEMP(-1))	4.343676	1.129335***
LMALA(-1)	0.249101	0.104620**
LRAIN(-1)	−0.499685	0.300813*

Diagnostic tests: Rampsey RESET = 2.271595 (0.1350): null hypothesis that model has no omitted variable is not rejected implying no omitted variables in the model. White's test = 1.2668 (0.3869). Null hypothesis of homoscedasticity is not rejected implying that variance of the variables in the model is homogeneous. Breusch–Godfrey LM test = 0.868 (0.423). Null hypothesis of no serial correlation is not rejected implying that the model does not suffer from serial correlation.
Computed LMALA logarithm of malaria, LRAIN logarithm of rainfall, LTEMP logarithm of temperature, (−1 and −2 indicate lags).
*, **, *** Means significance at 10%, 5%, and 1%, respectively.

The model passes all basic time series tests. There is no autocorrelation or serial correlation, no omitted variables; variance is homogeneous and residuals are normally distributed as confirmed by Durbin Watson statistic, Ramsey RESET test, Breusch-Godfrey LM, White's test and Jarque-Bera test. The R-Squared for the UECM is 50%, which indicates a relatively good and satisfactory fit in this case. The appropriate lag-length automatically selected by SBC is 3. Empirical studies report non-uniform lag time for malarial response to climatic variation. There seems to be an average malaria response within three months from the onset of the rainy season. Briet (2008) reports rainfall lag time of zero to three months, while Hashizume et al. (2009) report two to three months. Regarding temperature, Zhou et al (2004) finds minimum and maximum temperature lag time to be between one to two months and two to five months, respectively.

Bounds test (cointegration) results are presented in Table IV.

Table IV : Cointegration Properties.

Dependent variable	F stat	Critical bounds (5%)	
		Bottom	Top
d (lmala)	8.29	3.23	4.35

k = 3. Computed, critical bounds are obtained from Narayan (*2004*). d (lmal) is the first difference of logarithm malaria.

The *F-statistic* is outside the critical bounds (8.29 lies outside 4.35_{top} and 3.23_{bottom}). We therefore reject the null hypothesis of no cointegration at a 5% significance level, and conclude that a long-run relationship (cointegration) exists between malaria and the climatic variables.

The long-run relationship is reported in Table V, while the short-run results are reported in Table VI.

Table V : Long-Run Relationship Between Malaria Cases with Rainfall and Temperature.

Variable	Coefficient	Standard error
C	−6.155823	0.0006***
LRAIN	−0.373873	0.2648
LTEMP	4.557185	0.0000***

LRAIN the logarithm of rainfall, LTEMP logarithm of temperature.
*** Means significance at 1%, respectively.

Table VI : Short-Run Relationship Between Malaria Cases with Rainfall and Temperature.

Variable	Coefficient	Standard error
C	−0.080311	0.2668
D (LMALA(−2))	−0.231066	0.0047***
D (LMALA(−3))	−0.205359	0.0120**
D (LRAIN)	−0.263281	0.1509
D (LTEMP(−1))	4.784184	0.0000***
Ecm $_{t-1}$	0.005002	0.9783

−1 and −2 indicate lags.
LMALA logarithm of malaria, LRAIN logarithm of rainfall, LTEMP logarithm of temperature.
** and *** Mean significance at 5% and 1%, respectively.

In both short- and long-run instances, temperature maintains a very high level of significance: 4.784184 (0.0000) and 4.557185 (0.0000); while rainfall is low in both: -0.263281 (0.1509) and 0.373873 (0.2648).

DISCUSSION

We report GIS results of five districts (Capricorn, Greater Sekhukhune, Mopani, Waterberg, and Vhembe) in Limpopo Province. The Vhembe district consistently shows more malaria cases, while very few cases were reported in Capricorn, Waterberg, and Greater Sekhukhune throughout the period of analysis. In the Mopani district, malaria cases appear to be erratic. Spatial differences could be explained by socio-economic reasons, migration, malaria control programs, and even climate change. Understanding the differences in spatial distribution and areas burdened is crucial for targeted control measures.

In this study, rainfall and temperature are positively correlated with malaria, while temperature shows a stronger influence as compared to rainfall. We find the correlation coefficient of temperature and rainfall to be 0.5212 and 0.2810 respectively. Positive correlation between malaria and climate variables has been reported elsewhere. Rainfall: Huang et al. (2011); for Tibet: Briët et al. (2008), for Sri Lanka: Rainfall and temperature: Craig et al., (2004); Githeko and Ndegwa (2001) studies on Kenyan Highlands in Eastern Africa. Rainfall, temperature, humidity and vegetation cover: Haque et al., (2010) for Bangladesh. In Ghana, a positive correlation was found to exist between malaria and climate elements (Nkomo et al., 2006). The strength of the effect seems to flow from humidity to temperature and rainfall. This result is consistent with Huang et al. (2011), who found the correlation coefficient for Tibet to be 0.518 and 0.348 for temperature and rainfall respectively, concluding that temperature had a greater influence on malaria.

Regardless of the greater influence of temperature, warming and rainfall would create the conditions for malaria vectors to thrive (Epstein et al., 1997), boost the population of disease-carrying mosquitos, and result in increased malaria epidemics (Lindsay and Martens, 1998; Nkomo et al., 2006). Increases in temperature generally accelerate vector life cycles, and also decrease the incubation period of the parasite (Kovats and Martens, 2000; Huang et al., 2011). However, at a very high temperature, the mosquito life cycle cannot be completed and transmission cannot occur (Zucker, 1996; Williams et al., 1999). It is interesting to observe a strong influence of temperature on malaria transmission in Limpopo; Ngomane and de Jager (2012), however, have reported rainfall as the main driver in the neighbouring Mpumalanga province.

The limitations of this study relates to the fact that temperatures in the study area is limited to a range on the curve where it is linear. Also, the study did not show whether year to year variations in malaria was driven by year to year variability in temperature/precipitation. This will be the focus of the forthcoming paper.

CONCLUSION

This paper has utilised spatial, correlation methods as well as bound testing approach to cointegration developed within an autoregressive distributed lag framework to test spatial malaria distribution at district levels, test the strength of correlation, and determine the existence of a long-run equilibrium relationship between climatic variables with malaria. There is strong evidence that climate influences malaria significantly both in the short and long run. We find that malaria pressure varies in different districts. We recommend (1) a study to ascertain the thresholds of temperature and rainfall under which malaria cases are probable; (2) the development and enhancement of early warning systems for malaria at the district level; (3) strengthening collaboration, partnership, and response integration with other principle sectors, such as meteorological departments; and finally,4, (4) long-term public health planning to combat malaria as a part of the key functions of the public health systems.

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