Quantifying Weather and Climate Impacts on Health in Developing Countries (QWeCI)

Using ARDL-bounds test and spatial-temporal approaches to examine the influence of temperature and rainfall on malaria in Limpopo Province, South Africa

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Outline

- Introduction
- Summary of Review
- Conceptual Framework and Method(s)
- Hypothesis
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- Conclusion and Policy Recommendation

Introduction

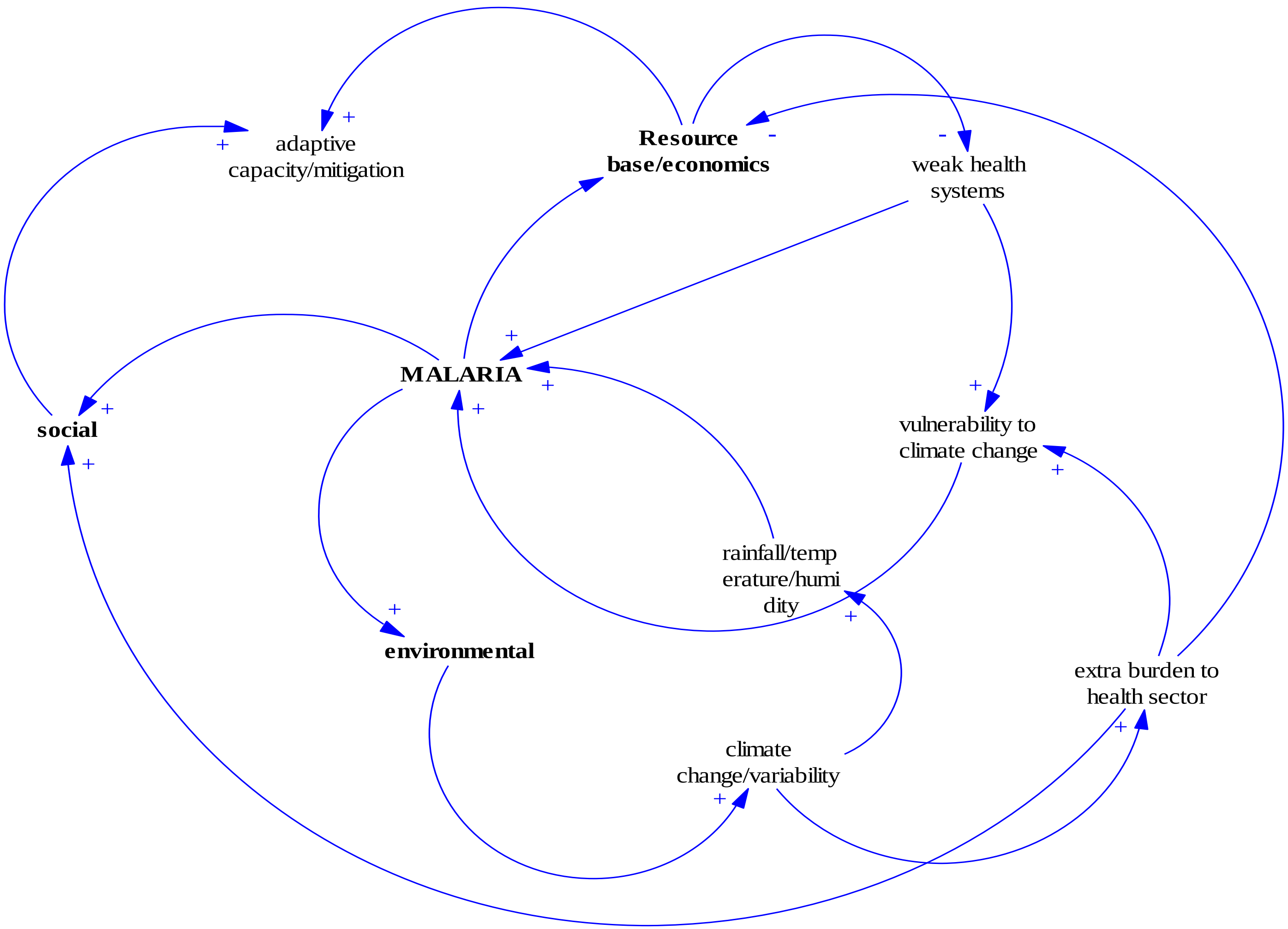
- Malaria is the most important parasitic infection in people, accounting for an estimated 500 million clinical attacks worldwide and more than 1 million deaths a year, mostly in sub-Saharan Africa
- Incidence of malaria in regions that were rarely observed has led to a supposition that the changing climate could be catalyzing the transmission by creating favourable conditions.
- Malaria in Limpopo Province of South Africa is shifting and now observed in originally *non-malaria* districts.
- The determination of the existence/non-existence of long or short-run relationship between malaria and meteorological variables, and dissociation between the influence (and the strength thereof) associated with either rainfall or temperature, is important for any meaningful planning for malaria intervention.

Introduction

❑ Summary of the Outcome of Literature Review

- Climate change does not create a novel type of environmental exposure.
- The adverse health impacts will be greatest in low-income countries.
- In this sense climate change is largely a development issue which requires addressing the underlying factors that cause vulnerability.
- The direct health impacts of climate change include: respiratory and cardiovascular disease; flood related mortality and morbidity.
- The indirect health impacts include: changes in disease transmission; water related disease; food security and nutrition; and those linked to multiple stresses – population, migration, conflict, changes in ecosystems.
- Adaptation costs in the health sector are likely to be large. However benefits to health will come largely from strategies outside the health sector (e.g. in water, agriculture, human settlements).
- Our knowledge remains limited. The evidence base is weak in relation to the complexity of the issue and the magnitude of the health risks, and the majority of studies so far have focused on data from middle-and high-income countries.

Conceptual Framework



Data and Data Sources

- The study uses time series of average rainfall and temperature, as well as malaria cases spanning the period from 1998 to 2007.
- Climate data was obtained from the South Africa Weather Services.
- Daily station data of precipitation and temperature (minimum and maximum) from 1998 to 2007 was used to construct climate disease envelopes at municipal and district levels, while malaria data were obtained from the South African Department of Health and from the Malaria control Centre in Tzaneen (Limpopo Province).

Mathematical Representation

$$\log(E/Y)) = \alpha + NS(TEMP_{0-3,}\, 3df) + NS(RAIN_{0-3}, 3df) + NS(HUM_{0-3}, 3df) + NS(NDVI_{0-3,}\, 3df)$$

Model Specification

$$LOG(Y) = \alpha + \beta_2 LOGRAIN + \beta_1 LOGTEMP + \varepsilon$$

$$Null - Hypothesis : H_0 = \beta_1 = \beta_2 = 0$$

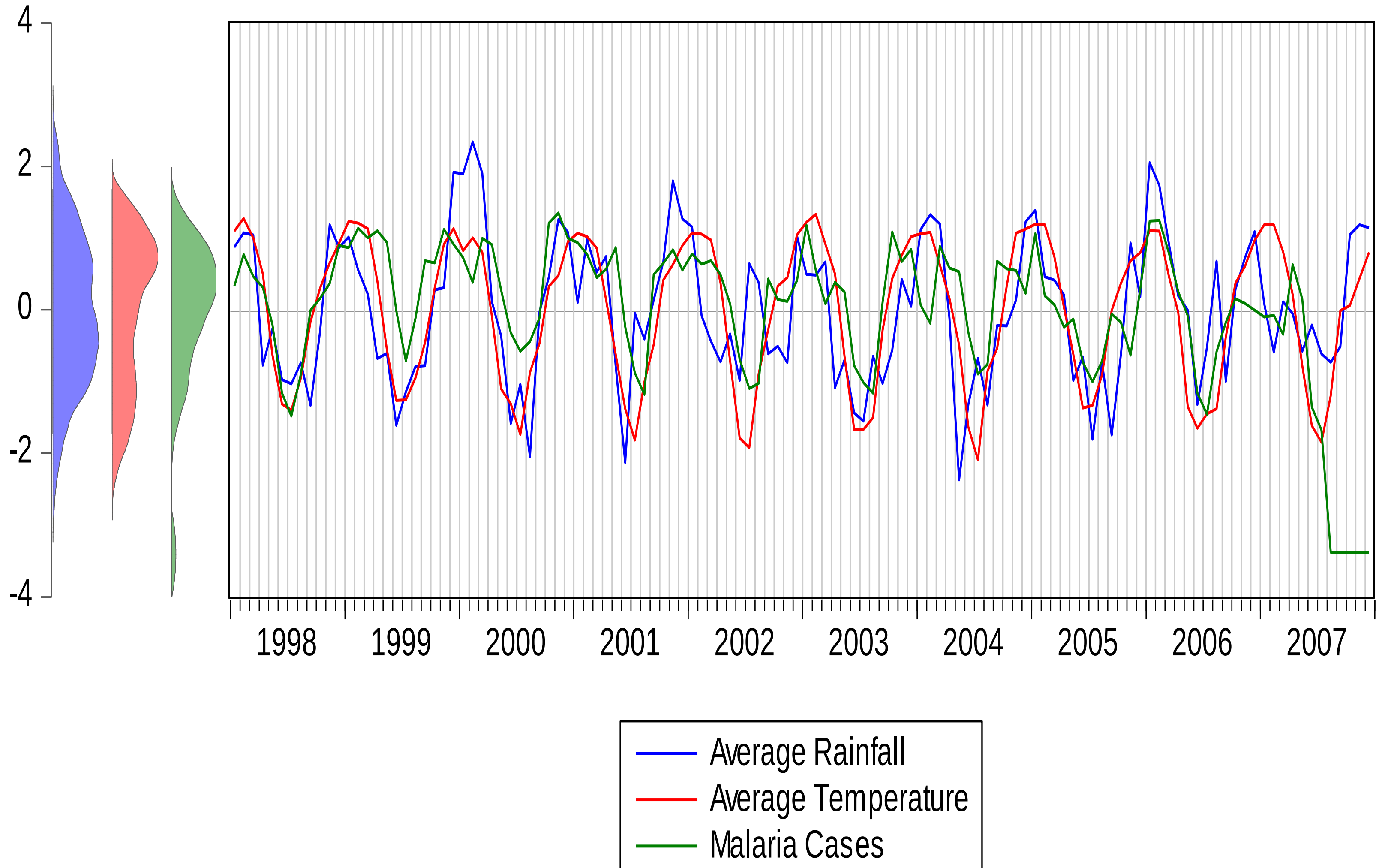
$$Alternative - Hypothesis : H_1 = \beta_1 \neq \beta_2 \neq 0$$

Correlation

Given seasonalized climate variables; temperature (T) and total precipitation (P) and malaria cases (M), a linear relationship between T & M, P & M and T & P can be derived from the Pearson correlation coefficients ($\gamma_{T,M}$; $\gamma_{P,M}$and $\gamma_{T,P}$) as reported in Wilks (1995). According to Mardia et al., (1979) and Panofsky and Brier, (1968), the linear relationship between say, T & M with the influence of P removed can be determined from the partial correlation given by

Here, $\gamma_{T,M}$ is computed as a simple correlation between

Plot for Average Rainfall, Average Temperature and Malaria Cases



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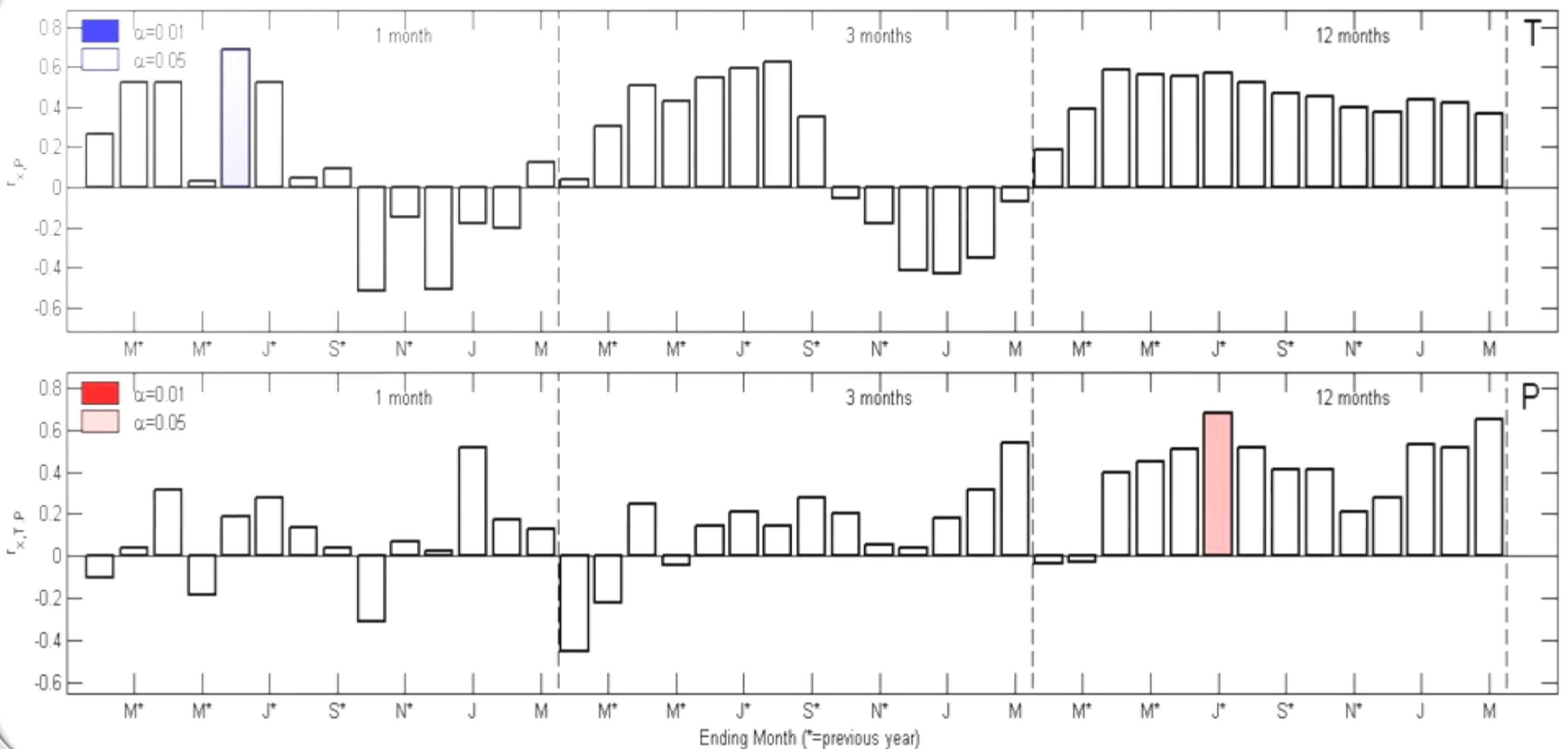
Results:

Correlation of monthly/seasonal climate signal with malaria cases



Cross Correlation

pwcorr logmal	lrain ltemp,	star(5)	
	lmal	lrain	ltemp
lmal	1.0000		
lrain	0.2810*	1.0000	
ltemp	0.5212*	0.6656*	1.0000

Autoregressive Distributed Lag Model (ARDL) Specification

$$\Delta \ln mala_t = \gamma + \sum_{i=0}^{m} \alpha_i \Delta \ln rain_{t-i} + \sum_{i=0}^{n} \delta_i \Delta \ln temp_{t-i} + \sum_{i=1}^{k} \varpi_i \Delta \ln mala_{t-i} +$$
$$\beta_1 \ln rain_{t-1} + \beta_2 \ln temp_{t-1} + \beta_3 \ln mala_{t-1} + \varepsilon_t$$

ARDL estimation proceeds in two steps.

1. Estimate the above equation by OLS in order to establish the existence of a long run relationship.
2. Once Cointegration is confirmed, the second stage is to estimate the long run coefficients and the short run coefficients using the respective ARDL and ECMs..

We then estimate the unrestricted model and progressively reduce it by eliminating the statistically insignificant coefficients and reformulating the lag structure where appropriate in terms of levels and differences to achieve orthogonality.

Results: Unit Root

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***		0.033***		0.021***	
$KPSS_{\mu}$	0.620					
$KPSS_{\tau}$						
Conclusion	Stationary at levels: I(0)		Stationary at levels: I(0)		Non-Stationary	Stationary at First Difference: I(1)

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*

Rampsey RESET = 2.271595 (0.1350):

- *implying that Ramsey's RESET; Null hypothesis: Model has no omitted variable is not* rejected

White's test = 1.2668 (0.3869)

- *implying that White's test Null hypothesis of homoscedasticity is not rejected*

Breusch-Godfrey LM test = 0.868 (0.423)

- *implying that Breusch-Godfrey LM test: null hypothesis of No serial correlation is not rejected*

Cointegration Properties

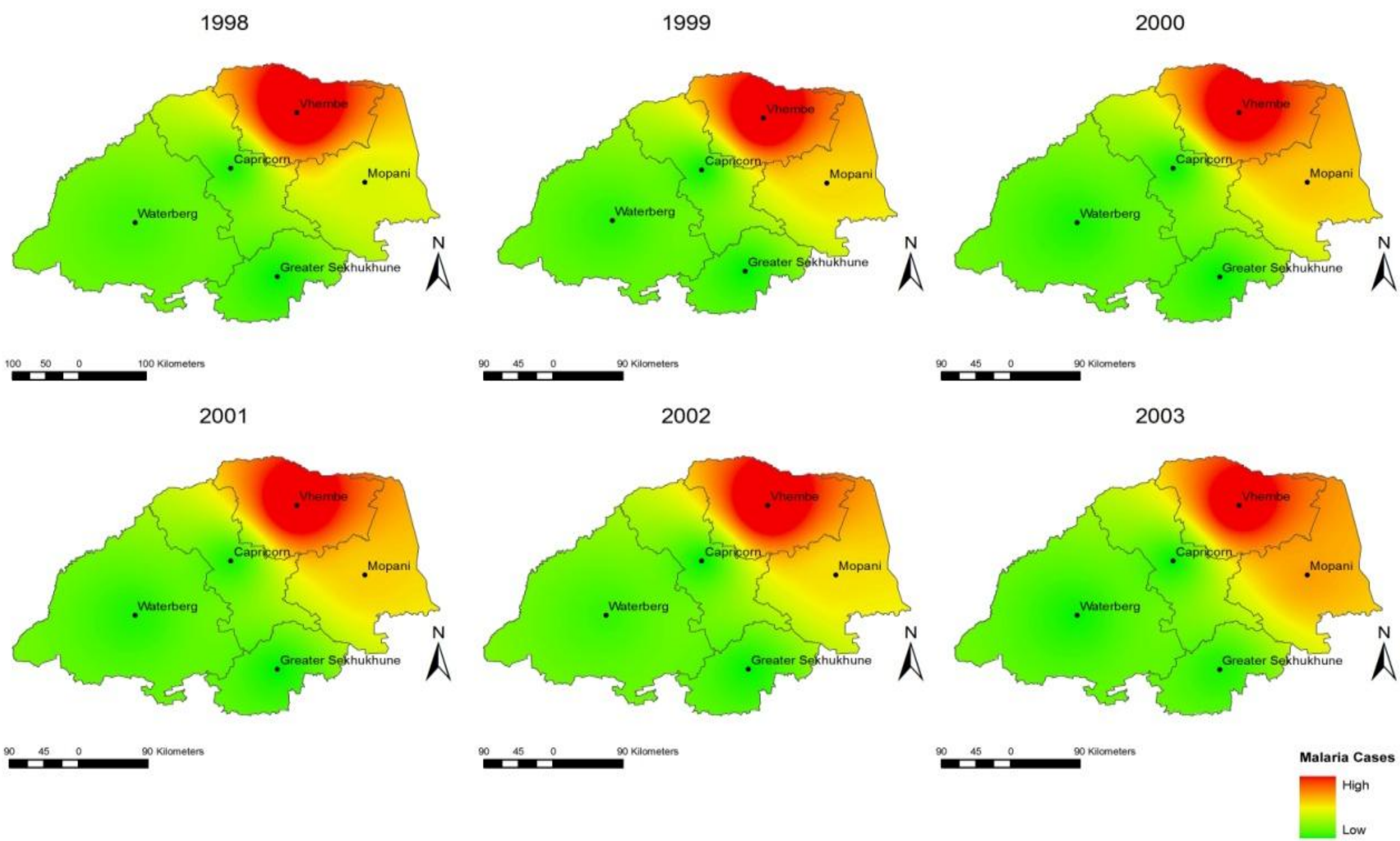
Testing the presence (or absence) of cointegrating in variables implies a test of the existence of long run relationship.

We use the Wald test (Bounds Test). **Pesaran, Shin and Smith (2001)**; k=3 provides computed, critical bounds of the F-Statistic. F-statistics should lie outside the bounds for a longrun relationship to exist.

Table IV: Bounds Test Results

		Critical bounds (5%)	
Dependent variable	F-stat	Bottom	Top
d(lmala)	8.29	3.23	4.35
Since the F-statistic is outside the critical bounds ((8.29 is outside the top (4.35) and bottom (3.23)); we reject the null hypothesis of no cointegration at 5% significance level and conclude that there exist a long-run relationship between malaria and the climate variables (rainfall and temperature).			

10 years municipal and district spatial distribution of Malaria in Limpopo



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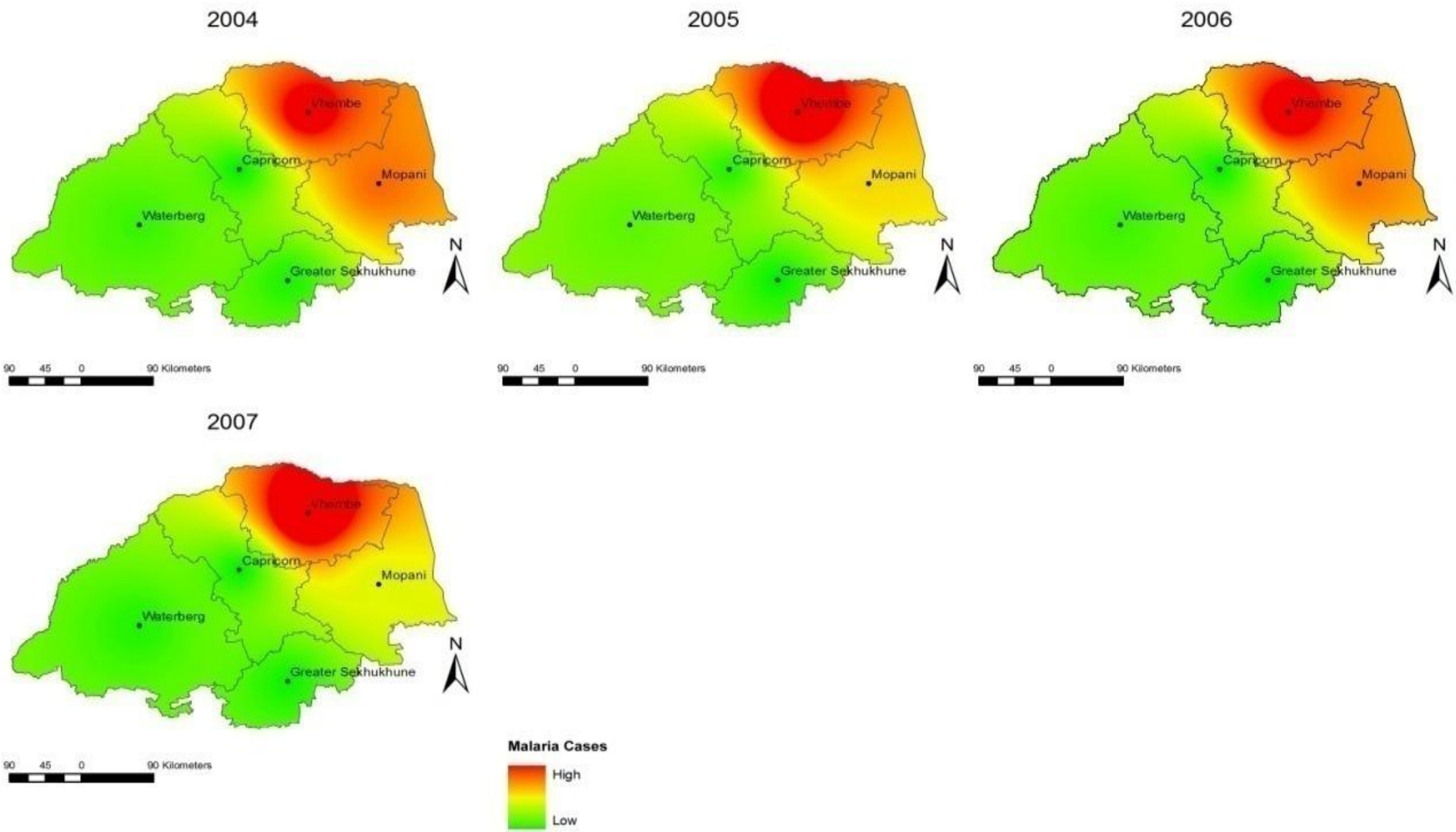

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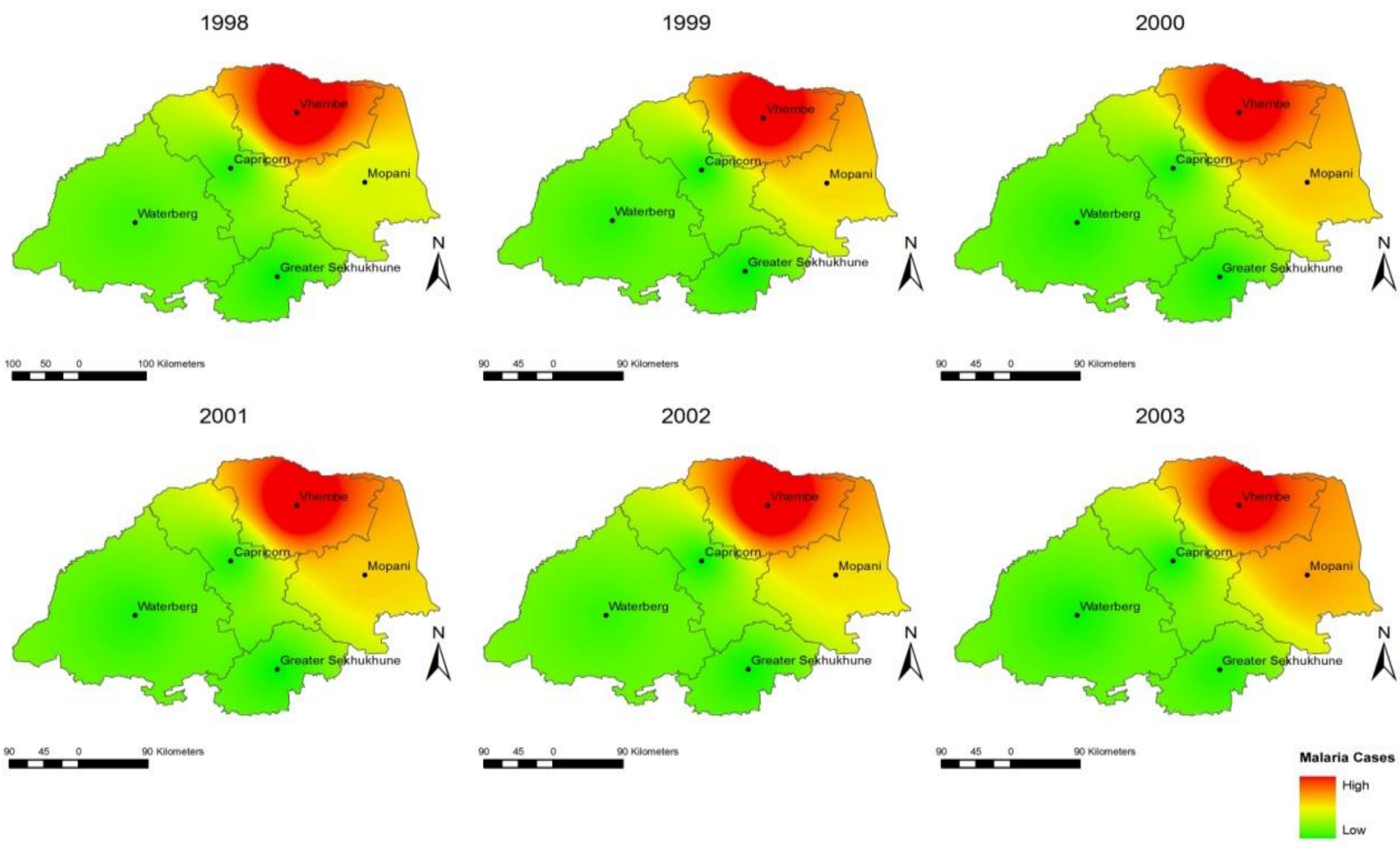

Summary and Conclusion

•Spatial results indicate a reduction in total malaria cases from 1998 to 2008 but not all districts show the same change.

•Vhembe district consistently shows more Malaria incidences while in Mopani district, incidences are erratic (i.e. increases and sometimes decreases). Malaria and temperature are found to be stationary variables at levels, while rainfall is non-stationary.

•Climate-disease correlation output shows that although rainfall and temperature are positively correlated with malaria, temperature (correlation coefficient of 0.5212) has a stronger influence compared to rainfall (correlation coefficient 0.2810). A 1% increase in rainfall will result in 0.74% increase in malaria cases in Limpopo Province.

•Consequently, a 1% increase in temperature will result in 4.34% increase in malaria cases. The error term, the speed of adjustment of the model towards equilibrium, is positive 0.005002 (0.9783) and statistically insignificant. The long-run malaria-rainfall and malaria-temperature relationships is -0.373873 (0.2648) and 4.557185 (0.0000) respectively, while the short-run malaria-rainfall and malaria-temperature is found to be -0.263281 (0.1509) and 4.784184 (0.0000) respectively.

Summary and Conclusion

•Malaria changes and pressures vary in different districts.

•Temperature drives malaria transmission in Limpopo Province, while rainfall has a positive-weak relationship with malaria.

•Rainfall and temperature influence malaria in the long–run. Any malaria intervention should focus in the long-run.

•It is interesting to find that malaria in Limpopo is found to be driven by temperature, while in Mpumalanga (the neighbouring province), malaria is driven by rainfall (*Ngomane* and *de Jager* 2012)

Thank You