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Title: Predictability of malaria transmission intensity in the Mpumalanga Province, South Africa, using land surface climatology and autoregressive analysis

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Popular Summary:

There has been increasing effort in recent years to employ satellite remotely sensed data to identify and map vector habitat and malaria transmission risk in data sparse environments. In the current investigation, available satellite and other land surface climatology data products are employed in short-term forecasting of infection rates in the Mpumalanga Province of South Africa, using a multivariate autoregressive approach. The climatology variables include precipitation, air temperature and other land surface states computed by the Off-line Land-Surface Global Assimilation System (OLGA) including soil moisture and surface evaporation. Satellite data products include the Normalized Difference Vegetation Index (NDVI) and other forcing data used in the Goddard Earth Observing System (GEOS-1) model. Predictions are compared to long-term monthly records of clinical and microscopic diagnoses. The approach addresses the high degree of short-term autocorrelation in the disease and weather time series. The resulting model is able to predict 11 of the 13 months that were classified as high risk during the validation period, indicating the utility of applying antecedent climatic variables to the prediction of malaria incidence for the Mpumalanga Province.

Significance:

The good results obtained using the multivariate model indicate the utility of applying satellite data and antecedent climatic variables to the prediction of malaria incidence, at least for the Mpumalanga Province that possesses a sparse hydrometeorological observational network. As the spatial and temporal resolution of satellite based terrestrial products improve, together with more accurate data assimilation methods, it is reasonable to expect a corresponding improvement in predicting malaria using a similar multivariate approach.

Predictability of malaria transmission intensity in the Mpumalanga Province, South Africa, using land surface climatology and autoregressive analysis

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Abstract

There has been increasing effort in recent years to employ satellite remotely sensed data to identify and map vector habitat and malaria transmission risk in data sparse environments. In the current investigation, available satellite and other land surface climatology data products are employed in short-term forecasting of infection rates in the Mpumalanga Province of South Africa, using a multivariate autoregressive approach. The climatology variables include precipitation, air temperature and other land surface states computed by the Off-line Land-Surface Global Assimilation System (OLGA) including soil moisture and surface evaporation. Satellite data products include the Normalized Difference Vegetation Index (NDVI) and other forcing data used in the Goddard Earth Observing System (GEOS-1) model. Predictions are compared to long-term monthly records of clinical and microscopic diagnoses. The approach addresses the high degree of short-term autocorrelation in the disease and weather time series. The resulting model is able to predict 11 of the 13 months that were classified as high risk during the validation period, indicating the utility of applying antecedent climatic variables to the prediction of malaria incidence for the Mpumalanga Province.

1. Introduction

The last two decades have witnessed a global re-emergence of malaria in areas where infection rates had been low or not measurable (WHO, 1996). The predictability of infection rates is non trivial and it is based on numerous environmental and socio-economic factors. Environmental factors include those that affect the mosquito and parasite metabolic rates and life cycles such as rainfall and temperature, and the spatial and temporal extent of mosquito habitat. Socio-economic factors include demographic changes and the existence or effectiveness of control efforts or reporting methodologies.

The purpose of the present study is to examine the environmental portion of the problem using a suite of currently available gridded satellite and climate data and data products. Associations are investigated between monthly malaria incidence and environmental conditions that influence development and reproduction rates of the parasite and vector. The immediate goal is to investigate the extent to which knowledge of antecedent land surface climatology can improve the efficacy of malaria prediction using a statistical model. The variables utilized consist not only of commonly employed quantities such as temperature and precipitation, but also soil moisture, specific humidity and evaporation rate that have recently become available through global data assimilation models. The approach is not to build a physical model of malaria transmission, but to conduct a reliable statistical analysis among the various environmental factors that have been reported in the literature to affect malaria transmission, focusing on the Mpumalanga Province of South Africa.

1.1 Survey of Previous Studies

The utility of using remotely sensed data to map mosquito habitat has been demonstrated in California (PITCAIRN, 1988), Mexico (REJMANKOVA *et al.*, 1995; BECK *et al.*, 1997), Belize (MONTGOMERY *et al.*, 1998), The Gambia, (BREWSTER *et al.*, 1993) India (BOUMA *et al.*, 1996a), Pakistan (BOUMA *et al.*, 1996b) and Kenya (PATZ *et al.*, 1998; HAY *et al.*, 1998). Most of the research applying time series analysis

of environmental factors to disease outcomes, relates air pollution levels to mortality rates. Some applications of time series analysis to infectious disease are described below. HAY *et al.*, (1998) found the Normalized Differential Vegetation Index (NDVI) to be a useful leading indicator of malaria admissions in Kenya. PATZ *et al.* (1998) used modelled soil moisture, lagged 6 weeks, to predict 56% of the variability in the entomological inoculation rate in Kenya. Lastly, LINTHICUM *et al.* (1999) found that sea surface temperatures, when coupled with vegetation index data, could be used to forecast Rift Valley fever outbreaks five months in advance in East Africa. For a more thorough review of the use of satellite data to study malaria distribution and transmission, the reader is referred to HAY *et al.*(1996), HAY *et al.* (1997), THOMAS *et al.*(1997), CONNOR (1999), and HAY *et al.* (2000).

While the above studies clearly have brought attention to the utility of satellite remote sensing technology for malaria transmission, they have also pointed out its current limitations. For instance, current satellite observations do not provide all the quantitative land-surface states needed to identify vector habitat, but only indicators of that habitat. For example, NDVI represents an indication of relative vegetation greenness or productivity, but not the extent, nor the duration of standing water in which mosquitoes breed. There is no singular relation between NDVI and surface wetness, as it depends on other factors such as soil moisture and mineral content, vegetation architecture, and pixel scale (Jasinski, 1990). This type of limitation suggests a need for a more detailed description of land surface conditions that might be met through the application of a land surface data assimilation model, that produces non-routinely observed quantities such as soil moisture and evapotranspiration. The problem is particularly acute in data sparse regions such as Africa.

1.2 Environmental Effects on Vector Population Dynamics

The high sensitivity of the mosquito and parasite lifecycles to abiotic factors makes it possible to study the effects of climate on malaria transmission. Of the environmental factors that influence mosquito population dynamics, rainfall and temperature have been

studied the most thoroughly. The amount of rainfall dictates the availability of habitat for the aquatic stages of the vector life cycle (oval, larval, and pupal). A secondary effect of increased rainfall is prolonged mosquito longevity due to high (above 60%) relative humidity (GILLES, 1993). The distribution of rainfall over time is also important. Periodic rain that corresponds to reproductive cycles, or about two weeks from egg to egg (MOLINEAUX, 1988), allows mosquitoes to breed in profusion (MUIR, 1988; GILLES, 1993). The MARA/ARMA project estimated that 80 mm of precipitation during 3-5 months was necessary for annual malaria transmission (MARA/ARMA, 1998). In addition, TEUSCHER (1999) found that distance to permanent water bodies and persistence of standing water had a measurable effect on parasite ratios.

Ambient temperature affects mosquito population dynamics by influencing vector and parasite metabolic rates. Increased metabolic rates cause increased feeding frequency, more rapid adult vector development, elevated extrinsic incubation rate, and decreased longevity (MOLINEAUX, 1988). Optimal temperatures for the sexual development of the parasite in the mosquito are: 30 °C for *P. falciparum* and 22 °C for *P. malariae* (WHO, 1996). More generally, favourable temperatures for parasite and vector survival range from 20 to 30 °C (GILLES, 1993). Parasite development reportedly stops below 16 °C and above 40 °C (GILLES, 1993; CRAIG *et al.*, 1999). In addition, the sensitivity of mosquito survival rates to relative humidity increases at higher temperatures (WHO, 1996). Thus, the importance of temperature, and how it affects other land surface states, must be considered in combination in order to better understand the impact of the natural environment on vector populations.

2. Study Area

2.1 Physical Description

The Mpumalanga Province, situated in the east of South Africa, nestles between KwaZulu-Natal in the south, Swaziland and Mozambique in the east and other South African provinces in the north and in the west. The Province is served by 27 public

hospitals and 221 clinics/health centres. The rainy season in the Region lasts from October to May with a mean annual rainfall of 650 mm. Mean summer (September – April) and mean winter (May – August) temperatures range between 17°C to 30°C and 8°C to 17°C, respectively. Relative humidity in summer is fairly constant at 80%.

2.2 Malaria Incidence and Control

Malaria transmission is restricted to the Lowveld Region with 300,000 people living in the high-risk area defined by the National Department of Health (DEPT. OF HEALTH, 1996) and 470,274 in the low risk area. There are well-defined patterns of population movement that are of direct relevance to the distribution of malaria and other communicable diseases (DURRHEIM *et al.* 1998a). For example, labour intensive farming in the Lowveld Region attracts large numbers of workers from Mozambique where malaria is hyperendemic. Many of the migrants are parasite carriers (DURRHEIM, 1995).

During 1996 to 1999, an average of approximately 8,000 malaria cases per year were reported in the Province with a fatality ratio of 0.7% (DURRHEIM *et al.*, 1999). *Anopheles arabiensis*, a savannah species that favours temporary rain pools, is the major vector of malaria in the Province (SHARP and LE SUEUR, 1994; GOVERE *et al.*, 2000). In elevated temperatures this vector exhibits a high rate of aquatic development that allows it to mature before pollution, predators, or competitors can compromise its breeding site (MOLINEAUX, 1988). Three *Plasmodium* species causing human malaria, *P. falciparum*, *P. malariae* and *P. ovale*, occur in Mpumalanga Province with an overall species prevalence of about 95% *P. falciparum*, and 5% *P. malariae* and *P. ovale*.

Malaria control in Mpumalanga is realized by a combination of residual intradomicillary spraying with synthetic pyrethroids and prompt effective therapy of cases at primary health care clinics. Indoor house spraying is carried out annually between September and December. The major challenges for malaria control in Mpumalanga Province include immigrants from uncontrolled bordering areas in Mozambique, changes in the biology and behaviour of the main vector, *P. falciparum*, resistance to antimalarial

drugs, and changes in climate and community practices of washing and replastering sprayed wall surfaces are (GOVERE et al., 2000).

3. Climatology and Malaria Data

3.1 Climate and Satellite Data Products

Land surface quantities used in the present analysis are output of the Off-line Land-Surface Global Assimilation System (OLGA) (Bosilovich et al., 1999) for the period January 1987 through December 1995. OLGA computes a suite of land surface energy and moisture fluxes and states using the MOSAIC hydrology model (Koster and Suarez, 1996) forced by the Goddard Earth Observing System Multiyear Assimilated Dataset (GEOS-1). GEOS-1 is a global, gridded atmospheric data product set produced by assimilating rawinsonde reports, satellite retrievals of geopotential thickness, cloud-motion winds, aircraft, ship and buoy reports with forecast employing the GEOS-1 atmospheric general circulation model (Schubert et al., 1993). GEOS-1 output quantities used to force MOSAIC include atmospheric temperature, solar radiation, atmospheric infrared radiation, surface pressure, precipitation, and specific humidity. OLGA outputs additional land surface quantities related to land surface energy and moisture fluxes and states. Those products have a large spatial resolution of 2° latitude by 2.5° longitude, but the scale is commensurate with the size of the Mpumalanga Province.

The selection of the variables extracted from the OLGA database was made on the basis of associations between environmental conditions and malaria incidence established in prior studies. Mean values were calculated for the 2 × 2 degree gridbox array that best corresponded to the Mpumalanga Province study site (28.75-33.75°E, 23-27°S). The variables extracted included average available soil moisture (kg/m²), evaporation rate (mm/day), ground specific humidity (g/kg), two-meter air temperature (K), surface skin temperature (K), large-scale (frontal, supersaturated) rainfall rate (mm/s), and convective rainfall rate (mm/s).

According to the climatology time series, the monthly rainfall was greatest between December and January. As expected, soil moisture peaks coincided with the periods of highest rainfall, and an overall decreasing trend in the amount of yearly rainfall was reflected in soil moisture quantities. The highest mean temperatures were observed between January and February. Overall, the climatology is in very good agreement with the seasonal trends seen in meteorological station data from Nelspruit, South Africa.

The satellite data include the 1° by 1° monthly NDVI computed using the Pathfinder Advanced Very High Resolution Radiometer (AVHRR) and corresponding to the Mpumalanga Province (31-32°E, 25-26°S). NDVI was obtained directly from the GSFC Earth Sciences Distributed Active Archive Center.

The NDVI time series from 1987 through 1995 indicates a maximum usually around February. The number of reported malaria cases consistently reaches its yearly maximum around March. The increase in malaria cases seen at the end of the austral summer generally lags two to three months behind the beginning of the rainy season and one month behind the beginning of the 'greening' season. The time series of NDVI, climate and malaria incidence data are shown in Figure 1.

3.2 Malaria Data

The Mpumalanga Provincial Department of Health records two broad categories of malaria cases: active and passive. Malaria control personnel who regularly visit households in malaria areas detect active cases. This detection testing residents for malaria infection using blood smears and ICT. Active detection is essential to identify uncomplicated or mild malaria, particularly in areas where curative health services are not easily accessible.

Detection of passive cases involves diagnosis and reporting of malaria cases by health personnel at curative facilities. It is important to note that the reported number of malaria cases is based on definitive diagnosis with ICT or blood smear in both active and passive case detection. For the current study, the malaria incidence data from the Tonga,

Nelspruit, Kabokweni, and Shongwe Districts that make up the Mpumalanga were aggregated to create a representative record of total malaria cases.

The time series of malaria data are shown in Figure 1. Overall, the malaria data follow an annual cycle consistent with rainfall patterns. In 1988, 1989, 1991, 1993, and 1996, the malaria incidence curve was bimodal, with a second lesser peak appearing in October or November.

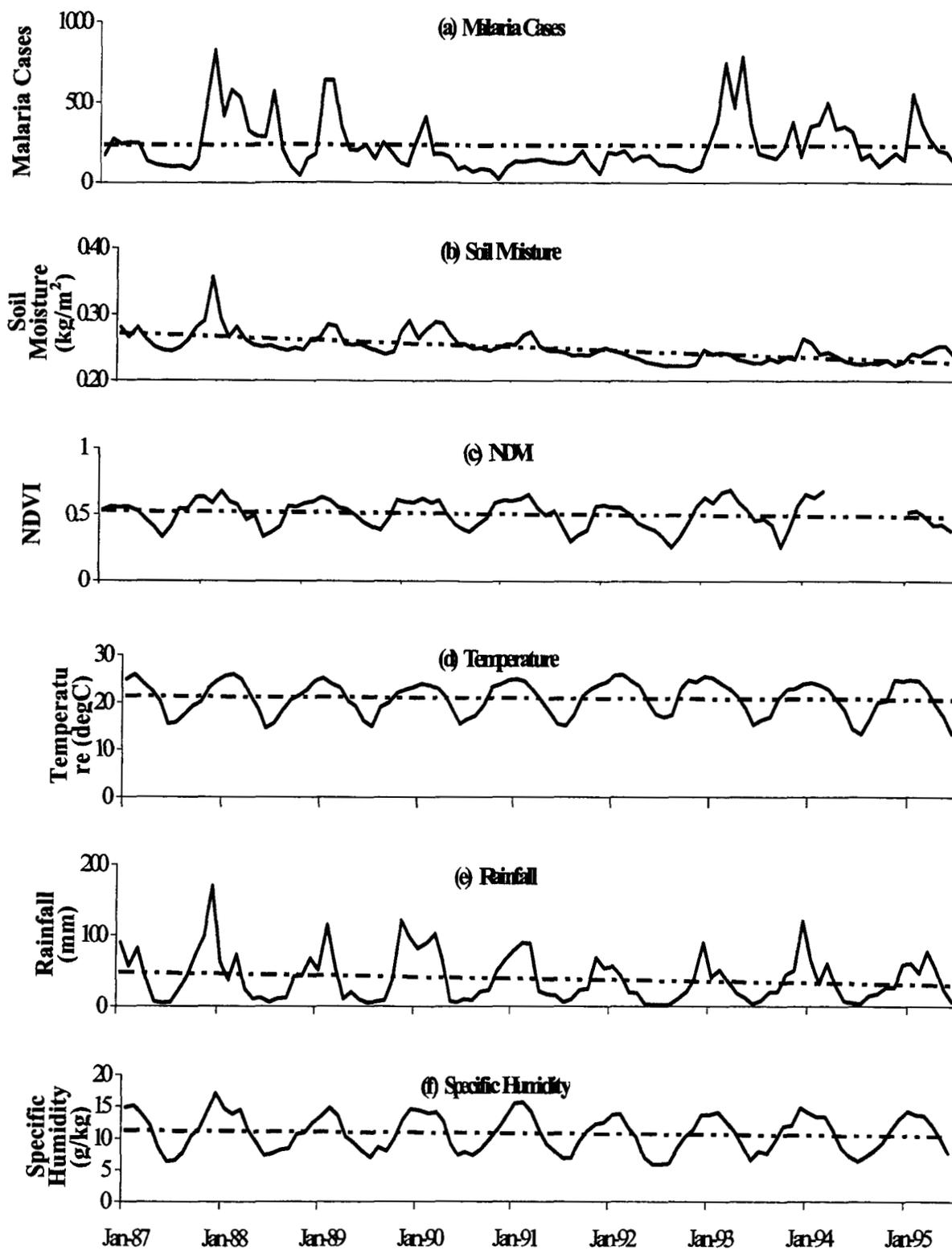


Fig 1. Original time series, January 1987-June 1995; the dashed lines indicate trends.

Missing data points in the NDVI signal were removed due to instrument error.

4. Multivariate analysis

The analysis consisted of regressing climate and eco-epidemiological variables with malaria to determine significant correlation. The climate variables and their derivatives were first regressed on malaria to determine which of these independent variables exhibited the strongest association based on the r^2 and F values. Bivariate analyses were performed to explore the structure of the association between each independent variable and malaria incidence lagged 0 to 13 months (See Figure 2). All data were transformed to achieve normality and stationarity using forward differencing and a Box-Cox transformation, when necessary. Three additional eco-epidemiological variables, vector survival rate, biting rate, and extrinsic incubation period were calculated using surface skin temperature based on MARTENS's (1998) formulas. Those the latter two did not yield significant correlations and were deleted from the analysis. For the sake of brevity, reported below are only those data that resulted in the strongest correlation.

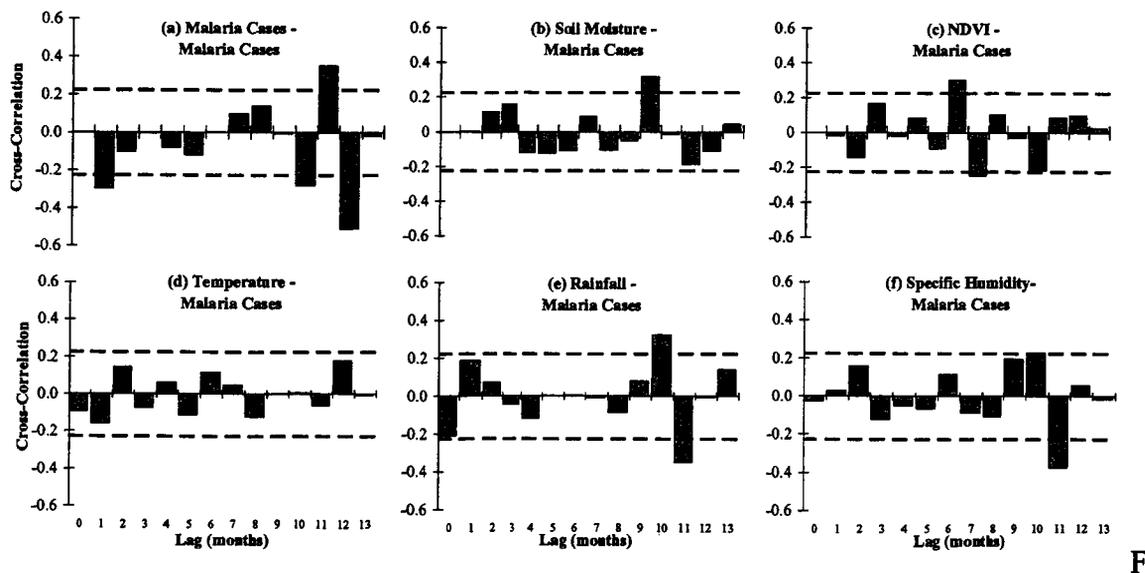


Fig. 2. Cross-correlation between each climatological risk factor and malaria cases. The y-axis corresponds to the number of months that the malaria record is lagged behind the climate variable. The dashed line indicates statistical significance with $P < 0.05$.

The cross-correlation matrix, Table 1, indicates that even in the transformed time series there is a high correlation between the climatological variables such as soil moisture, rainfall, evaporation rate, and specific humidity. There is also a strong correlation, $r^2 = 0.55$, between survival rate and rainfall, and survival rate and soil moisture.

	<i>Malaria</i>	<i>Soil Moisture</i>	<i>NDVI</i>	<i>Rainfall</i>	<i>Survival Rate</i>	<i>2m air temp</i>	<i>evaporation</i>	<i>sp. humidity</i>
<i>Malaria</i>	1							
<i>Soil Moisture</i>	0.08	1						
<i>NDVI</i>	-0.03	0.12	1					
<i>Rainfall</i>	-0.15	0.75	-0.17	1				
<i>Survival Rate</i>	-0.02	0.55	0.05	0.55	1			
<i>2m Air Temp</i>	-0.08	-0.03	-0.17	0.08	-0.24	1		
<i>Evaporation</i>	-0.09	0.83	-0.10	0.93	0.67	0.05	1	
<i>Sp. Humidity</i>	-0.06	0.66	-0.07	0.72	0.35	0.40	0.72	1

Table 1. Zero-lag correlation matrix of transformed time series

Some variables, including evaporation rate, skin temperature, and biting rate were eliminated in pre-selection routines to reduce the computational effort of the aggregate multivariate analysis. The six remaining variables, NDVI, soil moisture, total rainfall, vector survival rate, specific humidity, and air temperature, were included in a forward stepwise discriminant analysis. Each environmental variable was time-lagged to produce a lead-time of 0 to 13 months with respect to the malaria record. The malaria record itself was lagged to produce a lead-time of 1 to 13 with respect to the original malaria record. This created a pool of 97 independent variables from which a subset of 9 variables was selected using 'step-up' stepwise multiple regression (see Table 2) on the 'un-shifted' malaria incidence time series (ZAR, 1973). Changes in the goodness of fit and significance of the model (measured by r^2 and F value, respectively) as each variable was added are shown in Figure 3.

I	X_i	Lead time (months)	β_i
1	Malaria incidence	12	0.02
2	Malaria incidence	2	- 33.17
3	Total rainfall	1	- 26.47
4	Soil Moisture	5	- 15.26
5	Soil Moisture	7	0.00
6	Soil Moisture	10	-0.39
7	Total rainfall	10	-0.23
8	NDVI	3	0.01
9	Total rainfall	7	-4.57

Table 2. Parameters of the multivariate regression equation

The multivariate model is thus written:

$$Y_t = \alpha + \beta_1 X_{1t} + \beta_2 X_{2t} + \beta_3 X_{3t} + \beta_4 X_{4t} + \beta_5 X_{5t} + \beta_6 X_{6t} + \beta_7 X_{7t} + \beta_8 X_{8t} + \beta_9 X_{9t} \quad (1)$$

Where Y_t is the modelled or predicted malaria cases at time step t , i is the order in which the independent variables were incorporated into the multivariate model, X_{it} is the independent variable X_i at time t , and β_i is a regression coefficient for variable X_i , with the coefficients indicated in Table 2.

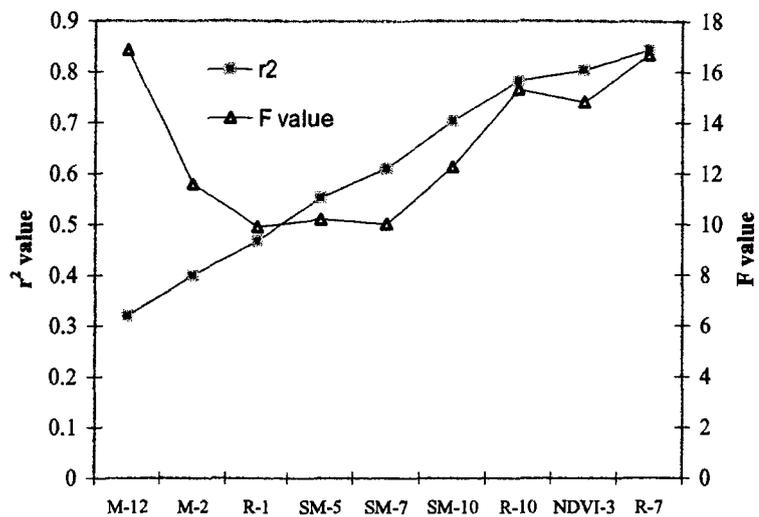


Fig. 3. Development of forward step-up multivariate autoregressive model. Variables were added from left to right. The numbers following the number of months of lead-time Variable names are abbreviated as follows: M=Malaria incidence, R=Rainfall, SM=Soil Moisture, and NDVI= Normalized Differential Vegetation Index

The variable selection and the computation of the regression equation employed only the data recorded between January 1987 and April 1992. This period, which establishes the “dose-response” relationship between the environmental conditions and disease outcomes, is referred to as the calibration period. Estimates of malaria calculated during this period are referred to as ‘modelled malaria’ since the malaria data itself were used to define the regression equation. This algorithm was then applied to the data from the validation period (May 1992 to June 1995) in order to make one-month lead-time predictions of malaria incidence.

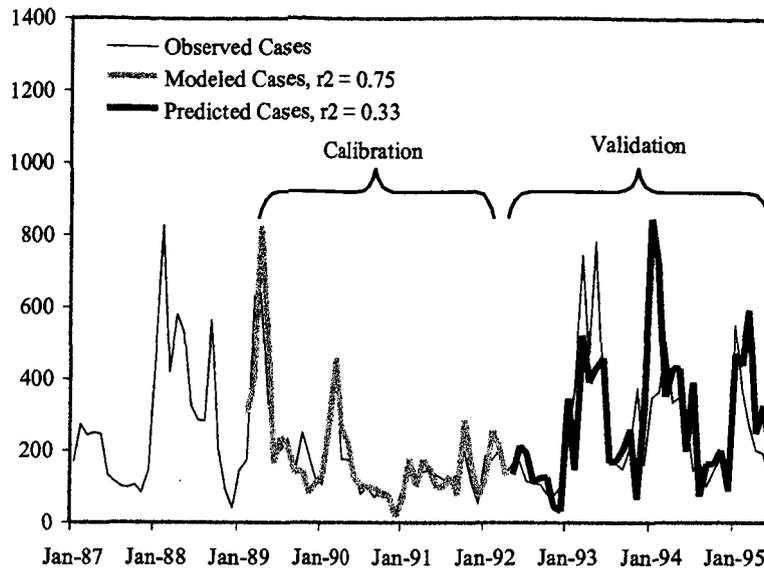


Fig. 4. Observed, modelled and predicted malaria cases in the Mpumalanga Province, South Africa using an autoregressive multivariate regression analysis.

The model described in Equation (1) and Table 2 is shown graphically in Figure 4. Results indicate that the model accounts for 75% of the variation in the observed malaria cases during the calibration period and 33% of the variation in the observed record during the validation period. The relative mean absolute error (the mean of the residuals divided by the mean of the observed values) was 0.45 (LETTENMAIER and WOOD, 1993). In terms of systemic error, the bias of the predictions (difference of the mean of the predictions and the mean of the observed values) was 23.5 malaria cases. In order to determine the accuracy of predictions, the malaria record was divided into three groups of equal size consisting of: low risk months (<160 cases), moderate risk months (>160 cases and <320 cases), and high risk months (>320 cases). With a lead-time of one month, the model predicted 11 of 13 months in the validation period that were classified as high risk. The model also classified 4 months as high risk that were actually moderate risk or low risk months (false positives). When the lead-time of predictions was increased to 2, 3, and 4 months, the predictive ability of the model decreased (see Table 3).

Lead time (months)	1	2	3	4
r^2	0.34	0.10	0.08	0.06
Standard Error	155	343	466	609
Bias	24	70	93	107
Correct predictions of high risk months (out of 13 possible)	11	7	6	6
False positives	4	5	6	6

Table 3. Measurements of forecast accuracy with 1 to 4 months of lead-time.

5. Discussion

The model presented here, which incorporates NDVI and derived climatic variables, is able to predict 11 of the 13 months that were classified as high risk during the validation period. It accounts for more of the variability in the malaria incidence data (75%) than an autoregressive model that includes malaria incidence alone (33%) or malaria incidence, rainfall and temperature (45%), each model using nine parameters. The results indicate that even with rather coarse resolution variables of the derived land surface climatology, the model performs fairly well in forecasting malaria incidence.

There are several limitations to the current approach. First, its use as a prediction model based only on environmental conditions omits consideration of important demographic changes and socio-economic factors that influence the number of reported cases in the analysis and interpretation of results. Examples of such factors would include seasonal migration of infected workers, changes in control efforts or reporting methodology. Consequently, this model is probably best suited as one component of a multi-tiered early warning system. Such a system, as described in COX (1999), incorporates long-range forecasting based on climate cycles (such as ENSO parameters), medium-range early warning based on monitoring environmental risk factors (such as climatological variables or vegetation density), and surveillance of malaria incidence at the

local level. A second limitation may be the current rather coarse resolution of the OLGA climatology variables. The $2^{\circ} \times 2.5^{\circ}$ resolution is perhaps too coarse for making policy recommendations, even at Provincial level. However, despite the known limitations, this work can serve as a point of departure for future applications of finer scale resolution land-surface hydrological models to explore the dynamic relationships between climate, vector ecology, and disease outcomes.

In future work it may be worthwhile to consider that the combination of climate variables that serve as the best leading indicators of malaria incidence may vary over the course of the phenological year. HAY *et al.* (1998) hypothesized that malaria transmission is influenced by rainfall only during the drier part of the year until the onset of the rainy season. Once the rainy season has begun malaria transmission will show little sensitivity to fluctuations in rainfall. Future analyses may benefit from partitioning available data in order to detect relationships between climatic conditions and malaria incidence that are only discernable during part of the year. It is also worth noting that the generation time of malaria cases, the time between bite and manifestation of symptoms, decreases with increased temperature (~45 days at 20 °C, ~23 days at 30 °C; MOLINEAUX, 1988). Therefore, one would expect the lag between the occurrence of favourable environmental conditions and increased reporting of malaria to be shorter during the summer and longer during the winter

Overall, however, the good results obtained using the multivariate model indicates the utility of applying antecedent climatic variables to the prediction of malaria incidence, at least for regions such as the Mpumalanga Province that possesses a sparse hydrometeorological observational network. As the spatial and temporal resolution of satellite based terrestrial products improve, together with more accurate data assimilation methods, it is reasonable to expect a corresponding improvement in predicting malaria using a similar multivariate approach.

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