Use of Vectorial Capacity in Describing and Forecasting of Malaria Cases in Kericho, Kenya

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ABSTRACT

Temperature and rainfall play a key role in mosquito vector abundance and, as a result are crucial to malaria disease transmission. Over the last decade, climate-integrated malaria intervention techniques in Africa have been widely overlooked; however, providing evidence of the impact of interventions on malaria decline, as opposed to other factors such as climate, is becoming increasingly important in ensuring continued political and financial support. Therefore, in this study, our objective was to show that a rainfall and temperature driven model of vectorial capacity (VCAP) -the potential for vector-borne disease transmission in humans- can describe and predict malaria transmission. In doing so, we aim to indicate the role of climate in the kinetics of malaria transmission. We used an Autoregressive Integrated Moving Average model (ARIMA 1,0,1) to fit monthly malaria cases from a tea estate in Kericho, Kenya. The relationship of VCAP to log-malaria incidence was strongest two months prior (r = 0.42). Likelihood ratio test of nested models identified the full model as a better fit than the restricted model (p-value< 0.05, DF=1, X2 = 12.03). VCAP-based malaria predictions showed strong correlation to malaria incidence (r=0.62) and successful 2-month lead forecast of malaria outbreaks following the El Niños of 1990, 1997/1998, and 2002. Of the 86 monthly epidemic warnings from 1989 to 2004, 61 were correctly identified and 25 were falsely identified.

INTRODUCTION

Background: To describe and predict malaria transmission in this study, we used Vectorial Capacity (VCAP), which can be defined as the daily rate at which future infections occur from a currently infective host, if all female mosquitoes biting the host become infected. The role of climate in mosquito and parasite ecology[1–4] allows for a weather-driven VCAP. The components of VCAP, namely mosquito population, mosquito-parasite survivorship, gonotrophic cycle and sporogony, are all influenced by weather. Mosquitoes depend on rainfall for habitat formation and persistence and for aquatic-stage progression. At an optimal temperature range of 18-32ºC[5], *Anopheles gambiae* mosquitoes successfully thrive and *Plasmodium falciparum* species readily complete the extrinsic incubation cycle within the mosquito.

To estimate VCAP, we used high-quality historical records of rainfall and temperature. The meteorology and mosquito interaction as exemplified in the VCAP estimate is relatively simple and backed by experiment[6-8], and as such reduces the problem of added uncertainty and enlarged number of assumptions, common in complex models.

METHODOLOGY

Study Site: Plantation 2, is among several tea plantations situated in a tea estate in Kericho district, Kenya. Kericho is 1,200-3000m above sea level in the western highlands of Kenya. The fertile soil and reliable rainfall, make crops such as tea commercially viable in the region[9]. On average 18,000-18,500 individuals, with three to four dependents, work at tea plantation 2[10]. We assume that the total population at Plantation 2 has remained fairly constant[11], during the period of study- 1979 to 2004. Similar population projections in, Kisii, Kenya, have been reached in previous analysis[12].

Vectorial capacity: Because actual mean temperature is difficult to obtain, it is often expressed as the average of maximum and minimum temperature- two variables that are typically asymmetric in behavior. Therefore, we used minimum temperature to compute VCAP. Preliminary analysis indicated that minimum temperature is more strongly linked to malaria than mean or maximum temperature. Also, previous research has shown that in locations such as Kericho Kenya, where conditions are cool, use of mean temperature underestimates parasite development[13].

The weather-driven VCAP[14] formula used here is as follows:

$$VCAP = -\frac{(ma^2)p^n}{\ln(p)}, \qquad (equation\ 1),$$

where m =density of mosquito, is represented as

$$m = 10.0 * (-Rf^2 + Rf + C), (equation\ 2),$$

Rf is rainfall and C is a constant, α = human-biting rate[14], ρ =vector survivorship[7] and n =parasite extrinsic incubation period[14].

Model: Recent malaria cases can affect current cases, due to increased availability of gametocytes in the population. This presents an autocorrelation problem, in which cases at time t may be dependent on cases at time t_{-x}, thereby reducing the number of random observations and errors. Thus, we fitted an ARIMA (1,0,1) model with harmonic seasonality as follows:

$$Y_t = \alpha s(t) + \beta 1t + \gamma 1\sin(\pi_t/12) + \gamma 2\cos(\pi_t/12) + \theta V_t + w_t, \ (equation\ 3),$$

where $w_t = \mu + \varphi_1 Y_{t-1} - \theta_1 e_{t-1} \sim NID(0, \sigma^2)$,where e is random, normally and independently distributed with mean = 0 and variance σ^2. $Y_t = \log(I_t/N_t)$, N_t = population count, V_t = 2-months lagged VCAP, I_t = number of incident cases, $t=t^{1/2}$ represents the slowly increasing trend in the training data.

Analysis: Likelihood test ratio (LTR) indicated whether the full model is a better fit than the nested model, further indicating whether the weather-driven VCAP is a significant confounder of malaria transmission. Using a rolling-origin approach, we forecasted malaria incidence with the full and nested models to evaluate what malaria incidence would have been with and without the impact of climate in the form of VCAP.

Epidemic threshold: In Kericho, the risk of malaria is moderately high and seasonal. Therefore to account for the seasonality and to obtain a distinct detection signal, we used a seasonally-adjusted threshold, defined as:

Seasonal mean + 1.282* seasonal standard deviation, where seasonal grouping is as follows: January to February (shorter, weaker transmission season), April to August (longer, stronger transmission season), and March, September to December (periods of lowest transmission). As a result of the historical conditioning of the epidemic threshold, three unique cutoff marks were adopted for each season. Observed and forecasted monthly malaria incidence above the cutoff values for months within a season indicated an outbreak.

2x2 contingency table, based on clearly defined epidemic threshold settings, allowed for the evaluation of the VCAP model's success in predicting outbreaks.

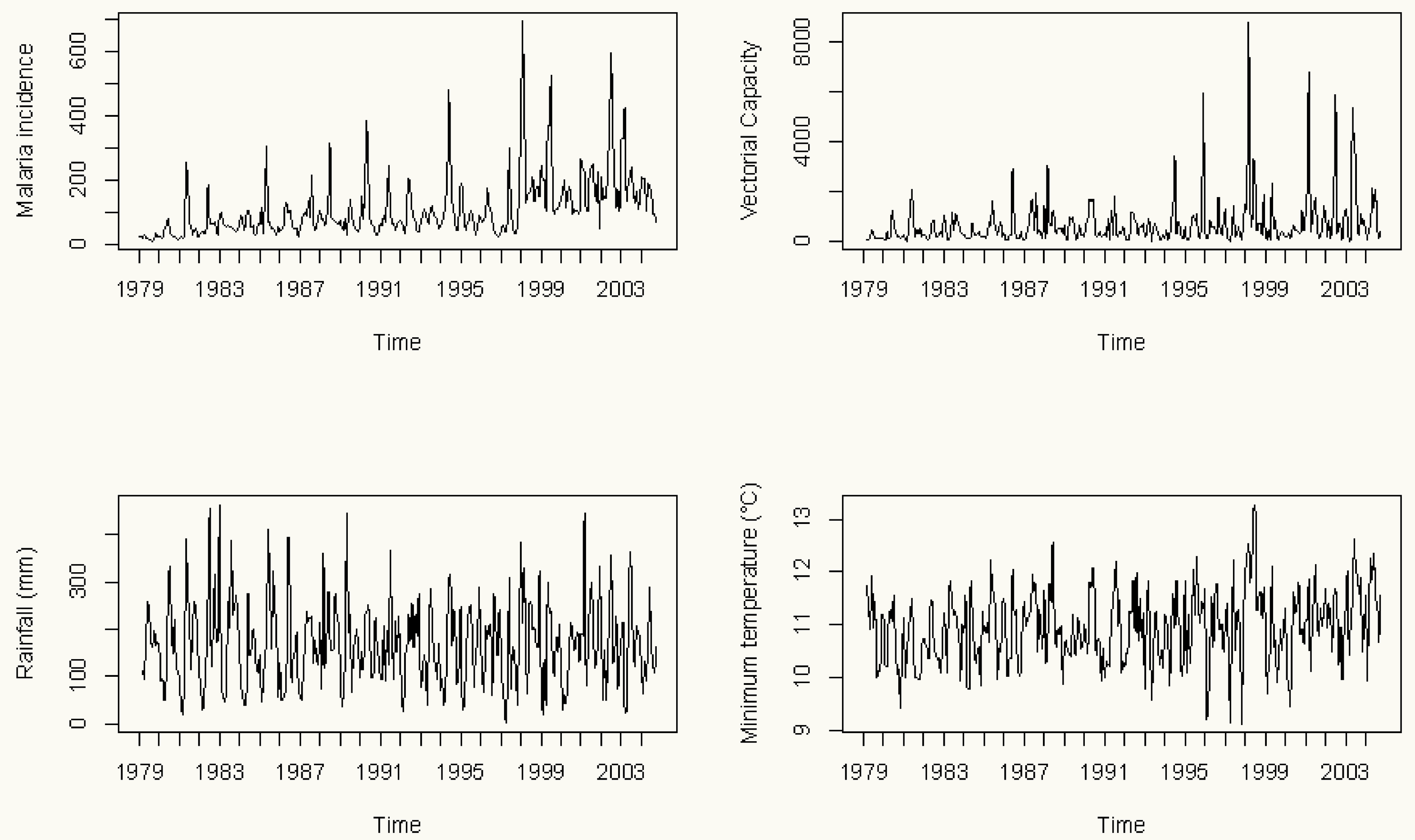

Figure 1. Time series of data. Top left malaria incidence; top right vectorial capacity; bottom left rainfall (mm); bottom right minimum temperature (°C).

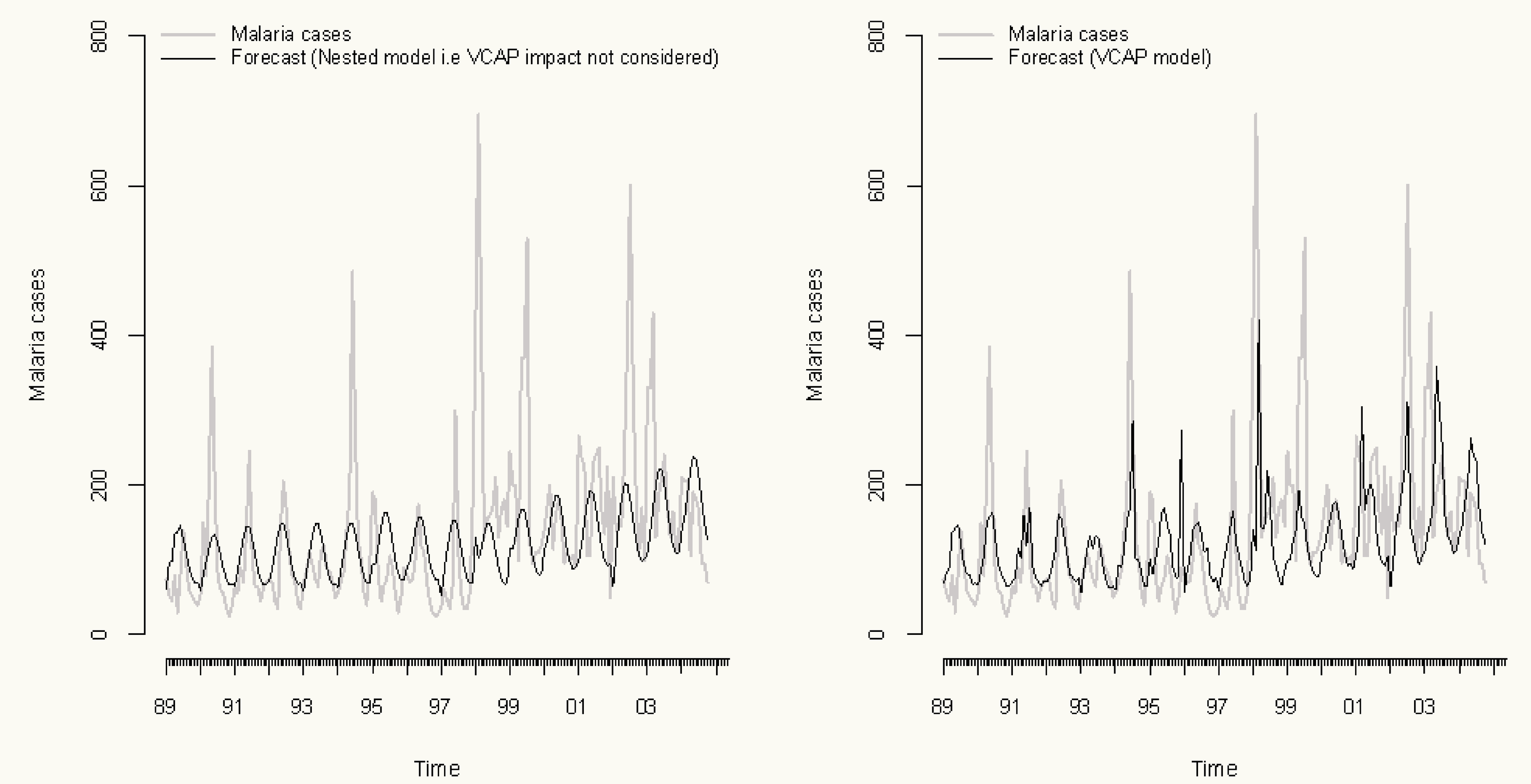

Figure 2. Forecast of malaria incidence. Left panel impact of VCAP not considered and right panel impact of VCAP is accounted for.

Table 1: Estimates and standard errors for nested model with and without adjustment for vectorial capacity.

	Nested model			VCAP model		
Variable	Estimate	Standard error	T-ratio	Estimate	Standard error	T-ratio
AR1	-0.66	7.1E-02	-9.29	-0.59	9.7E-02	-6.08
MA1	1.00	5.9E-02	16.89	0.92	4.6E-02	20.17
Intercept	2.76	1.4E-01	19.91	2.68	1.4E-01	18.75
COS 1	-0.37	6.4E-02	-5.84	-0.32	6.7E-02	-4.77
SIN 1	0.10	6.4E-02	1.63	0.10	6.3E-02	1.57
Trend	0.16	1.8E-02	9.15	0.16	1.9E-02	8.42
VCAP	-	-	-	2.2E-04	1.2E-04	1.91

Table 2: 2x2 contingency table of forecasted and observed malaria outbreaks for Kericho Kenya, using VCAP model.

		Observed outbreaks		
		High	Low	Total
Forecasted outbreaks	High	61	19	80
	Low	25	85	110
	Total	86	104	190

Sensitivity	71%
Specificity	82%
Accuracy	77%
NPV	77%
PPV	76%

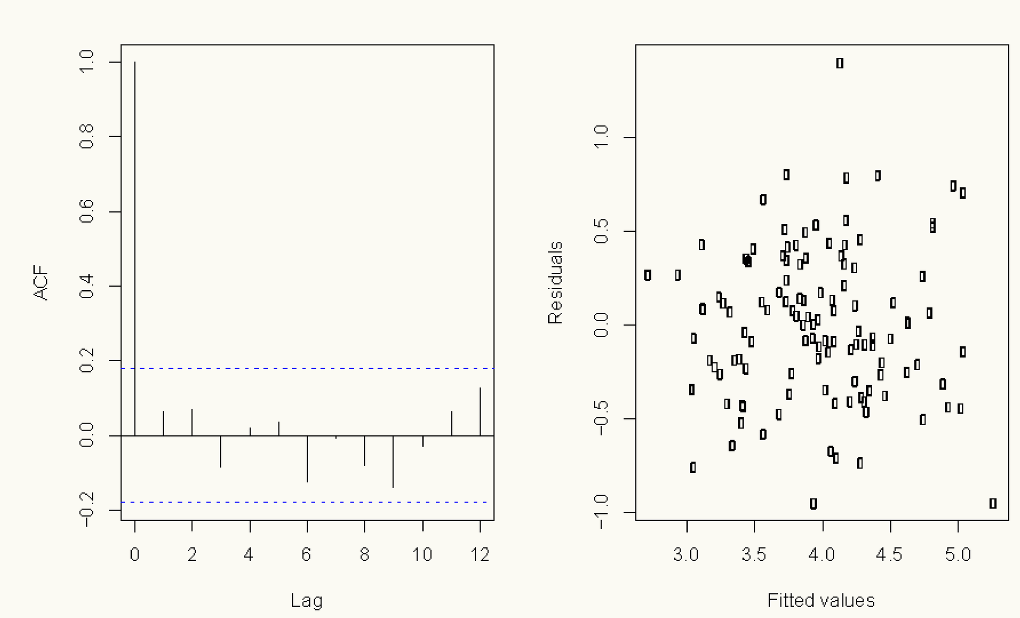

Figure 3. VCAP model diagnostic: On the left panel is the correlogram of the residuals from the fitted model and on the right panel is a plot of the residuals against fitted values.

RESULTS

Figure 1 shows the time series of malaria incidence, rainfall, minimum temperature, and vectorial capacity. Malaria incidence shows a weak trend over the time period. Rainfall and minimum temperature show seasonal rise and falls but do not show a clear trend. Similarly, vectorial capacity shows an increase in the magnitude of peaks, post 1997 (Figure 1). Vectorial capacity, rainfall, and minimum temperature show a positive correlation to log-malaria incidence (r = 0.42, r=0.22, r=0.39 respectively).

Likelihood test ratio indicates that the addition of the 2 month-lagged VCAP, improved the seasonality-trend model (baseline model) significantly (p-value< 0.05, DF=1, X2 = 12.03). Variables in the model without adjustment for vectorial capacity show mean 7% drop in coefficient estimates with the addition of VCAP (Table 1). A plot of residuals against fitted values from the VCAP model shows no discernible pattern; and the correlogram of the residuals failed to indicate serial correlation even after 12 months (Figure 3).

Forecasts of what malaria incidence would have been under two different scenarios are shown in figure 2. The nested model (r= 0.54, RMSE= 99.14), captures the seasonal variation of malaria transmission, but failed to indicate malaria outbreaks compared to the VCAP model (r= 0.62, RMSE=93.46). The full model accurately predicted malaria outbreaks following periods of high climate suitability due to El Nino (Figure 2).

Harmonic-ARIMA (1, 0,1) model was used in a rolling origin fashion to cross-validate, as well as, forecast the monthly malaria cases from January 1980 to December 2004. In the model, we also included average VCAP from 2 months ago as a predictor. Based on the discrimination threshold (seasonal mea + 1.282* seasonal standard deviation), the model was able to detect malaria cases with 77% accuracy, 71% sensitivity and 82% specificity. Of the 86 monthly epidemic warnings from 1989 to 2004, 61 were correctly identified and 25 were falsely identified (Table 2). The observed number of epidemic events and the forecasted number of epidemic events matched reasonably well, and the correlation between forecast and actual cases was fairly strong and positive (r=0.62).

CONCLUSIONS

Malaria is a climate-sensitive disease, and as a result, climate data can be used to monitor and predict malaria transmission dynamics. The results obtained successfully show that in a simple ARIMA model framework, weather-driven VCAP better captures malaria variation than the nested model, indicating that climate information such as VCAP is a significant confounder of malaria transmission and therefore can be used in assessing the impact of climate on malaria transmission. The existing relationship between VCAP and malaria transmission also allowed for the successful forecast of malaria cases within acceptable levels of accuracy and confidence. Climate data such as VCAP, when taken into proper consideration, could not only guide intervention strategies but also ensure the accurate assessment of malaria intervention programs, as changes in malaria incidence may occur independently of interventions as a result of changes in climate risk.

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