

# Predicting key malaria transmission factors, biting and entomological inoculation rates, using modelled soil moisture in Kenya

Jonathan A. Patz<sup>1</sup>, Kenneth Strzepak<sup>2</sup>, Subhash Lele<sup>3</sup>, Maureen Hedden<sup>4</sup>, Scott Greene<sup>5</sup>, Bruce Noden<sup>6</sup>, Simon I. Hay<sup>7</sup>, Laurence Kalkstein<sup>8</sup> and John C. Beier<sup>9</sup>

<sup>1</sup> Department of Environmental Health Sciences, Johns Hopkins School of Hygiene and Public Health, Baltimore, USA

<sup>2</sup> Department of Civil, Environmental and Architectural Engineering, University of Colorado, USA

<sup>3</sup> Department of Biostatistics, Johns Hopkins School of Hygiene and Public Health, Baltimore, USA

<sup>4</sup> Applied Physics Laboratory, Johns Hopkins University, Baltimore, USA

<sup>5</sup> Oklahoma Climate Survey, University of Oklahoma, USA

<sup>6</sup> Department of Microbiology and Immunology, University of Maryland, USA

<sup>7</sup> TALA Research Group, Department of Zoology, University of Oxford, UK

<sup>8</sup> Center for Climatic Research, Department of Geography, University of Delaware, USA

<sup>9</sup> Department of Tropical Medicine, Tulane University, School of Public Health, USA

## Summary

While malaria transmission varies seasonally, large inter-annual heterogeneity of malaria incidence occurs. Variability in entomological parameters, biting rates and entomological inoculation rates (EIR) have been strongly associated with attack rates in children. The goal of this study was to assess the weather's impact on weekly biting and EIR in the endemic area of Kisian, Kenya. Entomological data collected by the U.S. Army from March 1986 through June 1988 at Kisian, Kenya was analysed with concurrent weather data from nearby Kisumu airport. A soil moisture model of surface-water availability was used to combine multiple weather parameters with landcover and soil features to improve disease prediction. Modelling soil moisture substantially improved prediction of biting rates compared to rainfall; soil moisture lagged two weeks explained up to 45% of *An. gambiae* biting variability, compared to 8% for raw precipitation. For *An. funestus*, soil moisture explained 32% variability, peaking after a 4-week lag. The interspecies difference in response to soil moisture was significant ( $P < 0.00001$ ). A satellite normalized differential vegetation index (NDVI) of the study site yielded a similar correlation ( $r^2 = 0.42$  *An. gambiae*). Modelled soil moisture accounted for up to 56% variability of *An. gambiae* EIR, peaking at a lag of six weeks. The relationship between temperature and *An. gambiae* biting rates was less robust; maximum temperature  $r^2 = -0.20$ , and minimum temperature  $r^2 = 0.12$  after lagging one week. Benefits of hydrological modelling are compared to raw weather parameters and to satellite NDVI. These findings can improve both current malaria risk assessments and those based on El Niño forecasts or global climate change model projections.

**keywords** *Anopheles*, climate, El Niño, greenhouse effect, malaria, modelling, weather

**correspondence** Jonathan A. Patz, Department of Environmental Health Sciences, Johns Hopkins School of Hygiene and Public Health, 615 North Wolfe Street, Baltimore, MD 21205–2179. E-mail: jpatz@jhsph.edu

## Introduction

Of all the mosquito-borne diseases, malaria caused by *Plasmodium falciparum* remains the most widespread, affecting over 110 million people and killing 1–2 million people annually (Knudsen & Slooff 1992). In 1995, 2.1 million malaria fatalities were reported by WHO (WHO 1996). Drug-resistance persists and antimalarial vaccines have shown limited efficacy (Institute of Medicine 1991; Valero *et*

*al.* 1993; Alonso *et al.* 1994; Nosten *et al.* 1996). In many regions where malaria had been almost eliminated, the disease has returned, sometimes at levels surpassing earlier prevalence (Institute of Medicine 1991).

The relationship between weather and malaria has been validated by entomological models (Garrett-Jones 1964; Reisen & Boreham 1982) as well as by the analysis of long-term trends in human malaria cases (Swaroop 1949). In addition to seasonality, there is substantial interannual

heterogeneity of malaria incidence around the globe (Fontenille *et al.* 1997). Extreme alteration of rainfall patterns associated with El Niño events (when above-average sea surface temperatures occur in the eastern equatorial Pacific) (Ropelewski & Halpert 1987) have been recently identified as one large-scale climatic driving force behind such malaria variability (Bouma & van der Kaay 1994, 1996; Bouma *et al.* 1994, 1997).

In addition to linkages between El Niño events and malaria, recent trends and future projections of global climate change (Houghton *et al.* 1996) have highlighted the need to re-assess the potential impact of climate on many public health problems, including vector-borne diseases (Reeves *et al.* 1994; Lindsay & Birley 1996; Patz *et al.* 1996). Malaria has been identified by the World Health Organization to be the vector-borne disease most sensitive to long-term environmental change (WHO 1996).

Vector-borne parasites such as *Plasmodium* are sensitive to ambient climate conditions because part of the life cycle occurs inside an invertebrate host (Bradley 1993), and weather is considered to be the most important cause of atypically large epidemics in nonendemic areas (Gilles 1993). In the laboratory, ambient temperature, which can raise or lower the internal temperature of poikilothermic vectors, influences the duration of the gonotrophic cycle (Briegleb & Lea 1975), the extrinsic incubation period of the parasites and vector survival (Boyd 1949). Surface water availability for mosquito breeding sites has been known to determine mosquito densities, and in many regions the seasonality of malaria is attributed to rainfall patterns. Given these relationships, malaria transmission intensity still remains difficult to predict.

Beier *et al.* (1994) showed a strong relationship between malaria incidence and concomitant entomological inoculation rate in Kenya. EIR explained 74% of the attack rates in child cohorts. The human biting rate (HBR) alone accounted for 68% of the variability. The purpose of our study was to determine the effects of weather on these transmission components in the field. Specifically, we examined the extent to which temperature and precipitation affect HBR, sporozoite rates and EIR. We used a soil moisture model to test whether this methodological tool could improve predictability of biting rates over that based on raw precipitation data and the satellite normalized-difference vegetation index (NDVI).

## Methods

### Study site

Kisian is in western Kenya, 10 km west of Kisumu, located on the shore of Lake Victoria (Winam Gulf area). The study site covered 12.4 km<sup>2</sup> and included 660 houses with an estimated

human population of 5280. Rainfall averages 1000–1500 mm annually, with an extended rainy season from March to May and a brief rainy season from September to November. The amount and duration of the rainfall varies markedly from year to year (Beier *et al.* 1990).

Malaria is holoendemic in this region and transmitted by *An. gambiae sensu strictu*, *An. arabiensis* and *An. funestus* (Petrarca *et al.* 1991). Larval habitats consist of surface pools and animal hoof prints. Permanent larval habitats, including papyrus swamps, also occur in proximity to Lake Victoria. There was no irrigation in Kisian at the time of the mosquito collections. During the study period, no mosquito control measures or large-scale prophylactic programmes against malaria were in effect.

### Entomological data

We used entomological data from a previous study (Beier *et al.* 1990) collected weekly from March 1986 through June 1988 in preparation for malaria vaccine trials. The species-specific mosquito datasets were those of *An. gambiae s.l.* and *An. funestus*. We used a data set of human-biting rate (HBR) that followed all-night, human-biting collection techniques per WHO protocol (WHO 1975). Briefly, teams of two men working in each of three houses collected host-seeking mosquitoes from one another, for 30 min per hour, from sunset to sunrise one night per week (Beier *et al.* 1990). HBR values estimate the number of female *Anopheles* bites per person per night. The sporozoite rate (SR) was the proportion of female mosquitoes containing infective stage parasites in their salivary glands upon dissection (Beier *et al.* 1987). SR multiplied by HBR provides the entomological inoculation rate (EIR) (Beier *et al.* 1990).

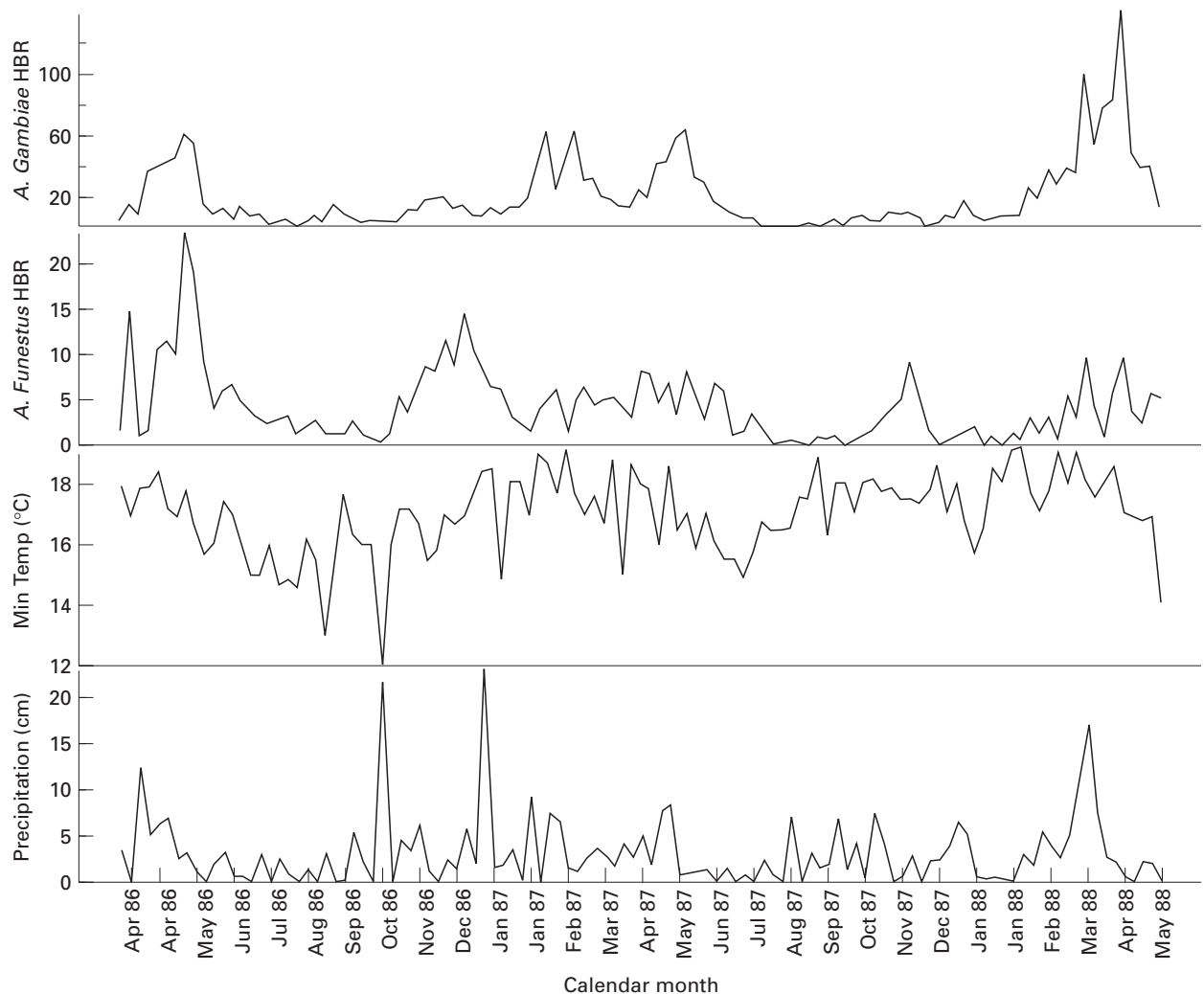
### Weather data

Meteorological data from Kisumu Airport, 5 km from the study site, were obtained from the U.S. National Climatic Data Center and included hourly temperature, dew point, and daily precipitation. Maximum and minimum temperatures came from dedicated daily maximum/minimum thermometers. Figure 1 shows the time series of minimum temperature, along with precipitation and HBR datasets.

All statistical analysis of weather and entomological data was performed using S-Plus Statistical Software (Becker *et al.* 1988). Univariate regression analysis was applied to identify weather parameters with the strongest correlation to EIR, HBR and SR. The Monte Carlo permutation test was applied to correlation coefficients to test for statistical significance.

### Modelling river runoff and soil moisture

A water balance model (WatBal) (Yates 1996) was used to estimate the weekly soil moisture and river runoff of the Lake



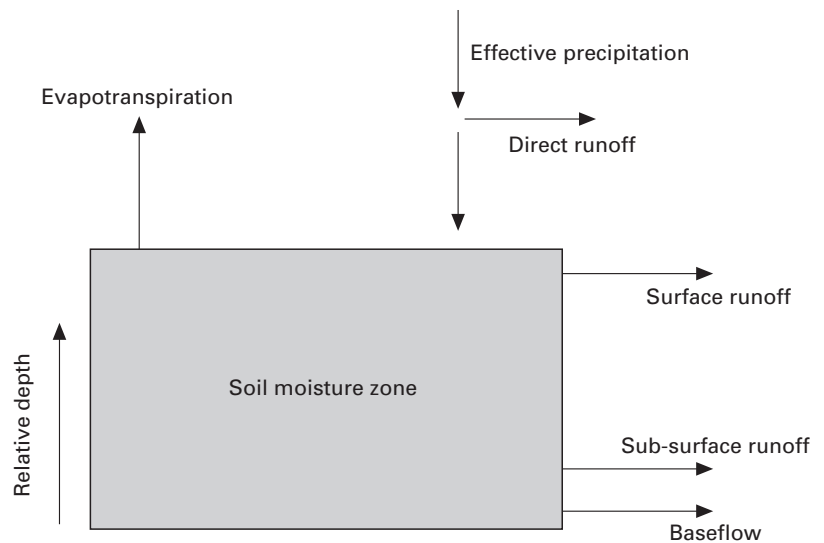
**Figure 1** Time series of human biting rates (HBR) of *An. funestus* and *An. gambiae*, minimum temperature, and precipitation over the study period.

Victoria Basin. WatBal models changes in soil moisture by taking into account precipitation, runoff, soil characteristic, and actual evapotranspiration, while using potential evapotranspiration to drive the extraction of water from the soil moisture (Figure 2).

Evapotranspiration is a function of *potential* evapotranspiration and the soil moisture state of the watershed. Potential evapotranspiration is modelled by using the Priestly Taylor method (Shuttleworth 1993). This method was chosen because of its simplicity and the evidence supporting such an empirical relationship on a regional basis,

which is the case for river basin modelling. Since detailed data on the local watershed were unavailable, model parameters were used from a hydrologic study of the Lake Victoria Basin (Yates & Strzepek 1997). These parameters were combined with the climate data (temperature, precipitation, relative humidity, and solar radiation) to model the weekly soil moisture state and river runoff. A moving average, with a 5% filter, was used to 'smooth' the HBR dataset. Modelled soil moisture values represent the percentage of maximum capacity or relative soil moisture (e.g. 0.8 means that soil moisture is at 80% of full capacity).

**Figure 2** Conceptualization of water parameters used in the WatBal model of soil moisture.



#### Normalized difference vegetation index (NDVI)

A monthly NDVI was obtained from Advanced Very High Resolution Radiometry (AVHRR) satellite images, centred over Kisumu and including our study site. Monthly values of NDVI are generally more robust than weekly indices. Weekly NDVI can be problematic due to missing data from cloud cover, so we regressed monthly NDVI with averaged weekly HBR.

## Results

#### Entomological inoculation rates (EIR) and sporozoite rates (SR)

The correlation coefficients for *An. gambiae* EIR and maximum and minimum temperatures, respectively, were:  $r = -0.22$  ( $P = 0.01$ ) and  $+0.026$  (NS). Neither maximum nor minimum temperatures statistically correlated with sporozoite rates ( $r = +0.15$  and  $-0.09$  for maximum and minimum temperatures, respectively). It is possible that the small temperature variability at Kisumu during the study period may have limited determination of any correlations for temperature alone; 75% of minimum temperature values were between 16 °C and 19 °C, and 90% of maximum temperatures lay between 28 °C and 32 °C. Though not reported here, sporozoite rates for *An. funestus* were considerably lower than for *An. gambiae* and temperature correlations were not statistically significant.

#### Human-biting rates (HBR)

Since weak correlations were found for EIR and sporozoite rates, we focused on weather and biting rate relationships, and found stronger correlations between HBR and maximum and minimum temperatures for *A. gambiae*.  $R = -0.36$  ( $P < 0.001$ ) and  $+0.24$  ( $P = 0.005$ ), respectively. Using log of HBR slightly improved correlation for maximum temperature ( $r = -0.41$ ), as did one week lagging ( $r = -0.40$  and  $+0.35$  for maximum and minimum temperatures, respectively).

To study the effect of precipitation on the HBR, we first regressed the log of HBR on raw precipitation. There was high variability of the raw precipitation data, and lagged  $r^2$ , which peaked at 4 weeks, reached only 0.13 and 0.05 for *An. gambiae* and *An. funestus*, respectively. Next, we applied the smoothed precipitation for the two anopheline species, and linear regressions were fitted. The correlation increased for *An. gambiae* ( $r^2 = 0.18$ ) and for *An. funestus* ( $r^2 = 0.12$ ), indicating some improvement in the relationship between smoothed precipitation and biting rate at the study site. Multiple regression including maximum and minimum temperatures with smoothed precipitation increased the correlation for both species, but especially for *An. gambiae* (Table 1).

Applying the hydrological WatBal model, essentially a more physically based type of precipitation smoothing that includes temperature and other weather and landcover parameters, showed improvement in predicting the biting rate of the two mosquito species. As an intermediate parameter of modelled soil moisture, river runoff also was examined.

**Table 1** Coefficients of determination ( $r^2$ ) for the regression of smoothed log human biting rates (HBR) for *An. gambiae* with local weather variables and with modelled soil moisture of the Lake Victoria Basin (for both species), lagged from 0 to 4 weeks. A 5% statistical filter was also applied to precipitation values

No. of weeks lagged	Raw precipitation	Smoothed precipitation	Precipitation and max. temp.	Precipitation and min. temp.	Precipitation and max & min temp	Modelled soil moisture	
						<i>A. gambiae</i>	<i>A. funestus</i>
0	0.03	0.05	0.27	0.32	0.33	0.31	0.06
1	0.05	0.08	0.22	0.20	0.38	0.40	0.15
2	0.08	0.13	0.21	0.29	0.40	0.45	0.22
3	0.11	0.17	0.21	0.34	0.41	0.42	0.27
4	0.13	0.18	0.20	0.38	0.41	0.36	0.32

Regression of log HBR and river runoff (which should closely reflect smoothed precipitation) appropriately resulted in an  $r^2$  of 0.16 for *An. gambiae* and 0.12 for *An. funestus*. Unlagged regression of log HBR vs. modelled soil moisture increased the  $r^2$  value to 0.31 and 0.06, respectively, for the two species.

Lagging the precipitation values enhanced the robustness of the correlation with HBR. For *An. gambiae*, the peak soil moisture correlation occurred after 2 weeks ( $r^2 = 0.45$ ). For *An. funestus*, the correlation progressively increased out to 4 weeks lagging (Table 1).

Figure 3 shows the time series of *An. gambiae* HBR and the modelled soil moisture of the Victoria Basin with two weeks lagging. To compare interspecies differences in response to soil moisture, a *t*-test was applied to the slopes of the regression lines of soil moisture vs. the log of HBR for *An. gambiae* and *An. funestus*. The two species' response to soil moisture at this study site (Figure 4) proved to be significantly different ( $P < 0.00001$ ).

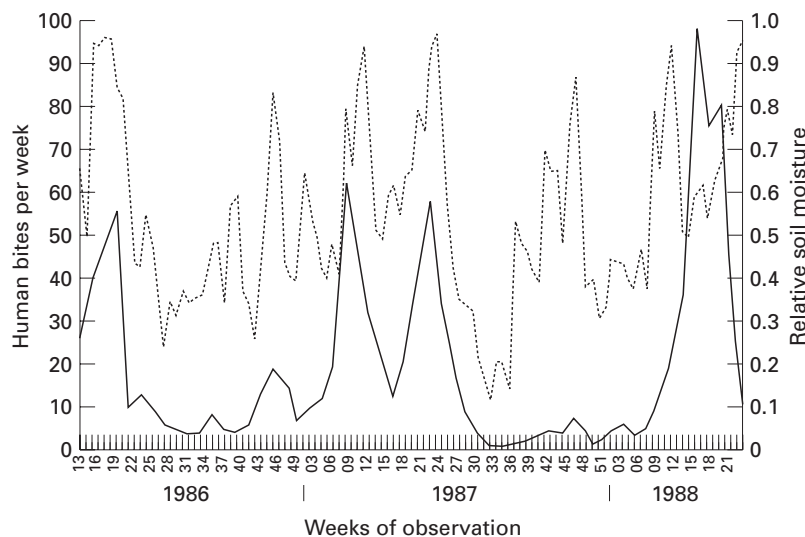
Modelled soil moisture accounted for up to 56% variability

of *An. gambiae* EIR. Lagged  $r^2$  values steadily rose after one week, peaking at six weeks, then declined at a similar rate thereafter (Table 2). The normalized-difference Vegetation Index (NDVI) obtained from AVHRR satellite images correlated with *An. gambiae* HBR, yielding an  $r^2$  of 0.42.

## Discussion

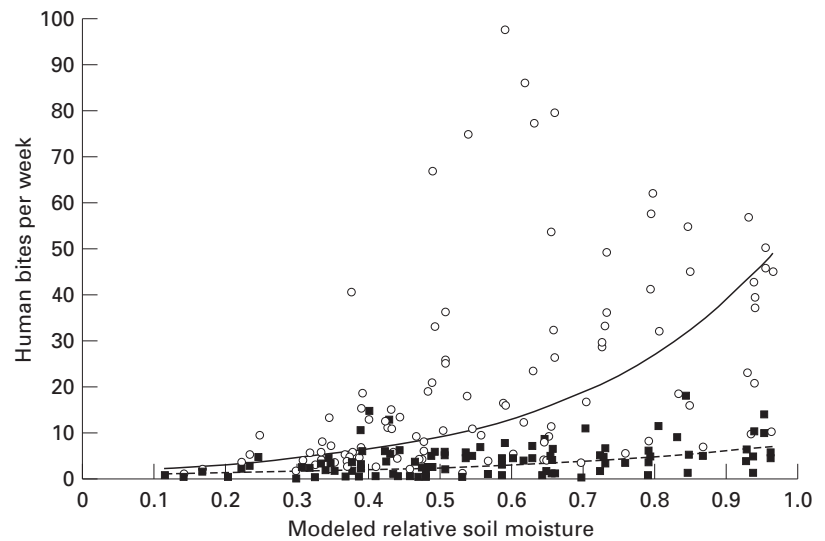
While malaria transmission is known to vary seasonally in areas of high endemicity, large interannual heterogeneity of malaria incidence also occurs. This variability has been attributed to entomological components of transmission (Fontenille *et al.* 1997). However, year-to-year predictability of malaria still remains difficult.

Our study used innovative interdisciplinary methods to analyse this heterogeneity and documents the weather's influence on *An. gambiae* biting rates and EIR, found previously to account for up to 74% of attack rates in children (Beier *et al.* 1994). In particular, modelled soil



**Figure 3** Time series of *An. gambiae* HBR and modelled soil moisture, with a 2-week lag. — *An. gambiae* observed; ..... Modelled soil moisture.

**Figure 4** Regression of the log of *An. gambiae* and *An. funestus* HBR and modelled soil moisture. ○ *An. gambiae* observed; ■ *An. funestus* observed; — *An. gambiae* predicted; ..... *An. funestus* predicted.



**Table 2** Coefficients of determination ( $r^2$ ) for the regression of smoothed log entomological inoculation rates (EIR) for *An. gambiae* with modelled soil moisture of the Lake Victoria Basin, lagged from 0 to 12 weeks

No. of weeks lagged	Modelled soil moisture $r^2$
0	0.24
1	0.14
2	0.24
3	0.34
4	0.45
5	0.53
6	0.56
7	0.55
8	0.50
9	0.42
10	0.32
11	0.21
12	0.13

moisture correlations found in our study are biologically plausible, and these results could improve predictions of malaria transmission based on weather conditions. Hydrological modelling can incorporate temperature, precipitation, landcover, soil type and other environmental factors highly relevant to mosquito ecology.

Our analysis demonstrated the added benefit of hydrological modelling compared to reliance on conventional weather parameters often used by infectious disease scientists. For *An. gambiae*, the soil moisture model predicted up to 45% and 56% of the variability of HBR and EIR,

respectively. The peak in correlation between modelled soil moisture and HBR occurring at 2 weeks is not inconsistent with larval development times. Likewise, peak correlation for EIR at 6 weeks is not inconsistent with development time of sporozoites (approximately 12–14 days) plus mosquito survival, averaging 3–4 weeks.

Probably the most important malaria vector in Africa, *An. gambiae* is known to breed in swamps and temporary puddles. High soil moisture conditions and puddles can remain well after precipitation events depending on the outflow of water from the watershed via runoff and evapotranspiration. The outflow is a function of watershed characteristics and potential evapotranspiration (itself a function of temperature, wind speed, humidity, and solar radiation). The modelled soil moisture therefore is likely a better explanatory variable of mosquito breeding sites than raw weather variables such as temperature and precipitation. This methodology would be especially useful under conditions of extreme rainfall variability, such as those driven by El Niño/La Niña events. In addition, climatologists are projecting a more extreme hydrologic cycle to accompany long-term global warming and climate change; hydrologic modelling for predicting malaria transmission may therefore become that much more important.

Considering the difference in geographical scales, soil moisture modelling could likely be expected to explain even more variability in entomological transmission factors given local hydrological parameters for a study site. Modelled soil moisture for the entire Lake Victoria Basin predicted *An. gambiae* biting rates slightly better than the combination of local temperature, precipitation variables and NDVI. These

methods may be particularly useful in regions of Africa where the malaria incidence is highly variable, and where predictive models can optimize control measures.

Diverse topography and soil composition worldwide require better methods for determining surface water availability for mosquito breeding. For example, the effect of rainfall over steep rocky terrain would substantially differ from that of a flat silty area. Soil moisture modelling can account for landuse changes, such as draining of swamps or water development projects for agriculture. Raw or smoothed precipitation data can not account for such changes that could substantially influence mosquito ecology and subsequent malaria transmission. Studies in multiple sites would further test the utility of this type of modelling for use in malaria prediction.

This study also showed statistically significant interspecies differences in response to soil moisture. *An. gambiae* and *An. funestus* are known to have different ecological niches; *An. gambiae* breeds in surplus surface water, whereas *An. funestus* breeds in stagnant water at the edge of rivers (Evans & Garnham 1936). One would therefore expect *An. gambiae* to be more sensitive to soil moisture values and *An. funestus* populations to be less so, excepting very wet conditions that can wash away eggs and larvae from stream edges (Oliver & Grobler 1992). For example, in Senegal *An. funestus* abundance was found to peak during the dry season (Fontenille *et al.* 1997). Furthermore, the change in correlation shown by the different lagging profiles of the two species (maximum strength at 2 weeks for *An. gambiae* and at 4 weeks or longer for *An. funestus*) is consistent with larval development rates observed in the laboratory (J. Beier, unpublished data).

Soil moisture modelling and satellite NDVI nearly equally predicted HBR. Remote sensing has proved useful in the prediction of disease distributions and abundance when their distribution in space and time depends largely on climate and landscape features (Washino & Wood 1994; Hay *et al.* 1997, 1998a). Plant composition and activity in a region reflects and can modify local temperature, precipitation and humidity. Meteorological satellite sensors can measure such climate and vegetation variables directly (Hay *et al.* 1996) and the NDVI has been strongly related to the incidence of severe malaria in three sites in Kenya (Hay *et al.* 1998b) and in The Gambia (Thompson *et al.* 1996; Thompson *et al.* 1997).

Hydrological modelling has some advantages over NDVI, however, in the application to malaria predictions. Firstly, while NDVI is good for observed historical analysis, it cannot be used easily for long-term modelled forecasts, such as general circulation model simulations of climate change. Secondly, daily and weekly modelled soil moisture can be calculated, whereas satellite NDVI is most robust at a monthly timescale and cannot capture weekly variability in

biting rates. The most critical periods to assess surface water for mosquito breeding sites often occur during the rainy season; clouds during these periods can impede acquisition of uninterrupted longitudinal data. A soil moisture model does not have this limitation. Finally, hydrological modelling is relatively inexpensive and may be more practical for use by resident public health scientists who have access to local streamflow and weather data in areas with disease risk.

NDVI has utility in assessing disease risk over remote regions where meteorological data may be unavailable. In such locations, satellite remote sensing can be utilized to determine soil moisture (Washino & Wood 1994); vegetative index and surface temperatures provided by satellite can be used to estimate evapotranspiration. Diurnal temperature difference obtained from satellites has been used as a surrogate for soil moisture to predict prevalence of bancroftian filariasis in the Nile delta (Thompson *et al.* 1996). Remote sensing has been used to predict malaria transmission in several endemic regions (Beck *et al.* 1997).

Warmer sea surface temperatures and variable rainfall patterns accompanying El Niño events also have been correlated with malaria epidemics in many regions of the world (Bouma & van der Kaay 1996), and predictable temporal cycles of malaria incidence have resulted. For example, malaria in Surinam and Venezuela recurred so regularly (on a 5-year cycle) that the term 'paraquinquennial' was coined (Gabaldon 1949). Recent findings by Bouma *et al.* (1997) show such epidemic periodicity to be linked to the cyclical phenomenon of El Niño. This further demonstrates the strong relationship between weather variability and heterogeneity of malaria transmission, and underscores the need for more in-depth studies of climatic factors influencing malaria.

In our study, the strength of the correlation between soil moisture and HBR dropped after the most extreme dry period during the study, and HBR was slow to recover (Figure 4). Possible changes in reporting accuracy were looked for, but none were found. When HBR finally did increase, it sharply rose to the highest biting rate for the entire study period. This finding is consistent with past observations of large epidemics following on the heels of droughts (Gilles 1993). Given the projection of 'more extremes in the hydrologic cycle' as a result of global warming (Karl *et al.* 1995), our findings are especially relevant to the assessment of malaria risk under such conditions. Shorter-term El Niño events offer a natural experiment in extreme climate variability to apply our methods for gaining insight into such long-range climate scenarios.

In the laboratory, ookinete development shortens as temperatures increase from 21 °C to 27 °C, whereas higher temperatures (30 °C to 32 °C) interfere with the developmental processes (Noden *et al.* 1995). Unfortunately,

there was little temperature variability in Kisian and so temperature/SR analysis was limited. In addition, mosquitoes seek microclimates most suitable for their survival (Service 1993). This species-specific natural behaviour may require greater variability in temperatures to see any relationship between SR and ambient temperatures in the field. In African highland areas, temperatures fluctuate more widely. In the typically nonendemic highlands of Kenya (Garnham 1948), Rwanda (Loevinsohn 1994), and Zimbabwe (Freeman & Bradley 1996) increases in ambient temperature and rainfall have been linked to malaria epidemics. Also in Zimbabwe, summer/fall temperatures partially determine the severity of malaria in the following rainy season from December through March (Freeman & Bradley 1996). In the highlands of Ethiopia, the increase in falciparum malaria has strongly correlated with a steady rise in minimum temperatures over a 25-year period (Tulu *et al.* unpublished observation), the study controlled for drug-resistance and population migration. Mathematical models show malaria vectorial capacity increasing, as global temperatures rise from the accumulation of greenhouse gases in the atmosphere (Martens *et al.* 1995; Martin & Lefebvre 1995; Matsuoka & Kai 1995; Bryan *et al.* 1996; Jetten *et al.* 1996).

## Conclusion

The importance of further understanding climate's impact on malaria comes from recent communications by climatologists that the global climate is projected to change substantially over the coming century (Houghton *et al.* 1996). The methods used in our study should improve the assessment of current and past trends in malaria transmission intensity and geographical distribution. Use of physical-based soil moisture models can enhance predictive modelling of malaria, especially considering how different anopheline species respond to rainfall. Also, landuse and landcover subtleties at the local scale can readily be integrated into the models. The predictive power gained from hydrological modelling can ultimately help improve the risk assessment of malaria under near-term weather fluctuations, as well as long-term climate change scenarios.

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