The relative effect of climate variability on malaria incidence after scale-up of interventions in western Kenya: A time-series analysis of monthly incidence data from 2008 to 2019

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ABSTRACT

Background: Despite considerable progress made over the past 20 years in reducing the global burden of malaria, the disease remains a major public health problem and there is concern that climate change might expand suitable areas for transmission. This study investigated the relative effect of climate variability on malaria incidence after scale-up of interventions in western Kenya.
Methods: Bayesian negative binomial models were fitted to monthly malaria incidence data, extracted from records of patients with febrile illnesses visiting the Lwak Mission Hospital between 2008 and 2019. Data pertaining to bed net use and socio-economic status (SES) were obtained from household surveys. Climatic proxy variables obtained from remote sensing were included as covariates in the models. Bayesian variable selection was used to determine the elapsing time between climate suitability and malaria incidence.
Results: Malaria incidence increased by 50% from 2008 to 2010, then declined by 73% until 2015. There was a resurgence of cases after 2016, despite high bed net use. Increase in daytime land surface temperature was associated with a decline in malaria incidence (incidence rate ratio [IRR] = 0.70, 95% Bayesian credible interval [BCI]: 0.59–0.82), while rainfall was associated with increased incidence (IRR = 1.27, 95% BCI: 1.10–1.44). Bed net use was associated with a decline in malaria incidence in children aged 6–59 months (IRR = 0.78, 95% BCI: 0.70–0.87) but

not in older age groups, whereas SES was not associated with malaria incidence in this population.

Conclusions: Variability in climatic factors showed a stronger effect on malaria incidence than bed net use. Bed net use was, however, associated with a reduction in malaria incidence, especially among children aged 6–59 months after adjusting for climate effects. To sustain the downward trend in malaria incidence, this study recommends continued distribution and use of bed nets and consideration of climate-based malaria early warning systems when planning for future control interventions.

1. Introduction

Malaria remains a leading cause of morbidity. Indeed, in 2020, the World Health Organization (WHO) reported 241 million clinical malaria cases globally, an increase from 227 million cases reported in the preceding year (WHO, 2021). An overwhelming majority of the cases (95%) and deaths (96%) occurred in the WHO African region (WHO, 2021). Concerted efforts to reduce malaria in sub-Saharan Africa led to a reduction of morbidity and mortality incidence by 27% and 59% between 2000 and 2020, respectively (WHO, 2021). In Kenya, the incidence of confirmed outpatient malaria cases decreased from 57 to 36 cases per 1000 population between 2013 and 2017 (Ministry of Health - Kenya, 2019a). This reduction in malaria burden has been attributed to scaling-up of malaria control interventions, such as the distribution of insecticide-treated nets (ITNs), indoor residual spraying (IRS), enhanced surveillance, prompt diagnosis and treatment of malaria using effective artemisinin-based combination therapy (ACT) (Ministry of Health - Kenya, 2019b).

Apart from interventions, variability in malaria trends has been associated with changes in climatic conditions, especially in temperature and rainfall patterns, which are the main drivers of malaria transmission (Mordecai et al., 2019; Thomson et al., 2017). Since 1960, the mean annual temperature in Kenya has increased by 1.0 °C with an average rate of 0.21 °C per decade (NEMA, 2015). Global climate models predict that the mean annual temperature will further increase by 0.8–1.5 °C by the 2030s, raising concerns that droughts and floods will occur without clear patterns in the future (NEMA, 2015). Environmental factors, including land cover (Kweka et al., 2016), land use such as farming and deforestation (Babamale et al., 2020; Stefani et al., 2013) and altitude (Baidjoe et al., 2016), have also been previously associated with malaria incidence. Other variables, including socio-economic status (SES), distance to freshwater bodies (Ssempiira et al., 2018), human mobility (Grillet et al., 2019), drug and insecticide resistance (Hay et al., 2002) and urbanization (Padilla et al., 2015) have also been identified as factors that influence malaria transmission.

While earlier studies investigated the relationship between malaria transmission with climate (Kipruto et al., 2017; Sewe et al., 2017; Wardrop et al., 2013) and control interventions (Gimnig et al., 2016; Gimnig et al., 2003) separately, more recent studies have looked at the interplay between these factors with conflicting results. Many of the studies observed relationships between climatic factors (i.e., rainfall and temperature) and malaria incidence (Bennett et al., 2016; Endo et al., 2017; Fletcher et al., 2020; Ssempiira et al., 2018). While Hay and collaborators did not observe any effect of climate, thus attributing the increase in malaria burden to other factors such as drug resistance and changes in land use (Hay et al., 2002), another research group observed that climate change was unlikely to increase the burden of malaria in West Africa (Yamana et al., 2016). The disagreements in these studies may be explained by different methods or variables included in the analyses. Gething et al. observed that while evaluating the effect of changes in climate on malaria burden, it is important to include non-climatic factors such as SES, distance to major freshwater bodies and malaria control interventions for a deeper understanding of the net effect of these changes (Gething et al., 2010). Furthermore, some of the previous studies used data from malaria indicator surveys, which are temporally limited and therefore not able to capture seasonal variation in malaria transmission.

Taken together, there is a paucity of quality, long-term malaria data that include non-climatic factors. There are several health and demographic surveillance systems (HDSS) in Africa that routinely collect data on malaria incidence and mortality, malaria interventions, vector densities and household-related indicators. Longitudinal data collected by such HDSS offer unique opportunities for modelling the spatio-temporal interactions between climatic and non-climatic factors on the burden of malaria. The Kenya Medical Research Institute (KEMRI), in collaboration with the US Centers for Disease Control and Prevention (CDC), runs a HDSS and a population-based infectious disease surveillance (PBIDS) in western Kenya in which several diseases, interventions and socio-economic factors within the population are monitored (Feikin et al., 2011; Odhiambo et al., 2012). Using the monthly malaria incidence, SES and bed net use data from this HDSS and PBIDS, this study investigated the relative effect of climate variability on the burden of malaria in the face of intensified malaria control programmes in western Kenya using a Bayesian modelling approach.

2. Methods

2.1. Study area and population

Since 2005, KEMRI in collaboration with CDC have conducted a PBIDS, which is embedded within the HDSS in Asembo, as previously described (Feikin et al., 2011). In brief, the PBIDS covers approximately 30,000 people residing in 33 villages within an approximate 5 km radius from St. Elizabeth Lwak Mission Hospital (referred to as Lwak Mission Hospital, LMH in short) in Asembo, Rarieda sub-county, Siaya county (Fig. 1). These villages are near Lake Victoria, where malaria is holoendemic with year-round

transmission (Odhiambo et al., 2012). The population is culturally homogeneous with over 95% being members of the Luo tribe and mainly live on subsistence farming and fishing (Hamel et al., 2011). The HDSS estimated life expectancy at birth was 63 years in 2018, with a crude death rate of 8 deaths per 1000 residents (internal reports). Infant and under-five mortality ratios were estimated at 41 and 53 deaths per 1000 live births in 2018, respectively.

2.2. Data sources

2.2.1. Malaria incidence data

This study utilized malaria data collected from LMH between January 2008 and December 2019. Briefly, all patients visiting LMH with symptoms of febrile illness (axillary temperature $\geq$ 37.5 °C or history of fever within the past 24 h) were consented to provide finger prick blood for microscopy to determine whether they had malaria (presence of *Plasmodium* parasites in thick and thin blood films). All patients testing positive were treated using ACT. Monthly malaria incidence was estimated by dividing the monthly number of new malaria cases by the total monthly person-time of follow-up in years (pyo). Malaria incidence was further stratified by the following age categories: All ages >5 months (overall), 6–59 months, 5–14 years and $\geq$ 15 years. Children aged <6 months were excluded from this analysis as malaria is not common in this age group as the young infants are protected through maternal antibodies (D'Alessandro et al., 2012).

2.2.2. SES and bed net use data

During the study period, the HDSS collected socioe-conomic indicators every two years from every household. Using these data, a composite SES index was generated by household and year using multiple correspondence analysis (MCA) as previously described (Amek et al., 2015). Annual average SES index scores were generated for the entire area and the previous year's score applied for the years when SES were not conducted. Existing interventions were evaluated through the PBIDS by estimating the proportion of individuals who reported bed net use during the previous night before the interview, using bi-weekly household visits data collected between January 2008 and April 2015 (Feikin et al., 2011), aggregated by month. Visits to each household were reduced to two in a year thereafter but the data collection instruments remained unchanged. It is important to note that there was mass bed net distribution targeting children aged <5 years and pregnant women in malaria high risk areas of Kenya in 2006 and other mass distributions every 3–4 years since 2011, aimed at achieving universal coverage (i.e., at least one bed net for every two people) (Hightower et al., 2010; Kamau et al., 2017). IRS was last conducted in this study area in the 1970s (Fontaine et al., 1975).

2.2.3. Climatic data

Daytime land surface temperature (LSTD) and nighttime land surface temperature (LSTN) data with a 1×1 km^2 spatial and 8-day
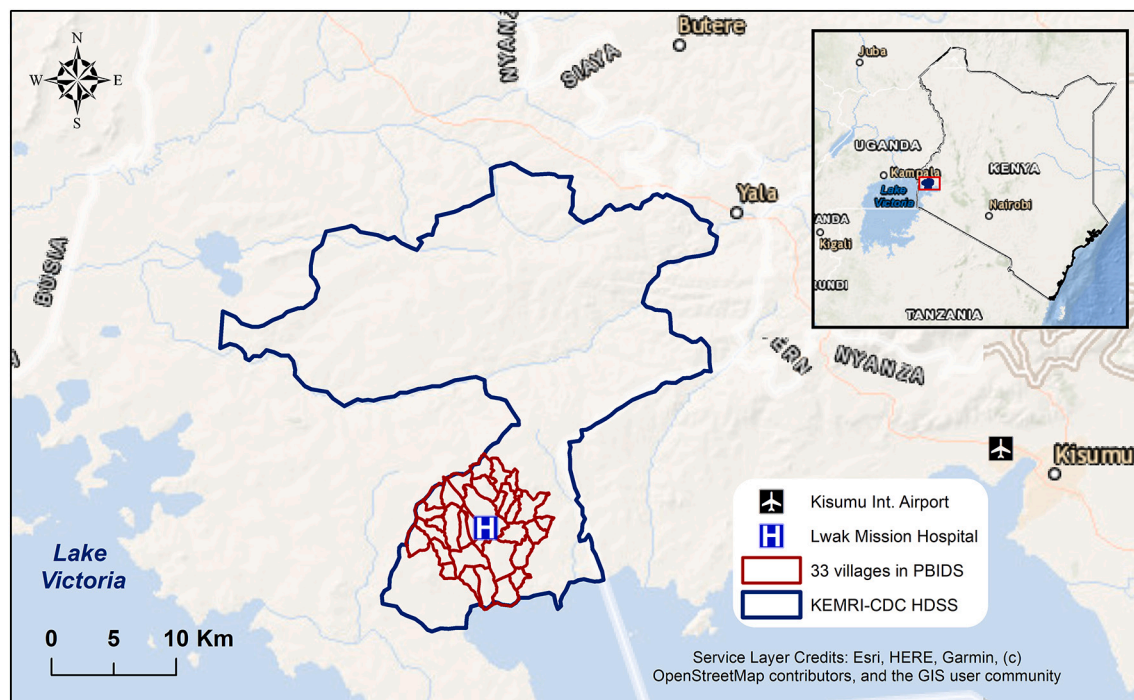

Fig. 1. Map showing the KEMRI-CDC health and demographic surveillance system (HDSS) study area, the location of the 33 villages participating in population-based infectious disease surveillance (PBIDS), the location of Lwak Mission Hospital and the Kisumu international airport.

temporal resolution were extracted from the Moderate Resolution Imaging Spectroradiometer (MODIS) on board NASA's Terra and Aqua satellites (Wan et al., 2015). Rainfall data were obtained from the Climate Hazards Group InfraRED Precipitation with Station data (CHIRPS) at 5.6×5.6 km^2 spatial and 5-day temporal resolutions (Funk et al., 2015). Monthly averages of these climatic factors were calculated at their original scale and then averaged within the area for linkage with the monthly malaria incidence data. Missing LSTN data for a specific month were imputed by averaging the preceding and succeeding 1-month values. To better understand the effect of temperature on malaria incidence, historical and projected daily near-surface air temperature data were extracted from the ERA5-Land (Muñoz Sabater, 2019) and NASA's Earth Exchange Global Daily Downscaled Climate Projections (NEX-GDDP) datasets (Thrasher et al., 2012), respectively. The projections were averaged from Coupled Model Intercomparison Project - Phase 5 (CMIP5) models assuming the historical, rcp45 and rcp85 scenarios. These remote sensing products, reanalysis data and climate projections were used because there was no weather station within the study area during the study period; the closest station was situated approximately 60 km away, at the Kisumu international airport (Fig. 1). Table S1 describes the sources and the spatio-temporal resolution of the data used.

2.3. Statistical analyses

2.3.1. Descriptive analysis

Malaria incidence was calculated at monthly intervals for all ages >5 months (overall) and stratified into three age groups: (i) 6–59 months; (ii) 5–14 years; and (iii) ≥15 years. Time series plots were used to describe the inter- and intra-year variation of malaria incidence by age groups, variation in climatic factors and bed net use. Cubic smoothing B-splines with 5 degrees of freedom (df) were used to highlight the annual trends of changes in climatic factors, bed net use and malaria incidence. Pearson correlation was used to explore bivariate associations between the climatic predictors and malaria incidence.

Considering the elapsing period between climate suitability and the occurrence of malaria cases, time lagged variables were generated for each climatic factor. Eight-time lagged variables were computed corresponding to 1 (lag1), 2 (lag2), 3 (lag3) and 4 (lag4) months before the month of reported cases, as well as cumulative lag times corresponding to the average of the current and the previous 1 (lag01), 2 (lag012), 3 (lag0123) and 4 (lag01234) months. Bayesian variable selection (BVS) using stochastic search was used to identify the most important climatic factors as well as their best lag times. BVS was chosen because it accounts for potential temporal correlation in malaria incidence. Details on the BVS implementation are provided in the Appendix.

2.3.2. Statistical modelling

Bayesian negative binomial models were fitted to estimate the effect of climatic factors and interventions on malaria incidence. Let y_t be the number of malaria cases reported at LMH at month $t = 1, 2, …, 144$ (i.e., 12 months for 12 years). For each age group, it was assumed that y_t followed a negative binomial distribution, $y_t \sim \text{NB}(p_t, r)$, where $p_t = r/(r + \mu_t)$, r is the dispersion parameter, μ_t is the average number of monthly malaria cases, such that:

$$\mu_t = \lambda y_{t-1} + \nu_t, (0 < \lambda < 1, \nu_t > 0);$$

where λy_{t-1} is a first order autoregressive term AR(1), with temporal correlation (λ), accounting for malaria incidence in the previous month (i.e., y_{t-1}) and ν_t is modelled with a log link function defined as:

$$log(\nu_t) = log(P_t) + X_t^T \boldsymbol{\beta}$$

P_t is the offset term corresponding to the total person-years of follow up, $\boldsymbol{\beta}$ is a vector of regression coefficients associated with the matrix of covariates (including climatic factors and interventions) - $\boldsymbol{X}_t$. Normal priors for β with mean 0 and variance of 100, that is $\beta \sim N(0,100)$ and a non-negative uniform prior for λ, that is $\lambda \sim U(0,1)$ given that λ is constrained (>0) were assumed. Markov chain Monte Carlo (MCMC) simulation was used to estimate the model parameters. All the covariates were standardized to reduce the computational time of MCMC and to allow direct comparison of the covariate effects. The parameter estimates are reported as incidence rate ratios (IRR) and are considered to be statistically important when their respective 95% Bayesian credible intervals (BCI) exclude 1. The negative binomial age-specific models were fitted using the Just Another Gibbs Sampler (JAGS) software (Plummer, 2003). Two Markov chains of 300,000 iterations, each with a burn-in of 30,000 iterations were run. Convergence was assessed using density plots, trace plots and the Gelman-Rubin diagnostics (Brooks and Roberts, 1998) implemented in the coda package (Plummer et al., 2006) in R software.

Data management and exploratory analyses were conducted using Stata version 16 (Stata Corp, College Station, Texas, USA) and R version 3.6.3 (Vienna, Austria). The study area map was developed in ESRI's ArcGIS 10.2.1 (https://www.esri.com/en-us/home).

2.4. Ethical considerations

The HDSS and PBIDS study protocols were reviewed and approved by the KEMRI scientific and ethics review unit (SSC #1801 and #2761) and CDC's institutional review board (CDC IRB #3308 and #6775). Written informed consent was obtained from all patients or from their parents/guardians if minors, and from compound heads for the household-based evaluation.

3. Results

3.1. Descriptive analysis

For the period from 2008 to 2019, a total of 71,733 patients visiting LMH with febrile illnesses had malaria. Approximately one third of the cases were aged 6–59 months and 42% were 5–14 years old. Malaria incidence shows a bimodal seasonality, with the first and more pronounced peak during May–July, and the second peak during November–January (Fig. 2a). The highest incidence was observed in children aged 6–59 months (Fig. 2a).

The median (interquartile range - IQR) LSTD, LSTN, air temperature and rainfall were, 32.2 °C (29.5–35.2 °C), 18.3 °C (17.4–19.0 °C), 22.9 °C (22.4–23.5 °C) and 100 mm (64–143 mm), respectively. These climatic factors also depict a bimodal seasonal pattern. Rainfall peaked from March through May with a second peak observed during November (Fig. 2c). Variation in monthly LSTD and LSTN was observed with a decrease in temperature when rainfall increases. Bed net use was highest among children aged 6–59 months, followed by individuals aged ≥15 years and 5–14 years, median (IQR) proportions – 0.96 (0.92–0.98), 0.93 (0.87–0.96) and 0.90 (0.80–0.94), respectively (Fig. 2d).

LSTD declined from an annual average of 33.7 °C in 2009 to 31.9 °C in 2013, then increased steadily to 34.8 °C in 2017 before declining to 31.8 °C in 2019. It is projected that the mean air temperature in this study area will rise, from approximately 24.4 °C to 26.7 °C between 2020 and 2100 (Fig. S1). Future projections from climate models (Thrasher et al., 2012) also suggest an increase in the amount of rainfall in the study area (Fig. S1). A steady rise in the proportion of individuals using bed nets from 0.75 in 2008 to 0.93 in 2012 was observed. Thereafter, >92% of individuals within the HDSS reported using bed nets. The crude incidence of malaria increased from 210 cases per 1000 person-years in 2008 to 358 in 2010 before declining to 99 in 2015. The incidence increased thereafter to 207 cases per 1000 person-years in 2019. Fig. 3 shows smoothed time series plots of the annual trends.

The correlation between lagged monthly averages of LSTD vs. rainfall, and air temperature vs. rainfall was −0.60 and − 0.46, respectively. Correlation between lagged climatic factors and malaria incidence was similar for the three age groups (Table S2). LSTD was negatively correlated with malaria incidence, whereas the correlations between incidence with rainfall were positive, except for rainfall which was significantly negative during the current month. LSTN was not correlated with crude malaria incidence, and hence, was not considered for BVS.
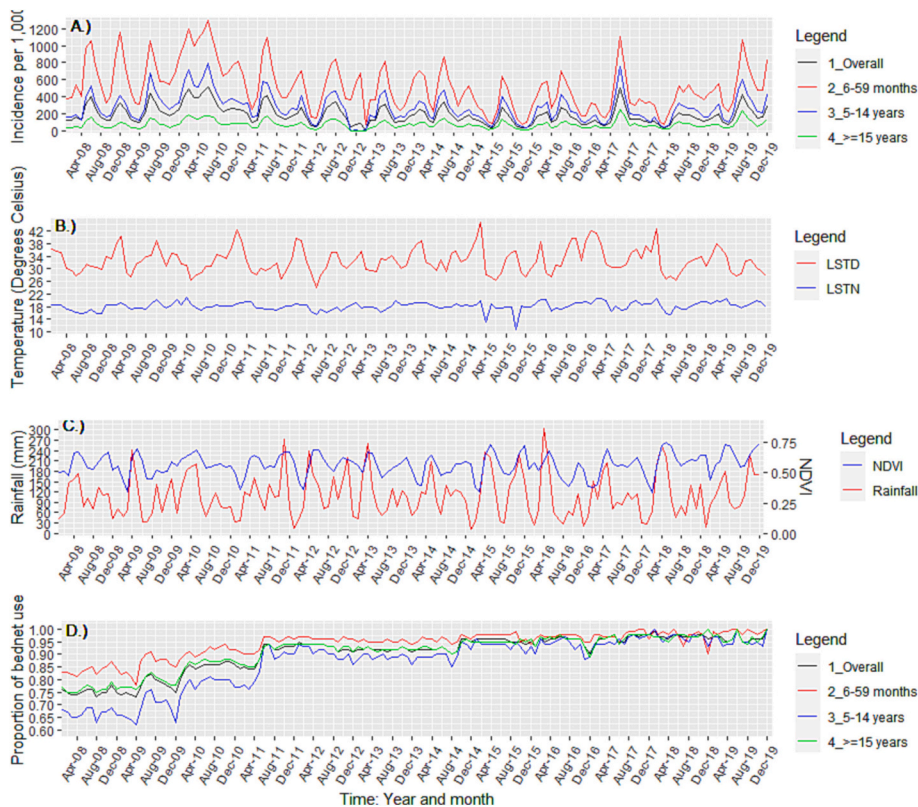

Fig. 2. Monthly time-series (2008–2019) of malaria incidence per 1000 person-years by age groups (A), mean daytime and nighttime land surface temperature (LST) in °C (B), mean rainfall in mm (C) and bed net use (D).
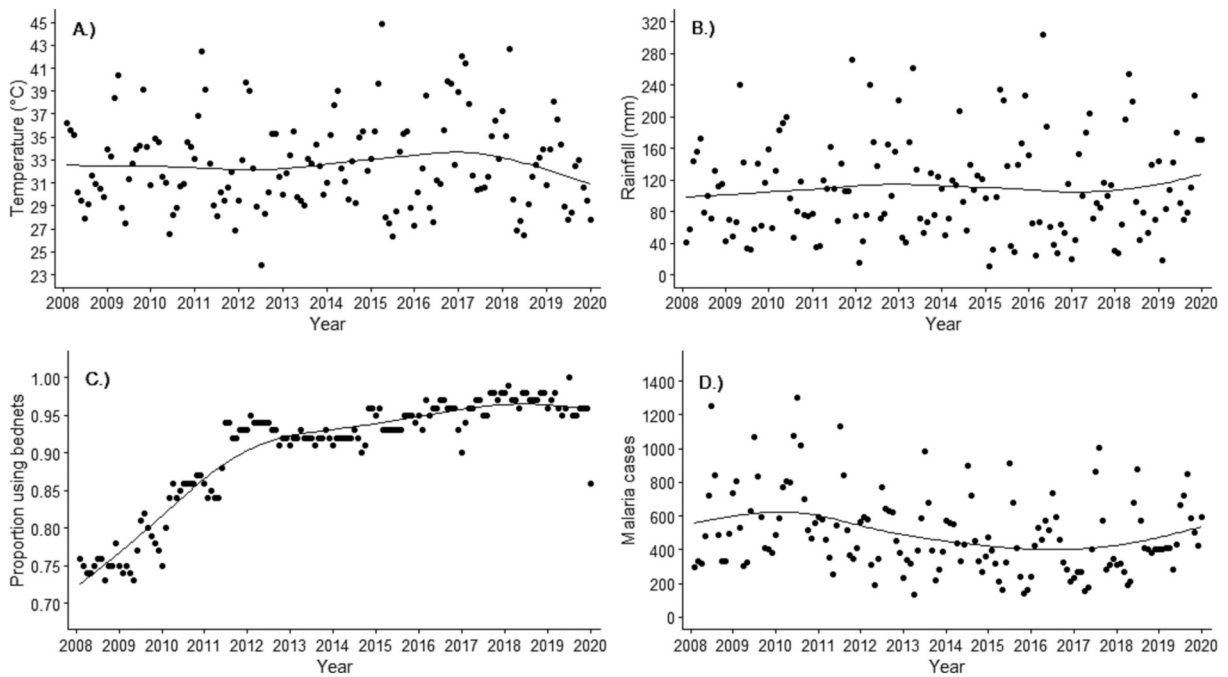
Fig. 3. Time-series showing trends of daytime land surface temprerature (A), rainfall (B), bed net use (C) and modelled trends of malaria cases (D) by year. Cubic smoothing B-splines with 5 degrees of freedom were used to highlight the annual trends.

3.2. Bayesian variable selection (BVS)

Table 1 summarises the posterior inclusion probabilities of climatic factors, showing the lags that fit the malaria incidence data best. Different models were fitted for climatic factors (considering temperature and rainfall pairs) and for different subsets of the data corresponding to different age groups. For example, 71% of the models generated from all lag combinations of LSTD and rainfall included LSTD in the previous 1 month (lag1) and rainfall in the previous 2 months (lag2) when all age data were analysed (Table 1). Similarly, 97% of models from the air temperature and rainfall combination included the previous 1 month (lag1) and previous 2 months (lag2) lags for air temperature and rainfall, respectively.

Table 1

The best three model combinations (by age group) with the highest posterior probabilities as identified by the Bayesian Variable Selection (BVS).

Temperature variable	All ages		6–59 months		5–14 years		≥15 years	
	Covariates	Posterior probability	Covariates	Posterior probability	Covariates	Posterior probability	Covariates	Posterior probability
LSTD								
Combination 1	LSTD_1 + Rain_2	70.91	LSTD_1 + Rain_2	32.73	LSTD_1 + Rain_3	31.19	LSTD_3 + Rain_3	98.20
Combination 2	LSTD_1 + Rain_0123	10.34	LSTD_1 + Rain_0123	19.71	LSTD_1	25.85	LSTD_3	0.10
Combination 3	LSTD_1 + Rain_012	6.50	LSTD_1 + Rain_1	17.15	LSTD_1 + Rain_0	12.90	LSTD_3 + Rain_1	0.75
Air temperature								
Combination 1	AirT_1 + Rain_2	96.88	AirT_1 + Rain_2	45.89	Rain_2	32.48	AirT_3 + Rain_0123	38.34
Combination 2	AirT_0 + Rain_2	1.81	Rain_0123	22.13	AirT_3 + Rain_2	27.52	Rain_0123	21.93
Combination 3	Rain + 2	0.99	AirT_01 + Rain_0123	13.7	AirT_1 + Rain_2	12.25	AirT_01 + Rain_0123	18.45

-LSTD- Daytime land surface temperature.

-AirT- Air temperature.

-LSTD/ AirT/ Rain_1, 2, 3 indicate lags of 1, 2, and 3 months.

-LSTD/ AirT/ Rain_01, 012, 0123 indicate lags averaged over the current and previous 1, 2, and 3 months, respectively.

3.3. The joint effect of climate variability, SES and bed net use on malaria incidence

When modelling the joint effect of LSTD, rainfall, SES and bed net use (Model 1) for all the ages (overall) category, we observed that an increase in LSTD was associated with a decrease in malaria incidence (IRR = 0.70, 95% BCI: 0.59–0.82) and an increase in rainfall was associated with an increase in malaria incidence (IRR = 1.27, 95% BCI: 1.10–1.44) (Table 2). Using a model fitted with actual values of climatic and bed net use (i.e., non-standardized covariates) this study estimated that an increase in LSTD by 1 °C was associated with a 9% decrease in malaria incidence (IRR = 0.91, 95% BCI: 0.86–0.95), an increase in rainfall by 10 mm was associated with a 4% increase in malaria incidence (IRR = 1.00, 95% BCI: 1.00–1.01) and a 100% increase in bed net use was associated with a 19% decline in malaria incidence (IRR = 0.81, 95% BCI: 0.72–0.91). Bed net use was associated with a decrease in malaria incidence (IRR = 0.82, 95% BCI: 0.72–0.91) whereas SES was not statistically important (IRR = 0.98, 95% BCI: 0.87–1.10). Similar observations were made for children aged 6–59 months. However, for children aged 5–14 years, only LSTD was statistically important among these covariates (IRR = 0.82, 95% BCI: 0.72–0.91). Furthermore, LSTD and rainfall were found to be statistically important for individuals aged ≥15 years (IRR = 2.74, 95% BCI: 1.72–4.23) and (IRR = 2.06, 95% BCI: 1.32–3.21), respectively. However, unlike the other age groups, an increase in LSTD was associated with an increase in malaria incidence.

In model 2 which included air temperature, rainfall, SES and bed net use, this study observed that an increase in air temperature was associated with a decrease in malaria incidence (IRR = 0.83, 95% BCI: 0.71–0.96), an increase in rainfall was associated with an increase in malaria incidence (IRR = 1.41, 95% BCI: 1.23–1.61), bed net use was associated with a decrease in malaria incidence (IRR = 0.82, 95% BCI: 0.73–0.93) and that SES was not statistically important (IRR = 0.98, 95% BCI: 0.86–1.11) for all the ages (overall) category (Table 2). Similar observations were made for children aged 6–59 months and 5–14 years, except that air temperature was not selected by BVS for the later age group. For those aged ≥15 years, rainfall and bed net use were associated with increase (IRR = 1.72, 95% BCI: 1.21–2.35) and marginally important decrease (IRR = 0.79, 95% BCI: 0.59–1.01) in malaria incidence, respectively. Air temperature and SES were not statistically important in the ≥15 years age group.

3.4. Seasonal and annual trends of malaria incidence

The posterior median of the model-based expected malaria cases indicate a good agreement with the observed monthly cases, depicting similar seasonal patterns (Fig. 4). Plots by age categories indicate a sustained decline in incidence among children aged 6–59 months, unlike the other two age groups, where malaria incidence depict a similar trend throughout the study period. It was also observed that malaria incidence was on the decline until 2016 but there was a resurgence post-2016 (Fig. 3d).

4. Discussion

This study was able to evaluate the joint effect of climate variability, SES and control interventions on malaria incidence in the study area. Increase in temperature and bed net use were negatively associated with malaria incidence, whereas increase in rainfall when lagged over 2 months was positively associated with malaria incidence. It was further observed that an increase in rainfall and temperature had equal but opposing effects on malaria incidence, especially among children aged 6–59 months, and that both temperature and rainfall had a slightly greater effect on malaria incidence compared to bed net use. The reduction in malaria incidence was greatest among children aged 6–59 months, potentially due to bed net distribution campaigns targeting this group and pregnant

Table 2

Effects (posterior median and 95% Bayesian credible interval [BCI]) of climatic factors, socio-economic status and bed net use on the incidence of malaria in Asembo, 2008–2019.

Characteristics by age categories	All ages	6–59 months	5–14 years	≥15 years
	IRR (95% BCI)	IRR (95% BCI)	IRR (95% BCI)	IRR (95% BCI)
Model 1				
LSTD	0.70 (0.59,0.82)	0.71 (0.61,0.81)	0.54 (0.41,0.67)	2.74 (1.72,4.23)
Rainfall	1.27 (1.10,1.44)	1.23 (1.07,1.38)	0.93 (0.76,1.11)	2.06 (1.32,3.21)
Bed nets[a]	0.81 (0.72,0.91)	0.78 (0.70,0.87)	0.88 (0.71,1.07)	0.77 (0.53,1.05)
Wealth index	0.98 (0.87,1.10)	1.01 (0.91,1.13)	0.92 (0.75,1.11)	0.92 (0.68,1.22)
Temporal correlation (λ)	0.50 (0.39,0.62)	0.50 (0.38,0.62)	0.61 (0.46,0.77)	0.83 (0.70,0.95)
Dispersion (r)	7.41 (5.69,9.21)	9.37 (7.19,11.84)	3.97 (3.05,5.03)	4.38 (3.33,5.63)
DIC	1865.4	1540.6	1703.2	1517.8
Model 2				
Air temperature	0.83 (0.71,0.96)	0.80 (0.69,0.91)		1.25 (0.97,1.57)
Rainfall	1.41 (1.23,1.61)	1.35 (1.19,1.53)	1.57 (1.32,1.83)	1.72 (1.21,2.35)
Bed nets[a]	0.82 (0.73,0.93)	0.79 (0.70,0.89)	0.83 (0.69,0.99)	0.79 (0.59,1.01)
Wealth index	0.98 (0.86,1.11)	1.00 (0.89,1.12)	0.96 (0.80,1.15)	0.90 (0.68,1.17)
Temporal correlation (λ)	0.50 (0.38,0.63)	0.51 (0.39,0.63)	0.57 (0.42,0.72)	0.76 (0.63,0.89)
Dispersion (r)	6.73 (5.16,8.37)	8.54 (6.58,10.83)	3.78 (2.86,4.77)	4.08 (3.07,5.21)
DIC	1879.6	1554.0	1709.0	1527.5

[a] Bed net use modelled on a scale from 0 to 1, thus a unit increase corresponds to 100% increase.
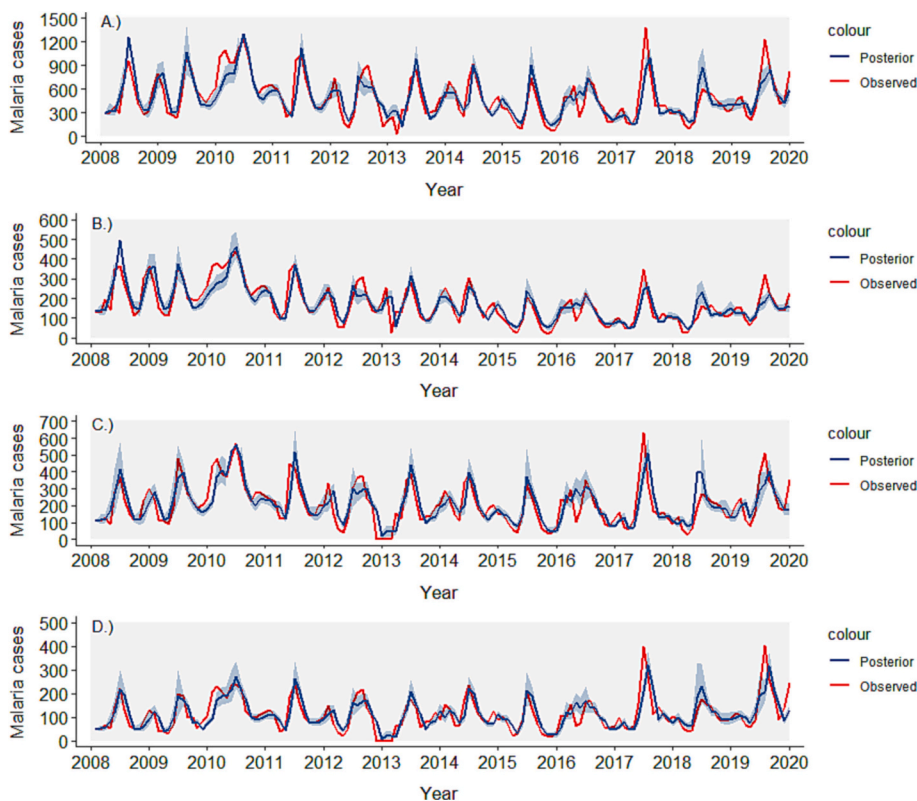
Fig. 4. The observed (red line) and posterior median (blue line) estimates of monthly malaria cases from model 1, in all ages (A), children aged 6–59 months (B), children aged 5–14 years (C) and adolescents and adults aged ≥15 years (D). The blue shaded area represent the 95% Bayesian credible intervals around the posterior median. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

women. These findings suggest that, despite the fact that climatic factors drive malaria incidence in this part of Kenya, mass distribution of bed nets also have an important effect. Moreover, since it is projected that temperature and rainfall amounts will increase in this study area towards the year 2100 and the finding that climatic factors have a larger effect on transmission, model-based malaria early warning systems are important adaptation tools to climate change impacts as they can guide optimising responses and timing of interventions.

A rise in temperature (both LSTD and air) was associated with a decline in malaria cases. This decline in malaria incidence may be associated with a decline in the malaria causing vectors, female *Anopheles* mosquitoes. Previous studies have indicated that mosquitoes thrive within a range of 22–30 °C (Mordecai et al., 2019; Mordecai et al., 2013). Bayoh and Lindsay found that there was a non-linear relationship between temperature and mosquito development; at very low and high (which is the case in this area during the dry seasons) temperatures, adult mosquitoes fail to thrive (Bayoh and Lindsay, 2003). Ssempiira et al. and Sewe et al. observed in studies conducted in Uganda and western Kenya that extreme LSTD had a negative effect on malaria incidence and mortality (Sewe et al., 2016; Ssempiira et al., 2018), similar to findings in this study. In addition, Yamana and colleagues and Ryan et al. made similar observations in West Africa (Ryan et al., 2015; Yamana et al., 2016). This relationship suggests that when only temperature is considered, a warmer climate will result in a reduction in malaria incidence in the lake endemic region, unlike in the western highlands and other epidemic-prone regions of Kenya, where it is projected that the incidence of malaria is likely to increase (Githeko and Ndegwa, 2001).

Unlike in the younger age groups, it was observed that LSTD was positively associated with increase in malaria incidence among individuals aged ≥15 years whereas air temperature did not have an important effect. This is an indication that in older age groups, it may be difficult to capture the effects of climatic factors as they are confounded by other factors, including acquired immunity (Färnert et al., 2015), land use and mobility (Grillet et al., 2019; Kweka et al., 2016).

Rainfall lagged over a 2-month period had a positive effect on the incidence of malaria, especially in the younger age groups. In the same region as this study, Sewe et al. found that rainfall was positively associated with malaria mortality (Sewe et al., 2016). Other studies, including analyses in Sri Lanka (Briët et al., 2008), Uganda (Ssempiira et al., 2018), the Rift Valley-in Kenya (Kipruto et al., 2017) and western Kenya (Chaves et al., 2012) found similar relationship between lagged rainfall and malaria. However, too much rainfall has a negative effect on malaria incidence, this is attributable to washing of mosquito larvae which destabilizes the mosquito reproduction cycle (Briët et al., 2008). Unlike these studies, Ototo and colleagues reported that rainfall was not a significant predictor

of malaria incidence (Ototo, 2020), possibly due to correlation in the predictors (Gregorich et al., 2021; Vatcheva et al., 2016) or differences in analysis methods.

Bed net distribution was scaled-up in the study area and other malaria-endemic areas in Kenya during the period between 2006 and 2014 (Hightower et al., 2010; Kamau et al., 2017). It was observed that an increase in bed net use had an important protective effect, especially during 2013–2015. Similar findings were reported elsewhere (Ng'ang'a et al., 2021). However, an increase in malaria incidence post-2016 was observed, despite high bed net use. A plausible explanation could be the observed decrease in temperature and the slight increase in rainfall during this period. It is also feasible that the efficacy of the bed nets distributed during mass distribution campaigns had waned over time. In the literature, other factors such as changes in mosquito biting patterns with a shift to outdoor biting (Ng'ang'a et al., 2021), waning efficacy of antimalarial drugs (Ndwiga et al., 2021), vector resistance to insecticides (Owuor et al., 2021) or use of torn bed nets (Ochomo et al., 2013) have also been reported and may have contributed to this observation.

Climatic models (Ongoma et al., 2018; Thrasher et al., 2012) predict an increase in both temperature and rainfall in this study area. However, from this study's findings, an increase in temperature is associated with a decline in malaria incidence, while an increase in rainfall is related to an increase in transmission. This would imply that malaria incidence is likely to remain the same given that the effect size of both temperature and rainfall were similar. On the other hand, bed net use-associated reduction in incidence was observed, especially among children aged 6–59 months, indicating that if efforts towards consistent distribution and use of ITNs are sustained and issues around vector and drug resistance addressed, a further reduction of malaria incidence in the future is conceivable.

Other factors such as urbanization, SES, deforestation, altitude and distance to freshwater bodies, all have an effect on malaria incidence, but not all these factors apply to the current setting. This study was conducted in a mainly rural area next to the shores of Lake Victoria with little variability in SES and altitude. The relatively little variability in SES may explain the reason why this study did not observe a meaningful effect of SES on malaria incidence. Close proximity to Lake Victoria and relatively high temperatures might explain year-round transmission of malaria (Ssempiira et al., 2018). The area is characterized by few trees and shrubs throughout, therefore this study could not assess the impact of land cover changes which may be impactful in other regions.

This study has several limitations that are offered for consideration. The study did not evaluate the effects of other malaria interventions such as ACT use, IRS and intermittent preventive treatment of malaria in pregnancy (IPTp). It has been shown that ACT contribute to a reduction in the gametocyte loads in infected individuals (John et al., 2009), and therefore it is associated with a reduction in transmission (Ssempiira et al., 2018). IRS reduces indoor vector density (John et al., 2009) while IPTp prevents malaria during pregnancy. However, in this setting all patients diagnosed with malaria were offered ACT, and hence, no variation in ACT use during the study period and IRS was not employed during the study period while IPTp data was not available. The study did not adjust for the potential impact of community case management initiated in 2013. However, two recent studies evaluating the impact of intermittent mass testing and treatment in the western Kenya HDSS observed that the incidence and prevalence of malaria was similar for the intervention and control arms of the study (Desai et al., 2020; Samuels et al., 2021), implying that exclusion of case management from our analysis may not bias our findings.

5. Conclusion

This study provides evidence that variability in temperature and rainfall play important roles in the dynamics of malaria, despite high bed net use in this part of Kenya. The observation that the effect of temperature and rainfall is similar but in opposing directions and slightly more pronounced than that of bed net use suggests that in the face of climate change, model-based malaria early warning systems could help in optimising the timing and mix of control interventions.

Author contributions

BON and PV conceived the study. All authors contributed to the study design and implementation. BON and PV analysed and interpreted the data. AB supported data analysis. BON drafted the manuscript. All authors critically reviewed the manuscript for its intellectual content and approved the final version prior to submission.

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Disclaimer

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Declaration of Competing Interest

None.

Date availability

The PBIDS and HDSS data can be accessed by contacting gbigogo@kemri.go.ke, dobor@kemri.go.ke or munga_os@yahoo.com.

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Appendix A. Bayesian variable selection

To select the best lags for the climatic variables while accounting for temporal correlation, Bayesian variable selection (BVS) using stochastic search (Chammartin et al., 2013) was implemented considering the joint effect of temperature, rainfall, SES and bed net use. Covariates were standardized to reduce the Markov chain Monte Carlo (MCMC) simulation computational time and to achieve better correlation properties between the predictors and malaria incidence (Kuo and Mallick, 1998). For the lagged climatic predictors X_p, a categorical variable was created with ten values where $I_p = 1$ represents exclusion of the variable from the model and $I_p = 2$ represents inclusion of the variable in the current month (lag0). $I_p = j$ where $j = 3,4,5,6$ represents inclusion of the lagged variables over the previous 1 (lag1), 2 (lag2), 3 (lag3) and 4 (lag4) months and $j = 7,8,9,10$ represents the inclusion of the lagged variables averaged over the current and previous 1 (lag01), 2 (lag012), 3 (lag0123) and 4 (lag01234) months, respectively. A non-informative Dirichlet distribution with $\alpha = (1,1,1,1,1,1,1,1,1,1)^T$ was used for the indicators of the lagged climatic variables. For estimation of the corresponding β_p, a spike and slab prior distribution $\beta_p \sim (1 - I_p)N(0,\vartheta_0\tau_p^2) + I_pN(0, \tau_p^2)$ assuming a non-informative prior for β_p when X_p is included in the model (slab) and an informative normal prior with a huge variance $\vartheta_0 = 10^6$ shrinking β_p to zero (spike) if X_p is excluded from the model. Inverse Gamma priors were assumed for the precision hyper parameter τ_p^2. Temperature and rainfall variables with the highest inclusion probabilities were deemed the most important thus used in the modelling. Models were run in JAGS and parameters estimated using two Markov chains with 300,000 iterations each and a burn-in of 30,000 iterations.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.parepi.2023.e00297.

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