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Forecasting the Potential Effects of Climate Change on Malaria in the Lake Victoria Basin Using Regionalized Climate Projections

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Abstract
Background Malaria epidemics are increasing in East Africa since the 1980s, coincident with rising temperature and widening climate variability. A projected 1–3.5 °C rise in average global temperatures by 2100 could exacerbate the epidemics by modifying disease transmission thresholds. Future malaria scenarios for the Lake Victoria Basin (LVB) are quantified for projected climate scenarios spanning 2006–2100.

Methods Regression relationships are established between historical (1995–2010) clinical malaria and anaemia cases and rainfall and temperature for four East African malaria hotspots. The vector autoregressive moving average processes model, VARMAX (p,q,s), is then used to forecast malaria and anaemia responses to rainfall and temperatures projected with an ensemble of eight General Circulation Models (GCMs) for climate change scenarios defined by three Representative Concentration Pathways (RCPs 2.6, 4.5 and 8.5).

Results Maximum temperatures in the long rainy (March–May) and dry (June–September) seasons will likely increase by over 2.0 °C by 2070, relative to 1971–2000, under RCPs 4.5 and 8.5. Minimum temperatures (June–September) will likely increase by over 1.5–3.0 °C under RCPs 2.6, 4.5 and 8.5. The short rains (OND) will likely increase more than the long rains (MAM) by the 2050s and 2070s under RCPs 4.5 and 8.5. Historical malaria cases are positively and linearly related to the 3–6-month running means of monthly rainfall and maximum temperature. Marked variation characterizes the patterns projected for each of the three scenarios across the eight General Circulation Models, reaffirming the importance of using an ensemble of models for projections.

Conclusions The short rains (OND), wet season (MAM) temperatures and clinical malaria cases will likely increase in the Lake Victoria Basin. Climate change adaptation and mitigation strategies, including malaria control interventions could reduce the projected epidemics and cases. Interventions should reduce emerging risks, human vulnerability and environmental suitability for malaria transmission.

Keywords Climate change · Malaria · Regionalized climate projections

Introduction
Malaria is a major health concern in large parts of the world. Roughly half of the world’s population is at risk of malaria [1]. Within Africa, one in every five (20%) childhood deaths are due to the effects of the disease. In East Africa, the probability of malaria deaths is high, but all the East African Community (EAC) Partner States are still at the level of control, and achieving elimination will likely be impeded by widening climatic variability and change. Due to scale up of malaria prevention measures, malaria prevalence has declined significantly in the EAC region since the 2000s [1]. However, since the 1980s, malaria epidemics have been increasing in the East African highlands. This trend has been attributed to climatic variability and change, antimalarial drug resistance, land use change, vector migration [2, 3] and epidemiology of the disease.

The epidemiology of the vector borne disease is largely influenced by climate variability and change as evidenced by recent outbreaks and disease patterns [4]. Notably, both malaria parasites and vectors are highly sensitive to changes in rainfall, humidity, air and water temperatures [5]. Rising
temperatures shorten the sporogonic cycle of the parasites and accelerate the vector growth and development [6]. Malaria transmission threshold is 18 °C [7] but 20.8 °C is the optimal global temperature at which malaria mortality increases for all ages [8]. It follows that the projected increase in annual global temperatures by up to 3.5 °C by 2100 will likely elevate both malaria transmission and mortality [9, 10].

Temperature is an important predictor of malaria transmission in different regions [6, 11]. Consequently, future scenarios of malaria risk under changing climatic conditions have been explored using multiple modelling approaches [12]. Results of these models suggest that due to precipitation and temperature changes, the geographical distribution of malaria in Africa will likely change by 2100 [13]. The anticipated changes differ markedly geographically. Thus, by 2050 and 2080, for example, some regions will become more suitable, whereas others, such as southern central Africa, may become unsuitable for malaria transmission [14].

Similarly, because of climate change, changes can be expected in the distribution, range, prevalence, incidence and seasonality of vector borne and waterborne diseases in East Africa. However, the nature and magnitude of the anticipated future changes in the Lake Victoria Basin have not yet been quantified. Lake Victoria basin has a high poverty index and poor health infrastructure and hence its residents are exposed to a high risk of being affected by these diseases [15]. Climatic extremes, such as the El Niño-Southern Oscillation and Indian Dipole events, can be expected to increase the frequency and intensity of disease outbreaks based on historic patterns [16, 17]. The projected future climate change and variability under various scenarios and the anticipated effects of these changes on the pattern and intensity of disease outbreaks should thus form the basis for developing effective and far-sighted control methods and policies.

We examined future malaria scenarios for the Lake Victoria Basin in East Africa in response to climate variability based on projected climate scenarios for 2006–2100 defined by the Representative Concentration Pathways (RCPs) RCP2.6, RCP4.5, and RCP8.5.

**Materials and Methods**

**Study Area**

Malaria transmission hotspots in the Lake Victoria Basin were chosen based on the following characteristics: (1) highland regions at altitudes exceeding 1500 m; (2) rainfall during the wet season months of March to May exceeding 150 mm; (3) minimum temperature of 18 °C, the temperature threshold that determines malaria vector breeding sites; and (4) occurrence of infective vectors which can be measured by calculating entomological inoculation rate (EIR), and have clusters of clinical malaria episodes [7, 18]. Based on geospatial data on rainfall, temperature,
altitude and slopes, a hot spot map was derived (Fig. 1). We selected four hotspot sites with long-term clinical malaria data, comprising Muleba (Tanzania), Kericho and Mukumu (Kenya) and all hospitals, including at Kabale, in Uganda. Anaemia was also considered for Muleba in Tanzania (Table 1).

**Data and Analysis**

**Historical Rainfall and Temperature Data**

We used the historical rainfall data based on the gridded observation/satellite blended Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS). CHIRPS is a 30+ year quasi-global rainfall dataset that starts in 1981. The temperature data were downloaded from the Climate Hazards Group website (http://chg.geog.ucsb.edu/tools/geoclim/index.html) and covered the period 1995–2010. The GeoCLIM software tool was used to extract the rainfall and temperature data for each of the study sites. Details of the GeoCLIM tool can be found at http://chg-wiki.geog.ucsb.edu/wiki/GeoCLIM.

**Projected Climate Data**

Climate change analysis and projections were based on the regional downscaled climate model. The downsampling is performed using multiple regional climate models (RCMs) as well as statistical downsampling (SD) techniques. We used the simulated data from the Rossby Center Regional Atmospheric Model (RCA4) driven by the Earth system version of the Max Planck Institute for Meteorology (MPI-ESM-LR) coupled with the global climate model from the Coordinated Regional Downscaling Experiment (CORDEX) program [19]. This was supplemented with simulated data from seven additional General Circulation Models (GCMs).

The regional climate models (RCMs) work at finer spatial resolutions over limited geographic regions and are presumed to perform better at regional scales. The eight RCMs from the Coordinated Regional Climate Downscaling Experiment program (CORDEX) that we used in the analyses were sourced from the Swedish Meteorological and Hydrologic Institute (SMHI), Koninklijk Nederlands Meteorologisch Instituut (KNMI) and Max Plank Institute (MPI) Climate Service Centre (CSC) at ~ 50 km spatial resolution. The data were downsampled by the Rossby Centre regional climate model-RCA4 model and Climate Model Intercomparison Project (CMIP5). The GCM’s and RCMs we considered, their names and associated references are summarized in Table 2.

Three climate change scenarios were used to project rainfall and temperatures. These correspond with three Representative Concentration Pathways (RCPs) RCP2.6, RCP4.5, and RCP8.5, with the numeric suffixes referencing radiative forcings (global energy imbalances), measured in watts/m², by the year 2100. The three Representative Concentration Pathways give various possibilities of rainfall and temperature changes based on global initiatives to limit gaseous emissions. RCP 2.6 represents an optimistic projection characterized by a very low concentration and emission levels of greenhouse gases. RCP 4.5 scenario represents medium emission scenario in which the international communities are working on limiting emissions with limited implementation of climate change policies. RCP 8.5 scenario represents a pessimistic projection with high levels of concentrations of gases emitted and assumes no implementation of climate change policies [20].

The projected rainfall and temperature changes were analyzed for the three scenarios for the five countries bordering Lake Victoria for the 2030s (2016–2045), 2050s (2036–2065) and 2070s (2055–2085) to provide information on the expected magnitude of the climate changes over each time window [21]. The period 1971–2000 is considered as a reference for the present climate (Figs. 2, 3). The
projected climate change signals for each time window are calculated as the difference between the projection for the future time window and the reference period. Rainfall in the LVB is divided into three distinct seasons, the main long rains (March–April–May (MAM), short rains (October–November–December (OND) and the long dry season (June–July–August–September (JJAS). We also consider the annual rainfall, the total cumulative rainfall from January to December.

**Statistical Analysis and Forecasting**

Monthly malaria data from selected sites from three countries, Kenya, Uganda and Tanzania, and spanning the period 1995–2010 were used to develop regression relationships with historic rainfall and temperature data. The established regression relationships were then used with projected rainfall and temperature data from eight Global Circulation Models provided by the Intergovernmental Authority on Development (IGAD) Climate Prediction and Applications Centre (ICPAC) for the period 2006–2100 for each of the three scenarios. The relationships between malaria incidences and cases and historic rainfall or temperature were carefully statistically modelled. This involved relating the incidences or cases to various lagged values and cumulative moving averages of rainfall, minimum and maximum temperatures using the Pearson product moment correlation that assumes bivariate normality of the two variables being correlated and linearity of the relationship between them. The Spearman rank correlation, which is more appropriate if the relationship between two variables is nonlinear and monotonically increasing or decreasing was also computed. Lastly, the Akaike information criterion (AIC) and its corrected variant, the corrected Akaike information criterion (AICc) [22], were computed to rank contending models (linear and nonlinear regression models) in terms of the weight of evidence in support of each. The best AICc-supported models and rainfall or temperature components from the preceding step were then used to build final regression models. These were then used to estimate the associated intercept and slope coefficients and their standard errors and assess statistical significance of the parameter estimates.

The VARMARX \((p,q,s)\) model used for forecasting can accommodate the following features. (1) Modelling of several time series simultaneously (vector). (2) Accounting for relationships among the individual component series with current and past values of the other series \((X)\). (3) Feedback from the response series and cross-correlated explanatory series. (4) Cointegration of component series to achieve stationarity. (5) Autoregressive errors (of order \(p\)). (6) Moving average errors (of order \(q\)). (7) Distributed lags in the explanatory series (of order \(s\)). (8) Seasonality. (9) Mixed autoregressive and moving average errors. (10) Unequal or heteroscedastic covariances for the residuals using various
Fig. 2  a Projected rainfall changes over EAC by 2030s in the annual (1st column), MAM (2nd column), JJAS (3rd column), and OND (4th column) components. Each row corresponds to emission scenarios: RCP2.6 (1st row), RCP4.5 (2nd row) and RCP8.5 (3rd row). b Projected rainfall changes over EAC by 2050s in the annual (1st column), MAM (2nd column), JJAS (3rd column), and OND (4th column) components. Each row corresponds to emission scenarios: RCP2.6 (1st row), RCP4.5 (2nd row) and RCP8.5 (3rd row)
Fig. 3  a  Projected maximum temperature changes over EAC by 2030s in the annual (1st column), MAM (2nd column), JJAS (3rd column), and OND (4th column) components. Each row corresponds to emission scenarios: RCP2.6 (1st row), RCP4.5 (2nd row) and RCP8.5 (3rd row).

b Projected maximum temperature changes over EAC by 2050s in the annual (1st column), MAM (2nd column), JJAS (3rd column), and OND (4th column) components. Each row corresponds to emission scenarios: RCP2.6 (1st row), RCP4.5 (2nd row) and RCP8.5 (3rd row).

c Projected minimum temperature changes over EAC by 2030s in the annual (1st column), MAM (2nd column), JJAS (3rd column), and OND (4th column) components. Each row corresponds to emission scenarios: RCP2.6 (1st row), RCP4.5 (2nd row) and RCP8.5 (3rd row).

d Projected minimum temperature changes over EAC by 2050s in the annual (1st column), MAM (2nd column), JJAS (3rd column), and OND (4th column) components. Each row corresponds to emission scenarios: RCP2.6 (1st row), RCP4.5 (2nd row) and RCP8.5 (3rd row).
Fig. 3 (continued)

generalized autoregressive conditional heteroscedasticity (GARCH) models [23]. (11) The modelling framework used also allows for testing the dependence of one response series on another (testing for weak exogeneity). (12) Moreover, under certain special regularity conditions, the model allows for testing for Granger causality between two specified...
groups of variables. For example, the Granger causality test may be used by defining one group consisting of the response series and the other of climatic predictor series. (13) Lastly, the modelling framework allows for putting various restrictions on the estimated parameter coefficients of the model or their linear combinations and testing hypotheses on linear combinations of the parameter coefficients.

The second model used for forecasting the response series is the unobserved components model (UCMs). This model was only used for those response series that were nonlinearly related to one of the explanatory series. The UCM is a structural time series model and a special case of the general state space model, appropriate for modelling and forecasting time series. The UCM model can accommodate non-linear relationships between the response and the explanatory series. Nonlinearity was modelled using penalized cubic basis splines, or equivalently, random regression or varying coefficients regression models. In addition, the UCM used can accommodate autoregression, seasonality, multiple cyclical patterns, dynamic level shifts, dynamic trend and other features. The UCMs can thus also be viewed as dynamic regression models with multiple predictors. The UCM can provide smoothed trend and cyclical patterns. For more complex univariate or multivariate models that cannot be handled by the UCM, the general state space model, which is much more general and versatile than the UCM and can accommodate more general univariate models and multivariate time series, among other features, can be used for forecasting [23–26].

More detailed descriptions of the statistical modelling and forecasting methodology are provided in SI 1–9. The historic data and the future forecasts under the three emission scenarios for the ensemble of eight projection models are provided in SI 2–4 and in S1–S3 data. SI 10 provides the SAS program codes used to fit the forecasting models and produce plots of the forecast trajectories.

Results

For brevity, we summarize here only the projected rainfall and temperature data simulated by the Rossby Center Regional Atmospheric Model driven by the Earth system version of the Max Planck Institute for Meteorology (Model 1 in Table 2) coupled with the global climate model from the
Fig. 5  Projected changes in minimum temperature in LVB between 2006 and 2070s

Table 3  Projected mean annual maximum temperature changes in LVB for the periods 2030s, 2050s, and 2070s for RCP2.6, 4.5 and 8.5
Coordinated Regional Downscaling Experiment (CORDEX) program. Additionally, we present the projected trajectories of malaria and anaemia cases for the ensemble of eight models and the associated historic series.

**Projected Temperatures Change in LVB**

The maximum temperature is projected to increase by at least 1.5 °C by 2050s in the rainy season months of March–May (MAM) under all the three scenarios across all the countries in the Lake Victoria Basin. Notably, the maximum temperature during MAM is expected to rise by up to 3.76 °C by 2050s under RCP 8.5. The highest extent of warming under all the scenarios is projected for the dry season months of June–September. During the dry season, maximum temperatures will likely rise by 1.5 °C under RCP 2.6 in 2030s and by up to 4.33 °C in 2070s under RCP 8.5. Maximum temperature warming in the short rainy season (October–December) is projected to be up to 2.7 °C under RCP 8.5 but to be minimal for all the other scenarios and time windows (Figs. 4, 5) (Table 3).

The projected changes in the minimum temperatures through time for the three scenarios (Table 4) suggest a larger increase in the minimum than the maximum temperature component in future. By 2030, almost all the EAC region will likely be 1.0–2.5 °C warmer than the base period, with the greatest warming expected during the dry season months (JJAS). JJAS is projected to have the highest increase in minimum temperatures, above 1.5 °C under RCP 2.6, above 2.5 °C in RCP 4.5 and above 3.0 °C in RCP 8.5. In the rainy season months of MAM and OND, RCP 4.5 and RCP 8.5 scenarios are projected to have higher increases in minimum temperatures than the other scenarios.

### Table 4

Projected mean annual minimum temperature changes in the Lake Victoria Basin for the periods 2030s, 2050s, and 2070s for RCPs 2.6, 4.5 and 8.5

|          | RCP2.6     | RCP4.5     | RCP8.5     |
|----------|------------|------------|------------|
|          | 2030s  | 2050s  | 2070s | 2030s  | 2050s  | 2070s | 2030s  | 2050s  | 2070s |
| Annual   |         |        |        |         |        |        |         |        |        |
| Burundi  | 1.39    | 1.66   | 1.59   | 1.65    | 2.28   | 2.61   | 1.81    | 2.96   | 4.39   |
| Kenya    | 1.27    | 1.49   | 1.37   | 1.35    | 1.95   | 2.25   | 1.57    | 2.57   | 3.80   |
| Rwanda   | 1.49    | 1.74   | 1.61   | 1.70    | 2.38   | 2.80   | 1.90    | 3.09   | 4.58   |
| Uganda   | 1.33    | 1.57   | 1.44   | 1.48    | 2.11   | 2.51   | 1.72    | 2.80   | 4.13   |
| Tanzania | 1.26    | 1.49   | 1.39   | 1.37    | 1.95   | 2.28   | 1.59    | 2.58   | 3.86   |
| MAM      |         |        |        |         |        |        |         |        |        |
| Burundi  | 1.27    | 1.54   | 1.51   | 1.48    | 2.05   | 2.40   | 1.73    | 2.67   | 4.10   |
| Kenya    | 1.11    | 1.37   | 1.26   | 1.22    | 1.77   | 2.08   | 1.51    | 2.36   | 3.52   |
| Rwanda   | 1.26    | 1.57   | 1.55   | 1.46    | 2.11   | 2.56   | 1.77    | 2.76   | 4.27   |
| Uganda   | 1.17    | 1.44   | 1.32   | 1.27    | 1.89   | 2.27   | 1.61    | 2.52   | 3.81   |
| Tanzania | 1.15    | 1.39   | 1.31   | 1.19    | 1.73   | 2.07   | 1.51    | 2.34   | 3.57   |
| JJAS     |         |        |        |         |        |        |         |        |        |
| Burundi  | 1.63    | 1.88   | 1.73   | 1.95    | 2.56   | 2.89   | 2.01    | 3.38   | 4.87   |
| Kenya    | 1.48    | 1.68   | 1.59   | 1.63    | 2.26   | 2.59   | 1.79    | 2.91   | 4.31   |
| Rwanda   | 1.66    | 1.82   | 1.60   | 1.91    | 2.57   | 2.94   | 1.99    | 3.38   | 4.91   |
| Uganda   | 1.52    | 1.73   | 1.58   | 1.78    | 2.45   | 2.84   | 1.92    | 3.21   | 4.70   |
| Tanzania | 1.48    | 1.71   | 1.58   | 1.69    | 2.28   | 2.65   | 1.81    | 2.98   | 4.45   |
| OND      |         |        |        |         |        |        |         |        |        |
| Burundi  | 1.24    | 1.60   | 1.60   | 1.44    | 2.20   | 2.52   | 1.58    | 2.74   | 4.11   |
| Kenya    | 1.04    | 1.27   | 1.15   | 1.05    | 1.69   | 2.03   | 1.28    | 2.26   | 3.28   |
| Rwanda   | 1.45    | 1.80   | 1.69   | 1.56    | 2.37   | 2.78   | 1.75    | 2.99   | 4.41   |
| Uganda   | 1.21    | 1.34   | 1.34   | 1.24    | 1.90   | 2.30   | 1.52    | 2.58   | 3.74   |
| Tanzania | 1.09    | 1.30   | 1.30   | 1.16    | 1.78   | 2.09   | 1.36    | 2.36   | 3.46   |
to have an increase in minimum temperatures of above 2.0 °C. By 2070, the projected increase in the annual minimum temperatures will likely be 4–5 °C higher under the RCP 8.5 scenarios relative to the base period (Table 4).

Projected Rainfall Changes in LVB

Rainfall projections vary across the five LVB countries both spatially and temporally. In general, the OND short rains will likely increase compared to the long rains falling in MAM for all the three RCPs (Fig. 6). The JJAS season will likely be much drier for RCP 2.6 compared to RCP 4.5 and RCP 8.5 for all the periods. The increase in rainfall during OND, especially under RCP 4.5 and RCP 8.5 for the periods 2050s and 2070s, makes a large contribution to the anticipated increase in the annual rainfall in the LVB especially on its eastern section.

Relationship Between Malaria and Historical Climate Fluctuations

Extreme rainfall events reported in Kenya in 1997–1998 were related to the upsurge of malaria cases in Central Unilever, Litein and Mukumu hospitals (SI 11). We established linear relationships between malaria incidences and rainfall and 4-month running means of the total monthly rainfall in Unilever and Mukumu hospitals. These relationships suggest that malaria incidences increase linearly with increase in the 4-month running mean of the total monthly rainfall. In contrast, malaria incidences in Litein hospital increased linearly with increase in the 6-month running mean of the average monthly maximum temperature (Fig. 7, Table 5).

Data from Tanzania showed that the 1997–1998 El Niño episode, one of the strongest on instrumental record, was associated with a pronounced upsurge in reported malaria incidences. The analyses show that more malaria cases were reported in Muleba for all ages and 5-year-olds and above during 1997–1998 than for any other year, providing direct evidence that high rainfall is associated with increased malaria incidences (SI 12). Higher incidences of anaemia in the under-fives were also reported for that period than for the other years. Anaemia cases are related to malaria infections (SI 13).

Further, statistical analyses of the data from Muleba hospital established positive and significant correlations and regression relationships between malaria incidence and the...
4–5-month running means of the total monthly rainfall and 3–5-month running means of the average monthly maximum temperature (Fig. 8). This suggests that upsurges in malaria cases will likely not occur immediately after high rainfall or maximum temperature events but rather will also respond to the carry-over effects of prior rainfall conditions experienced up to 4 months earlier. This delayed or lagged effect of rainfall on malaria cases reflects a delayed response linked to the vector life cycle and disease transmission cycle (Table 6).

Country-wide data on malaria cases in Uganda spanning 1997–2010 show that far more children aged 5 years and above were affected than children below 5 years of age (SI 14). The trends for both age classes demonstrate a persistent decline in the number of cases following the 1997–1998 El Niño floods up to a low in 2003 followed by a persistent rise in the number of cases thereafter. It seems likely that a high investment in prevention measures, such as use of nets, following the 1997–1998 rains had a positive effect for both age classes but this was not maintained after about 5 years hence compromising the overall benefits of the measures. Figure 9 shows a significant regression relationship between malaria cases and the 5-month running mean of the average monthly minimum temperature.

The relationship shows that malaria cases recorded in the various districts of Uganda increased with either increasing minimum temperatures or rainfall depending on age class. Thus, malaria cases increased with increasing rainfall for the under-five age group, but increased with increase in the 5-month moving average of the minimum temperature for the 5 years and above age group (Fig. 9, Table 7, SI 14).

Malaria Projections for the Kenyan Section of the LVB over 2006–2100

The transmission of the malaria parasite in Central Unilever and Litein Missionary hospitals showed strong quasi-cyclic fluctuations in all the three scenarios, with evidently time varying amplitudes and phases. Moreover, there were evident variations in the timings and amplitudes of the oscillations across the eight different GCM trajectories but no apparent temporal trend in the projected malaria or anaemia cases. Historical cases in Litein Missionary Hospital responded to changes in temperature. In Mukumu, the

![Fig. 7](image)

**Fig. 7** Regression relationships between the 6-month moving average of the average monthly maximum temperature and reported malaria cases in Litein hospital located in Kericho and the 4-month moving average of the total monthly rainfall and reported malaria cases in Central Unilever hospital located in Kericho and Mukumu hospital in Kakamega in Kenya

| Table 5 | Results of the linear regression of malaria cases on running means of rainfall and temperature for three hospitals in Kenya |
|---------|------------------------------------------------------------------------------------------------------------------|
| Hospital | Effect | Estimate | SE | df | T  | $P > |T|$ |
| Litein Missionary Hospital, Kericho | Intercept | −1628.3929 | 737.6111 | 82 | −2.208 | 0.030062 |
| | Mavmaxtemp6 | 67.9544 | 22.5784 | 82 | 3.010 | 0.003474 |
| Mukumu Hospital, Kakamega | Intercept | 25.2664 | 106.4551 | 143 | 0.237 | 0.81273 |
| | Mavrain4 | 4.0528 | 0.9025 | 143 | 4.491 | 1.45 × 10−5 |
| Central Unilever Tea Hospital, Kericho | Intercept | −9.0479 | 32.4533 | 129 | −0.279 | 0.780847 |
| | Mavrain4 | 1.0193 | 0.2781 | 129 | 3.666 | 0.000359 |

A numeric suffix in rainfall or temperature component name denotes the time window in months over which the running average was computed.
trajectory of the projected transmission portrays an increase in transmission, implying more cases can be expected in the future, especially under the RCP 4.5 and RCP 8.5 scenarios (Figs. 10, 11, 12, 13, SI 15–18). Under RCP 8.5, the observed cases were high in 1995–2007, the period when the 1997–1998 El Niño was experienced. During the 2008–2030 period, malaria cases will likely be reduced due to the efforts of integrated malaria control that are currently underway. There will likely be a marked variability in both the incidence and prevalence of malaria cases under the three scenarios in the future. In the worst-case scenario (RCP 8.5), malaria cases are projected to increase (Figs. 10, 11, 12, 13). The RCP 8.5 scenario shows that there will likely be a steady increase in the mean malaria cases reported at the hospitals over time as a result of the anticipated widening variability in rainfall and temperature (Figs. 10, 11, 12, 13).

Malaria Projections for the Tanzanian Section of the LVB over 2016–2100

The Under-five age group responded to increases in maximum temperatures and increased over time most especially under the RCP 8.5 scenario. The malaria cases in this age group will likely increase steeply in the future. The 5 years and above age group also shows an increase in malaria cases in both the RCP 4.5 and RCP 8.5 scenarios, with the steepest increase projected for the RCP 8.5 scenario. More rainfall in

**Table 6** Results of the linear regression of malaria cases on running means of rainfall and temperature for Muleba hospital, Tanzania

| Age               | Effect          | Estimate | SE  | DF | T      | P>|T| |
|-------------------|-----------------|----------|-----|----|--------|-----|
| All ages          | Intercept       | −0.1227  | 0.0674 | 63.0 | −1.821 | 0.07339 |
| All ages          | Mavrain4        | 0.0029   | 0.0007 | 63.0 | 4.316  | 5.71 × 10−5 |
| 5 years and above | Intercept       | −1.6848  | 0.0598 | 63.0 | −28.176 | 2.04 × 10−37 |
| 5 years and above | Mavrain4        | 0.0039   | 0.0006 | 63.0 | 6.841  | 3.77 × 10−9 |
| Under 5 years     | Intercept       | −3.3353  | 1.4992 | 52.0 | −2.225 | 0.030467 |
| Under 5 years     | Mavmaxtemp4     | 0.0910   | 0.0523 | 62.8 | 1.739  | 0.087013 |

A numeric suffix in rainfall or temperature component name denotes the time window in months over which the running average was computed.
Table 7 Results of the regression of malaria cases reported for Uganda on rainfall and temperature

| Age                  | Effect  | Estimate | SE    | df  | T     | P>|T| |
|----------------------|---------|----------|-------|-----|-------|-----|
| Under 5 years        | Intercept | −1.7430  | 0.5901 | 12  | −2.954| 0.012057 |
| Under 5 years        | Mavannual2 | 0.0006   | 0.0005 | 12  | 1.178 | 0.261772 |
| 5 years and above    | Intercept | −3.3344  | 1.1720 | 12  | −2.845| 0.014757 |
| 5 years and above    | Lagmintemp5 | 0.1655   | 0.0715 | 12  | 2.315 | 0.039130 |

A numeric suffix in rainfall or temperature component name denotes the time window in months over which the running average was computed.

Summary of observed and forecast Malaria cases/Mean in Kenya

Fig. 10 Summary of observed and forecast malaria cases/mean in Kenya for the period 1995–2100 under RCP2.6, RCP4.5 and RCP8.5 scenarios based on GCM model 1 in Table 2
the future will likely result in increased malaria and anaemia cases in this and all the other age groups (Figs. 14, 15, 16, 17, 18, SI 19–21). Similar projections of future increases in malaria cases for the 5 years and above age group under the RCP 8.5 scenario are apparent for Muleba (Figs. 14a, 16).

**Malaria Projections for the Ugandan Section of the LVB over 2006–20100**

The observed malaria cases decreased during 2009–2010, but the average level of transmission in the future is expected
to remain stable under the RCP 2.6 scenario. However, considerable inter-annual fluctuations in the level of transmission can be expected as an increase in cases depending on rainfall and temperature patterns under the RCP 2.6 scenario (Figs. 19, 20, 21, SI 22). The RCP 4.5 and RCP 8.5 scenarios show an upward trend in malaria cases in the future. This is much more pronounced for the RCP 8.5 than the RCP 4.5 scenario (Figs. 19, 20, 21, 22, SI 23).

**Discussion**

Climate change is expected to affect malaria transmission, and the extent to which the transmission will likely change should be established so that this can be appropriately addressed by the public health sector and governments. To understand these changes, we examined future malaria scenarios for the Lake Victoria Basin in East Africa in response

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**Fig. 12** Malaria cases projected for Litein hospital in Kericho, Kenya, for the period 2008–2100 under the RCP2.6, RCP4.5 and RCP8.5 scenarios, using an ensemble of 8 general circulation models.
It is crucial to minimize uncertainty in future projections to reliably assess anticipated influences of simulated climatic variability and change. This is often done by considering a range of plausible projection scenarios and using an ensemble of GCMs. However, there are typically too many potential sources of uncertainty to exhaustively consider in any single study in practice. Thus, even though we consider multiple countries, malaria transmission hotspots, rainfall, minimum and maximum temperature components, periods and seasons, we perform extensive model selection using three climate scenarios for 2006–2100 defined by the representative concentration pathways (RCPs) RCP 2.6, RCP 4.5, and RCP 8.5 and projected by an ensemble of eight GCMs.

Fig. 13 Malaria cases projected for Mukumu hospital in Kakamega, Kenya, for the period 2008–2100 under the RCP2.6, RCP4.5 and RCP8.5 scenarios, using an ensemble of 8 general circulation models.
the historical data and consider an ensemble of eight different future projections for each of the three scenarios to reduce uncertainty. We account for uncertainty in the projected future scenarios by considering several sources of uncertainty associated with the simulated scenarios, rainfall and temperature component uncertainty, model selection uncertainty relating to the functional form of the relationship between malaria or anaemia cases and rainfall and temperature, parameter uncertainty in the selected models and model projection uncertainty. To account for uncertainty in the projected future scenarios, we consider three RCP scenarios, including the best case (RCP 2.6), intermediate (RCP 4.5) and worst case (RCP 8.5) scenarios. Using these three scenarios allows us to capture future uncertainties inherent in
We extensively consider model selection uncertainty in the regression relationships between the historical malaria and anaemia cases and historical rainfall and temperature components and use information theoretics, residual and influence diagnostics and statistical tests to choose between specific rainfall and temperature components (lags or...
cumulative moving averages) and functional forms of competing models relating malaria and anaemia cases to the selected rainfall and temperature components. First, we use the corrected Akaike Information Criterion plus residual and influence diagnostics and multiple other criteria to choose the models and rainfall and temperature components. Second, we quantify parameter uncertainty using standard errors of the model parameter estimates. Third, for each scenario and GCM combination, we use 95% pointwise confidence bands to quantify projection uncertainty. Lastly, we benchmark the performance of the projection models against the historical malaria (or anaemia) outbreak time series. In all the cases, we find reasonable agreements between the model projections and the historic time series but remarkable agreement.
variation in the projected series across the ensemble of eight GCMs, reaffirming the importance of using ensemble projections for each scenario.

Our results suggest a likely greater increase in the minimum than the maximum temperatures during 2006–2100. Specifically, minimum temperatures will likely increase by 1–2.5 °C by 2030, and 4–5 °C by 2100 compared to the base period. The projected future warming trend is a regional manifestation of global warming and reinforces IPCC’s [10] projection that by 2100, the average global temperatures will likely have risen by 1–3.5 °C. We project a likely increase in the maximum and minimum temperature components for the

![Forecasting malaria cases in relation to rainfall and temperature](image)

Fig. 17 Malaria cases among people of all ages projected for Muleba hospital, Tanzania, for the period 2006–2100 under the RCP2.6, RCP4.5 and RCP8.5 scenarios, using an ensemble of 8 general circulation models
three RCP scenarios compared to the base period in the Lake Victoria Basin. Rwanda and Burundi are projected to have some of the highest increases in both the minimum and maximum temperature components. However, the available clinical malaria data for Rwanda and Burundi were insufficient to project malaria cases under the three RCPs scenarios.

Rainfall is projected to increase in the short rainy season (OND) compared to the long rainy season (MAM) for RCP 4.5 and RCP 8.5 for the periods 2050s and 2070s and this will likely make a large contribution to the increase in the annual rainfall in the LVB, especially on its eastern section. The dry season will likely be much drier than in the base period. An increase in precipitation in the short rainy season
will likely prolong the malaria transmission season in the Lake Victoria Basin due to the increase in the rain-fed vector breeding habitats [27, 28].

For the intermediate scenario, RCP 4.5, projections show that increased rainfall and warming of the highlands will likely increase the mean number of malaria cases. The most affected time periods will be 2008–2030. El Niño events were reported during 1994–1995, 1997–1998, 2002–2003, 2004–2005, 2006–2007, 2009 and 2015–2016 [29–31] and the projections clearly show an increase in malaria cases in the Lake Victoria Basin in the years when an El Niño event occurred. Epidemics were also reported during these years [32–34]. The under-fives still remains the most vulnerable group to malaria infections under the RCP 4.5 scenario.

These climatic changes have multiple implications for malaria transmission. Increased temperatures expected in the Lake Victoria Basin will likely elevate malaria transmission in the highlands by altering malaria vector ecology and biology [35, 36]. The anticipated temperature rise will likely reduce vector development time and also increase the rate of development of the malaria parasite inside the vector [37]. This will likely cause an increase in malaria transmission in areas where malaria already exists and also in areas that are already malaria transmission hotspots [38, 39]. The increase in minimum temperatures will likely increase the geographic spread of malaria parasites and malaria cases to new areas outside the present malaria distributional range.

Thus, highland regions with average temperatures below 18 °C will likely experience new cases due to the projected increase in both the minimum and maximum temperatures [40]. The frequency and intensity of epidemics may thus be expected to increase in these regions. However, high temperatures expected in the lowlands may have a negative effect on holoendemic malaria transmission [37].

An increase in rainfall in the short rainy season (OND) will likely prolong the malaria transmission season and shift seasonal malaria transmission. More malaria cases will likely be reported during this season in the Lake Victoria Basin in future than in the base period. This will likely strain the health systems of the LVB countries as they will be forced to deal with more cases than are usually presented in hospitals during the short rainy season [41].

There will also likely be an increase in anaemia cases which are directly related to malaria infections and are a major cause of morbidity and mortality in the under-5 years [42, 43]. For every 130 cases of malaria reported in 1996, 20 anaemia cases were reported in the under-five age group. This trend is projected to increase in the future and to peak in 2051–2070. An increase in malaria cases in future will thus almost certainly lead to increased anaemia cases. Historical malaria cases in the region were strongly influenced by climate variability from the upsurge in the number of reported clinical cases after El Niño events in 1995–1996, 1997–1998 and 2002–2003. Malaria epidemics were reported during
These years [44]. This shows that climate variability influences malaria transmission. Future climatic extremes will also likely cause similar upsurges in clinical malaria cases as evidenced by episodic spikes in the trajectory of the projected malaria cases suggesting epidemic outbreaks.

Despite the changes in climate and its variability, malaria interventions can prevent or reduce the impacts of climate change and reduce the incidence and prevalence of malaria in the Lake Victoria Basin [7, 45]. In 2006, distribution of bed nets to vulnerable groups, such as pregnant women and mothers with children under 5 years, reduced malaria prevalence significantly [46]. In 2011, the roll back malaria campaign for universal bed net distribution also reduced malaria prevalence significantly [47]. Targeted distribution of long-lasting insecticide treated nets in malaria hotspots has prevented outbreaks of epidemics in these regions [48]. Other interventions such as the use of Indoor residual spraying have a major impact in reducing malaria incidence and prevalence in the Lake Victoria Basin.
Basin [49]. However, there is a risk of intervention failure mainly because of insecticide resistance, shift in biting time, less anthropophily, increased zoophily and exophily and also a shift in species abundance [50, 51]. There is also a looming threat of drug resistance, but new vaccines, if effective, will hopefully be an added tool to the existing malaria control toolbox.

**Fig. 21** Malaria cases among 5-year old’s and above projected for all the hospitals in Uganda, for the period 2011–2100 under the RCP2.6, RCP4.5 and RCP8.5 scenarios, using an ensemble of 8 general circulation models

**Conclusions**

Early detection of malaria epidemics and accurate future projections are major strategies in malaria control as they increase preparedness and reduce morbidity and mortality. Climatic changes are expected to greatly impact the highland regions of the Lake Victoria Basin as temperature rise will likely increase the survival rates of the malaria vectors.
and parasite transmission. Some highland regions will likely experience new cases of malaria transmission for the first time. Larger populations will likely be at risk and novel malaria hotspots will likely emerge. This calls for universal coverage of control interventions to minimize transmissions. Interventions should be restructured to address emerging risks of malaria transmission caused by increasing human vulnerability and suitability of new regions for malaria transmission. Future malaria research should prioritize understanding of the role of vector ecology on malaria, vector abundance and species change in response to climate change and widening variability. Widespread adoption of land uses that reduce vector habitats and lower temperatures should be promoted as adaptation and mitigation strategies for controlling malaria prevalence and spread in the anticipated warmer and wetter future climates.

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Availability of Data and Materials  The datasets used and/or analysed during the current study are provided in the supporting information in S1-S3 data.

Declarations

Conflict of interest The authors declare that they have no competing interests.

Ethics approval and consent to participate This study obtained ethical clearance from the Ethical Review Board at the Kenya Medical Research Institute (SSC no 1382). Written consent was obtained from children’s parents/guardians before enrolling them in this study. Inclusion criteria were the provision of a signed informed consent and no reported chronic or acute illness except malaria. Exclusion criteria included those who were unwilling to participate in the study.

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References

1. World Health Organisation (2019) World Malaria Report. World Health Organization, Geneva. https://www.who.int/publications/i/item/9789241565721 (ISBN: 978-92-4-156572-1)
2. Hay SI, Rogers DJ, Randolph SE, Stern DI, Cox J, Shanks GD et al (2002) Hot topic or hot air? Climate change and malaria resurgence in East African highlands. Trends Parasitol 18(12):530–534. https://doi.org/10.1016/S1471-4922(02)02374-7
3. Himeidan YE, Kweca EJ (2012) Malaria in East African highlands during the past 30 years: impact of environmental changes. Front Physiol 3:315. https://doi.org/10.3389/fphys.2012.00315
4. World Health Organisation (2013) Methods for achieving universal coverage with long-lasting insecticidal nets in malaria control. Geneva
5. Githeko AK, Ogallo L, Lemnge M, Okia M, Ototo EN (2014) Development and validation of climate and ecosystem-based early malaria epidemic prediction models in East Africa. Malar J 13(1):329
6. Pascual M, Ahumada JA, Chaves LF, Rodo X, Bouma M (2006) Malaria resurgence in the East African highlands: temperature trends revisited. Proc Natl Acad Sci 103(15):5829–5834
7. Githeko AK, Ndewa W (2001) Predicting malaria epidemics in the Kenyan highlands using climate data: a tool for decision makers. Glob Change Hum Health 2(1):54–63
8. Dasgupta S (2018) Burden of climate change on malaria mortality. Int J Hyg Environ Health 221(5):782–791
9. IPCC (2018) Global Warming of 1.5 °C. An IPCC Special Report on the impacts of global warming of 1.5 °C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty [Masson-Delmotte, V., P. Zhai, H.-O. Pörtner, D. Roberts, J. Skea, P.R. Shukla, A. Pirani, W. Moufouma-Okia, C. Péan, R. Pidcock, S. Connors, J.B.R. Matthews, Y. Chen, X. Zhou, M.I. Gomis, E. Lonnoy, T. Maycock, M. Tignor, and T. Waterfield (eds.)]
10. IPCC (2014) Mitigation of climate change. Technical summary
11. Mordecai E, Paaijmans K, Johnson L, Balzer C, Ben-Horin T, de Moor E et al (2013) Optimal temperature for malaria transmission is dramatically lower than previously predicted. Ecol Lett 16:22–30
12. Ryan S, McNally A, Johnson L, Mordecai E, Ben-Horin T, Paaijmans K et al (2015) Mapping physiological suitability limits for malaria in Africa under climate change. Vector Borne Zoonotic Dis 15:718–725
13. Ebi KL, Hartman J, Chan N, Mcconnell J, Schlesinger M, Weyant J (2005) Climate suitability for stable malaria transmission in Zimbabwe under different climate change scenarios. Clim Change 73(3):375–393
14. Thomas CJ, Davies G, Dunn CE (2004) Mixed picture for changes in stable malaria distribution with future climate in Africa. Trends Parasitol 20(5):216–220
15. Olago D, Marshall M, Wandiga SO (2007) Climatic, socio-economic, and health factors affecting human vulnerability to cholera in the Lake Victoria basin, East Africa. Ambio 36:350–358
16. Ototo EN, Githeko AK, Wanjala CL, Scott TW (2011) Surveillance of vector populations and malaria transmission during the 2009/10 El Niño event in the western Kenya highlands: opportunities for early detection of malaria hyper-transmission. Parasit Vectors 4:144
17. Polgreen PM, Polgreen EL (2017) Infectious diseases, weather and climate. Clin Infect Dis 66:815–817
18. Bousena T, Drakeley C, Gesase S, Hashim R, Magesa S, Mosha F et al (2010) Identification of hot spots of malaria transmission for targeted malaria control. J Infect Dis 201(11):1764–1774
19. Endris HS, Omondi P, Jain S, Lennard C, Hewitson B, Chang’a L et al (2013) Assessment of the performance of CORDEX regional climate models in simulating East African rainfall. J Clim 26(21):8453–8475
20. Van Vuuren DP, Edmonds J, Kainuma M, Riahi K, Thomson A, Hibbard K et al (2011) The representative concentration pathways: an overview. Clim Change 109(1–2):5
21. Giorgi F (2006) Regional climate modeling: status and perspectives. In: Journal de Physique IV (proceedings): EDP sciences, vol 139, pp 101–18
22. Burnham KP, Anderson DR (2002) A practical information-theoretic approach. In: Model selection and multimodel inference, vol 2, pp 70–1
23. Engle RF (2002) Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models. J Bus Econ Stat 20:339–350
24. Engle RF, Granger CWJ (1987) Co-integration and error correction: representation, estimation, and testing. Econometrica 55:251–276
25. Hosking JRM (1980) The multivariate portmanteau statistic. J Am Stat Assoc 75:602–608
26. Johansen S (1995) Likelihood-based inference in cointegrated vector autoregressive models. Oxford University Press, New York
27. Githeko A, Ototo E, Guiyun Y (2012) Progress towards understanding the ecology and epidemiology of malaria in the western Kenya highlands: opportunities and challenges for control under climate change risk. Acta Trop 121(1):19–25
28. Siderius C, Gannon K, Ndiiyo M, Operae A, Batsani N, Olago D et al (2018) Hydrological response and complex impact pathways of the 2015/2016 El Niño in Eastern and Southern Africa. Earth’s Future 6(1):2–22
29. Patz JA, Campbell-Lendrum D, Holloway T, Foley JA (2005) Impact of regional climate change on human health. Nature 438(7066):310–317
30. Trenberth KE, Hoar TJ (1996) The 1990–1995 El Niño-southern oscillation event: longest on record. Geophys Res Lett 23(1):57–60
31. Hay SI, Cox J, Rogers DJ, Randolph SE, Stern DI, Shanks GD et al (2002) Climate change and the resurgence of malaria in the East African highlands. Nature 415(6874):905–909. https://doi.org/10.1038/415905a
32. Lindblade KA, Walker ED, Onapa AW, Katungu J, Wilson ML (1999) Highland malaria in Uganda: prospective analysis of an epidemic associated with El Niño. Trans R Soc Trop Med Hyg 93(5):480–487
33. Zhou G, Minakawa N, Githeko AK, Yan G (2004) Association between climate variability and malaria epidemics in the East African highlands. Proc Natl Acad Sci USA 101(8):2375
34. Yé Y, Louis VR, Simboro S, Sauerborn R (2007) Effect of meteorological factors on clinical malaria risk among children: an assessment using village-based meteorological stations and community-based parasitological survey. BMC Public Health 7(1):101
35. Githeko AK, Lindsay SW, Confalonieri UE, Patz JA (2000) Climate change and vector-borne diseases: a regional analysis. Bull World Health Organ 78(9):1136–1147
36. Paaajimans KP, Blanford S, Bell AS, Blanford JI, Read AF, Thomas MB (2010) Influence of climate on malaria transmission depends on daily temperature variation. PNAS 107(34):15135–15139
37. Malakooti MA, Biomndo K, Shanks GD (1998) Re-emergence of epidemic malaria in the highlands of western Kenya. Emerg Infect Dis 4(4):671
38. Wanja JLA, Waitumbi J, Zhou G, Githeko AK (2011) Identification of malaria transmission and epidemic hotspots in the Western Kenya highlands: its application to malaria epidemic prediction. Parasit Vectors 4(1):81
39. Chen H, Githeko AK, Zhou G, Githure JJ, Yan G (2006) New records of Anopheles arabiensis breeding on the Mount Kenya highlands indicate indigenous malaria transmission. Malar J 5(1):17
40. McMichael AJ, Woodruff RE, Hales S (2006) Climate change and human health: present and future risks. Lancet 367(9513):859–869
41. Snow R, De Azevedo IB, Lowe B, Kaburu E, Nevill C, Mwangusye S et al (1994) Severe childhood malaria in two areas of markedly different falciparum transmission in East Africa. Acta Trop 57(4):289–300
42. Newton C, Warn P, Winstanley P, Peshu N, Snow R, Pasvol G et al (1997) Severe anaemia in children living in a malaria endemic area of Kenya. Trop Med Int Health 2(2):165–178
43. Zhou G, Minakawa N, Githeko AK, Yan G (2005) Climate variability and malaria epidemics in the highlands of East Africa. Trends Parasitol 21(2):54–56
44. Lindblade K, Gnimig J, Kamau L, Hawley W, Odhiambo F, Olang G et al (2006) Impact of sustained use of insecticide-treated bednets on malaria vector species distribution and culicine mosquitoes. J Med Entomol 43(2):428–432
45. Zhou G, Afrane YA, Vardo-Zalik AM, Atieli H, Zhong D, Wamae P et al (2011) Changing patterns of malaria epidemiology between 2002 and 2010 in Western Kenya: the fall and rise of malaria. PLoS ONE 6(5):e20318
46. Roll Back Malaria (2011) Global Malaria Action Plan. Back Malaria Partnership Secretariat, Geneva. http://www.rollbackmalaria.org/mgap/
47. Boussena T, Griffin JT, Sauerwein RW, Smith DL, Churcher TS, Takken W et al (2012) Hitting hotspots: spatial targeting of malaria for control and elimination. PLoS Med 9(1):e1001165
48. Okumu FO, Moore SJ (2011) Combining indoor residual spraying and insecticide-treated nets for malaria control in Africa: a review of possible outcomes and an outline of suggestions for the future. Malar J 10(1):208
49. Ochomo EO, Bayoh NM, Walker ED, Abongo BO, Ombok MO, Ouma C et al (2013) The efficacy of long-lasting nets with declining physical integrity may be compromised in areas with high levels of pyrethroid resistance. Malar J 12:368
50. Ototo EN, Mbugi JP, Wanjala CL, Zhou G, Githeko AK, Yan G (2015) Surveillance of malaria vector population density and biting behaviour in western Kenya. Malar J 14(1):244
51. Kinung’hi SM, Mshauri W, Mwanga JR, Nkoo SE, Kaatano GM, Malima R et al (2010) Knowledge, attitudes and practices about malaria among communities: comparing epidemic and non-epidemic prone communities of Muleba district, North-western Tanzania. BMC Public Health 10:395. https://doi.org/10.1186/1471-2458-10-395
52. Jones C, Hughes J, Bellouin N, Hardiman S, Jones G, Knight J et al (2018) The HadGEM2-ES implementation of CMIP5 contribution to CORDEX. AGU fall meeting abstracts A32E-06
53. Bousema T, Griffin JT, Sauerwein RW, Smith DL, Churcher TS, Takken W et al (2012) Hitting hotspots: spatial targeting of malaria for control and elimination. PLoS Med 9(1):e1001165
54. Wandiga SO, Opondo O, Olago D, Githeko A (2009) Vulnerability to epidemic malaria in the highlands of Lake Victoria basin: the role of climate change/variability, hydrology and socio-economic factors. Clim Changes 99:473–497
55. Malakooti M, Biomndo K, Shanks G (1998) Re-emergence of epidemic malaria in the highlands of Western Kenya. Emerg Infect Dis 4:671–676
56. Talisuna AO, Noor AM, Okui AP, Snow RW (2015) The past, present and future use of epidemiological intelligence to plan malaria vector control and parasite prevention in Uganda. Malar J 14:158. https://doi.org/10.1186/s12936-015-0677-4
57. Jones AE, Wort UU, Morse AP, Haining IM, Gagnon AS (2007) Climate prediction of El Nino malaria epidemics in north-west Tanzania. Malar J 6:162. https://doi.org/10.1186/1475-2875-6-162
58. Emori S et al (2010) Improved climate simulation by MIROC5: mean states, variability, and climate sensitivity. J Clim 23(23):6312–6335
59. Roll Back Malaria (2011) Global Malaria Action Plan. Back Malaria Partnership Secretariat, Geneva. http://www.rollbackmalaria.org/mgap/
60. Roll Back Malaria (2011) Global Malaria Action Plan. Back Malaria Partnership Secretariat, Geneva. http://www.rollbackmalaria.org/mgap/
61. Giorgetta MA, Jungclaus J, Reick CH, Legutke S, Bader J, Böttinger M et al (2013) Climate and carbon cycle changes from 1850 to 2100 in MPI-ESM simulations for the Coupled Model Intercomparison Project phase 5. J Adv Model Earth Syst 5(3):572–597

62. Bentsen M, Bethke I, Debernard JB, Iversen T, Kirkevåg A, Seland Ø et al (2013) The Norwegian Earth System Model, NorESM1-M–part 1: description and basic evaluation of the physical climate. Geosci Model Dev 6(3):687–720

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