Correction of the surface water formation parameter used in a malaria transmission model and future malaria projections for Africa

Inna Syafarina¹, Arnida Lailatul Latifah¹, Yosuke Miura², Tomoko Nitta³ and Kei Yoshimura³

¹Research Center for Informatics, National Research and Innovation Agency, Indonesia
²Meteorological Research Institute, Japan
³Institute of Industrial Sciences, The University of Tokyo, Japan

Abstract:

The surface water formation parameter ($K_w$) currently used in malaria transmission models can dramatically affect larval development calculations. However, the parameter is often unrealistic due to the unavailability of observational datasets. This research presents an adjusted $K_w$ by reference to an entomological inoculation rate (EIR) over the period 1983–2006, tuning the parameter by minimizing root mean square deviation of the water fraction from model calculations and satellite observations from 2014–2018. A scaling factor, topography factor, and inverse distance weighting were used to reduce the gap between macro- and microscales and to derive the appropriate spatial distribution of $K_w$ for a projection period from 2020–2100. The average EIR over the projection period under Representative Concentration Pathway (RCP) scenarios 2.6, 7.0, and 8.5 in West Africa decreased by –29%, –43% and –35%, respectively, from the historical period. By contrast, for central southern Africa, the respective values increased by 3%, 6%, and 29% from the historical period. The reduced EIRs under RCPs 7.0 and 8.5 in West Africa were mostly affected by temperature, while monthly mean precipitation triggered a decrease in EIRs under RCP 2.6. By contrast, consecutive wet days have the most influential role in increasing the EIR in central southern Africa under all RCP scenarios. This research will help policy-makers eradicate vulnerable malaria areas and improve related policy design.

KEYWORDS malaria model; entomological inoculation rate; surface water; projection; Representative Concentration Pathway scenario; climate change

INTRODUCTION

Malaria has become an endemic disease, with 409,000 deaths globally due to malaria in 2019 (World Health Organization (WHO), 2020). Approximately 67% of the total mortality has been in children under five years old, with 35% of pregnancies having suffered from malaria in Africa (WHO, 2020). Clearly, malaria transmission from mosquitoes to humans remains a major public health problem, despite much effort made to control it (Lei et al., 2020; Motohira et al., 2019; Rabinovich et al., 2017; Wanzira et al., 2016; Ndyomugenyi et al., 2016). A lack of expertise, poverty, poor health infrastructure and equipment, political instability, and government policies are all partly to blame (Tambo et al., 2012). Nonetheless, epidemiological studies on malaria have been conducted in several African countries (Diało et al., 2017; Assouho et al., 2020; Finda et al., 2018). Such research is high-risk, costly, time-consuming, and many cases of malaria have not been reported due to a lack of awareness within local communities. Malaria transmission in Africa thus remains poorly understood, and data relating to the status of malaria cases across the African continent remains limited. Consequently, researchers have to rely on mathematical models.

Stochastic approaches describe the dynamics of the malaria model more realistically. Gemperli et al. (2005) used the Garki model to map the spatial distribution of malaria in Mali. Ermert et al. (2011) developed the Liverpool Malaria Model to understand mechanism of malaria transmission. It evaluated the distribution map of a climate change impact assessment. However, interaction between the host and vector was not considered in this model. Yamana and Eltahir (2010) constructed a hydrology, entomology, and malaria transmission simulator (HYDREMATS) to forecast mosquito populations and vectorial capacity in Banizoumbou village in western Niger for the period 2005–2007. However, HYDREMATS was limited to a community scale. Tompkins and Ermert (2013) developed a dynamic vector-borne infectious disease (VECTRI) model developed by the International Center for Theoretical Physics (Trieste, Italy) in 2013. This model accounted for interaction between the host and vector at a regional scale. In VECTRI, surface water levels for mosquito breeding sites were calculated using a simple water balance model (Tompkins and Ermert, 2013), refining this approach by modifying the relationship between the water volume and pond surface water (Asare et al., 2016). However, the surface water formation parameter in the VECTRI model has not been corrected at a regional scale and requires urgent revision. That is, the currently used surface water formation parameter at a regional scale is unrealistic, being set as a constant with a default value of 0.001 for each grid. In reality, the surface water formation...
parameter is different in each grid depending on the elevation.

Future climatic uncertainty has encouraged researchers to estimate malaria transmission over the next 80 years. A study by Ongoma et al. (2018) has shown that rainfall is projected to increase under two RCP scenarios in East Africa, and that temperature has a dominant effect on malaria cases, particularly at high latitudes. Environmental factors such as temperature and rainfall affect larval growth and mosquito development (Barreaux et al., 2018). The mosquito life cycle, development, and mortality rates are sensitive and temperature-dependent (Beck-Jhonson et al., 2017) with the larvae living in temporary and still water (Mala et al., 2011) and the optimal temperature for malaria transmission being 25°C (Mordecai et al., 2013). Based on previous RCP scenario studies, climate change is likely to reduce the risk of malaria (Mordecai et al., 2020; Murdock et al., 2016; Ryan et al., 2015).

This study aims to improve malaria transmission model performance, making the simulations more reliable, and enabling more realistic projections of malaria risks using the latest climate projections. Moreover, for society, this study aims to help policy-makers decide which areas are more vulnerable to malaria and should be dealt with first, and to improve policies designed to reduce the number of malaria patients.

MATERIALS AND METHODS

Malaria model

This study applied the VECTRI (Tompkins and Ermert, 2013) malaria model which considers precipitation, temperature, and population dynamics at a regional scale, mimicking the mosquito life cycle from egg transfer to larva, to pupa, to hatching into an adult mosquito. When a mosquito becomes an adult, its development phase can be divided into two parts: the gonotrophic and sporogonic cycles. The gonotrophic cycle is a cycle in which an adult mosquito produces an egg. The sporogonic cycle is the developmental phase of the parasite within the mosquito’s body. In their adult phase, mosquitoes transmit the parasite from fertile humans to others. The VECTRI model uses daily precipitation, daily temperature, population density, and topographic datasets, estimating the entomological inoculation rate (EIR) as its output.

Experimental design

This study conducted three historical experiments (HIST-1, HIST-2, and HIST-3) and one projection experiment (PROJ). Detailed experimental scenarios are presented in Table 1. The HIST-1 experiment was conducted to derive the pond growth rate (Kw) parameter and tuned to the entomological inoculation rate observations. The HIST-2 and HIST-3 experiments were conducted to derive the pond growth rate parameter tuned to the water fraction. The pond growth rate parameter from HIST-1 was then optimized using the pond growth rate parameter from HIST-2 and HIST-3. The optimized pond growth rate parameter was used to conduct the projection experiment. The details of the datasets used are explained in the Supplements (Text S1).

Methodology

The methodology used in this study is shown in Figure 1. First, we ran the VECTRI model for three historical experiments, as explained in Table 1. Second, we collected entomological inoculation rate observation datasets from previous studies. The entomological inoculation rate observation sites used in this study are being shown in Figure S1. Third, the pond growth rate parameter was optimized, the optimization being divided into two steps: the validation of the pond growth rate parameter against the entomological inoculation rate and the calibration of the pond growth rate parameter against the water fraction. The pond growth rate parameter was validated against the entomological inoculation rate by tuning the pond growth rate parameter against the entomological inoculation rate observations (HIST-1 experiment), to derive a point-wise optimized pond growth rate.
rate parameter defined as $K_{g\nu}$. Calibration of the pond growth rate parameter against the water fraction was conducted by minimizing the root mean square deviation (RMSD) of the water fraction from the model output (HIST-2 experiment) and satellite observation (HIST-3 experiment), leading to an optimized pond growth rate parameter defined as $K_{g\nu}$.

**Scaling factor and interpolation**

Next, calculation of a scaling factor and interpolation of the pond growth rate were conducted. A scaling factor ($\alpha$) was needed to refine the pond growth rate parameter and was calculated by dividing $K_{g\nu}$ by the multiplication of topographic factor ($z$) and $K_{sg\nu}$, as expressed in (1).

$$\alpha = \frac{K_{g\nu}}{K_{w\nu}z} \quad (1)$$

The topographic factor determines the slope that matches the pond growth rate parameter and reflects the effect of precipitation and temperature on the pond growth rate. The point-wise optimized pond growth rate ($K_{g\nu}^{opt}$) could then be obtained. Next, we used an inverse distance weighting interpolation (see Supplement) to derive the spatial distribution of the optimized pond growth rate parameter, as shown in Figure S2. The scheme of the relationship between entomological inoculation rate and pond growth rate parameters can be found in Figure S3.

**Impact of precipitation and temperature on malaria transmission in the projection period**

Finally, we analyzed the results of the historical and future projection experiments. The impact of the climate on malaria transmission is uncertain. The monthly average precipitation, monthly average standard deviation of the precipitation, monthly maximum consecutive wet days ($CWD$), and monthly average temperature all have an impact on the entomological inoculation rate:

$$EIR = f(\bar{P}, \sigma_p, CWD, T) \quad (2)$$

where $EIR$ is the monthly average $EIR$, $\bar{P}$ is the monthly average precipitation, $\sigma_p$ is the monthly average standard deviation of the precipitation, $CWD$ is the monthly maximum consecutive wet days, and $T$ is the monthly average temperature. $CWD$ is defined as the maximum number of successive rainy days within one month of daily rainfall greater than 1 mm (Klutse et al., 2018). After the standardization of all variables, multivariate regression was performed to derive the coefficients for them (see Supplement).

**RESULTS AND DISCUSSION**

**The change of the EIR in the projection period**

The climate characteristics in Africa for the historical period are explained in Text S2. This section describes the expected malaria transmission shown by entomological inoculation rate in the projection period under the RCP scenarios. Figure 2 shows the change in the EIR in RCPs 2.6, 7.0, and 8.5 from the historical data in West Africa. Some land areas in all three scenarios are shown in white, representing an enormous change in the EIR – that is, the higher the emission scenario, the wider the white area. The average rates under RCP 2.6, 7.0, and 8.5 increased by 3%, 6%, and 29%, respectively, from the historical period. The change in the EIR (Figure 3) indicates a sizeable malaria risk in the projection period against the historical data as this area exhibits a higher temperature in the projection period and is predicted to have more than 2.5 million additional people suffering from malaria transmission by the 2080s (Ryan et al., 2020).

There is a huge difference between the spatial average of the EIR change in West and central southern Africa caused by large deviations in minimum and maximum values in these areas. Consequently, we restricted the values of the mean, minimum and maximum in the range of $-100\%$ and $100\%$, respectively. The (minimum, maximum) range of the EIR change in West Africa under RCP 2.6, 7.0, and 8.5 was ($-96\%, 54\%$), ($-96\%, 54\%$), and ($-98\%, 69\%$) from the historical period, respectively. Meanwhile, in central southern Africa, the range of the EIR change is ($-66\%, 100\%$), ($-69\%, 100\%$), and ($-45\%, 100\%$) from the historical period, respectively.

In western Guinea, northern Cote D’Ivoire, northern Ghana, northern Togo, northern Benin and some parts in western Senegal, under RCPs 2.6 and 8.5 there was a significant change in the EIR (Figure 2), except in western Senegal where the change of the EIR under RCP 8.5 was
not significant. Our results were in good agreement with a study conducted by Semakula et al. (2017), who found that climate change does not significantly increase the malaria burden in West Africa under RCP 8.5. This was due to drier conditions in West Africa than in East Africa under RCP 8.5 (Yamana et al., 2016).

Meanwhile, under RCP 7.0, the change in EIR in these locations exhibited a smaller change compared to the other two RCPs scenarios. This is caused by the precipitation and temperature in these locations having a significant contribution to the monthly mean precipitation average under RCPs 2.6 and 7.0, with a contribution range of 0.4–0.6. Meanwhile, under RCP 8.5, the contribution of monthly mean precipitation was between 0.2 and 0.4. Moreover, the consecutive wet days under RCPs 2.6 and 7.0 in western Senegal contributed more compared to other locations, with a range between 0.4 and 0.6. Guinea, Cote d’Ivoire, southern Mali, southern Burkina Faso also had a positive contribution with a range between 0.2 and 0.4 under RCPs 2.6, 7.0, and 8.5.

In other countries (Nigeria, southern Niger, southern Ghana, southern Togo, southern Benin), the change in the EIR was negative, the projection of malaria transmission in these locations being less than the historical values or it did not exist in future projections under RCP scenarios 2.6, 7.0, and 8.5 based on our simulations. This is because the contribution of the average temperature in these locations was negative against the EIR – that is, the higher the EIR, the lower the temperature meaning that when the temperature dropped, the EIR increased. This finding corresponds with a study by Ryan et al. (2015), which revealed malaria transmission to be optimal under moderate temperatures diminishing under high temperature.

In southern Africa, particularly in Tanzania, Malawi, Zambia, Angola, Zimbabwe and western Madagascar, the change in the EIR decreases compared to the historical period under RCP 2.6, with a reduction of up to 60–80%. Similar results were also demonstrated in the same region as RCP 2.6, for RCP 7.0 except for Zimbabwe and Malawi, and for RCP 8.5, except for southern Tanzania, Zambia and Malawi. The contribution of monthly mean precipitation in these regions was more significant than in other regions, with >0.2 contributions to the EIR under RCP 2.6, and <0.2 under RCPs 7.0 and 8.5.

In the Democratic Republic of Congo, Gabon, and Congo, the change in the EIR was the most significant, with an increase of 60–80% under RCPs 2.6 and 7.0, and >100% under RCP 8.5. Similar results were also demonstrated in the same region as RCP 2.6, for RCP 7.0 except for Zimbabwe and Malawi, and for RCP 8.5, except for southern Tanzania, Zambia and Malawi. The contribution of monthly mean precipitation in these regions was more significant than in other regions, with >0.2 contributions to the EIR under RCP 2.6, and <0.2 under RCPs 7.0 and 8.5.

In the Democratic Republic of Congo, Gabon, and Congo, the change in the EIR was the most significant, with an increase of 60–80% under RCPs 2.6 and 7.0, and >100% under RCP 8.5. In southern part of Kenya, there was a significant change of 20–40% under RCP 2.6, >40% under RCP 7.0, and between 40–60% under RCP 8.5. Meanwhile, in eastern Madagascar, the change was in the range of 40% under RCP 2.6, and >80% under RCPs 7.0 and 8.5. This was because the contribution of the consecutive wet days to the EIR in eastern Madagascar was more significant than that of other parameters, with a contribution of 0.2.

According to Tompkins and Caporaso (2016), the Model Intercomparison Research on Climate (MIROC) earth system model and the Couple Model Intercomparison Project Phase 5 (CMIP5) dataset showed that the long-term risk of malaria transmission was higher in southeast Africa, particularly in Mozambique and southern Tanzania, than elsewhere under RCP 2.6. Our results were the opposite, indicating that the change in the EIR for the projection period in Tanzania decreased by approximately 60% from the historical period under RCPs 2.6 and 7.0. Under RCP 8.5, the change in the EIR decreased by approximately 60% in northern Tanzania and increased by more than 100% in southern Tanzania. This was because in southern Tanzania the contribution of CWD was more than that in northern Tanzania (Figure 4).

**Contribution of precipitation and temperature on malaria transmission in the projection period**

This section examines the contribution of monthly mean precipitation, standard deviation of precipitation, consecutive wet days and temperature to the EIR projection in West Africa (Figure 5) and central southern Africa (Figure 4). The quantification of the contribution of the four variables to the EIR in the western region of Africa is shown in Table SI. Under the three projection scenarios, the variables exhibited the same behavior, except for the standard deviation of precipitation and temperature. Both monthly average precipitation and consecutive wet days positively contributed to the EIR. The standard deviation of precipitation had a positive impact on the EIR under RCPs 2.6 and 8.5, but a smaller negative impact on the EIR under RCP 7.0.

Meanwhile, the temperature negatively contributed to the EIR under the three RCP scenarios. The contribution of each variable to central southern Africa is shown in Table SI. Here, two variables contributed positively to the EIR, with the other two variables reducing it. The monthly average of precipitation and consecutive wet days had a positive contribution to the EIR, while the standard deviation of precipitation and temperature has a negative contribution to it under the three RCP scenarios. From Table SI, we can see that in central southern Africa, the EIR change was mostly affected by consecutive wet days under RCPs 2.6, 7.0, and 8.5, with 42.8%, 44.4%, and 48.3%, respectively. In West Africa, the EIR change was mostly affected by the temperature – that is, ~52.0% under RCP 7.0 and ~48.1% under RCP 8.5, except in RCP 2.6, which was more affected by monthly average precipitation (35.2%).

Tompkins and Caporaso (2016) found no significant difference in malaria transmission among the three earth system models, with only the MIROC predicting any significant change. They concluded that increasing the temperature caused by land use changes would increase the parasite rate and length of the transmission season in Tanzania, whereas decreasing the temperature would reduce malaria transmission across the high latitudes of Burundi and Rwanda, in line with our results. Our study found consecutive wet days to be an important driver of the EIR, and that increasing the temperature significantly reduced the EIR, in Rwanda and Burundi under the RCP 2.6 scenario. When precipitation has more frequent and intense consecutive days, it increased the mosquito breeding habitat. This situation could increase the number of larvae and mosquitoes as vectors. Consequently, the probability of people infected with malaria and the EIR would increase.

Meanwhile, an increasing temperature in future projection could decrease the EIR as mosquitoes only survive at a peak temperature of 25°C, with warmer temperatures decreasing the incidence of malaria (Mordecai et al., 2020). In addition, Yamana and Eltahir (2013) stated that higher
precipitation would enhance the availability of breeding water bodies and vectorial capacity in West Africa, while increasing temperature would decrease vectorial capacity defined as the sequence of biological characteristics used to measure mosquitoes’ ability to disseminate Plasmodium (Ceccato et al., 2012) and to describe areas that suffered from heightened malaria transmission risk. The vector survival probability starts at a lower air temperature of 20°C (Asare et al., 2016), so a higher temperature would decrease the number of mosquitoes, which would decrease
the vectorial capacity or the EIR. Similarly, we found that under the wetter RCP 2.6 scenario, the EIR in West Africa increased, while rising temperatures reduced it. Our finding contrasts with a study by Endo and Eltahir (2020), which revealed that increasing temperatures in the plateau region of Africa would increase malaria transmission by the end of the 21st century.

Chemison et al. (2021) found that their melting experiments caused an increase in malaria transmission in East Africa. The reduction of malaria transmission in West Africa and malaria emersion in southern Africa were caused by drought and changes in the African rain-belt, respectively. This study is in line with our finding that temperature plays a dominant role in the reduction of the EIR in West Africa and consecutive wet days contributes significantly to the increase in the EIR in southern Africa.

CONCLUSIONS

This research proposed the calibration of surface water formation parameters to improve malaria model performance and to project malaria transmission into the future using the latest climate model. The results showed that in West Africa, temperature plays a major role in reducing the entomological inoculation rate. In central southern Africa, consecutive wet days was the most influential factor.

With the wider applicability of the study, policy-makers and stakeholders could establish the most important malaria high-risk regions in Africa and arrange improved control programs there first, followed by other, less critical, locations. This method could also be applied to other epidemic malaria areas such as Thailand, Indonesia, Latin America and South America.

We limited the study by using historical entomological inoculation rate observations from 1983–2006 due to the scarcity of such observation data from a specific location in Africa. Moreover, surface water observations for the calibration pond growth rate parameter, with high daily temporal resolution, was limited. We assumed the water fraction for the mosquito’s breeding places to be approximately 10 km resolution due to the scarcity of high-resolution data. We used a daily satellite dataset of the water fraction from 2014–2018. The satellite water fraction used in this study was of the latest high spatial resolution – that is 0.1° x 0.1° resolution.

We found that the surface water formation parameters used in previous studies were unreliable, as they did not consider topography and were thus identical among all grid squares. We used the optimized pond growth rate parameter to predict the future malaria transmission rate, considering the effects of precipitation and temperature. The results of the method applied in this research were satisfactory, as can be seen from the water fraction model calculation and satellite observations. We calculated the root mean square deviation (RMSD) of the water fraction from the model calculations and satellite observations, an RMSD of less than 5% showing that the model was satisfactory for describing malaria transmission in the projection period.

We did not consider the impact of malaria projection in economic terms, which could be a good prospect for further research. Moreover, a more detailed analysis of the effect of soil structure on the surface water formation parameter, higher-resolution daily surface water data (with <10 m spatial resolution) and consideration of the impact of malaria control measures would make our malaria model more comprehensive and reliable.

ACKNOWLEDGMENTS

This study was supported by The Ministry of Research and Higher Education of Indonesia for PhD Research Scholarship and Institute of Industrial Sciences, The University of Tokyo for providing the server. The work was also supported by the Japan Society for the Promotion of Science (JSPS) via Grants-in-Aid No. 18H03794 and 16H06291; the Integrated Research Program for Advancing Climate Models (TOUGOU) (Grant No. JPMXD0717935457); ArCS II (Grant No. JPMXD1420318865); and the Environment Research and Technology Development Fund S-20 of the Environmental Restoration and Conservation Agency of Japan (Grant No. JPMEEF21S12020).

SUPPLEMENTS

Text S1. Detail of the datasets and methods used
Text S2. Climate characteristics in Africa
Figure S1. Sites in Africa at which the entomological inoculation rate was estimated
Figure S2. Spatial distribution of the optimized pond growth rate parameter (m)
Figure S3. Relationship between the entomological inoculation rate and pond growth rate parameter
Table S1. Spatial contributions of the variables of interest to the entomological inoculation rate in West and central southern Africa

REFERENCES

Asare EO, Tompkins AM, Bambles A. 2016. A regional model for malaria vector developmental habitats evaluated using explicit, pond-resolving surface hydrology simulations. *PLOS ONE* 11: e0150626. DOI: 10.1371/journal.pone.0150626.

Assoulou KF, Adja AM, Guindo-Coulibaly N, Tai E, Kouadio AMN, Zoh DD, Koné M, Kessé N, Koffi B, Sagna AB, Poinsignon A, Yapi A. 2020. Vectorial transmission of malaria in major districts of Côte d’Ivoire. *Journal of Medical Entomology* 57: 908–914. DOI: 10.1093/jme/tjz207.

Barreaux AMG, Stone CM, Barreaux P, Koella JC. 2018. The relationship between size and longevity of the malaria vector *Anopheles gambiae* (s.s.) depends on the larval environment. *Parasites & Vectors* 11: 1–9. DOI: 10.1186/s13071-018-3058-3.

Beck-Johnson LM, Nelson WA, Paaijmans KP, Read AF, Thomas MB, Bjørnstad ON. 2017. The importance of temperature fluctuations in understanding mosquito population dynamics and malaria risk. *Royal Society Open Science* 4: 160969. DOI: 10.1098/rsos.160969.

Ceccato P, Vancutsem C, Klaver R, Rowland J, Connor SJ. 2012. A vectorial capacity product to monitor changing malaria transmission potential in epidemic regions of Africa. *Journal of Tropical Medicine* 2012: 1–6. DOI: 10.1155/2012/595948.
