GeoHealth

RESEARCH ARTICLE

10.1029/2025GH001356

Special Collection:
Climate change and infectious diseases

Key Points:

- Anthropogenic causes have already increased the malaria burden and will increase it further in the next few decades
- Extremes of entomological inoculation rate are projected to increase, making infectious outbreaks more likely in the future
- Both climate and population density play important roles

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Citation:
Franzke, C. L. E., & Parihar, R. S. (2025). Time of emergence and future projections of extremes of malaria infections in Africa. *GeoHealth*, *9*, e2025GH001356. https://doi.org/10.1029/2025GH001356

Received 17 JAN 2025
Accepted 4 JUN 2025

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Time of Emergence and Future Projections of Extremes of Malaria Infections in Africa

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Abstract The spread of malaria is a major health burden, which affects many people in Africa, depends on climate but also socio-economic conditions. Thus, it is important to gauge the impact of anthropogenic global warming on malaria and attribute anthropogenic causes. Here we compute the Time Of Emergence of vector density and of the entomological inoculation rate (EIR) in the SSP3-7.0 scenario using 50 bias-corrected members of Community Earth System Model version 2 Large Ensemble simulations. This reveals that vector density, which depends on climate conditions, and EIR, which depends on both climate and population density, will rise significantly and permanently above the pre-industrial background variability due to anthropogenic causes in Africa. Both the vector density and EIR have areas, mainly in central Africa, where anthropogenic causes have already significantly changed, and many more areas will experience anthropogenic caused changes in the period 2030–2050 and toward the end of this century. Our simulations also show clear evidence that extremes of vector density and EIR increase in the future by almost 100%, suggesting that major malaria epidemic outbreaks will become much more likely. We also perform simulations with constant population and with no global warming which partly reveal underlying malaria dynamics. Our results highlight the need to prepare for an expansion and intensification of the malaria burden if no health interventions are being taken.

Plain Language Summary Malaria is a major health burden globally and is one of the most common infectious diseases. Children under 5 years of age are most at risk. Africa is a hot spot of malaria infections. We show evidence that the malaria burden will start to be significantly more intense in the coming decades than in the pre-industrial period due to anthropogenic causes. We also show that the likelihood of extreme malaria outbreaks will almost double by the end of this century.

1. Introduction

Malaria is a tropical disease that is spread by female mosquitoes to humans through their bite (Hay et al., 2004, 2009). The World Health Organization (WHO) reports that around 3.3 billion people across the globe are currently at risk of contracting malaria, resulting in the death of roughly half a million people each year (World Health Organization (WHO), 2018). Africa is one of the biggest hosts to malaria-transmitting mosquitoes. Africa is particularly suitable for malaria parasite survival and transmission because of its suitable climate (Yamba et al., 2023) and population density. African national health departments have occasionally advised foreigners to take precautionary measures due to malaria endemicity. Due to continued governmental efforts, malaria infections have substantially declined over most parts of Africa. While the malaria case incidence has decreased between 2000 and 2022 from 369 to 222 cases per 1,000 population at risk (World Health Organization (WHO), 2023), malaria still persists in Africa and affects too many people and children today with 263 million malaria cases in 2023 (World Health Organization (WHO), 2024).

Some malaria studies (Bashar & Tuno, 2014; Bayoh & Lindsay, 2003; Ceccato et al., 2005; Reiter, 2001; Zhou et al., 2007) have reported that the regional climate can support the emergence and re-emergence of malaria epidemics. Temperature, for example, has been shown to have a profound influence over the distribution of the Anopheles mosquito and the Plasmodium parasite, which causes malaria (Bayoh & Lindsay, 2003; Colón-González et al., 2021; Mordecai et al., 2019). Too cold and too hot temperatures reduce either their metabolism and growth rate or they reach their limit of survivability. In a warmer climate, mosquitoes can partly adapt by changing their feeding behavior, from day time to night time or from outside to inside (Hug et al., 2024). Whether they can biologically adapt to warmer temperatures is still an open question (Hug et al., 2024; Lahondère & Bonizzoni, 2022).

The records of vectors and epidemiology of malaria in Africa are limited, hampering health burden estimates and malaria spread modeling. However, a total of 17 Anopheles species have been identified in a report by the World Health Organization (WHO) (2018), and many of them are competent malaria vectors (World Health Organization (WHO), 2023; Glick, 1992).

Increased levels of rainfall also expand potential mosquito breeding sites and, when combined with optimum temperatures, help to provide optimal conditions for the spread of malaria. Several studies have investigated the relationship between mosquito abundance and regional climatic conditions (temperature and rainfall) over Africa (Lyimo et al., 1992; Paaijmans et al., 2007), while Zhou et al. (2004) and Pascual et al. (2008) considered the link between climate variability and malaria epidemics, that is, the rapid spread of malaria. Global warming is likely to affect many vector-borne infectious diseases, including malaria (de Souza & Weaver, 2024; Thomson & Stanberry, 2022). Hence, a systematic attribution of the causes of a malaria burden increase, whether due to anthropogenic global warming or population growth and their potential interaction, is needed.

Although many studies concentrated mainly on the situation of current African endemic regions for larvae and vector species distributions, very few have yet reported on historical and future malaria transmission if future climate and population projections are considered for the continent of Africa. Local and regional studies might miss potential malaria range extensions in the future. Hence, here we perform a continent wide simulation study.

Weather extremes can lead to infectious disease outbreaks (Alcayna et al., 2022; Franzke & Czupryna, 2020, 2021; Franzke & Torelló i Sentelles, 2020; McMichael, 2015; Semenza et al., 2022), such as malaria. For instance, in 2022 and 2023 severe Monsoon rainfall led to large malaria outbreaks in Pakistan (World Health Organization (WHO), 2023). Precipitation can provide standing water in ponds which can be used for breeding and larvae development. Precipitation events can create a large number of small ponds which can contribute to the rapid increase in the number of larvae (Asare et al., 2016; Fillinger et al., 2009). Malaria extremes have been so far not studied systematically, to the knowledge of the authors. This is of relevance, since there is evidence that malaria outbreaks can also contribute to civil violence (Cervellati et al., 2022), besides an increased health burden.

Another important factor in malaria transmission is the human population density. In the future not only climate will change but we expect also higher population densities, this means population projections need to be considered but there are some studies which did malaria projections with constant population densities (Chaturvedi & Dwivedi, 2021; Parihar et al., 2022; Talib et al., 2024). While this can isolate the pure climate effect on malaria transmission in the future, it only tells part of the story. Here we will show evidence for a nonlinear response of malaria transmission in parts of Africa due to both global warming and population change, which has not been discussed previously.

Here we will use daily data and examine malaria extremes in terms of extremes of vector density and the Entomological Infection Rate (EIR) in a future climate scenario. EIR is an indicator related to the number of infectious bites from a mosquito infected by malaria an individual is exposed to in a given time period (Porta, 2014). Here we focus on the climate and population density contributions to malaria infections, and neglect the impacts of health interventions, which play also an important role in malaria infections but for which no future projections exist.

In this study, we first evaluate the future time of emergence of vector density and EIR. Then we focus on the extremes of malaria outbreaks and identify potential hot spots in the near and far future. Identifying potential hotspot regions of malaria epidemic outbreaks will be useful for African policy planners to take early mitigation measures to prevent future malaria outbreaks.

2. Models and Methods

For examining the likely future spread of malaria we use the dynamical malaria model VECTRI (VECtor borne disease community model of International Centre for Theoretical Physics, TRIeste) (Tompkins & Di Giuseppe, 2015; Tompkins & Ermert, 2013; Tompkins & Thomson, 2018) for our simulations. The model's physics and associated parameters are chosen based on the life cycles of the key vector, namely, Anopheles gambiae (Coetzee et al., 2000), and the parasite Plasmodium falciparum. The underlying dynamical structure of the

VECTRI model describes the interaction between vector and host (Chenet et al., 2012; Parham et al., 2015; Parihar et al., 2019). The VECTRI model explicitly accounts for the human's population density in the calculation of biting rates and host-to-vector and vice versa transmission probabilities for the parasite (Chenet et al., 2012; Lunde et al., 2013; Okuneye et al., 2019). It further includes the impact of temperature and rainfall on the transmission dynamics of malaria. The model has previously been used in several malaria-endemic studies in different regions of the world to explore the relationship between the spread of malaria and climatic factors (Chaturvedi & Dwivedi, 2021, 2024; Parihar et al., 2019, 2022; Tompkins & Di Giuseppe, 2015; Tompkins & Ermert, 2013; Tompkins & Thomson, 2018; Yamba et al., 2023).

In the model, a series of modular bins govern each process of the vector and parasite growth stages in synchronization with gonotrophic and sporogonic cycles. The fractional development state of the mosquito larvae is distributed in different weighted bins. These bins represent larvae density at specific fractional stages of its growth. The first stage depicts the development of eggs within the female vector, and the second stage depicts the infective state (development of the parasite in the female vector's gut). All vectors in the optimal conditions advance from the egg to the last bin, where vectors become infectious to humans. A time step of one day integrates the model equations with input temperature and rainfall data. Tompkins and Ermert (2013) describe the underlying numerical structure, and the model architecture in detail.

In this work, we force the VECTRI model by daily climate data from the large ensemble CESM2-LE (Rodgers et al., 2021) using bias-corrected data. CESM2-LE covers the period 1850–2100 using the SSP3-7.0 scenario. For bias correction we use the Quantile Delta Mapping method (Cannon et al., 2015; Xavier et al., 2022). We used the population density data in Africa from the National Center for Atmospheric Research based on the SSP3-7.0 scenario (Jones & O'Neill, 2016) for the period 2000–2100. For the period 1850–2000, we use the population reconstruction product HYDE3.3 (History Database of the Global Environment) (Klein Goldewijk et al., 2017). Both data sets are spatially aggregated to the same grid as Community Earth System Model version 2 (CESM2). In order to achieve a daily resolution of population density to drive VECTRI, we linearly interpolate in the time domain using the Climate Data Operator "inttime" which linearly interpolates between two data points (Schulzweida, 2023).

While the full CESM2-LE consists of 100 members, for the bias correction and in this study we used 50 members. Of these 25 have observed fire emissions and 25 have smoothed fire emissions. See Rodgers et al. (2021), Yamaguchi et al. (2023), Kim et al. (2023) for more details. However, the treatment of the fire emissions has no effect on our results here (not shown).

The choice of this particular model (CESM2-LE), scenario and number of used ensemble members was made for practical reasons. The SSP3-7.0 scenario is a relatively high-emissions scenario leading to a warming of about 4C°. The use of daily data is necessary for forcing VECTRI, and VECTRI also produces daily output. This produces a large data set and is also computationally expensive. To compromise between computational expense, for bias correction and the VECTRI simulations, data storage and number of ensembles we decided to only use one scenario and 50 ensemble members. A large number of ensembles is necessary to robustly estimate changes in extremes.

The VECTRI model was configured for the entire of Africa. Daily rainfall and surface temperatures from the atmospheric model CESM2 Large ensemble members are used as inputs for the VECTRI model simulations. We first evaluate the spatiotemporal distribution of malaria. The model configuration and associated parameters follow the default VECTRI setup for the Anopheles species vector and the Plasmodium falciparum malaria parasite (Bayoh & Lindsay, 2003; Lyimo et al., 1992; Tompkins & Ermert, 2013). The values of input parameters such as maximum and minimum temperatures for larvae survival, time for egg hatching and pupae stages, minimal daily survival of larvae after intense rainfall, threshold temperature for egg development in vector, threshold temperature for parasite development, degree days for parasite development have been extensively evaluated (Tompkins & Ermert, 2013). The VECTRI model has been evaluated and successfully used in many previous studies (Asare & Amekudzi, 2017; Chaturvedi & Dwivedi, 2021, 2024; Colón-González et al., 2016, 2021; Leedale et al., 2016; Parihar et al., 2019, 2022; Tompkins & Caporaso, 2016; Tompkins & Thomson, 2018; Tompkins et al., 2019).

We compute the Time Of Emergence (TOE) to identify the time period when the vector density and EIR are significantly different from the pre-industrial period, for which we assume a unperturbed climate and population. In many previous studies TOE has been used to identify the time when anthropogenic global warming can be

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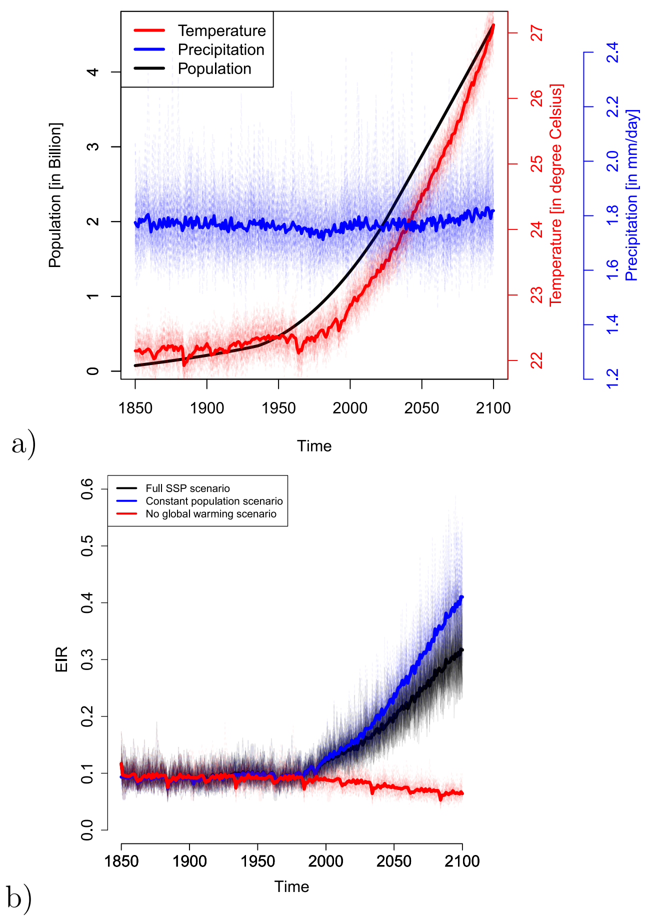

Figure 1. (a) Spatial and ensemble mean annual mean time series over Africa for population, temperature and precipitation. (b) Spatial mean annual mean time series over Africa for EIR (Infectious bites per person per day) for the full SSP3 scenario, constant population (mean over 1991–2020) but global warming and no global warming assumption (based on period 1850–1899) but including population growth. The solid lines are the ensembles means, while the light lines indicate all 50 ensemble members. This shows the large ensemble spread representing internal variability.

detected (e.g., Hawkins & Sutton, 2012; Sui et al., 2014). For TOE we compute the signal over noise (S/N) ratio and define the TOE once it is very likely ($P \geq 99.99\%$) that the level of vector density or EIR is greater than the fluctuations of the pre-industrial period and stays above the pre-industrial level till the end of the simulations in year 2100. In that case we have identified unprecedented malaria conditions. As the signal S we use the ensemble mean of vector density and EIR from the 50 VECTRI ensembles driven by individual CESM2-LE ensemble realizations of temperature and precipitation. As the noise N we compute the interannual variability, defined as the standard deviation of annual means, over the 50 VECTRI ensemble members for vector density and EIR for the pre-industrial period (1850–1899). Hence, our ToE is with respect to the pre-industrial period.

3. Evolution of African Malaria Infections

To illustrate the climate and population changes in Africa, we display spatially and ensemble averaged time series in Figure 1a, together with the full ensemble spread. As is visible, population and temperature show steep increases, especially after 1950 for population and the 1990s for temperature. Precipitation over Africa has strong interannual and decadal variability and also a large ensemble spread. While there is a slight increase projected after the 2050s in the ensemble mean, precipitation is dominated by internal variability, which is much stronger than any changes in the ensemble mean. This strong interannual to decadal scale variability of precipitation implies that large ensemble simulations will be necessary for robustly estimating systematic future changes in malaria, since large ensembles allow to estimate the forced response, the climate signal due to anthropogenic global warming, without the superposition of natural variability. The forced response indicates systematic changes due to anthropogenic causes. The forced response in precipitation over Africa is much smaller than that of temperature, while the internal variability of precipitation is stronger than that of temperature. This suggests that the temperature contribution to the malaria infections will be much clearer than the precipitation contribution.

Now we use the climate model and population data to drive VECTRI with daily input data on the same grid as CESM2. We perform a set of 50 VECTRI simulations driven by the 50 CESM2 ensemble members. The mean over the 50 VECTRI simulations are the forced response of the malaria infections. All 50 VECTRI members are driven by the same population density data (see Models and Methods). The spatial pattern of change in the population density is displayed in Figure 2. While there is generally an overall increase in population density, certain areas are projected to experience a faster growth than others, especially in urban areas.

To display the overall behavior of EIR we average over Africa (Figure 1b). These aggregated VECTRI simulations show a pronounced increase starting in the 1980s and a tripling by 2100 in the used SSP3 scenario. Since the EIR curve has a largely increasing shape, which is in contrast to the precipitation curve, this suggests that precipitation plays a minor role in the long-term behavior of malaria transmission in these scenario simulations, but can still play a pronounced role in epidemics. This suggests that the temperature is the main driver of the long-term EIR increase. Furthermore, a large ensemble spread is visible around the forced response, suggesting that internal variability still has a pronounced influence on the malaria infections. This is consistent with the study by Kaye et al. (2024). This large interannual variability of malaria infections has not been widely recognized so far. The large precipitation variability likely also contributes to the malaria infections variability.

In general, the spread of malaria is affected by climate, the population density, and also health interventions. However, health interventions, such as bed nets, are neglected in our study because we do not have future projections for them. In order to try to examine the two contributions from climate and population density. EIR is affected by both changes in climate and population density. In order to assess their relative contributions to

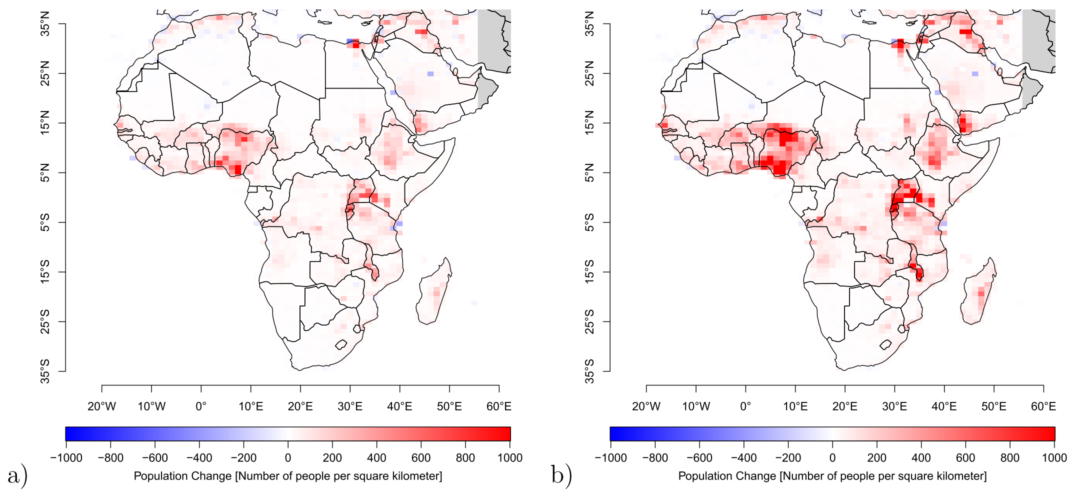

Figure 2. Population change (persons per km^2) over 30 year periods with respect to the period 1991–2020. (a) period 2031–2060 and (b) period 2071–2100.

changes in EIR we perform two further sets of VECTRI simulations, each consisting of 50 ensemble members. This is done to decompose the individual effects of climate and population density on malaria and their relative roles in malaria trends. The first set is with constant population (average over the period 1990–2020) but with the climate as simulated by CESM2-LE, and the second set with no global warming but the SSP3 population change. As the time period of no global warming we use the period 1850–1899 and then use this period periodically until we reach 251 years; the duration of the CESM2-LE simulations and all of our VECTRI simulations. We also used the period 1990–2020 but this period experiences a strong global warming effect, so cannot be used for this kind of "no global warming" experiment. However, using this period we get qualitatively similar results regarding the long-term behavior (not shown).

These two sets of simulations show that the constant population assumption leads to a larger increase in EIR compared to the full scenario (Figure 1b). This behavior is consistent with the no global warming simulation, which shows a decrease in EIR once the population growth in Africa increased considerably after the 1980s (Figure 1). This shows that in order to understand future malaria projections both global warming and population need to be considered, besides advances in health intervention such as malaria vaccines and health care for which currently no projections exist.

Another important aspect of these simulations is that the ensemble variance around the forced response is increasing in the global warming simulations but not in the "no global warming" scenario, where the variability stays the same over the simulation period. This suggests in a warmer climate also malaria volatility will increase and affect the likelihood of epidemic outbreaks. How malaria extremes change will be discussed below.

4. Time of Emergence of Malaria Infections

To gauge when anthropogenic actions have caused an unprecedented change in mosquito density and malaria infections, we estimate the Time of Emergence (TOE), as the decade when the vector density or EIR are significantly different from pre-industrial conditions (see Methods section). The TOE estimates are based on the CESM2-LE SSP3-7.0 scenario and, thus, contain both anthropogenic climate and population changes. Here we will compare the TOE of the vector density, which is mainly affected by climate, and EIR, which is affected by both climate and population density. The TOE of the vector density and EIR (Figure 3a) show TOE signals starting in the 1980s but many areas in Africa have TOE in the period 2030–2050s. There is no perfect overlap between vector density and EIR but they show mainly the same behavior. The TOE signal is also mainly concentrated on Central Africa, western West Africa and parts of East Africa and Madagascar. This shows that

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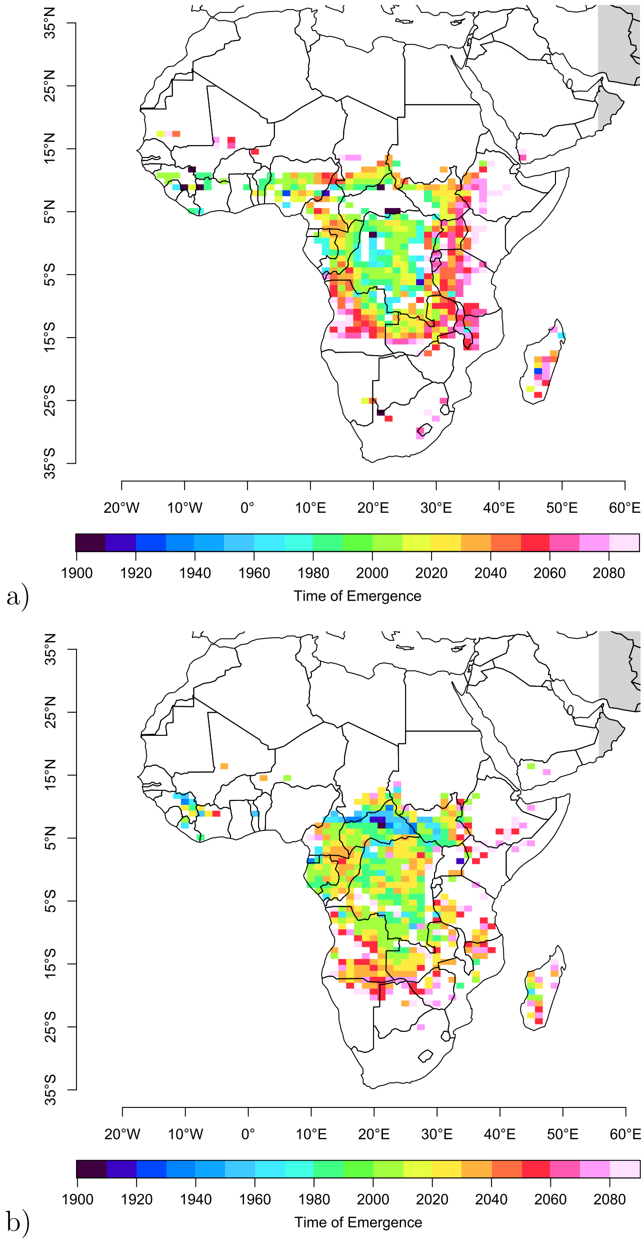

Figure 3. Time of Emergence of (S/N>5) for (a) vector density (vectors per m^2) and (b) EIR (infectious bites per person per day) based on 10 year means.

anthropogenic changes have already increased the malaria infections, but also that many regions in Africa will experience increased malaria infections in the next few decades due to anthropogenic causes.

A comparison with Figure 1b is instructive. While over the whole of Africa it is clearly visible that EIR increases above its pre-industrial range starting in the 1980–1990s, regionally the signal mainly emerges later, around the 2000s, because regional climate variability is larger than the continentally averaged variability. Areas with TOE in the 2030 and 2040s should be the focus of decision-makers to reduce the near term malaria infections.

Large areas of Africa show no TOE (the white areas) for the vector density. First, some regions are not suitable for malaria like the Sahara desert. Further, an inspection of the signal over noise (S/N) time series at individual grid points shows that either S/N stays below the threshold for the whole time period or turns again below the threshold after a while. This could suggest that the climate variability is too large in those areas for the anthropogenic signal in the vector density to permanently rise about our S/N threshold or that there is also pronounced decadal scale variability forced by decadal climate variations such as for example, the Atlantic Multidecadal Oscillation (Mann et al., 2014). Contributing to this could the strong internal variability of temperature and precipitation as visible in Figure 1.

5. Extremes of Malaria Infections

A distinct advantage of a large ensemble is the ability to examine how extremes change over time. Here we discuss now how the tail of the vector density and EIR change over the CESM2-LE simulation period. For every year of the VECTRI ensemble simulations we estimate the PDF (Figure 4) across the ensemble simulations. We can clearly see that extremes become much more likely in the future scenario, compared with the pre-industrial period or our current climate. For instance, we now illustrate how extremes change by using the 99.99th percentile. This is a very high value which is only very rarely exceeded and thus represents extremes. We find that the probability for vector density extremes of above 0.05 vectors/m^2, which corresponds to the 99.99th percentile value for vector density, will almost double (increase by 97%) between 1850 and 2100. An almost doubling (increase by 96%) of EIR extremes of larger than five infectious bites per person, this corresponds also to the 99.99th percentile of EIR, is also projected. This suggests that large malaria outbreaks will become more likely in the future.

Next we discuss the geographical distribution of EIR for the pre-industrial (1850–1899), present climate (1991–2020), near future (2031–2060) and far future (2071–2100) periods. Anomalies are with respect to the pre-industrial period. We can see that in the near and far futures there will in general be large increases in EIR over most of sub-Saharan Africa (Figure 5). Only in western Africa are some regions with a reduction in EIR.

The spatial 95th percentile fields also show a considerable increase in the SSP3-7.0 scenario, mainly in western and central Africa; in the far future the increase in extreme EIR outbreaks is almost 40% locally with respect to pre-industrial conditions (Figure 5). An interesting aspect is that while in central Africa the change in mean and extremes are both positive, in western Africa the mean values of the vector density increase, with the exception of the area around Senegal where the vector density is decreasing. Further south, in the area of Sierra Leone and Liberia the 95th percentile values are decreasing while the mean values are increasing. A similar behavior also occurs for EIR. A distinct feature is, that while the vector density increases in Nigeria, EIR is projected to decrease there. This is likely due to the projected pronounced population increase in Nigeria (Figure 2).

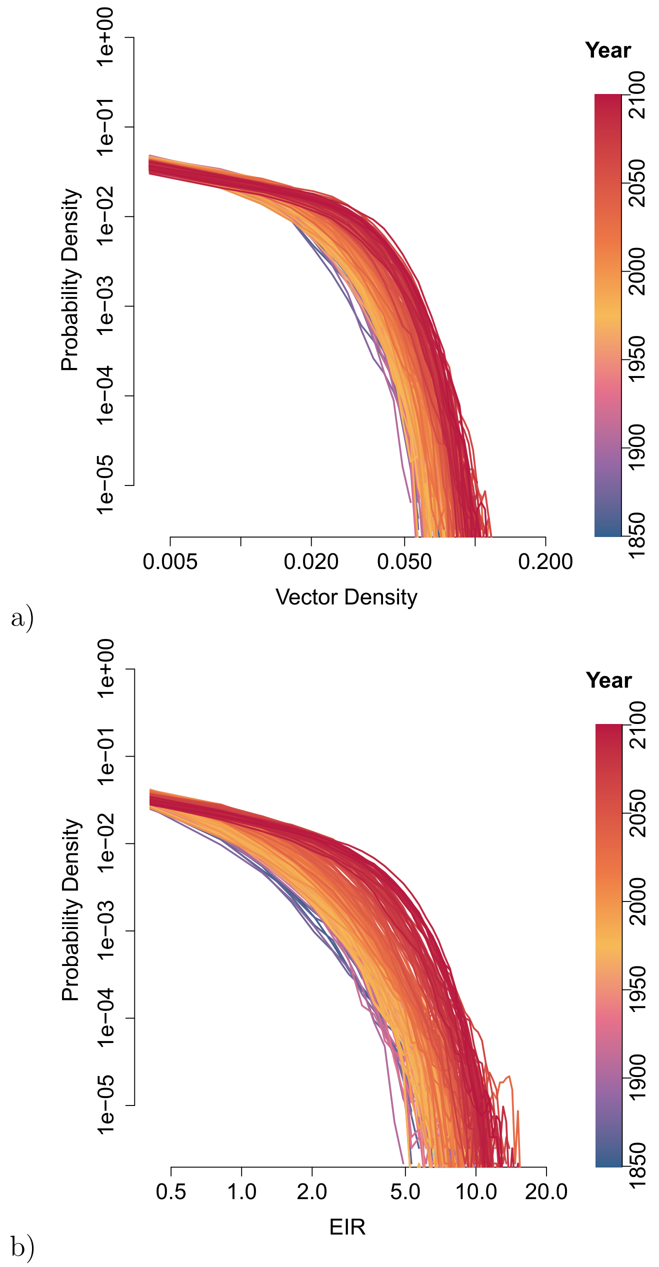

Figure 4. PDF of daily data of (a) vector density (vectors per m^2) and (b) EIR (infectious bites per person per day). Colors indicate different years.

Overall, the malaria infections will increase in the near and far future. The fact that in some west African areas the mean increases while the extremes decrease hints at that nonlinear dynamics are acting there and that the shape of the distributions of vector density and EIR change in this area.

6. Discussion

Our computation of the TOE reveals that many African regions will exhibit unprecedented malaria conditions between 2030 and 2050, in the near future. Furthermore, the TOE potentially highlights areas where health interventions in the next 2 decades could reduce the malaria infections. While we use here only one SSP scenario, it still suggests areas where health interventions could be most valuable in the near future. With respect to the global mean surface air temperature the 5 SSP scenarios are still relatively close to each in the period 2030–2050. So our one scenario might provide robust near term TOE estimates. As our simulations also show a large amount of internal variability, which also increases in the future, the use of large-ensembles seems to be very valuable in estimating the future malaria infections and its interannual variability.

Another important question is how weather and climate extremes affect the malaria infections. Scoping reviews found evidence that weather extremes are more likely to cause water-borne disease outbreaks and found mixed evidence for an impact on vector-borne epidemics (Alcayna et al., 2022; Coalson et al., 2021). Studies found that flooding (Boyce et al., 2016; Ding et al., 2014; Gao et al., 2016) and un-seasonal precipitation (Maes et al., 2014) can cause malaria outbreaks. But those studies typically examine local regions and particular events. How much they can be generalized remains subject to further research.

Here we examined extremes in vector density and EIR and show that they will considerable increase in a warmer world. Compared to pre-industrial conditions, we find that the probability of malaria extremes to occur will almost double. Major areas for the increase in extremes are the west coast of western Africa and central Africa. This makes epidemic malaria outbreaks much more likely, potentially increasing malaria infections if no preventive measures are taken.

We also find evidence for a nonlinear response due to the relationship between global warming and population growth for EIR. While this is not surprising but still reminds us that for projections of future malaria infections both anthropogenic global warming and population change need to be considered. Siraj et al. (2015) show that human population density is involved in the seasonal persistence of malaria and high house occupancies can lead to prolonged transmission seasons. The study by Villena et al. (2024) found a nonlinear relationship between malaria incidence and population density: malaria increases up to a point with increasing population density, and then decreases with further population increases.

An aspect our study has neglected are health interventions such as bed nets (e.g., Lindsay et al., 2021), vaccines (e.g., Duffy et al., 2024) and genetically modified mosquitoes (Hoermann et al., 2022). How effective they will be in the future needs to be seen and no current future projections exist, so they are difficult to consider in our study based on the SSP3 scenario.

Another aspect which also needs more attention is the impact of interannual and decadal scale variability. Many studies are based on multi model means (e.g., Chaturvedi & Dwivedi, 2021). But as our study shows, and also the study by Kaye et al. (2024), variability on long time scales can also be important for understanding future evolution of the malaria infections, since the malaria infections in response to natural climate variability will also

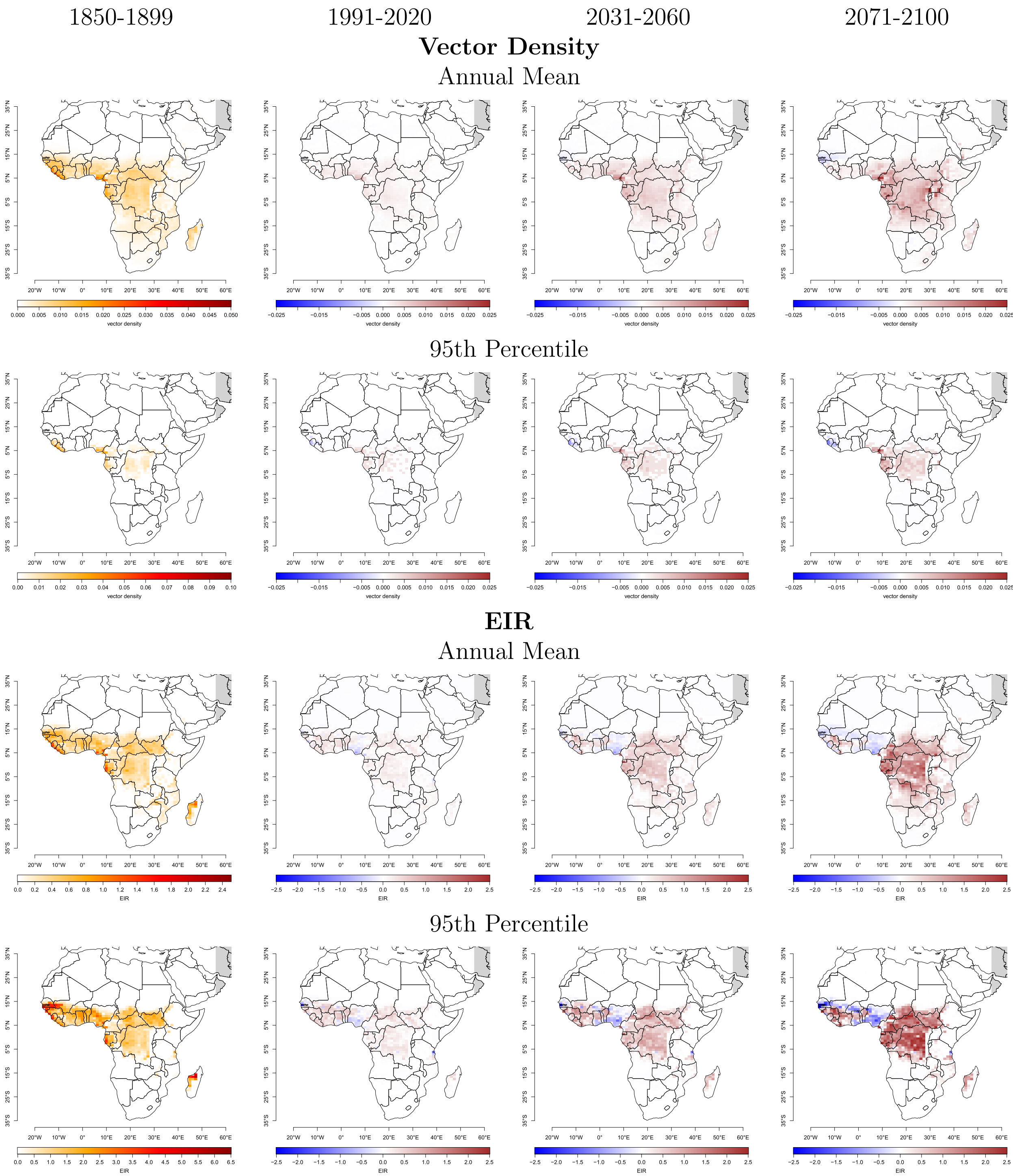

Figure 5. Annual means and 95th percentiles of vector density (vectors per m^2) and EIR (infectious bites per person per day). Displayed mean differences are statistically significant at the 5% level using a Student's *t*-test.

exhibit variability which can exacerbate the malaria infections. For instance, the EIR can be in individual ensemble members up to 35% larger than the ensemble mean. Hence, future projections based on multi-model or ensemble means can considerably misrepresent the malaria infections since also in a warmer future climate natural climate variability will play a pronounced role.

7. Conclusions

The impact of anthropogenic global warming on infectious vector-borne diseases is of obvious importance. Here, we have for the first time estimated the Time of Emergence (TOE) for the SSP3-7.0 scenario. Our results show that the mosquito vector density and EIR will experience its TOE in the near future, mainly between 2030 and 2050, but also in later decades. Parts of Central Africa already passed their TOE in the 1980 and 1990s. This shows that anthropogenic global warming already has and will continue to also directly affect the malaria health infections.

Furthermore, our projections show also a pronounced increase in extremes of vector density and EIR. Our results suggests that very high percentiles of vector density and EIR, such as the 99.99th percentile, almost double in likelihood between the pre-industrial and the far future periods. This suggests that epidemic Malaria disease outbreaks are becoming more likely in the a warmer world.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

The underlying CESM2 data are available from NCAR at https://www.cesm.ucar.edu/community-projects/lens2/data-sets. The model simulations are described in Rodgers et al. (2021). The used VECTRI model is available at https://users.ictp.it/tompkins/vectri/download.html.

Acknowledgments
We thank Drs. A. Timmermann, A. Tompkins and H. Oh for fruitful discussions. This study was supported by the Institute for Basic Science (IBS), Republic of Korea, under IBS-R028-D1 and by the National Research Foundation of Korea (NRF) grants funded by the Korean government (MSIT) (No. RS-2024-00416848 and NRF-2022M3K3A1097082). The CESM simulations were conducted on the IBS/ICCP supercomputer "Aleph," a 1.43 petaflops high-performance Cray XC50-LC Skylake computing system with 18,720 processor cores, 9.59 PB storage, and 43 PB tape archive space. We also acknowledge the support of KREONET.

References

Alcayna, T., Fletcher, I., Gibb, R., Tremblay, L., Funk, S., Rao, B., & Lowe, R. (2022). Climate-sensitive disease outbreaks in the aftermath of extreme climatic events: A scoping review. *One Earth*, *5*(4), 336–350. https://doi.org/10.1016/j.oneear.2022.03.011

Asare, E. O., & Amekudzi, L. K. (2017). Assessing climate driven malaria variability in Ghana using a regional scale dynamical model. *Climate*, *5*(1), 20. https://doi.org/10.3390/cli5010020

Asare, E. O., Tompkins, A. M., Amekudzi, L. K., & Ermert, V. (2016). A breeding site model for regional, dynamical malaria simulations evaluated using in situ temporary ponds observations. *Geospatial Health*, *11*(s1). https://doi.org/10.4081/gh.2016.390

Bashar, K., & Tuno, N. (2014). Seasonal abundance of anopheles mosquitoes and their association with meteorological factors and malaria incidence in Bangladesh. *Parasites & Vectors*, *7*, 1–10. https://doi.org/10.1186/1756-3305-7-442

Bayoh, M. N., & Lindsay, S. W. (2003). Effect of temperature on the development of the aquatic stages of anopheles Gambiae Sensu Stricto (DipTERA: CUlicidae). *Bulletin of Entomological Research*, *93*(5), 375–381. https://doi.org/10.1079/ber2003259

Boyce, R., Reyes, R., Matte, M., Ntaro, M., Mulogo, E., Metlay, J. P., et al. (2016). Severe flooding and malaria transmission in the western Ugandan highlands: Implications for disease control in an era of global climate change. *The Journal of Infectious Diseases*, *214*(9), 1403–1410. https://doi.org/10.1093/infdis/jiw363

Cannon, A. J., Sobie, S. R., & Murdock, T. Q. (2015). Bias correction of GCM precipitation by quantile mapping: How well do methods preserve changes in quantiles and extremes? *Journal of Climate*, *28*(17), 6938–6959. https://doi.org/10.1175/jcli-d-14-00754.1

Ceccato, P., Connor, S., Jeanne, I., & Thomson, M. (2005). Application of geographical information systems and remote sensing technologies for assessing and monitoring malaria risk. *Parassitologia*, *47*(1), 81–96.

Cervellati, M., Esposito, E., & Sunde, U. (2022). Epidemic shocks and civil violence: Evidence from malaria outbreaks in Africa. *The Review of Economics and Statistics*, *104*(4), 780–796. https://doi.org/10.1162/rest_a_01050

Chaturvedi, S., & Dwivedi, S. (2021). Understanding the effect of climate change in the distribution and intensity of malaria transmission over India using a dynamical malaria model. *International Journal of Biometeorology*, *65*(7), 1161–1175. https://doi.org/10.1007/s00484-021-02097-x

Chaturvedi, S., & Dwivedi, S. (2024). Impact of El Niño–Southern Oscillation and Indian Ocean dipole on malaria transmission over India in changing climate. *International journal of Environmental Science and Technology*, *21*(1), 91–100. https://doi.org/10.1007/s13762-023-04836-6

Chenet, S. M., Schneider, K. A., Villegas, L., & Escalante, A. A. (2012). Local population structure of plasmodium: Impact on malaria control and elimination. *Malaria Journal*, *11*, 1–13. https://doi.org/10.1186/1475-2875-11-412

Coalson, J. E., Anderson, E. J., Santos, E. M., Madera Garcia, V., Romine, J. K., Luzingu, J. K., et al. (2021). The complex epidemiological relationship between flooding events and human outbreaks of mosquito-borne diseases: A scoping review. *Environmental Health Perspectives*, *129*(9), 096002. https://doi.org/10.1289/ehp8887

Coetzee, M., Craig, M., & Le Sueur, D. (2000). Distribution of African malaria mosquitoes belonging to the anopheles Gambiae complex. *Parasitology today*, *16*(2), 74–77. https://doi.org/10.1016/s0169-4758(99)01563-x

Colón-González, F. J., Sewe, M. O., Tompkins, A. M., Sjödin, H., Casallas, A., Rocklöv, J., et al. (2021). Projecting the risk of mosquito-borne diseases in a warmer and more populated world: A multi-model, multi-scenario intercomparison modelling study. *The Lancet Planetary Health*, *5*(7), e404–e414. https://doi.org/10.1016/s2542-5196(21)00132-7

Colón-González, F. J., Tompkins, A. M., Biondi, R., Bizimana, J. P., & Namanya, D. B. (2016). Assessing the effects of air temperature and rainfall on malaria incidence: An epidemiological study across Rwanda and Uganda. *Geospatial Health*, *11*(S1), 18–37. https://doi.org/10.4081/gh.2016.379

de Souza, W. M., & Weaver, S. C. (2024). Effects of climate change and human activities on vector-borne diseases. In *Nature reviews microbiology* (pp. 1–16).

Ding, G., Gao, L., Li, X., Zhou, M., Liu, Q., Ren, H., & Jiang, B. (2014). A mixed method to evaluate burden of malaria due to flooding and waterlogging in Mengcheng County, china: A case study. *PLoS One*, *9*(5), e97520. https://doi.org/10.1371/journal.pone.0097520

Duffy, P. E., Gorres, J. P., Healy, S. A., & Fried, M. (2024). Malaria vaccines: A new era of prevention and control. In *Nature reviews microbiology* (pp. 1–17).

Fillinger, U., Sombroek, H., Majambere, S., van Loon, E., Takken, W., & Lindsay, S. W. (2009). Identifying the most productive breeding sites for malaria mosquitoes in the Gambia. *Malaria Journal*, *8*, 1–14. https://doi.org/10.1186/1475-2875-8-62

Franzke, C. L. E., & Torelló i Sentelles, H. (2020). Risk of extreme high fatalities due to weather and climate hazards and its connection to large-scale climate variability. *Climate Change*, *162*, 141–157.

Franzke, C. L. E., & Czupryna, M. (2020). Probabilistic assessment and projections of US weather and climate risks and economic damages. *Climate Change*, *158*(3–4), 503–515. https://doi.org/10.1007/s10584-019-02558-8

Franzke, C. L. E., & Czupryna, M. (2021). Global risks of infectious disease outbreaks and its relation to climate. *Environmental Research Letters*, *16*(8), 084063. https://doi.org/10.1088/1748-9326/ac188c

Gao, L., Zhang, Y., Ding, G., Liu, Q., & Jiang, B. (2016). Identifying flood-related infectious diseases in Anhui province, China: A spatial and temporal analysis. *The American Journal of Tropical Medicine and Hygiene*, *94*(4), 741–749. https://doi.org/10.4269/ajtmh.15-0338

Glick, J. I. (1992). Illustrated key to the female anopheles of southwestern Asia and Egypt (DIPTERA: CULICIDAE). *Mosquito Systematics*, *24*(2), 125–153.

Hawkins, E., & Sutton, R. (2012). Time of emergence of climate signals. *Geophysical Research Letters*, *39*(1), L01702. https://doi.org/10.1029/2011gl050087

Hay, S. I., Guerra, C. A., Gething, P. W., Patil, A. P., Tatem, A. J., Noor, A. M., et al. (2009). A world malaria map: Plasmodium falciparum endemicity in 2007. *PLoS Medicine*, *6*(3), e1000048. https://doi.org/10.1371/journal.pmed.1000048

Hay, S. I., Guerra, C. A., Tatem, A. J., Noor, A. M., & Snow, R. W. (2004). The global distribution and population at risk of malaria: Past, present, and future. *The Lancet Infectious Diseases*, *4*(6), 327–336. https://doi.org/10.1016/s1473-3099(04)01043-6

Hoermann, A., Habtewold, T., Selvaraj, P., Del Corsano, G., Capriotti, P., Inghilterra, M. G., et al. (2022). Gene drive mosquitoes can aid malaria elimination by retarding plasmodium sporogonic development. *Science Advances*, *8*(38), eabo1733. https://doi.org/10.1126/sciadv.abo1733

Hug, D. O., Kropf, A., Amann, M. O., Koella, J. C., & Verhulst, N. O. (2024). Unexpected behavioural adaptation of yellow fever mosquitoes in response to high temperatures. *Scientific Reports*, *14*(1), 3659. https://doi.org/10.1038/s41598-024-54374-5

Jones, B., & O'Neill, B. C. (2016). Spatially explicit global population scenarios consistent with the shared socioeconomic pathways. *Environmental Research Letters*, *11*(8), 084003. https://doi.org/10.1088/1748-9326/11/8/084003

Kaye, A. R., Obolski, U., Sun, L., Hart, W. S., Hurrell, J. W., Tildesley, M. J., & Thompson, R. N. (2024). The impact of natural climate variability on the global distribution of aedes aegypti: A mathematical modelling study. *The Lancet Planetary Health*, *8*(12), e1079–e1087. https://doi.org/10.1016/s2542-5196(24)00238-9

Kim, J.-E., Yamaguchi, R., Rodgers, K. B., Timmermann, A., Lee, S.-S., Stein, K., et al. (2023). Interannual fires as a source for subarctic summer decadal climate variability mediated by permafrost thawing. *npj Climate and Atmospheric Science*, *6*(1), 84. https://doi.org/10.1038/s41612-023-00415-1

Klein Goldewijk, K., Beusen, A., Doelman, J., & Stehfest, E. (2017). Anthropogenic land use estimates for the Holocene–Hyde 3.2. *Earth System Science Data*, *9*(2), 927–953. https://doi.org/10.5194/essd-9-927-2017

Lahondère, C., & Bonizzoni, M. (2022). Thermal biology of invasive Aedes mosquitoes in the context of climate change. *Current Opinion in Insect Science*, *51*, 100920. https://doi.org/10.1016/j.cois.2022.100920

Leedale, J., Tompkins, A. M., Caminade, C., Jones, A. E., Nikulin, G., & Morse, A. P. (2016). Projecting malaria hazard from climate change in eastern Africa using large ensembles to estimate uncertainty. *Geospatial Health*, *11*(1s), 102–114. https://doi.org/10.4081/gh.2016.393

Lindsay, S. W., Thomas, M. B., & Kleinschmidt, I. (2021). Threats to the effectiveness of insecticide-treated bednets for malaria control: Thinking beyond insecticide resistance. *Lancet Global Health*, *9*(9), e1325–e1331. https://doi.org/10.1016/s2214-109x(21)00216-3

Lunde, T. M., Bayoh, M. N., & Lindtjørn, B. (2013). How malaria models relate temperature to malaria transmission. *Parasites & Vectors*, *6*, 1–10.

Lyimo, E. O., Takken, W., & Koella, J. (1992). Effect of rearing temperature and larval density on larval survival, age at pupation and adult size of anopheles Gambiae. *Entomologia Experimentalis et Applicata*, *63*(3), 265–271. https://doi.org/10.1111/j.1570-7458.1992.tb01583.x

Maes, P., Harries, A. D., Van den Bergh, R., Noor, A., Snow, R. W., Tayler-Smith, K., et al. (2014). Can timely vector control interventions triggered by atypical environmental conditions prevent malaria epidemics? A case-study from Wajir county, Kenya. *PLoS One*, *9*(4), e92386. https://doi.org/10.1371/journal.pone.0092386

Mann, M. E., Steinman, B. A., & Miller, S. K. (2014). On forced temperature changes, internal variability, and the AMO. *Geophysical Research Letters*, *41*(9), 3211–3219. https://doi.org/10.1002/2014gl059233

McMichael, A. J. (2015). Extreme weather events and infectious disease outbreaks. *Virulence*, *6*(6), 543–547. https://doi.org/10.4161/21505594.2014.975022

Mordecai, E. A., Caldwell, J. M., Grossman, M. K., Lippi, C. A., Johnson, L. R., Neira, M., et al. (2019). Thermal biology of mosquito-borne disease. *Ecology Letters*, *22*(10), 1690–1708. https://doi.org/10.1111/ele.13335

Okuneye, K., Eikenberry, S. E., & Gumel, A. B. (2019). Weather-driven malaria transmission model with gonotrophic and sporogonic cycles. *Journal of Biological Dynamics*, *13*(sup1), 288–324. https://doi.org/10.1080/17513758.2019.1570363

Paaijmans, K. P., Wandago, M. O., Githeko, A. K., & Takken, W. (2007). Unexpected high losses of anopheles Gambiae larvae due to rainfall. *PLoS One*, *2*(11), e1146. https://doi.org/10.1371/journal.pone.0001146

Parham, P. E., Waldock, J., Christophides, G. K., Hemming, D., Agusto, F., Evans, K. J., et al. (2015). Climate, environmental and socio-economic change: Weighing up the balance in vector-borne disease transmission. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *370*(1665), 20130551. https://doi.org/10.1098/rstb.2013.0551

Parihar, R. S., Bal, P. K., Kumar, V., Mishra, S. K., Sahany, S., Salunke, P., et al. (2019). Numerical modeling of the dynamics of malaria transmission in a highly endemic region of India. *Scientific Reports*, *9*(1), 11903. https://doi.org/10.1038/s41598-019-47212-6

Parihar, R. S., Bal, P. K., Saini, A., Mishra, S. K., & Thapliyal, A. (2022). Potential future malaria transmission in Odisha due to climate change. *Scientific Reports*, *12*(1), 9048. https://doi.org/10.1038/s41598-022-13166-5

Pascual, M., Cazelles, B., Bouma, M., Chaves, L., & Koelle, K. (2008). Shifting patterns: Malaria dynamics and rainfall variability in an African highland. *Proceedings of the Royal Society B: Biological Sciences*, *275*(1631), 123–132. https://doi.org/10.1098/rspb.2007.1068

Porta, M. S. (2014). *A dictionary of epidemiology*. Oxford University Press.

Reiter, P. (2001). Climate change and mosquito-borne disease. *Environmental Health Perspectives*, *109*(suppl 1), 141–161. https://doi.org/10.2307/3434853

Rodgers, K. B., Lee, S.-S., Rosenbloom, N., Timmermann, A., Danabasoglu, G., Deser, C., et al. (2021). Ubiquity of human-induced changes in climate variability. *Earth System Dynamics*, *12*(4), 1393–1411. https://doi.org/10.5194/esd-12-1393-2021

Schulzweida, U. (2023). CDO user guide. https://doi.org/10.5281/zenodo.10020800

Semenza, J. C., Rocklöv, J., & Ebi, K. L. (2022). Climate change and cascading risks from infectious disease. *Infectious Diseases and Therapy*, *11*(4), 1371–1390. https://doi.org/10.1007/s40121-022-00647-3

Siraj, A. S., Bouma, M. J., Santos-Vega, M., Yeshiwondim, A. K., Rothman, D. S., Yadeta, D., et al. (2015). Temperature and population density determine reservoir regions of seasonal persistence in highland malaria. *Proceedings of the Royal Society B: Biological Sciences*, *282*(1820), 20151383. https://doi.org/10.1098/rspb.2015.1383

Sui, Y., Lang, X., & Jiang, D. (2014). Time of emergence of climate signals over China under the RCP4.5 scenario. *Climatic Change*, *125*(2), 265–276. https://doi.org/10.1007/s10584-014-1151-y

Talib, J., Abatan, A. A., HoekSpaans, R., Yamba, E. I., Egbebiyi, T. S., Caminade, C., et al. (2024). The effect of explicit convection on simulated malaria transmission across Africa. *PLoS One*, *19*(4), e0297744. https://doi.org/10.1371/journal.pone.0297744

Thomson, M. C., & Stanberry, L. R. (2022). Climate change and vectorborne diseases. *New England Journal of Medicine*, *387*(21), 1969–1978. https://doi.org/10.1056/nejmra2200092

Tompkins, A. M., & Caporaso, L. (2016). Assessment of malaria transmission changes in Africa, due to the climate impact of land use change using coupled model intercomparison project phase 5 earth system models. *Geospatial Health*, *11*(s1). https://doi.org/10.4081/gh.2016.380

Tompkins, A. M., Colón-González, F. J., Di Giuseppe, F., & Namanya, D. B. (2019). Dynamical malaria forecasts are skillful at regional and local scales in Uganda up to 4 months ahead. *GeoHealth*, *3*(3), 58–66. https://doi.org/10.1029/2018gh000157

Tompkins, A. M., & Di Giuseppe, F. (2015). Potential predictability of malaria in Africa using ECMWF monthly and seasonal climate forecasts. *Journal of Applied Meteorology and Climatology*, *54*(3), 521–540. https://doi.org/10.1175/jamc-d-14-0156.1

Tompkins, A. M., & Ermert, V. (2013). A regional-scale, high resolution dynamical malaria model that accounts for population density, climate and surface hydrology. *Malaria Journal*, *12*, 1–24. https://doi.org/10.1186/1475-2875-12-65

Tompkins, A. M., & Thomson, M. C. (2018). Uncertainty in malaria simulations in the highlands of Kenya: Relative contributions of model parameter setting, driving climate and initial condition errors. *PLoS One*, *13*(9), e0200638. https://doi.org/10.1371/journal.pone.0200638

Villena, O. C., Arab, A., Lippi, C. A., Ryan, S. J., & Johnson, L. R. (2024). Influence of environmental, geographic, socio-demographic, and epidemiological factors on presence of malaria at the community level in two continents. *Scientific Reports*, *14*(1), 16734. https://doi.org/10.1038/s41598-024-67452-5

World Health Organization (WHO). (2018). Mosquito-borne diseases 2018. Retrieved from https://www.who.int/news-room/fact-sheets/detail/vector-borne-diseases

World Health Organization (WHO). (2023). World malaria report 2023. Retrieved from https://www.who.int/teams/global-malaria-programme/reports/world-malaria-report-2023

World Health Organization (WHO). (2024). World malaria report 2024. Retrieved from https://www.who.int/teams/global-malaria-programme/reports/world-malaria-report-2024

Xavier, A. C. F., Martins, L. L., Rudke, A. P., de Morais, M. V. B., Martins, J. A., & Blain, G. C. (2022). Evaluation of quantile delta mapping as a bias-correction method in maximum rainfall dataset from downscaled models in São Paulo state (Brazil). *International Journal of Climatology*, *42*(1), 175–190. https://doi.org/10.1002/joc.7238

Yamaguchi, R., Kim, J.-E., Rodgers, K. B., Stein, K., Timmermann, A., Lee, S.-S., et al. (2023). Persistent ocean anomalies as a response to northern hemisphere heating induced by biomass burning variability. *Journal of Climate*, *36*(23), 8225–8241. https://doi.org/10.1175/jcli-d-23-0090.1

Yamba, E. I., Fink, A. H., Badu, K., Asare, E. O., Tompkins, A. M., & Amekudzi, L. K. (2023). Climate drivers of malaria transmission seasonality and their relative importance in sub-Saharan Africa. *GeoHealth*, *7*(2), e2022GH000698. https://doi.org/10.1029/2022gh000698

Zhou, G., Minakawa, N., Githeko, A. K., & Yan, G. (2004). Association between climate variability and malaria epidemics in the East African highlands. *Proceedings of the National Academy of Sciences*, *101*(8), 2375–2380. https://doi.org/10.1073/pnas.0308714100

Zhou, G., Munga, S., Minakawa, N., Githeko, A. K., & Yan, G. (2007). Spatial relationship between adult malaria vector abundance and environmental factors in western Kenya highlands. *The American Journal of Tropical Medicine and Hygiene*, *77*(1), 29–35. https://doi.org/10.4269/ajtmh.2007.77.29