Regular Article

Malaria ecology and climate change

G.C. McCord[a]

School of Global Policy and Strategy, University of California, San Diego, USA

Abstract. Understanding the costs that climate change will exact on society is crucial to devising an appropriate policy response. One of the channels through while climate change will affect human society is through vector-borne diseases whose epidemiology is conditioned by ambient ecology. This paper introduces the literature on malaria, its cost on society, and the consequences of climate change to the physics community in hopes of inspiring synergistic research in the area of climate change and health. It then demonstrates the use of one ecological indicator of malaria suitability to provide an order-of-magnitude assessment of how climate change might affect the malaria burden. The average of Global Circulation Model end-of-century predictions implies a 47% average increase in the basic reproduction number of the disease in today's malarious areas, significantly complicating malaria elimination efforts.

1 Introduction

Society's willingness to pay to avert climate change, for example through a carbon tax and higher energy prices, should optimally depend on the predicted damage from climate change. Therefore, understanding the costs that climate change will exact on society is crucial to devising an appropriate policy response. These costs will occur along many dimensions [1], including through changes in the geographical extent and intensity of vector-born diseases whose biology is sensitive to the ambient ecology. Malaria has afflicted human society for over 2 million years [2], and remains one of the great killer diseases today [3]. The disease is the fourth leading cause of death for children under five in low income countries (after neonatal disorders, diarrhea, and pneumonia) and despite an aggressive increase in resources for malaria control, it still infects an estimated 200 million people and killed an estimated 438,000 in 2015. Malaria is highly conditioned by ecology, because of which climate change is likely to affect the local dynamics of the disease through changes in ambient temperature and precipitation. This paper introduces the literature on malaria's cost on society and the literature on malaria and climate change to the physics community in hopes of inspiring synergistic research in the area of climate change and health. It then demonstrates the use of one ecological indicator of malaria suitability to provide an order-of-magnitude assessment of how climate change might affect the malaria burden.

---

[a] e-mail: `gmccord@ucsd.edu`

The paper is organized as follows: the first section describes the role of ecology in the epidemiology of malaria. It next describes the malaria and climate change literature, and explains the construction of the Malaria Ecology Index (MEI) and statistically tests whether the MEI has explanatory power over within-country year-to-year variation in malaria incidence and mortality rates. The paper uses output from a suite of climate models to illustrate how malaria ecology would evolve under a distribution of climate change possibilities. Finally, it discusses implications of this change for the malaria burden, and concludes.

2 Cost of malaria on society

The costs of malaria on human society have been written about extensively. These costs operate through direct medical expenditures on preventing and treating the disease, but also due to effects on children's cognition, school absenteeism, reduced adult productivity, reduced internal migration to pursue economic opportunities, reduced foreign direct investment and reduced tourism [5]. The lifetime effects of the disease are exemplified by studies of eradication campaigns in Paraguay and Sri Lanka, where malaria eradication led to increases in completed schooling and literacy [6], and in the United States, Brazil, Colombia and Mexico, where children born right after the beginning of eradication campaigns had significantly higher incomes as adults than children born right before eradication [7]. In utero and postnatal exposure to malaria in the United States led to reduced educational attainment and higher poverty rates later in life, explaining as much as 25% of the difference in educational attainment between children born in high and low malaria states [8].

Importantly, high child mortality leads to parents choosing to have many children, which in turn results in high population growth rates and a stalled demographic transition [9]. Families in this high-mortality high-fertility dynamic expend scarce resources on children that do not survive, and have fewer resources to spend on the health and education of each child. The fact that women spend so much of their adult life in child-rearing activities means that parents have little incentive to educate little girls, leading to a lack of female opportunity and empowerment. These myriad channels through which malaria afflicts society help explain why countries with endemic malaria have lower income per capita levels and reduced rates of economic growth (an average 1.3% slower growth rate in income per capita between malarious and malaria-free countries) [10].

3 The ecology of malaria

Malaria is a disease strongly regulated by climatic conditions for several reasons, leading scholars to generate multiple map products of malaria suitability around the globe [11,12]. First, higher ambient temperatures increase the metabolic rate of the *Plasmodium* parasite, resulting in a shorter sporogony period (the reproductive phase of the parasite inside the gut of the *Anopheles* mosquito). This increases likelihood that the *Plasmodium* will successfully undergo reproduction and make the mosquito infective before the end of the mosquito's life-span. The relationship between temperature and the *Plasmodium*'s sporogony period is nonlinear, with zero transmission below 15°C, optimal temperature at around 24°C, and significantly deleterious effects on parasite development rates above 31°C in the case of *P. falciparum* and 29.8°C in the case of *P. vivax* [13]. Additionally, while high temperatures speed up mosquito development and increase frequency of blood feeding, they also reduce mosquito survival [14], further introducing complexity into the relationship between temperature and malaria transmission.

Second, precipitation must be adequate to create breeding sites (in Africa, most *Anopheles* vectors breed in rain puddles, although some can breed in brackish standing water). Additionally, the intensity of malaria transmission depends on the specific mosquito species that is present and its relative preference to biting humans versus animals. These three factors – temperature, precipitation, and the human biting preference of the local *Anopheles* vector – are therefore key inputs into the general expression for the basic reproduction number of malaria [15]:

$$R_0 = \frac{ma^2bce^{-gn}}{r(-ln(p))}$$

m: ratio of mosquitoes to humans
a: human feeding rate
$1/g$: average mosquito life-span
n: incubation period
c: human-to-mosquito transmission efficiency
b: mosquito-to-human transmission efficiency
$1/r$: human infectious period
$1/-ln(p)$: daily mosquito survival probability.

In epidemiological terms, the basic reproduction number (R_0) is the expected number of secondary infections produced by each infected individual in its infectious period, in a population which is entirely susceptible. When $R_0 < 1$, each infected individual infects less than one individual on average, and the infection is expected to die out in the population. If $R_0 > 1$, the infection is expected to thrive in the population. The pre-intervention value of R_0 directly affects whether local elimination is feasible. Interventions that curb the rates of transmission and therefore reduce R_0, such as indoor residual spraying of DDT, are only successful in locally eliminating the disease if they reduce R_0 below the threshold of 1. Thus, the effectiveness of existing technologies strongly depends on the baseline R_0: if it is relatively close to unity, the intervention can help push it below the threshold. But in those locations where the baseline R_0 is very high (numbers higher than 100 are not uncommon in rural sub-Saharan Africa), these same interventions may be ineffective. This explains why many temperate regions eliminated malaria with interventions that do not achieve elimination in sub-Saharan Africa.[1]

4 Malaria and climate change

A number of scholars have tackled the question of how malaria's toll on humanity will change as a result of climate change. The first set of contributions focused not on climate change per se, but on using the ecological constraints on the development of the *Plasmodium* and *Anopheles* to map areas of malaria transmission intensity [11]. Specifically, the relationship between temperature and duration of sporogony is reported as:

$$n = \frac{DD}{T - T_{min}}$$

where n is the number of days in the sporogony cycle, DD is the total degree days for parasite development (111 in the case of *Plasmodium falciparum*), T is the mean temperature and T_{min} is the temperature below which parasite development ceases

---

[1] Note, however, that even with continuing transmission, control of illness and mortality is possible. Thus, maps of the presence of malaria transmission may not change even while the burden of illness and death is changing markedly.

(16°C for *P. falciparum*). Higher temperature also reduce daily mosquito survival rates as follows:

$$p = e^{-1/(-4.4 + 1.31T - 0.03T^2)}.$$

Finally, high temperatures reduce the duration of the larval stage of the *Anopheles*, which increases transmission:

$$ld = 1/(0.00554T - 0.06737).$$

The relationship between rainfall and malaria transmission is even more complicated, and less amenable to generalized physiological relationships with malaria transmission like those for temperature.

One of the first ecology-based malaria suitability maps used a fuzzy logic framework calibrated with monthly rainfall and temperature data from 20 different sites spanning perennial, seasonal, epidemic and malaria-free areas across African countries. The maps were found to correlate well to expert maps on malaria transmission as well as within-country variation in incidence rates, but not subjected to statistical tests using malaria incidence or mortality data [11].

An approach similar to the one presented in this paper generates an ecological map of malaria transmission estimating the number of months suitable for *Plasmodium falciparum* transmission. The maps are validated statistically using data from laboratory-confirmed parasite-ratio surveys, and then coupled with gridded population data and future climate change scenarios from the HadCM3 experiments to estimate the person-months of exposure under current and future climatic conditions. The results indicate that 2100 climate scenarios create a 16–28% increase person-months of exposure, 28–42% of which is in areas already suitable for transmission (as opposed to geographic expansion of suitability) [16]. This work does not, however, allow for measuring increased transmission intensity within months that already had transmission, and so likely underestimates the effect of climate change.

More recently, systematic multi-model analysis allows for comparison of uncertainty across models; this work finds that the tropical highlands are most at risk of increased malaria burden, however accurate forecasting will require projections of land use change, population growth, migration and economic development which are absent in existing malaria and climate change models [17].

5 Construction of the Malaria Ecology Index[2]

In order to illustrate the use of ecological principles of malaria epidemiology and statistical validation to model changes in malaria burden under climate change, this paper constructs a Malaria Ecology Index [12]. The index uses models of the disease's epidemiological dynamics (based on the interaction of climate with the dominant properties of *Anopheles* vectors that determine vectorial capacity) to construct an ecologically-based spatial index of the stability of malaria transmission. The index incorporates the effects of ambient temperature on the force of transmission of malaria, as expressed through the length of the extrinsic incubation period, and therefore the proportion of the vector population able to survive long enough to become infectious. The original version of the index averaged 1901–1990 monthly temperature and precipitation to generate a single value for each location [12], whereas this paper constructs a time-varying annual index for every year from 1900 to 2010. The index

---

[2] I am grateful to Anthony Kiszewski for guiding me through the details of the construction of the original version of the index.

is constructed on a 0.5 degree spatial grid to derive the climatic characteristics of individual months, and then summed over a 12-month period to compare to annual data from public health registries.

The first step is to identify the distribution of *Anopheles* species across the world using observation records, supplemented with satellite-based vegetation maps to identify likely habitats where observations have not been recorded. A dominant species thus is identified for each spatial zone, and for each month (in cases where there is a seasonal pattern to the dominant species). An ecological screen was created for the presence or absence of a vector during particular months. For those vectors that breed mainly in temporary water, a minimum precipitation threshold of 10 mm per month, lagged one month, is used to judge when the vector would be present in the site during a given month. Vectors that mainly exploit permanent or semi-permanent bodies of water were considered to be independent of seasonal fluctuations in rainfall unless empirical evidence indicated otherwise. In temperate or altitudinous regions, temperature thresholds are used to determine whether parasites can develop in mosquito vectors in a particular month, assuming that malaria parasites cannot develop when the mean monthly temperature remains below 15°C.

Note that the mosquito screen is ecology-based and not affected by human activity; indeed, it is worth keeping in mind that public health interventions against malaria serve to break the transmission cycle, but do not eliminate the presence of the vector itself (*Anopheles* mosquitoes capable of transmitting malaria can be found today throughout the US and Europe, places where malaria has been largely eliminated).

The basic formula for the Malaria Ecology Index combines climatic factors, the presence of different mosquito vector types and the human biting rate of each vector. The index expresses the exogenous factors that most powerfully and perennially influence the intensity of malaria transmission, using a subset of the reproduction number equation described above without terms for mosquito abundance, vector competence, or recovery rate for infected people:

$$MEI_{iy} = \sum_{m=1}^{12} \frac{a_{i,m}^2 p_{i,m}^E}{-\ln p_{i,m}} = \sum_{m=1}^{12} \frac{a_{i,m}^2 p_{i,m}^{\frac{111}{T-16}}}{-\ln p_{i,m}}$$

i = grid cell
y = year
m = month
a = proportion biting humans (0–1) of dominant vector in grid i and month m
p = daily survival rate (0–1)
E = sporogony period in days: $E = \frac{111}{T-16}$ for *Plasmodium falciparum*
T = mean monthly temperature.

The index can also be constructed to incorporate pernicious effects of higher temperatures for disease transmission. The optimal rates of development for *P. falciparum* and *P. vivax* occur at 23–24°C, whereas the development rates of the parasite begin to decrease beyond 31°C for *P. falciparum* and 29.8°C for *P. vivax*. The Malaria Ecology Index could thus be constructed using the following equation for development rate r to completion of sporogony, calibrated from observed data in the literature [13]:

$$r = \frac{0.06044 \frac{T}{296.65} exp\left[\frac{17545}{1.987}\left(\frac{1}{296.65} - \frac{1}{T}\right)\right]}{1 + exp\left[\frac{-142843}{1.987}\left(\frac{1}{288.85} - \frac{1}{T}\right)\right] + exp\left[\frac{110980}{1.987}\left(\frac{1}{306.90} - \frac{1}{T}\right)\right]}$$
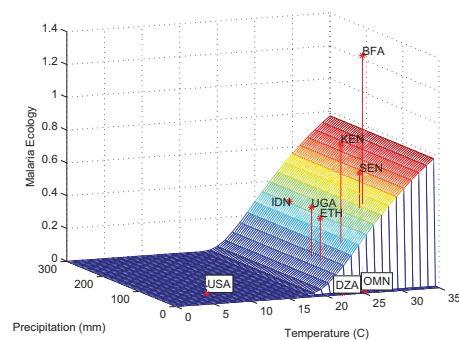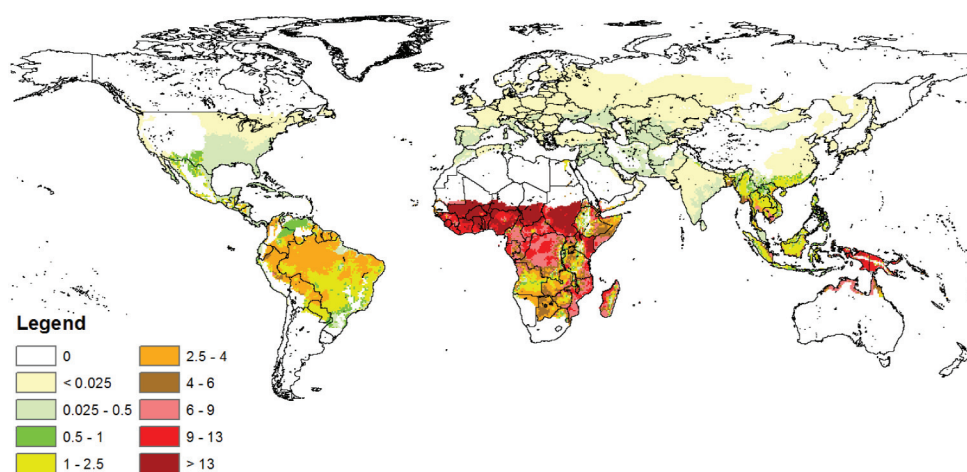
Fig. 1. Malaria ecology for HBI = 0.5.

Fig. 2. Average malaria ecology from 1980–2010.

Results presented below are all robust to using this other version of the index, likely because mean monthly temperatures at national level rarely reach those upper temperature thresholds for *Plasmodium* physiology.

Because it is built upon climatological and vector characteristics, the Malaria Ecology Index is exogenous to public health interventions and economic conditions, and thus can serve as an instrumental variable in regressions of economic performance on malaria risk [18,19]. Moreover, its particular functional form means that it is likely capturing a dynamic that will be relatively uncorrelated to other temperature- and precipitation-determined processes (like agricultural yields, for example). Figure 1 illustrates graphically how the index varies with temperature and precipitation for a given human biting index of 0.5.

The figure also indicates the average value of the index for nine countries (they are mostly off the surface because the average human biting index in those countries is not 0.5). Note the very particular functional form, with significant nonlinearities at 16 degrees Celsius and 10 mm of precipitation. The average Malaria Ecology Index for 1980–2010 is mapped in Fig. 2, constructed with climate data from the University of Delaware [20].
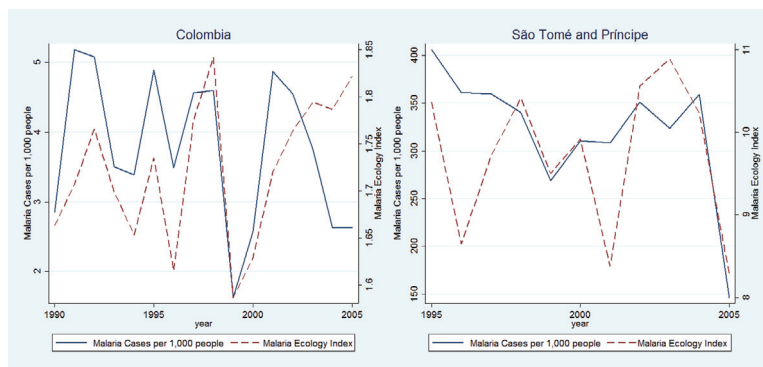
Fig. 3. Malaria mortality and ecology in Colombia and São Tomé & Príncipe.

6 Malaria ecology and malaria incidence & mortality

The Malaria Ecology Index is averaged within each country's national boundaries to create a national value, which can then be compared to yearly national-level malaria incidence and mortality data as reported by the World Health Organization [21]. The evolution of malaria ecology and malaria incidence (in cases per thousand people) is shown below for two very different countries: Colombia (a middle-income country where malaria mortality is lower in part because *Plasmodium vivax* is rarely lethal) and São Tomé & Príncipe (a low-income country where *Plasmodium falciparum* dominates, resulting in many more fatalities). Upon visual inspection the index does correlate to incidence in both countries.

To test the statistical strength of these relationships, Table 1 shows country-level regressions of the annual mortality from malaria (in deaths per thousand population) on the Malaria Ecology Index for that year (for these regressions, the index is constructed using University of Delaware climate data [20]). The first regression employs an indicator variable for each country (referred to as fixed effects in the econometrics parlance), which absorbs countries' time-invariant characteristics that might be correlated to both malaria ecology and malaria mortality and thus bias results. This is a concern, for example, if tropical countries tend to be poorer for reasons other than malaria; their less developed public health systems result in higher malaria mortality which might be only partially due to the ambient ecology. The regression also includes an indicator variable for each year to flexibly control for global trends affecting all countries at once (such as improvements in anti-malaria technology or financing).

The coefficient on the Malaria Ecology Index is 0.55, suggesting that when a country experiences a year with a 1-point higher MEI than average, malaria mortality tends to be around 55% higher. This association is significant at the 99% confidence level. Note that for the proper inference, standard errors are clustered at the country level to flexibly allow for non-independence in a country's observations across years. Regressions are also weighted by country population to account for higher variance among the smaller countries in the sample. The second regression presents a more conservative estimate by including a linear time trend for each country, thus absorbing secular trends in each country's malaria ecology and malaria mortality that might generate a spurious association. The resulting coefficient on Malaria Ecology drops to 0.36, still statistically significant at the 99% confidence level. This means that deviations in malaria ecology from a country's linear trend has explanatory power over deviations in that country's trend in malaria mortality. The drop in the coefficient magnitude from regression (i) to (ii) underscores the importance of controlling for trends in the variables that might generate a spurious correlation. The fact that the

Table 1. Malaria deaths and malaria ecology from 1990–2007.

Independent variable	Dependent Variable: ln(Malaria deaths per 1,000 population)		
	(i)	(ii)	(iii)
Malaria Ecology	0.55***	0.36***	0.17***
	(0.18)	(0.09)	(0.03)
N	654	654	12167
Countries	84	84	81
Years	1990-2007	1990-2007	1990-2007
Climate Data Used	UDel	UDel	16 GCMs
Within R-squared	0.19	0.64	
Country Fixed Effects	Y	Y	Y
Year Fixed Effects	Y	Y	Y
Country-Specific Linear Trend		Y	Y

Std. error in parentheses, *** indicates significant to 99% confidence.

Regressions include a constant (not reported)

Regressions report robust standard errors clustered by country

Regressions weigh observations by population

coefficient remains statistically significant controlling for country-level trends provides strong evidence for malaria ecology as a driver of variation in malaria outcomes over time.

Finally, regression (iii) employs a pooled regression of 16 blocks of data (one for each Global Climate Model used in the Malaria Ecology Index construction). This pooling strategy allows for robust identification of the association between malaria ecology and malaria mortality across GCM models, to verify that the association is not overly sensitive to the choice of climate data. The regression employs indicator variables for country and year interacted with the indicator variables for the model used, and interacts the country-specific linear trend with an indicator variable for model as well. Standard errors are clustered at the country level again to allow adjust for the lack of statistical independence across country observations in the data. The coefficient is now 0.17 and significant to the 99% confidence level. The decrease in coefficient magnitude compared to regression (ii) is likely due to attenuation from measurement error if the University of Delaware data provides more accurate weather over the period than the climate model output. The exercise is nevertheless useful because it shows that the association between the Malaria Ecology Index constructed from GCMs and malaria mortality is statistically significant, validating our next step of using GCM forecasts to discuss the effect of climate change on the ecology of malaria.

Figure 4 shows graphically how higher values of the malaria ecology index are associated with higher malaria mortality after partialling out country and year dummies in the model. The dotted line shows local regression estimates, while the solid line represents the linear approximation. The densities are provided to indicate that the positive relationship is present over the entire support of the malaria ecology variable.

7 Malaria ecology under climate change

The paper has thus far explained the role that ecology plays in malaria dynamics and constructed a year-to-year ecology-based index proportional to the strength of transmission. Places where malaria elimination occurred during the twentieth century are those where the Malaria Ecology Index (and therefore the pre-public health intervention R_0) was lowest. The index was shown to have explanatory power over year-to-year variation in both malaria incidence and mortality from 1990 to 2005. The next step, then, is to use results from General Circulation Models (GCMs) of the global climate
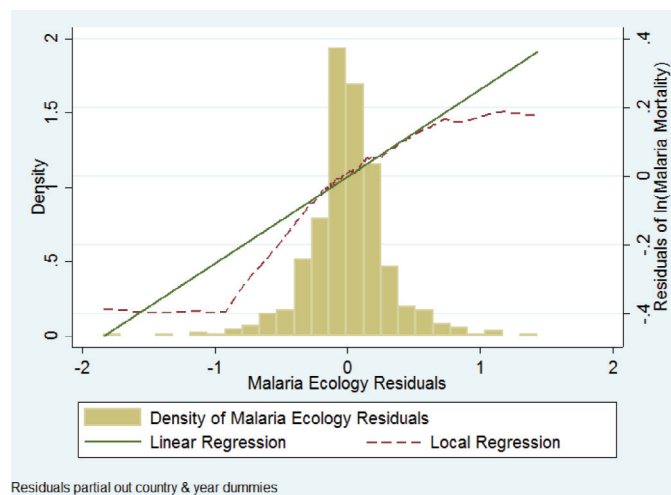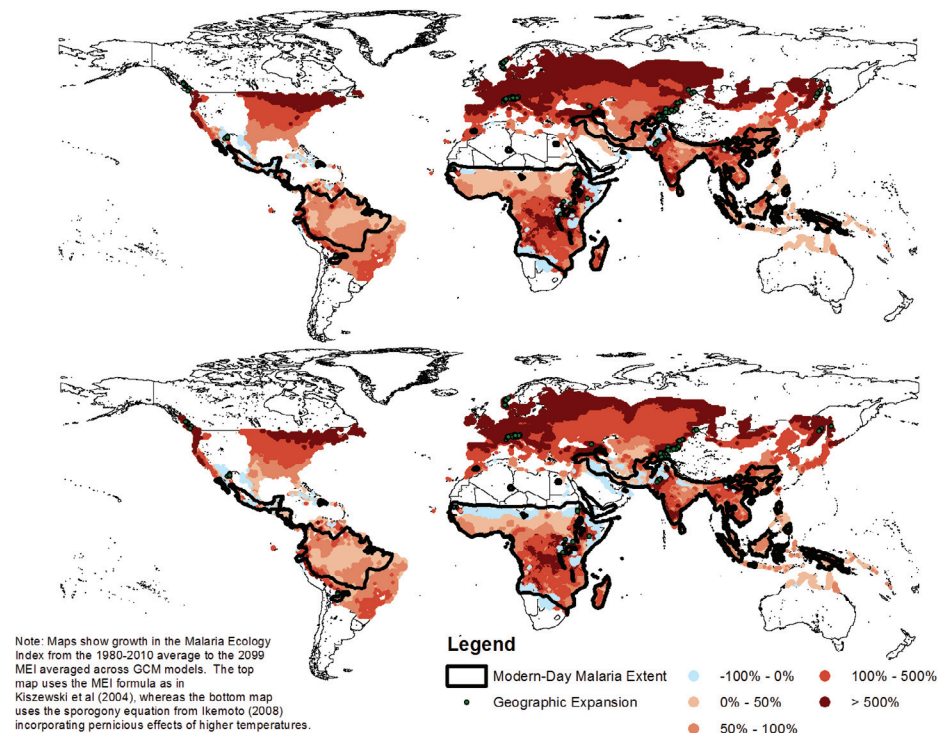
Fig. 4. Malaria mortality and ecology, 1990–2007.

to calculate the Malaria Ecology Index under a scenario of climate change in the late 21st century. Global climate model output[3] are from the World Climate Research Program's (WCRP's) Coupled Model Intercomparison Project phase 3 (CMIP3) multi-model dataset [22]. These data were downscaled using the bias-correction/ spatial downscaling method [23] to a 0.5 degree grid [24], based on 1950–1999 gridded observations [25]. The analysis employs the A1B scenario, which assumes a future world of very rapid economic growth, global population that peaks in mid-century and declines thereafter, and rapid introduction of new and more efficient technologies. Figure 5 results from constructing the Malaria Ecology Index with temperature and precipitation projections from each of the 16 GCMs and comparing the Malaria Ecology Index in 2099 averaged across models with the 1980–2010 average. The maps shows percentage growth rates of the Malaria Ecology Index in places with nonzero index values before 2010. The top map uses the basic MEI equation, and the bottom map constructs the MEI using the sporogony function that incorporates the adverse effects of high temperatures on parasite development [13]. The growth rates are positive in nearly the entire world, emphasizing the pernicious effect that climate change will have on the ecology of malaria. The growth is largest in the higher latitudes, where current index values are lower and changes in temperature are larger in absolute terms, but it is likely more important in places which already have high index values and currently experience some amount of malaria transmission (the dark black outline shows the 2002 geographic extent of malaria [26]). Moreover, green dots designate areas where malaria ecology is zero (or nearly zero) and is higher than 0.5 by 2099, thus indicating geographic expansion. Note that these occur in the highlands of East Africa, where scholars have been debating the role of climate change in increased malaria presence at ever higher altitudes [27–31].

To gauge the effects that increases in the malaria ecology index might have on public health efforts to control and eliminate the disease, we analyze the Malaria Ecology Index values within the area of malaria extent in 2002 (the black polygon). The average MEI (averaged across all 16 climate models) between 1980 and 2010 was 3.8 with a standard deviation of 5.7. These same regions, when averaged across 2099 projections of the climate models, have an average MEI of 5.6, a 47% increase. Since the Malaria Ecology Index is a subset of the R_0 equation, the higher index

---

[3] The data were obtained from `www.engr.scu.edu/~emaurer/global_data/`.

Note: Maps show growth in the Malaria Ecology Index from the 1980-2010 average to the 2099 MEI averaged across GCM models. The top map uses the MEI formula as in Kiszewski et al (2004), whereas the bottom map uses the sporogony equation from Ikemoto (2008) incorporating pernicious effects of higher temperatures.

Legend

Modern-Day Malaria Extent   -100% - 0%   100% - 500%
Geographic Expansion   0% - 50%   > 500%
50% - 100%

Fig. 5. Growth in Malaria Ecology Index using 2099 GCM Averages.

value suggests that in places where public health efforts are ongoing in attempts to push R_0 below the threshold value of 1, a 47% higher R_0 can significantly complicate control and elimination.

Any analysis of this geographic and temporal scope involves caveats, of course. Although the projection above employs the nonlinearities between temperature, precipitation and malaria as scholars understand them, they cannot account for fundamental transformations in the environment that might radically change disease transmission. These include changes in land cover or surface hydrology (drying of rivers, for example) which would affect the spatial extent of *Anopheles* vectors.

8 Implications and conclusion

The implications of climate change for malaria have been the subject of several studies [32–34]. This paper adds to this literature by constructing a year-to-year Malaria Ecology Index based solely on ecological factors exogenous to human intervention, and demonstrates the predictive power of the index over country-level year-to-year fluctuations in malaria morbidity and mortality. Since the MEI represents a part of the basic reproduction number (R_0) equation, and given that public health measures successfully eliminate a disease when they push the R_0 below 1, then results predicting significant increases in MEI (an average 47% higher average MEI in malarious areas by the end of this century) have profound implications for malaria control. In places of the world where policy choices, resource allocation, and current technologies have struggled to reduce R_0 to below 1 (not coincidentally those places where R_0 is highest), large increases of R_0 due to climate change would mean that eliminating the

disease will be a much more challenging prospect. Finally, the relationship between the Malaria Ecology Index and malaria mortality in Table 1 suggests that a 47% increase of the MEI (a nearly two-point increase from 3.8 to 5.6) would lead to a 31%–65% (0.17*1.8 – 0.36*1.8) increase in malaria mortality rates given calibration using 1990–2007 data (that is, keeping the prevailing public health technology and effort constant). Considering that malaria accounts for over 300 million clinical cases today, and kills over 0.5 million people, such large potential increases in incidence and mortality rates represent significant burdens on the human population. Since malaria has been showed to compromise education and exact a measurable economic burden [5–8,10], as well as hinder the demographic transition [9], a worsening of malaria would push many of the poorest societies further away from thresholds they need to reach in order to achieve sustained economic development and improvements in human welfare.

Understanding the effect of climate change on malaria and other diseases requires interdisciplinary collaboration between atmospheric science, ecology, entomology, epidemiology and social science. As disease ecology advances to better understand the relationship between parasite and vector physiology and the environment, atmospheric scientists and ecologists could collaborate to design climate data and landcover products suited for the specific needs of disease modeling. Scholars of climate change impacts on disease should increase the sophistication with which they deal with uncertainty, but can only do so if climate prediction products include transparent measures of uncertainty. Finally, systems modelers will find the society-environment-disease coupled system a ripe challenge full of feedbacks and nonlinearities that have yet to be fully characterized and whose consequences are not entirely understood.

References

1. IPCC, Summary for policymakers, in *Climate Change 2014: Impacts, Adaptation and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by C.B. Field, V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea, L.L. White (Cambridge University Press, Cambridge, UK, 2014)
2. R.E. Ricklefs, D.C. Outlaw, Science **329**, 226 (2010)
3. R.E Black, S.S Morris, J. Bryce, Lancet **361**, 2226 (2003)
4. World Health Organization, World Malaria Report 2015 (World Health Organization, Geneva, 2015)
5. J.D. Sachs, P. Malaney, Nature **415**, 680 (2002)
6. A.M. Lucas, Am. Econ. J. Appl. Econ. **2**, 46 (2010)
7. H. Bleakley, Am. Econ. J. Appl. Econ. **2**, 1 (2010)
8. A.I. Barreca, J. Human Res. **45**, 865 (2010)
9. G.C. McCord, D. Conley, J.D. Sachs, Improving empirical estimation of demographic drivers: Fertility, child mortality and malaria ecology, Working paper, Social Science Research Network (2010)
10. J.L. Gallup, J.D. Sachs, Am. J. Tropical Med. Hyg. **64**S, 85 (2001)
11. M.H. Craig, R.W. Snow, D. le Sueur, Parasitol. Today **15**, 865 (1999)
12. A. Kiszewski, A. Mellinger, A. Spielman, P. Malaney, S.E. Sachs, J. Sachs, Am. J. Tropical Med. Hyg. **70**, 486 (2004)
13. T. Ikemoto, J. Medical Entomol. **45**, 963 (2008)
14. J.A. Patz, T.K. Graczyk, N. Geller, A.Y. Vittor, Int. J. Parasitol. **30**, 1395 (2000)
15. D.L. Smith, F.E. McKenzie, Malaria J. **3** (2004)
16. F.C. Tanser, B. Sharp, D. le Sueur, Lancet **362**, 1792 (2003)

17. C. Caminade, S. Kovats, J. Rocklov, A.M. Tompkins, A.P. Morse, F.J. Colon-Gonzales, H. Stenlund, P. Martens, S.J. Lloyd, PNAS **111**, 3286 (2014)
18. J.D. Sachs, Institutions don't rule: direct effects of geography on per capita income, Working paper, National Bureau of Economic Research (2003)
19. K. Carstensen, E. Gundlach, World Bank Econ. Rev. **20**, 309 (2006)
20. K. Matsuura, C.J. Willmott, *Terrestrial air temperature: 1900–2012 gridded monthly time series* (Center for Climatic Research, Dep. of Geography, University of Delaware, Newark)
21. M. Aregawi, R. Cibulskis, M. Otten, R. Williams, C. Dye, et al., World Malaria Report, 2008 (World Health Organization, Geneva, 2008)
22. G.A. Meehl, C. Covey, T. Delworth, M. Latif, B. McAvaney, J.F.B. Mitchell, R.J. Stouffer, K.E. Taylor, Bull. Amer. Meteorol. Soc. **88**, 1383 (2007)
23. A.W. Wood, L. Leung, V. Sridhar, D.P. Lettenmaier, Climatic Change **62**, 189 (2004)
24. E.P. Maurer, J.C. Adam, A.W. Wood, Hydrol. Earth Sys. Sci. **13**, 183 (2009)
25. J.C. Adam, D.P. Lettenmaier, J. Geophys. Res. **108**, 1 (2003)
26. S.I. Hay, C.A. Guerra, A.J. Tatem, A.M. Noor, R.W. Snow, Lancet Infectious Diseases **4**, 327 (2004)
27. A.S. Siraj, M. Santos-Vega, M.J. Bouma, D. Yadeta, D.R. Carrascal, M. Pascual, Science **343**, 1154 (2014)
28. D. Alonso, M.J. Bouma, M. Pascual, Proc. R. Soc. **278**, 1661 (2011)
29. M. Pascual, J.A. Ahumeda, L.F. Chaves, X. Rodo, M. Bouma, Proc. Natl. Acad. Sci. **103**, 5829 (2006)
30. G. Zhou, N. Minakawa, A.K. Githeko, G. Yan, Proc. Natl. Acad. Sci. **101**, 2375 (2004)
31. S.L. Hay, J. Cox, D.J. Rogers, S.E. Randolph, D.L. Stern, G.D. Shanks, M.F. Myers, Nature **415**, 905 (2002)
32. S.W. Lindsay, W.J.M. Martens, Bull. World Health Organ. **76**, 33 (1998)
33. S.I. Hay, D.J. Rogers, S.E. Randolph, D.I. Stern, J. Cox, G.D. Shanks, R.W. Snow, TRENDS in Parasitol. **18**, 530 (2002)
34. M.J. Bouma, Trans. R. Soc. Tropical Med. Hyg. **97**, 133 (2003)