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The opposing effects of climate change and socio-economic development on the global distribution of malaria

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ABSTRACT

The current global geographic distribution of malaria results from a complex interaction between climatic and non-climatic factors. Over the past century, socio-economic development and public health measures have contributed to a marked contraction in the distribution of malaria. Previous assessments of the potential impact of global changes on malaria have not quantified the effects of non-climate factors. In this paper, we describe an empirical model of the past, present and future-potential geographic distribution of malaria which incorporates both the effects of climate change and of socio-economic development. A logistic regression model using temperature, precipitation and gross domestic product per capita (GDPpc) identifies the recent global geographic distribution of malaria with high accuracy (sensitivity 85% and specificity 95%). Empirically, climate factors have a substantial effect on malaria transmission in countries where GDPpc is currently less than US$20,000. Using projections of future climate, GDPpc and population consistent with the IPCC A1B scenario, we estimate the potential future population living in areas where malaria can be transmitted in 2030 and 2050. In 2050, the projected population at risk is approximately 5.2 billion when considering climatic effects only, 1.95 billion when considering the combined effects of GDP and climate, and 1.74 billion when considering GDP effects only. Under the A1B scenario, we project that climate change has much weaker effects on malaria than GDPpc increase. This outcome is, however, dependent on optimistic estimates of continued socioeconomic development. Even then, climate change has important effects on the projected distribution of malaria, leading to an increase of over 200 million in the projected population at risk.

1. Introduction

The influence of climatic factors on malaria vector density and parasite development is well established (Chaves and Koenraadt, 2010; Koenraadt et al., 2004; Macdonald, 1953). Previous studies have assessed the potential influence of climate change on malaria, using deterministic or statistical models (Gething et al., 2010; Hay et al., 2006, 2009; Martens et al., 1999; Parham and Michael, 2010; Pascual et al., 2006; Rogers and Randolph, 2000; van Lieshout et al., 2004). Empirical-statistical models cannot describe the full complexity of malaria transmission, but can incorporate interactions between climatic and socio-economic factors. Both GDP per capita (GDPpc) and climate are strongly associated with malaria risk. In addition, countries where malaria is present also tend to be poorer (Sachs and Malaney, 2002). Therefore, the reported effect of climate on malaria risk needs to be disentangled from the effect of socio-economic factors. Projections of future malaria risk areas need to be based on scenarios of both future development and climatic change.

In this study, we do not attempt to model the complex temporal relationship between weather and malaria prevalence. Instead, we use the global spatial pattern of the presence or absence malaria as our outcome of interest.

1.1. Previous estimates of population at risk of malaria

The World Health Organisation (WHO) estimated the current global population at risk of malaria in 1994 to be 2.3 billion people,

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or 41% of the world's population. Under scenarios of global climate change in the 2050s, around 600 million additional people at risk of year-round ("stable") falciparum malaria transmission are projected (Martens et al., 1999). Other researchers project much smaller changes in the population at risk in the 2050s (from +23 to −25 million people) (Rogers and Randolph, 2000).

The projected decreases in population at risk occur in areas that become too hot for the malaria vector, the Anopheles mosquito. Location shifts in the distribution of two major African malaria vector species, *Anopheles gambiae* and *Anopheles arabiensis*, are predicted by one study for the African continent by 2055 (Peterson, 2009). Decreases in habitat suitability are larger than newly suitable areas in this study. As a result, a decrease in the population at risk of malaria transmission by 11.3% and 24.1% of the current population is found for the *An. gambiae* and the *An. arabiensis* vector, respectively.

Hay et al. (2006) project changes in population at risk of malaria due to climate change, population increase and urbanization separately and in all possible combinations. Urbanization is modelled as a protective effect on populations, while climatic and population changes increase the population at risk. These authors find, for the 2030s, an increase in population at risk by 1146 million (+83%) due to the combined effects of urbanization, population increases and climate change, and an increase of 731 million (15%) due to climate change alone.

Over the past century, the distribution of malaria has contracted, suggesting that global climate change has been less important than other factors (Gething et al., 2010). However, Gething et al. did not quantify the effect of socioeconomic factors on malaria transmission. In this study, we quantify the independent effects of climate and socio economic factors on the historical and future-potential global distribution of malaria.

2. Methods

2.1. Malaria data

Malaria presence was defined according to a WHO estimate of *P. vivax* malaria risk as relevant to international travel and health in 2009, including areas of unstable transmission, as opposed to areas where malaria has disappeared, was eradicated or never existed. The data was extracted from Fig. 2 in (Guerra et al., 2010). Only four island states currently report transmission of *P. falciparum* only, which is why we take the described map as indicative of both *P. vivax* and *P. falciparum* transmission areas.

2.2. GDP and population data

We used the Climate Change scenario A1B developed for the IPCC Special Report on Emissions Scenarios. This scenario describes a world with decreasing global inequity, but policies focus more on economic growth than on the protection of environment and climate. Global population peaks in the middle of the 21st century at 8.3 billion (Nakicenovic and Swart, 2000). GDP per capita GDPpc and population growth estimates developed with this scenario for the years 1990, 2010 and 2050 were taken from the IMAGE 2.3 model developed at the Netherlands Environmental Assessment Agency (Bouwman et al., 2006). For sensitivity analyses with respect to GDPpc, we modify these projections as follows: In a worst-case scenario, we let GDPpc decline to 50% of its 2010 values by 2050. In a "growth reduction" scenario, we reduce the 2030 economic growth projections by 25% and the 2050 economic growth projections by 50%. Our sensitivity analysis is completed by a scenario where GDPpc stays constant at 2010 values. For back-projections of malaria risk to the year 1900, we used GDPpc estimates produced by Maddison where they were available, and a value of 700 US$ at 1995 market exchange rate elsewhere (Maddison, 2010).

2.3. Climate change scenario data

Simulations from three different General Circulation Models were used: The Bergen Climate Model (BCM2) (Otterå et al., 2009), the ECHO-G Middle Atmosphere Model (EGMAM) produced by Freie Universität Berlin (Huebener et al., 2007) and IPCM4, an Earth System Model produced by Institut Pasteur Simon Laplace (Paris) (Marti et al., 2006). These are coupled ocean/atmospheric models, in which the ocean and atmospheric components mutually affect each other during the simulation. Data from these models were statistically downscaled to a common resolution of $1^\circ \times 1^\circ$.

The best available estimate of 1991–2005 climate (monthly mean values), produced by the Climatic Research Unit (CRU) at the University of East Anglia, was used as baseline, or "no climate change", dataset (Mitchell and Jones, 2005). For each location within each dataset (3 climate model projections and one baseline), an average temperature and precipitation were calculated for three time periods: 1961–1990, 2016–2045, and 2036–2065. Subsequently, differences between the 30 year averages for the future and baseline (1961–1990) periods of these variables were calculated for each climate model dataset. These differences were added to the CRU baseline for 1961–1990 to obtain estimates of future climate. The mean temperature of the coldest and warmest month, mean precipitation of the wettest and driest month as well as annual mean temperature and precipitation were calculated in this way.

We fitted a logistic regression model to the data, using the presence or absence of malaria as the outcome variable and temperature, precipitation, and GDPpc as predictors. Interaction terms between the two climatic variables were evaluated but found not to contribute to model accuracy. Model selection was performed based on the number of correctly classified grid points in the presence and absence areas. Different temperature and precipitation variables were tested but did not alter the accuracy of the model substantially. The following logistic regression model proved to be most accurate in terms of model sensitivity and specificity:

$$\text{Malaria\_presence} \sim \text{T\_min} + \text{pr\_max} + \sqrt{(\text{GDPpc})}$$

T_min is the mean temperature of the coldest month, and pr_max is the mean precipitation of the wettest month during the period 1961–1990. GDPpc denotes the total annual GDP achieved in the area covered by one grid box divided by the population living in the area it covers. A square root transformation was applied to the GDPpc variable to reflect that increases in GDPpc have a stronger effect in areas where GDPpc is below 20,000 US$. The mean temperature of the coldest month and the mean precipitation of the wettest month were used as temperature and precipitation variables. We interpret these two variables as indicators of "typical winter severity" and "intensity of the rainy season", respectively.

3. Results

3.1. Recent distribution

The odds ratios corresponding to the fitted model parameters are given in Table 1. The total number of observations was 55178 and 92% of these were correctly classified. Sensitivity of the model: of the grid points within areas classified by as malarious in our input dataset, (n = 15,224), 85% were classified correctly by the model. Specificity of the model: of the areas classified as malaria free in our input dataset, (n = 39,954), 95% were classified correctly.

3.2. Historical distribution

Extrapolations of malaria risk using GDP and physical climate estimates for historical periods are used to validate the model. These "back-projections" are shown for the year 1990 and 1900 in Fig. 1.

Panel a Temperature and rainfall from the period 1961–1990 are used, together with GDPpc for 1990 from the IMAGE 2.3 model. The dark grey areas indicate locations where the two datasets agree. Areas where our model projects malaria presence, but which are not in the 1994 WHO dataset, are shown in green. Areas which according to WHO were malarious in 1994 and which are not projected to be malarious by our model are shown in red. Malaria-present areas are classified incorrectly in the Middle East and (Iraq, Arabian Peninsula, Iran), Zambia, and Mexico. Malaria-absent areas are predicted incorrectly mainly in China, South America, and near the Sahara desert. Good agreement is found over south-east Asia, India, and large parts of sub-Saharan Africa.

Panel b shows projections based on GDP estimated for the year 1900 (Maddison, 2010). The entire African continent and the Arabian Peninsula are classified as malaria-positive for the 1900s. Substantial increases in malaria distribution are predicted for the South American continent and in China.

The sensitivity and specificity of the back projections were comparable to those of the initial model (data not shown).

3.3. Projections for the years 2030 and 2050

We generated extrapolations of projected malaria risk based on the fitted model parameters, and future projections of climate and GDP for the years 2030 and 2050. Projections of geographic expansion and contraction for the year 2050 are shown in Fig. 2. **Panel a** shows the effect of climate change, without GDPpc growth (GDPpc constant at 2010 values). Small areas in South America, sub-Saharan Africa and China are projected to become suitable for local malaria transmission by this time. Areas suitable for malaria transmission are defined as areas where the projected probability of malaria transmission (from the logistic regression model) is above 50%.

Panel b shows the effect of GDP per capita increase according to the A1B scenario only, without taking the effects on temperature and precipitation into account. This corresponds to a scenario of full climate change mitigation, where all increase in GDPpc as assumed in the scenario is achieved without emitting greenhouse gases. With the exception of relatively small areas, the disease disappears in South America and Asia, but not in Africa. Even the optimistic A1B growth projections, which assume decreased inequity, are insufficient to help in eliminating the disease here.

Panel c shows the combined effect of GDPpc increase and climate change. Some differences to panel b (GDP increase only) can be observed: Zambia, which is projected to be malaria-free in the scenario of GDP increase only, continues to be an area with malaria transmission if changes in temperature and precipitation are taken into account. A similar effect is observed in central India.

Panel d shows the climate-attributable increase in "malaria risk", as defined as projected probability of malaria transmission. The figure is constructed by subtracting the transmission probabilities underlying panels b and c. Areas in red show the estimated effect of climate, after controlling for the effect of GDPpc.

The projections shown in Fig. 2 are combined with population growth projections from the IMAGE model in Table 2. In 2050, the projected population at risk is 5.2 billion when considering climatic effects only, 1.95 billion when considering the combined effects of GDP and climate, and 1.74 billion when considering GDP effects only. For the projections based on GDP only and the combined effect of GDP growth and climate change, the population at risk peaks in 2030 before declining towards 2050. This effect is in part due to the rapid population growth predicted for the first half of the 21st century by the A1B scenario.

3.4. Sensitivity analysis

To examine the sensitivity of our projections with respect to the A1B scenario, we constructed a range of different economic scenarios. The changes in malarious areas for these four scenarios are shown in Fig. 3. The range between the populations at risk projected with these scenarios is considerably higher than the

Table 1
Odds ratios and p values for individual predictors in the chosen model.

Predictor	Odds ratio[a]	P value	Δ specificity[b]	Δ sensitivity[b]
T_min [°C]	1.098 [1.093–1.104]	<0.001	−0.41	−7.52
pr_max [mm/day]	1.174 [1.158–1.191]	<0.001	−2.33	−2.58
GDP [1000 US$]	0.154 [0.143–0.167]	<0.001	−3.64	−13.24

[a] Values in brackets show 95% confidence intervals.
[b] These values refer to the decreases in model specificity and sensitivity when leaving out the respective variable from the model. Values are shown as absolute differences to the values of the full model (sensitivity = 84.62%, specificity = 94.71%).

Table 2
Effects of GDP and climatic changes on Population at Risk.

Model type	Population at Risk 2030 [billion]	Population at Risk 2050 [billion]
Socioeconomic changes only	3.52	1.74
Socioeconomic and climatic changes (A1B scenario)	3.58 [3.55–3.60]	1.95 [1.93–1.96]
Socioeconomic and climatic changes (GDPpc reduced by 25% in 2030 and 50% in 2050, compared to A1B scenario)	3.82 [3.39–3.84]	3.42 [3.28–3.45]
Climatic changes only (GDPpc constant at 2010 values)	4.61 [4.54–4.67]	5.20 [5.11–5.25]
Socioeconomic and climatic changes: pessimistic scenario (reduction of GDPpc to 50% of 2010 values)	5.18 [5.07–5.30]	6.27 [6.19–6.32]

Population projections according to the SRES A1B scenario are used in these calculations. Quoted uncertainties show the effect of using different climate model outputs for each projection. The top row shows the most optimistic scenario, the bottom row is the most pessimistic. The modelled population at risk for the year 2010 is 3.1 billion.

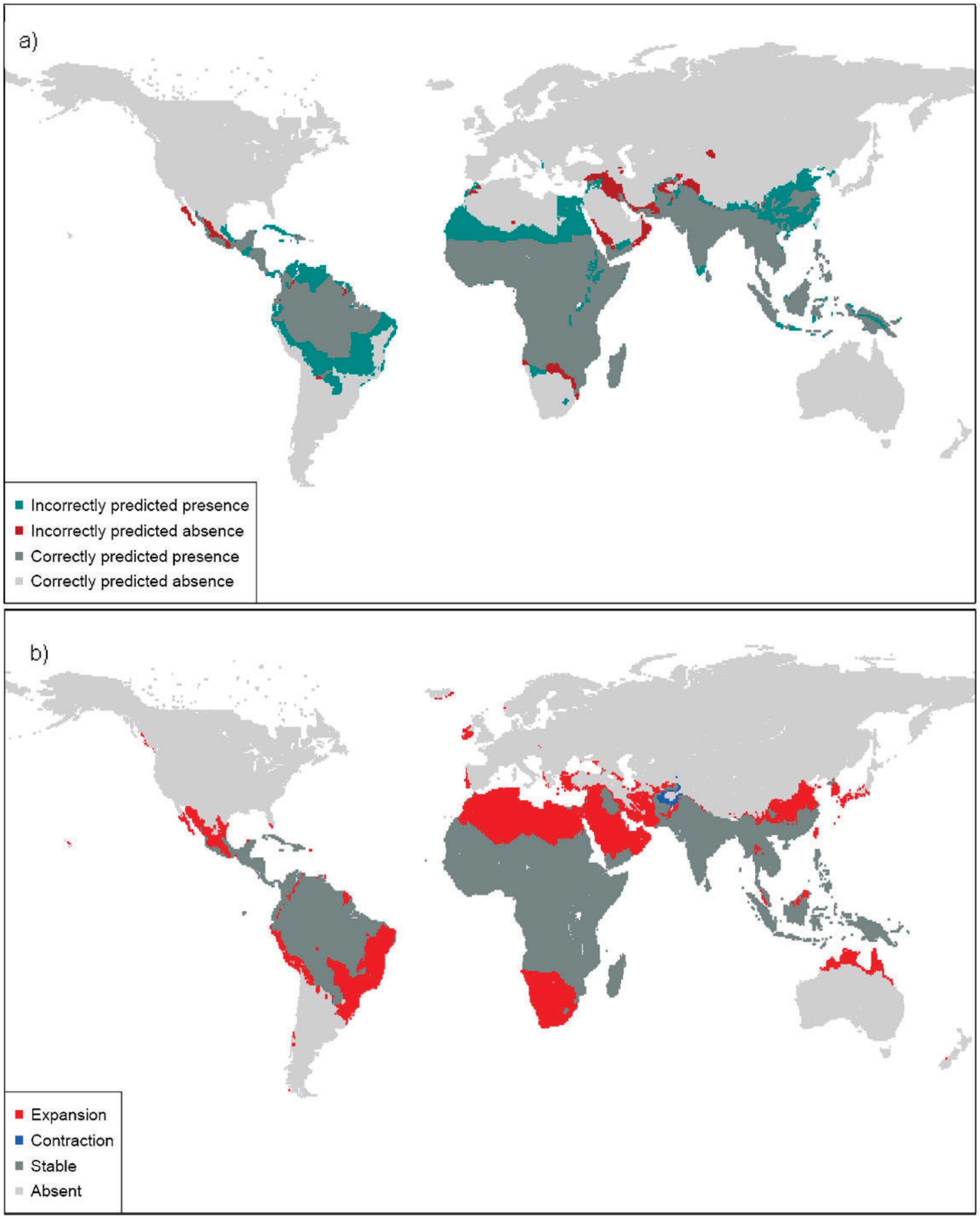

Fig. 1. Projected malaria areas for 1990 and 1900. a) Comparison between projections for 1990 model and WHO malaria region estimates from 1994 (WHO, 1997). b) Back-projection to values of GDP estimated for the year 1900.

range between values produced with different climate models (Table 2).

4. Discussion

The reported (2009) spatial distribution of all-cause malaria can be modelled empirically, with high accuracy, based on average climate and GDPpc. If the global climate changed as projected by global circulation models, but GDP remained constant, a modest expansion of malaria risk is projected, mainly in South America and Asia, by the 2050s. If GDP changed as projected by economic models but global climate remained constant, much of the world, with the notable exception of Africa, is projected to become malaria free by the 2050s. The projected geographic contraction in malaria is less marked, but still substantial, given simultaneous changes in GDP and climate in the 2050s.

Our model was constructed on the basis of spatial patterns and does not explicitly account for dynamic effects like year-to-year variability of transmission intensity. This study is the first to estimate the impact of climate change on the potential distribution of malaria while addressing the confounding effect of socio-economic factors. We found a strong independent relationship between GDPpc, climate and malaria risk. Empirically, climate factors have a substantial effect on malaria transmission in

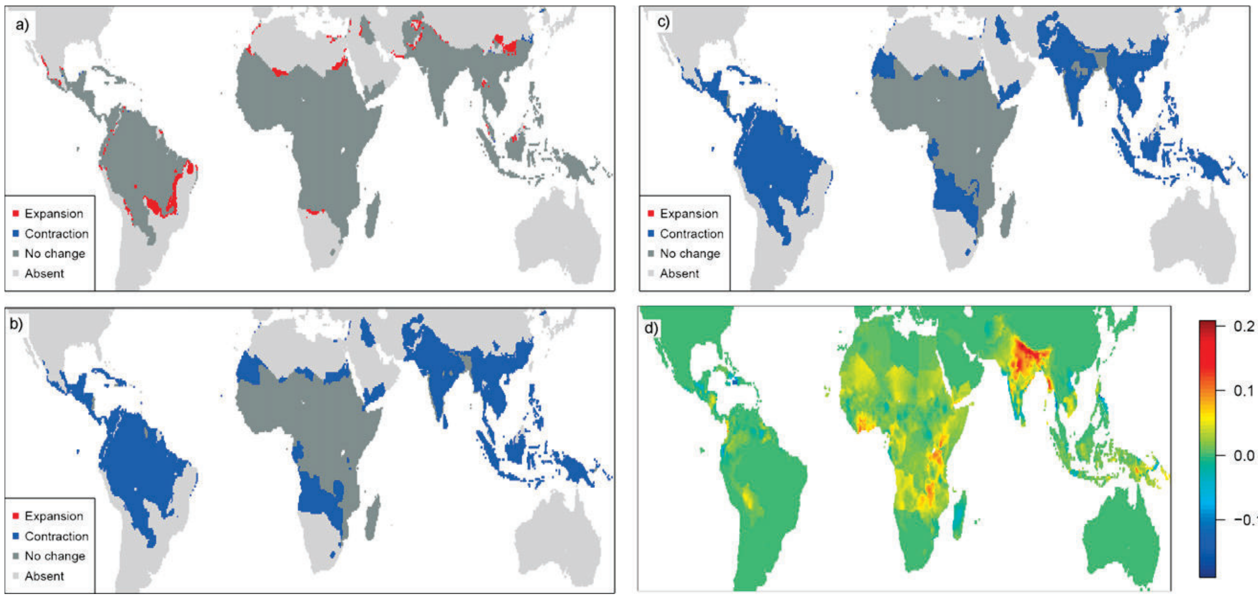

Fig. 2. Map of projected areas of malaria presence for 2050. The mean of the projections using the described A1B scenario climate change datasets is shown. Areas where the malaria status changes between the baseline and the scenario period are shown in colour. Panel a) illustrates changes due to climatic changes only, panel b) shows the effects of projected GDP increases only, and panel c) shows the combined effects of projected GDP increase and climatic changes. Panel d) shows the change in modelled transmission probability for panel c) with respect to panel b).

countries where GDPpc is less than US$20,000. We acknowledge that the relationships between malaria and development are complex and bi-directional. Therefore, GDPpc may not remain such a good proxy for malaria risk in the future. On the other hand, the model provides convincing back projections of malaria distribution over the past century. This increases confidence that empirical relationships based on recent geographic patterns of malaria can be used to project future changes.

We use GDPpc as a proxy for many aspects of welfare and economic status relevant to malaria risks. The geographic

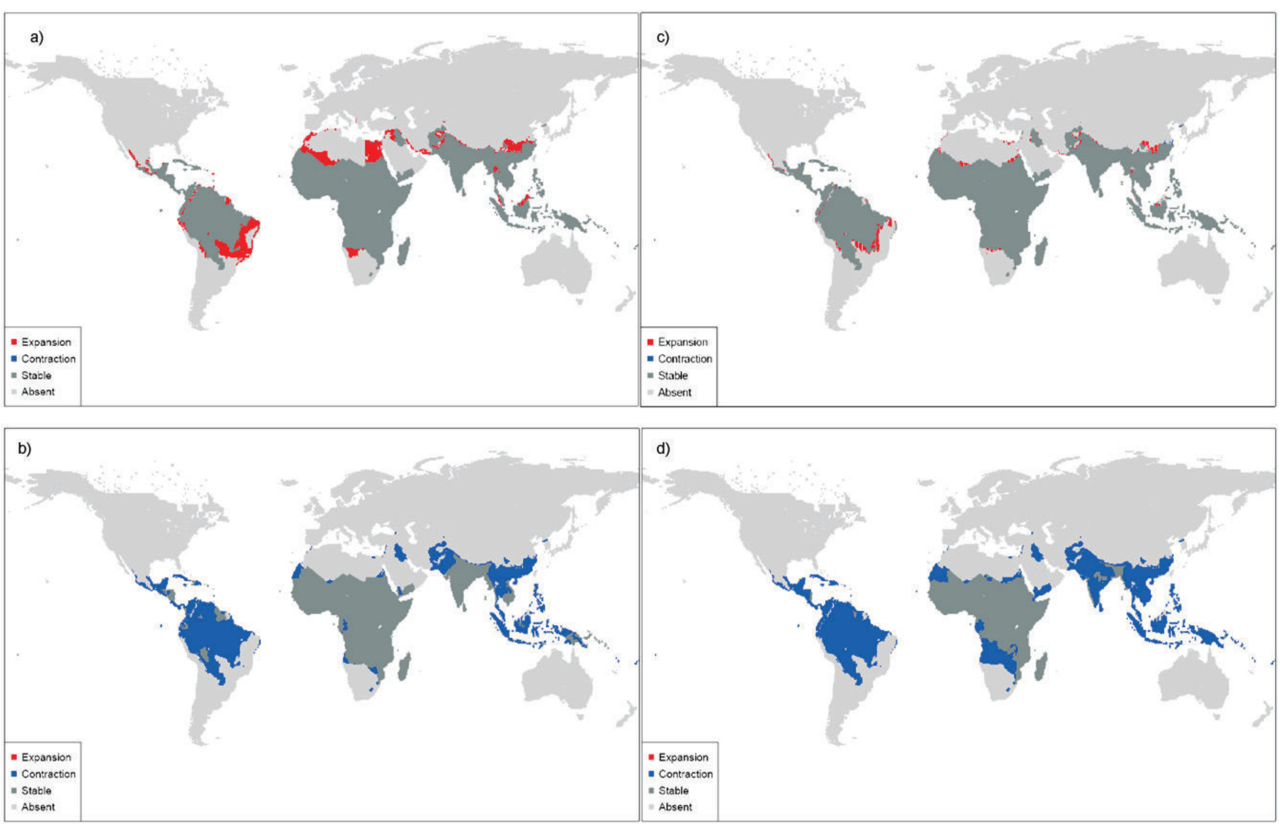

Fig. 3. Projections of malarious areas using different projections of GDP per capita. Panel a) decrease of GDP per capita by 50% in 2050; panel b) reduction in GDP growth to 50% of the projected 2050 values; panel c) GDPpc stays at 2010 values; panel d) GDPpc increases as projected by the A1B scenario.

relationship between malaria risk and socio-economic conditions is well established, but the reasons for this association are not clear. It is plausible that GDPpc is a proxy for preventive measures such as screened windows, insecticide treated nets or therapeutic measures (Sachs and Malaney, 2002).

The social burden of malaria has been proposed as an important factor retarding economic growth. In one study, countries with intensive malaria grew by 1.3% per year less than other countries (Gallup and Sachs, 2001). Therefore, the effects of climate change estimated in this study might be negatively biased.

National scale GDPpc is currently the best available proxy for socio-economic factors affecting malaria. The model reported here provides illustrative projections of the global geography of malaria risk, rather than precise predictions of actual disease prevalence in specific locations. Given the availability of appropriate data, future studies should account for current and projected sub national variation in wealth.

Projections of GDPpc are more uncertain than those for temperature or precipitation changes because of intrinsic differences between climatic and socioeconomic systems. While the equations governing the climate system are, although highly nonlinear, basically known, the dynamics of socioeconomic systems are governed by processes that are little understood. Therefore, weather and climate are easier to model than future socioeconomic development, which can be influenced to a large degree by unanticipated factors. Projections of economic growth must therefore be interpreted cautiously. Surprises in the development of GDP per capita like the recent financial crisis can alter future values of GDPpc significantly.

5. Conclusions

Over the past century, socioeconomic development has had a dominant influence on the geographic contraction of malaria. We project further substantial geographic contraction of malaria by the 2050s. Under the A1B climate scenario, climate change has much weaker effects than GDPpc increase on the geographic distribution of malaria. This outcome is, however, dependent on optimistic, and potentially unsustainable, economic growth. Even then, climate change has important effects on the projected distribution of malaria, leading to an increase of over 200 million in the projected population at risk.

The potentially beneficial effect of future economic development on the geographical extent of malaria is often mentioned as an argument in the debate surrounding the relative importance of climate change mitigation and poverty alleviation. Our model could be used to quantify the GDP growth necessary to offset an increase in malaria risk due to future climatic change.

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