Estimating the malaria transmission over the Indian subcontinent in a warming environment using a dynamical malaria model

Shweta Chaturvedi and Suneet Dwivedi

ABSTRACT

Malaria is a major public health problem in India. The malaria transmission is sensitive to climatic parameters. The regional population-related factors also influence malaria transmission. To take into account temperature and rainfall variability and associated population-related effects (in a changing climate) on the malaria transmission over India, a regional dynamical malaria model, namely VECTRI (vector-borne disease community model) is used. The daily temperature and rainfall data derived from the historical (years 1961–2005) and representative concentration pathway (years 2006–2050) runs of the Coupled Model Intercomparison Project Phase 5 models have been used for the analysis. The model results of the historical run are compared with the observational data. The spatio-temporal changes (region-specific as well as seasonal changes) in the malaria transmission as a result of climate change are quantified over the India. The parameters related to the breeding cycle of malaria as well as those which estimate the malaria cases are analyzed in the global warming scenario.

Key words | climate change, CMIP5, malaria transmission, VECTRI

Shweta Chaturvedi (corresponding author)
Suneet Dwivedi
K Banerjee Centre of Atmospheric and Ocean Studies and M N Saha Centre of Space Studies,
University of Allahabad,
Allahabad, Uttar Pradesh 211002,
India
E-mail: *shwetachaturvedi546@gmail.com*

INTRODUCTION

Malaria poses a significant public health problem in India. Even though there has been a decrease in the mortality rate as a result of malaria disease due to better treatment and control strategies, malaria still remains a leading disease in India. There is a growing concern about the changing pattern of some diseases across India, which are directly influenced by the climate variables. Malaria falls under this category. It is a proven fact that malaria is sensitive to climatic parameters (Martens *et al.* 1995; Lindsay *et al.* 1995; Goklany 2004). It is endemic in all parts of India, except at elevations above 1,800 m and in some coastal areas (Sharma 1996; Bhattacharya *et al.* 2006; https://www.who.int/ith/ith_country_list.pdf). The Indian malaria mosquito, *Anopheles stephensi*, and the malaria parasite, *Plasmodium falciparum*, are strongly affected by climate, mainly temperature and rainfall on key transmission-related traits (Craig *et al.* 1999). Rainfall over India (especially during the summer monsoon season) reduces the temperature of the region and provides water availability for mosquito-breeding/-resting sites. However, the excess rainfall may result into flushing away of the breeding sites. The temperature affects the developmental period related to different stages of a mosquito's lifecycle: blood-feeding rate, biting rate, gonotrophic cycle and longevity (Dhiman *et al.* 2008; Paaijmans *et al.* 2010).

It has been reported that as a result of climate change, the spread of the disease in the current malaria endemic areas will increase (Zhou *et al.* 2004, 2005; Pascual *et al.* 2006). Few studies also suggest that due to global warming, the malaria transmission may re-emerge in those areas which have controlled transmission or where the disease was eradicated in the past (Baldari *et al.* 1998; Krüger *et al.* 2001). On the contrary, it has also been reported that the malaria transmission is in no way associated with

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climate change (Hay *et al.* 2002). Endo *et al.* (2017) performed a combined modeling and observational study to investigate the impact of climate change on malaria in Africa. Their study showed disproportionate future risk of malaria due to climate change between East and West Africa. Ngarakana-Gwasira *et al.* (2016) carried out a mathematical modeling study to assess the role of climate change in malaria transmission over Africa. They found that as a result of climate change, malaria burden is likely to increase in the tropics, the highland regions, and East Africa. Le *et al.* (2019) have predicted the direct and indirect impacts of climate change on malaria in coastal Kenya. They found that the vegetation acclimation triggered by elevated CO_2 under climate change increases the risk of malaria in the region of study. The increase in air temperature under the climate change is shown to have opposing effects on mosquito larval habitats and the life cycles of both Anopheles vectors and Plasmodium parasites. Caminade *et al.* (2014) carried out the first multimalaria model intercomparison exercise to estimate the impact of future climate change and population scenarios on malaria transmission at global scale and to provide recommendations for the future. They showed that future climate might become more suitable for malaria transmission in the tropical highland regions. Climate projections developed for India for 2050s (MoEF, Government of India 2004) indicate an increase in average temperature by 2–4 °C, an overall decrease in the number of rainy days by more than 15 days in western and central India and an increase by 5–10 days near the Himalayan foothills and in northeast India. The projections also indicate an overall increase in the rainy days' intensity by 1–4 mm/day, except for small areas in northwest India where the rainfall intensities may decrease by 1 mm/day. There have been several studies in which the impact of climate change on malaria transmission over India has been investigated (Bhattacharya *et al.* 2006; Dhiman *et al.* 2008, 2010, 2011, 2019). It has been found that the changes in the climate affect mosquito-borne disease in several ways, namely their survival and reproduction rates, the intensity and temporal pattern of vector activity, and the rates of development, survival and reproduction of pathogens within vectors (Kovats *et al.* 2001).

Ferguson *et al.* (2010) suggested that malaria elimination and eradication requires urgent strategic investment into understanding the ecology and evolution of the mosquito vectors that transmit malaria. Several studies have been carried out to look into the potential changes in the ecology of malaria in the context of climate change. In addition to other factors such as land cover, human migration, interventions and socio-economic conditions which can alter the local disease prevalence significantly (Koram *et al.* 1995; Martens & Hall 2000), year-to-year fluctuations in climate can also lead directly to variability in malaria transmission intensity. Gething *et al.* (2010) suggested that the predictions of an intensification of malaria in a warmer world, based on extrapolated empirical relationships or biological mechanisms, must be set against a context of a century of warming that has seen marked global declines in the disease and a substantial weakening of the global correlation between malaria endemicity and climate. They quantified contraction in the range of malaria through a century of economic development and disease control to report global recession in malaria endemicity since approximately 1900. In their multimalaria model intercomparison study, Caminade *et al.* (2014) evaluated three malaria outcome metrics at global and regional levels in the context of climate change: climate suitability, additional population at risk and additional person-months at risk across the model outputs. Their findings showed an overall global net increase in climate suitability and a net increase in the population at risk, but with large uncertainties. They found a net increase in the annual person-months at risk from the 2050s to the 2080s with increasing greenhouse gas concentration. Piontek *et al.* (2014) developed a framework to study coinciding impacts related to water, agriculture, ecosystems and malaria at different levels of global warming and identify regional exposure hotspots. They found that the multisectoral overlap starts to be seen robustly at a mean global warming of 3 °C above the 1980–2010 mean, with 11% of the world population subject to severe impacts in at least two of the four impact sectors at 4 °C. In a low probability-high impact worst-case assessment, almost the whole inhabited world is at risk for multisectoral pressures. Caminade *et al.* (2019) argued that many key factors affect the spread and severity of human diseases, including the mobility of people, animals and goods; control measures in place; availability of effective drugs; quality of public health services; human behavior; and political stability and conflicts. With drug and insecticide resistance on the rise, significant funding and research efforts must be maintained to continue the battle against existing and emerging diseases, particularly those that are vector borne (for example, malaria).

Several methods have been used to estimate changes in the distribution of malaria in scenarios of global climate change. These methods include both observational studies as well as statistical and dynamical modeling of malaria transmission. Some studies used biological models for this purpose (Martens *et al.* 1995, 1999; Rogers & Randolph 2000). Endo *et al.* (2017) used a combination of observational and modeling study. There have been a number of studies related to the mapping and predictive modeling of the distribution, intensity and seasonality of malaria transmission (Hay *et al.* 1998; Snow *et al.* 1998; Craig *et al.* 1999; Kleinschmidt *et al.* 2000; Rogers *et al.* 2002). To understand and quantify the malaria transmission rates so that its hazardous effects can be minimized in the present and future climate, many scientific efforts were made, which include the construction of mathematical models (Beck Johnson *et al.* 2013). These models consider the life cycle of mosquitoes and the seasonality effect, which are very important aspects of the dynamics of malaria transmission. Recently developed models of malaria incorporate details of the climate-driven parasite and vector life cycles (Depinay *et al.* 2004; Eckhoff 2011; Lunde *et al.* 2013). The dynamical malaria models have been used to estimate the malaria transmission variations on a seasonal scale (Jones & Morse 2010, 2012; MacLeod *et al.* 2015; Tompkins & Di Giuseppe 2015). They have also been used for the estimation of malaria transmission rates over the multi-decadal timescales (Caminade *et al.* 2014; Piontek *et al.* 2014). The mathematical model 'VECToR borne disease community model of ICTP, TRIeste (VECTRI)' developed by Tompkins & Ermert (2013) has been used widely in many studies for investigating malaria transmission rates (Tompkins *et al.* 2019 and references therein) over the different parts of Africa.

The studies linking climate fluctuations and malaria transmission across the various regions of India are very limited due to the absence of comprehensive, good quality malaria transmission-related data continuous in space, and time over India. For example, there is no long-term-gridded data of malaria transmission which is available at all the grid points over India. Moreover, the long-term regional projections of malaria transmission over India in the context of climate change are also not available due to the lack of gridded transmission data for this purpose. The studies, which have been carried out in the past, are mainly observational in nature and are limited to a specific region of India (Bhattacharya *et al.* 2006; Dhiman *et al.* 2008, 2010, 2011, 2019). Sarkar *et al.* (2019) has recently analyzed shift in potential malaria transmission areas in India, using the fuzzy-based climate suitability malaria transmission model under changing climatic conditions. The examples of dynamical modeling studies carried out over India for this purpose are a few. Only recently, Parihar *et al.* (2019) employed VECTRI for investigating malaria transmission dynamics over a limited regional domain of the highly endemic state of Odisha in India. As such, it will be worthwhile to carry out a dynamical modeling study of malaria transmission over the entire Indian region by generating quality controlled continuous in time data for this purpose. It will also be imperative in this light to investigate the effect of climate change on malaria transmission over the densely populated Indian region. The main aim of this paper is to investigate the spatio-temporal variability in malaria transmission patterns over the Indian subcontinent in the context of climate change using the VECTRI model driven by rainfall and temperature datasets (historical and future projections) obtained from the Coupled Model Intercomparison Project Phase 5 (CMIP5). The results obtained in the manuscript are discussed with the help of Larvae and Entomological Inoculation Rate (EIR) as parameters. We have demonstrated the ability of the VECTRI model to provide malaria early warning information over the Indian subcontinent. The changes in the length of transmission season (LTS) over the different parts of India are also examined in a warming environment.

MODEL DESCRIPTION AND DATA

We use the VECTRI malaria model (Tompkins & Ermert 2013) for carrying out the present study. The VECTRI solves a set of equations using a daily time step that describes the life cycles of the key vector, An Gambiae and Plasmodium Falciparum (Tompkins & Ermert 2013; Tompkins &

Di Giuseppe 2015). However, it is possible to extend the VECTRI simulation for other vectors (Anopheles stephensi and Plasmodium app, for example) by making appropriate changes in the model parameterization for those mosquito species according to their characteristic life cycles. The VECTRI model for malaria transmission accounts for the impact of temperature and rainfall variability on the development cycles of the malaria vector in its larval and adult stage, and also of the parasite itself (http://users.ictp.it/~tompkins/vectri/model.html). The temperature affects the sporogonic and gonotrophic cycle development rates according to the standard degree-day model, and higher temperature increases the mortality rates for adult vectors (Craig *et al.* 1999; Lunde *et al.* 2013). In other words, the processes such as the gonotrophic cycle and the parasite and vector larvae development rates are temperature sensitive, as are the mortality rates of the vector in the larval and adult stages. The combination of these temperature effects results in the model reproducing the observed nonlinear relationship between temperature and malaria (Tompkins & Di Giuseppe 2015). Also, the relationship between rainfall and malaria is strongly nonlinear; while rainfall drives the creation of temporary water bodies (e.g. pond parameterization with no spatial representation of permanent open water bodies or wetlands), the model also includes a representation of the flushing effect, whereby intense rainfall increases the mortality of early stage larvae (Tompkins & Di Giuseppe 2015). This means that the intensity of malaria transmission will increase in locations with low rainfall amounts, whereas, above a certain threshold, the malaria transmission decreases with rainfall. The simple surface hydrology scheme of the VECTRI model estimates at each time step the fractional water coverage area in each grid cell. The key model processes in the VECTRI are resolved using the multi-compartmental approach. The VECTRI accounts for human population density in the calculation of biting rates and host-to-vector and vector-to-host transmission probabilities for the parasite. The higher population densities lead to a dilution effect, resulting in lower parasite ratios (PRs) in urban and peri-urban environments compared with nearby rural locations. In this respect, the model is able to reproduce the reduction in EIRs and PR with increasing population density that has been widely observed in African field studies (Kelly-Hope & McKenzie 2009; Tompkins & Ermert 2013). This study uses version v1.4.6 of the VECTRI model, which additionally represents larvae growth rates using the relationship of Craig *et al.* (1999), and water temperature-dependent larvae mortality rates derived from a combination of the growth rate and the data of Bayoh & Lindsay (2003, 2004). This version of VECTRI currently lacks the treatment of host immunity and assumes that bites received per person are randomly distributed, thus neglecting heterogeneities in the distribution of breeding sites relative to human habitations within a grid cell and also in host attractiveness to vectors (Tompkins & Di Giuseppe 2015). In this study, the VECTRI model is driven by daily rainfall and temperature measurements derived from a total of five CMIP5 models, namely CNRM-CM5, GFDL-CM3, MIROC-ESM, MPI-ESM-MR and HadGEM2-ES. These models are summarized in brief in Table 1. Two types of experiments of 45 years each are carried out for historical run and for future projection of these models. The first type of experiment uses as input the temperature and rainfall data from historical run of

Table 1 | Brief description of the CMIP5 models

CMIP5 models	References	Resolution (in degrees)	Period of temperature and rainfall dataset used: Historical	Projection
CNRM-CM5	Lucarini and Ragone (2011)	1.41×1.40	Years 1961–2005	Years 2006–2050
GFDL-CM3	Donner *et al.* (2011)	2.5×2.0		
MIROC-ESM	Nozawa *et al.* (2007)	2.81×1.77		
MPI-ESM-MR	Stevens *et al.* (2013); Jungclaus *et al.* (2013)	1.875×1.85		
HadGEM2-ES	Collins *et al.* (2008, 2011)	1.875×1.25		

these CMIP5 model between 1961 and 2005, whereas the second type of experiment uses the same input data for representative concentration pathway 8.5 (RCP8.5) future projection scenario between 2006 and 2050. For the present study, we use population density derived from the Gridded Population of the World project (SEDAC, 2015) at a resolution of 30 arc min during the historical period. The population data estimates from Inter-Sectoral Impact Model Intercomparison Project at 5′ resolutions are taken for the years 2006–2050. This dataset is based on the national SSP2 population projections as described in Samir & Lutz (2014) and is useful for us for evaluating the effect of temperature and rainfall on the malaria transmission intensity in a warming environment with the time-varying population. The VECTRI model output is stored as successive daily means. Using the methodology described above, we carry out the VECTRI model run over the Indian subcontinent region for the historical period (1961–2005) as well as for future climate (2006–2050).

RESULTS AND DISCUSSION

TEMPERATURE AND RAINFALL DATA OF CMIP5 MODELS

We begin by analyzing the monthly variability of the temperature and rainfall data of CMIP5 models (which are used to initialize VECTRI) over the Indian subcontinent against the corresponding observed values. The air temperature data from National Centers for Environmental Prediction (NCEP) reanalysis (Kalnay *et al.* 1996) and rainfall data from the Global Precipitation Climatology Project (GPCP) (Huffman *et al.* 2016) are used as observed dataset for this purpose. We compute the correlation coefficient (*r*) between the observed rainfall and corresponding rainfall data from all five CMIP5 models. The results are summarized in Table 2. We see that the model and observed rainfall datasets are highly correlated. These correlation values are significant at more than 99% level. Similarly, we also compute the root mean square error (*rmse*) between the model and observed rainfall dataset (Table 2). We see from the table that the *rsme* values are much lower than the standard deviation of observed rainfall (2.35 mm/day), thus confirming the quality of the model dataset. These

Table 2 | The correlation coefficient (*r*) and *rmse* between the observed and model rainfall and temperature of the CMIP5 models

	Rainfall		Air temperature	
Model	***r***	**rmse**	***r***	**rmse**
CNRM-CM5	0.99	0.48	0.94	3.52
GFDL-CM3	0.99	0.40	0.91	2.66
MIROC-ESM	0.99	1.66	0.88	3.39
MPI-ESM-MR	1.0	0.55	0.96	3.31
HadGEM2-ES	0.84	1.35	0.93	2.57

statistically quantified results clearly suggest that the quality of the CMIP5 model derived rainfall dataset of all the five models compares well with the observed rainfall. To look at the spatial variability of the rainfall, we also show in Figure 1 the seasonal variability of the observed rainfall over the Indian subcontinent and make a comparison with one of the CMIP5 models, namely CNRM-CM5. Other models also show similar results (not shown for sake of brevity). We see from the figure that as expected, the rainfall is generally very low (average rainfall in the range of 1–2 mm/day) in the DJF and MAM months. The highest rainfall (>10 mm/day) is observed during the monsoon season of JJA. The post-monsoon months of SON also receive a good amount of rainfall (average rainfall in the range of 3–6 mm/day). The third panel of Figure 1 shows the bias (defined as difference between model and observation data (model − observation)) map of rainfall. We see that the biases are very low (<± 0.5 mm/day) in the DJF and MAM months over the central Indian region. The biases are mostly positive (∼1–2 mm/day) over the central Indian region during the monsoon season (JJA), which suggests that the CNRM-CM5 model has a wet bias over these regions. The southern Indian region, Western Ghats and East Indian regions show dry bias. Similarly, a small wet bias in the northern Indian region and a dry bias in the eastern Indian subcontinent are seen during the post-monsoon season (SON).

We also compute the correlation coefficient and rmse between the observed air temperature and corresponding temperature data of all five CMIP5 models. These results are summarized in Table 2. We see from the table that the model data are significantly highly correlated (at more

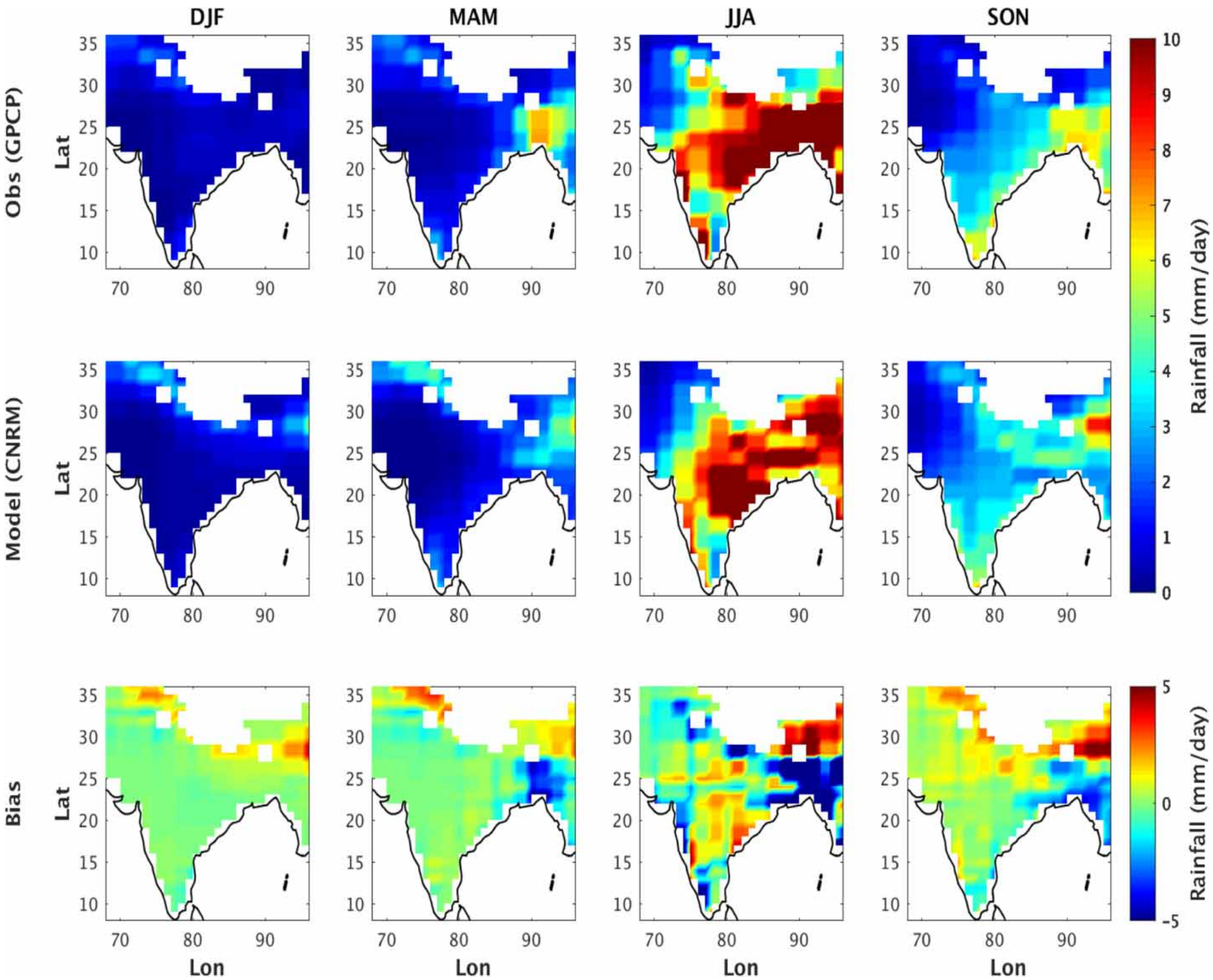

Figure 1 | Seasonal variability of precipitation (mm/day). Upper panel: GPCP observations (1961–2005), middle panel: CNRM-CM5 model (1961–2005), and lower panel: bias (model-observation).

than 99%) with the observed temperature. Moreover, the *rmse* values between the model and observed temperature are less than the standard deviation of observed temperature (4.2 °C). These statistical results clearly suggest that the climatological temperature data of all the five CMIP5 models used in the analysis are realistic and may be utilized to initialize the VECTRI malaria model with confidence. The spatial map of seasonally varying temperature data shown in Figure 2 suggests that the CNRM-CM5 model very well captures the temperature variability exhibited by the NCEP reanalysis data. As expected, the temperature of the central Indian region remains high (>35 °C) during spring (MAM) and monsoon (JJA) months and low (<15 °C) during winter (DJF). The bias map of temperature shows that the model slightly underestimates the temperature of the western Indian region during DJF and SON months, whereas it overestimates it in the southeast Indian region during JJA. It is likely that the slightly higher temperature and higher rainfall (when compared to observation) of the CNRM-CM5 model in the southeast Indian region during JJA, when used as an input of the VECTRI model, may result into slightly higher malaria transmission rates in the region. After having confirmed from Figures 1 and 2 and Table 2 that five CMIP5 models taken in this study are able to realistically represent the temperature and rainfall variability of the region, we used daily values of these

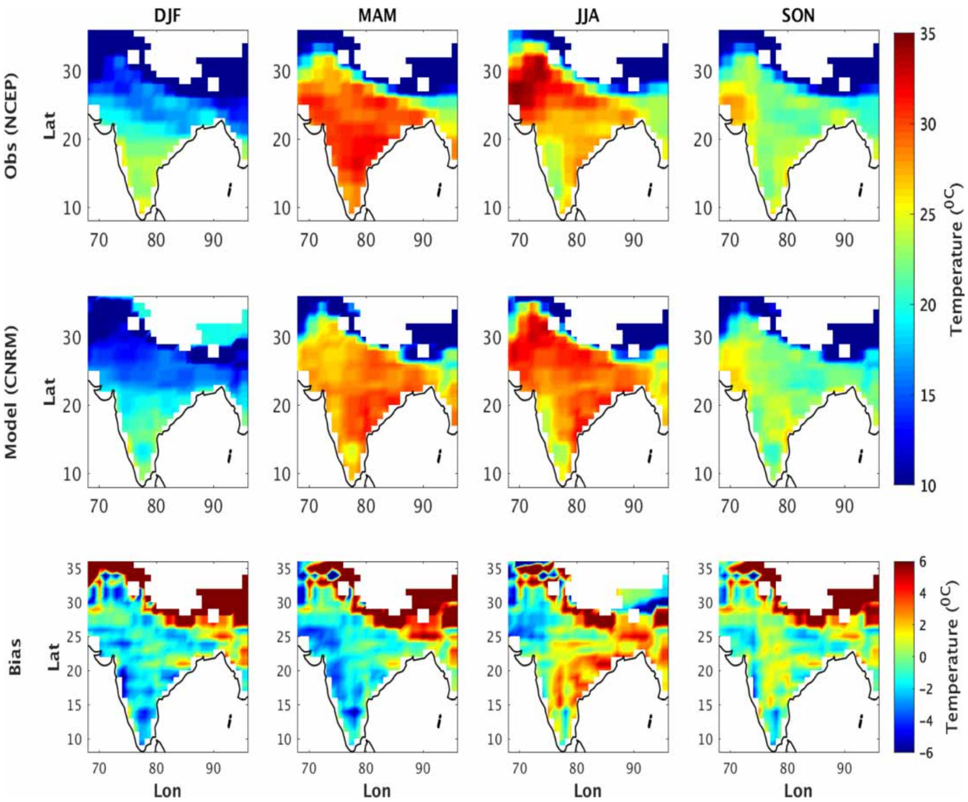

Figure 2 | Seasonal variability of air temperature at 2 m (°C): Upper panel: NCEP reanalysis (1961–2005), middle panel: CNRM-CM5 model (1961–2005), and lower panel: bias (model-observation).

variables from five CMIP5 models to initialize the VECTRI model. The VECTRI output is used to quantify the malaria transmission over the Indian subcontinent as explained in the following section.

ANALYSIS OF VECTRI OUTPUT

Figure 3 shows the VECTRI-simulated EIR, defined as the number of infectious bites. The daily temperature and rainfall of the CNRM-CM5 model is used as input here. The results of the VECTRI output using other model dataset are very similar and not shown here for brevity. The results clearly show that malaria transmission quantified in terms of EIR generally follows rainfall patterns over the India subcontinent. The timing of peaks in the EIR (July–October) follows peaks in rainfall. In the VECTRI model, malaria transmission is sustained if simulated EIR $\geq$0.01 (Tompkins & Ermert 2013) and no transmission occurs if simulated EIR $<$0.01. The month of September exhibits the maximum EIR, i.e. a maximum number of infectious bites spread over almost the entire Indian region. The EIR in the month of August mainly remains concentrated over the eastern and southeastern regions, whereas in the month of October, the EIR is high over the southeastern and northwest regions. The EIR starts to increase from July, becomes maximum in September, then starts to decrease and becomes negligibly small October onwards.

For mosquitoes, the environment in which larvae develop strongly determines adult characteristics such as individual size, teneral reserves, biting behavior, fecundity, longevity, and vector competence (i.e. their ability to develop and transmit pathogens) (Briegel 1990; Breaux *et al.* 2014; Araújo *et al.* 2012), which are all factors influencing vectorial capacity (i.e. the potential intensity of transmission by mosquitoes). We show in Figure 4 the monthly larvae map obtained from the VECTRI output over the region. In the monsoon and post-monsoon seasons, precipitation is higher and the temperature starts to

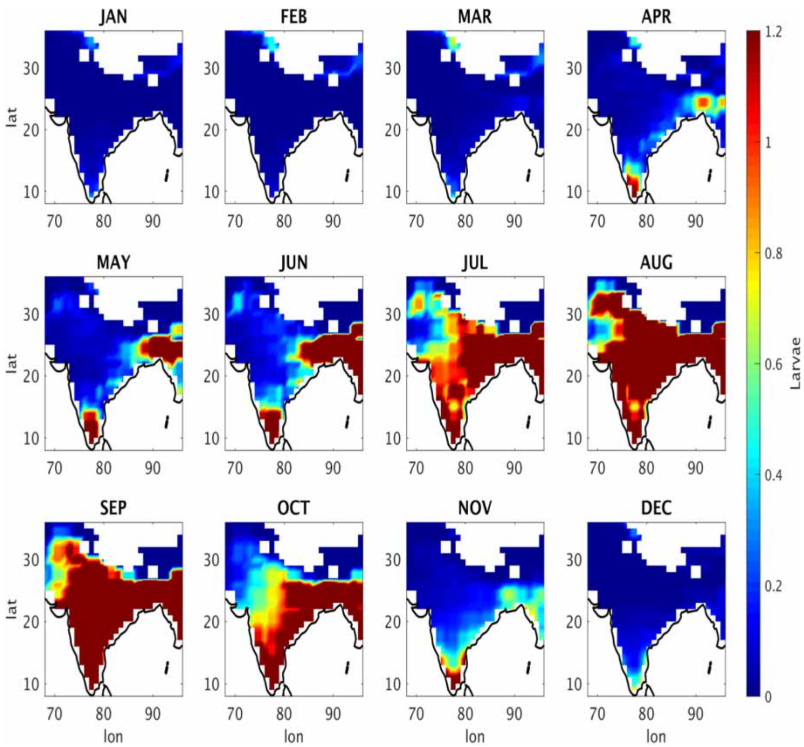

Figure 3 | Monthly climatological variability of the VECTRI-simulated EIR over India.

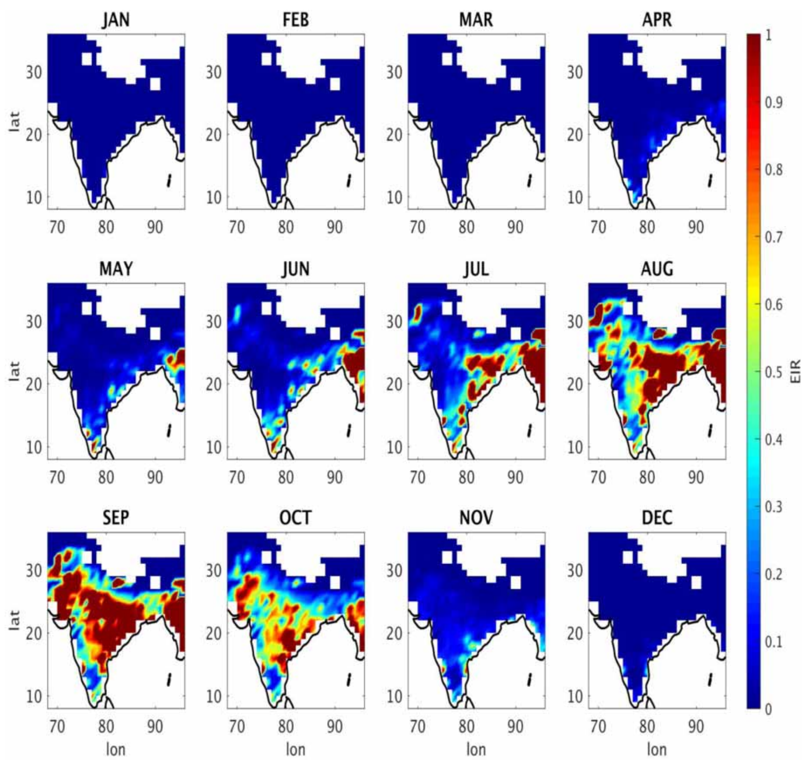

Figure 4 | Monthly climatological variability of the VECTRI-simulated Larvae over India.

decrease, thus making the conditions favorable for the reproduction and growth of malaria larvae. It is clear from the figure that the larvae population is high during July–October months with the highest larvae population seen in August–September months. The figure suggests that the maximum number of malaria vectors is found in August–September months.

After calculating the malaria transmission for the historical period, we made an effort to see the effect of climate change on malaria transmission by carrying out the VECTRI model run using the RCP8.5 future projection data of all the five CMIP5 models for the period 2006–2050. Figure 5 shows the difference map of temperature between RCP8.5 and historical run of the CNRM-CM5 model. The difference map clearly suggests that the maximum change in temperature will happen during the March–May and September–November months. The highest temperature change over the central Indian region is obtained in October. The monthly difference map of rainfall between RCP8.5 and historical run is shown in Figure 6. The difference map clearly suggests that the monsoon season will see high rainfall changes with a maximum change happening during the September month over the entire central Indian region. The difference map of rainfall suggests that rainfall in the month of September is going to decrease (up to 1 mm/day) from its historical values.

We compute the EIR and Larvae from the VECTRI model output using temperature and rainfall of the RCP8.5 future projection scenario data of all five CMIP5 models for the years 2006–2050. The mean monthly variability of EIR difference (RCP8.5 – historical) for these years is shown in Figure 7(a)–7(e) corresponding to CNRM-CM5, GFDL-CM3, HadGEM2-ES, MIROC-ESM, and MPI-ESM-MR CMIP5 models, respectively. We see that the EIR differences in the context of climate change are mainly occurring in the monsoon and post-monsoon months of July–October. It is interesting to note that out of these months, the

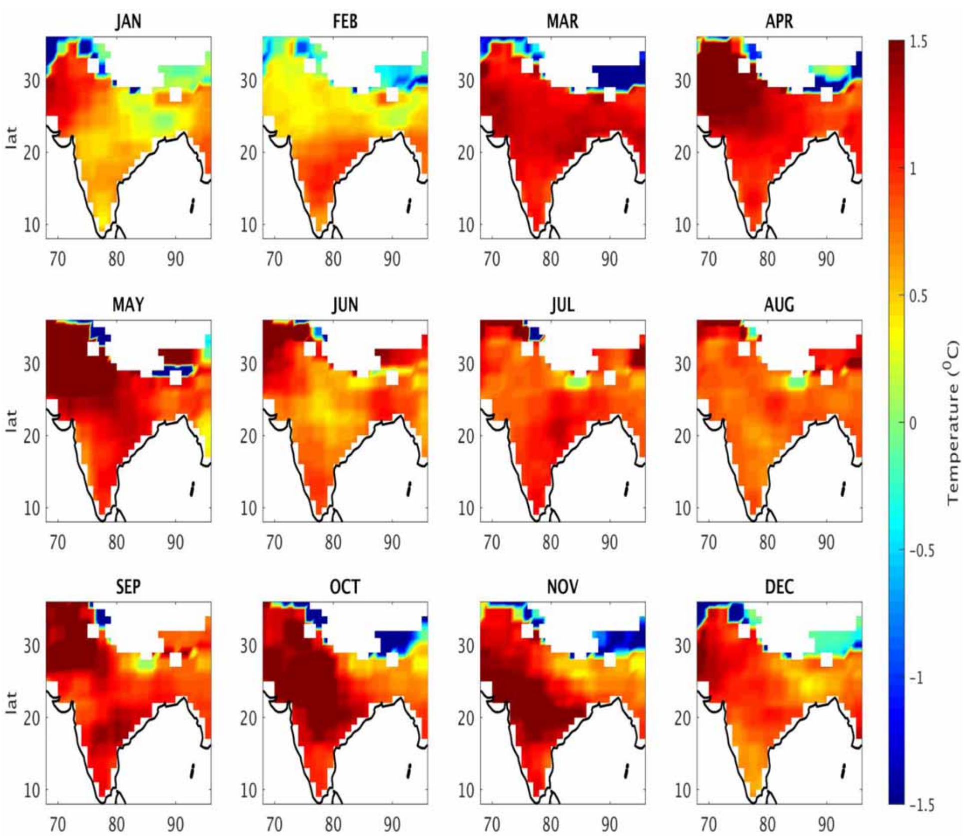

Figure 5 | Monthly difference map of the surface air temperature (°C) between RCP8.5 run (2006–2050) and historical run (1961–2005) of CNRM-CM5 model.

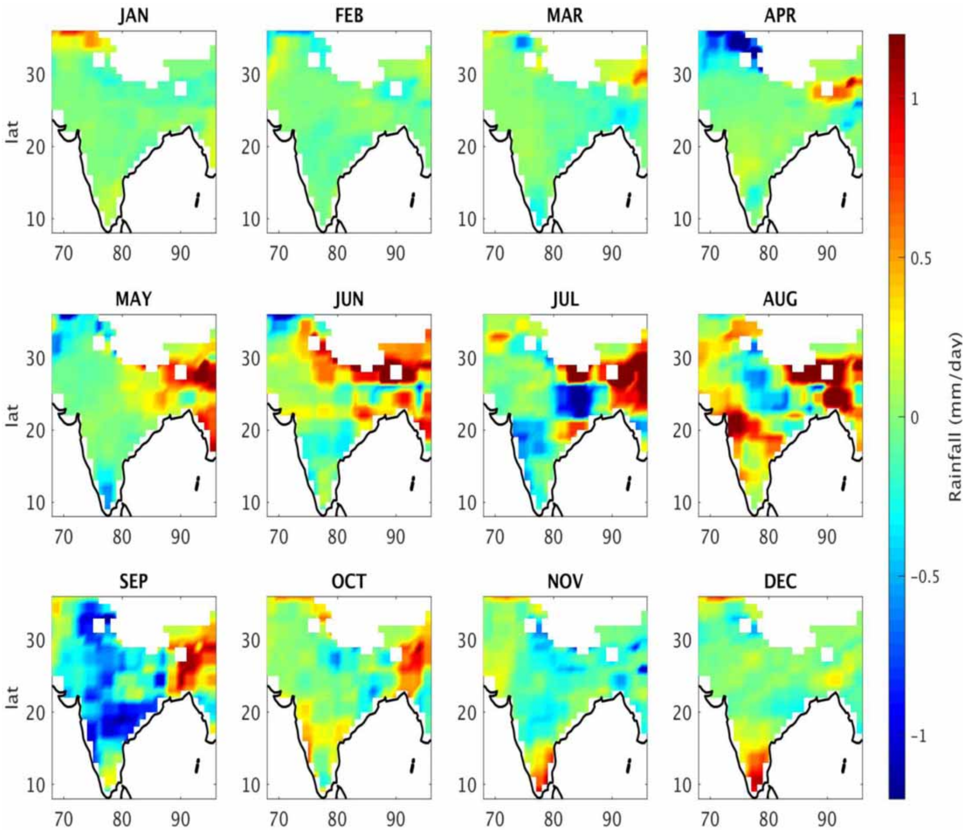

Figure 6 | Monthly difference map of the rainfall (mm/day) between RCP8.5 run (2006–2050) and historical run (1961–2005) of CNRM-CM5 model.

post-monsoon months of August–October see highest EIR differences with a positive sign, suggesting that the malaria transmission will increase in these months in a warming environment. It is also worthwhile to note that these VECTRI-simulated EIR differences are in general consistent across all the output obtained using the temperature and rainfall dataset of different models, though magnitudes may differ in different months. However, we also notice a decrease in the EIR (Figure 7(a)) in some parts of the northwestern Indian region in VECTRI simulation using climatological data of the CNRM-CM5 model. A similar decrease in some northwestern parts, as well as the southwestern region is seen in Figure 7(d) (MIROC-ESM model) and in eastern and southeastern coastal states during October–November months in Figure 7(c) (HadGEM2-ES model). Interestingly, the EIR is also increasing in the southern Indian region during November in nearly all the model simulations. This indicates that the malaria transmission will extend up to the month of November in the event of climate change and other parts of India will also become vulnerable to malaria transmission in a warming world.

The mean monthly variability of Larvae difference between the VECTRI output obtained using the RCP8.5 data and historical data is shown in Figure 8 for the CNRM-CM5 model (larvae maps with very similar characteristics using other CMIP5 model data not shown for brevity). The Larvae differences are mainly seen in the months of July–October. In the month of July, the malaria vectors will see a decrease in the eastern and southeastern regions, while the north central Indian region will see a slight increase in the malaria vectors. There will be a high increase in the Larvae population in the month of August in central and southern Indian regions, whereas the central and northern Indian region will see a decrease in the malaria population. In the month of September, the entire Indian region, except Western Ghats and southern Indian region, will see a decrease in the malaria population.

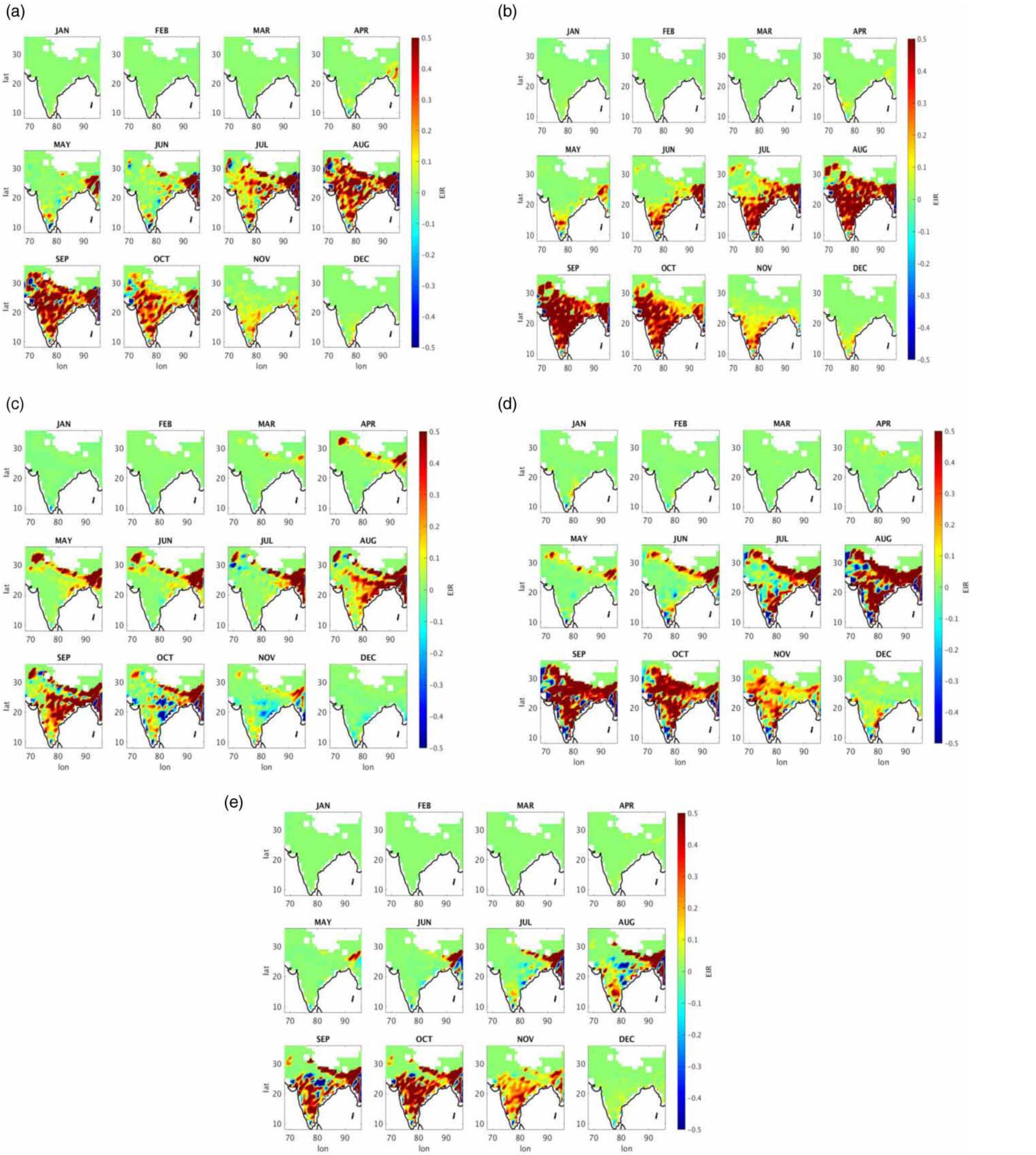

Figure 7 | Monthly difference map of the VECTRI-simulated EIR between RCP8.5 run (2006–2050) and historical run (1961–2005) of (a) CNRM-CM5, (b) GFDL-CM3, (c) HadGEM2-ES, (d) MIROC-ESM, and (e) MPI-ESM-MR models.

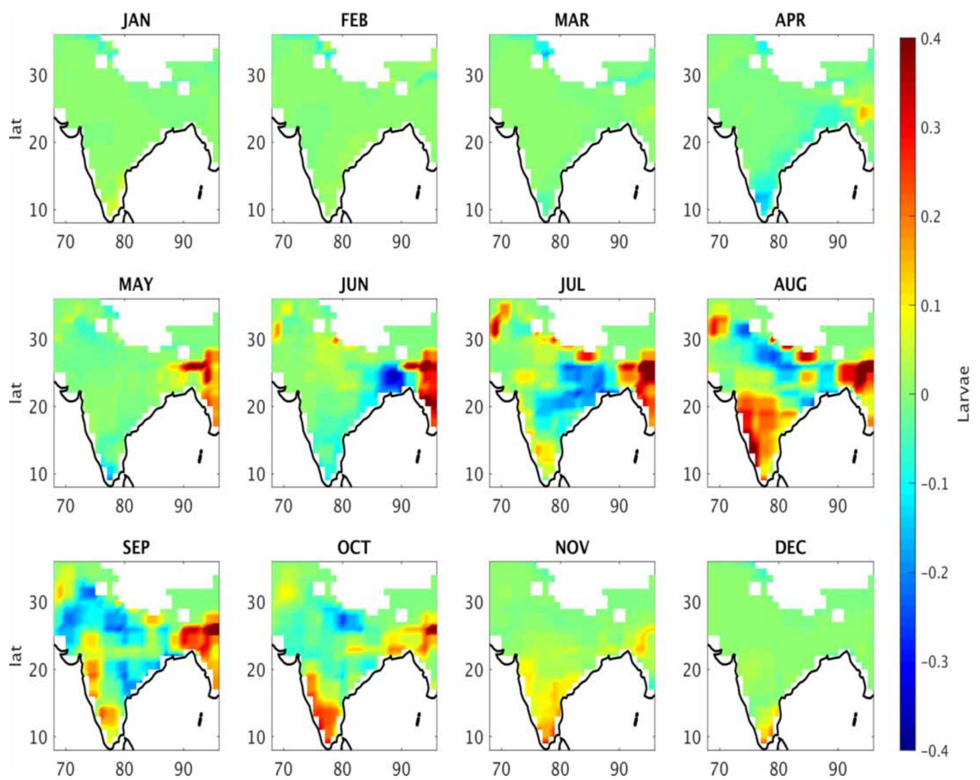

Figure 8 | Monthly difference map of the VECTRI-simulated Larvae between RCP8.5 run (2006–2050) and historical run (1961–2005) of CNRM-CM5 model.

During October, the increased Larvae population will be found only in the southern Indian region. In general, the VECTRI malaria model tends to show an increase in climate suitability for endemic malaria transmission over Western Ghats and northeast India between July and September.

In order to check the robustness of VECTRI-simulated malaria transmission results of the future projections and to see how they compare with the actual estimates, we compute the standardized (by its own standard deviation) anomaly of malaria cases over the Indian region for the years 2006–2018. The standardized anomaly of VECTRI-simulated malaria cases is computed for model runs using the RCP8.5 scenario of all the five CMIP5 models. The corresponding actual malaria cases data provided by the Directorate of National Vector Borne Disease Control Programme (NVBDCP), Ministry of Health and Family Welfare, Government of India (https://nvbdcp.gov.in/) are used for comparison. The results are shown in Figure 9. We see from the figure that out of all model simulations, the VECTRI-simulated results using the CNRM-CM5 and MIROC-ESM projection data are able to correctly get the observed trend of malaria cases. It is interesting to note that the malaria cases are decreasing in recent years suggesting usefulness of measures being adopted by the Government agencies to mitigate the malaria transmission. These results are, however, interpreted with the caveat that rainfall and temperature data of RCP8.5 scenario used as an input in the VECTRI may not be actual representation of these variables during 2006–2018. In other words, global warming may not be actually occurring at the same rate as depicted by the RCP8.5 runs of these models.

To put the results into perspective, we also compute the LTS of malaria in a year (Caminade *et al.* 2014). For the VECTRI model, LTS = 1 for a given month if EIR >0.01/day (Caminade *et al.* 2014). All those months of a year in which the EIR is greater than 0.01/day are counted for the purpose of computing LTS at each grid point. The LTS greater than 3 is considered as stable. We compute LTS for all the VECTRI simulations using the historical as well as RCP8.5 data. We show, in Figure 10, the LTS map over the Indian region using the CNRM-CM5 data. We see from the figure that the LTS is high (>8) and remarkably

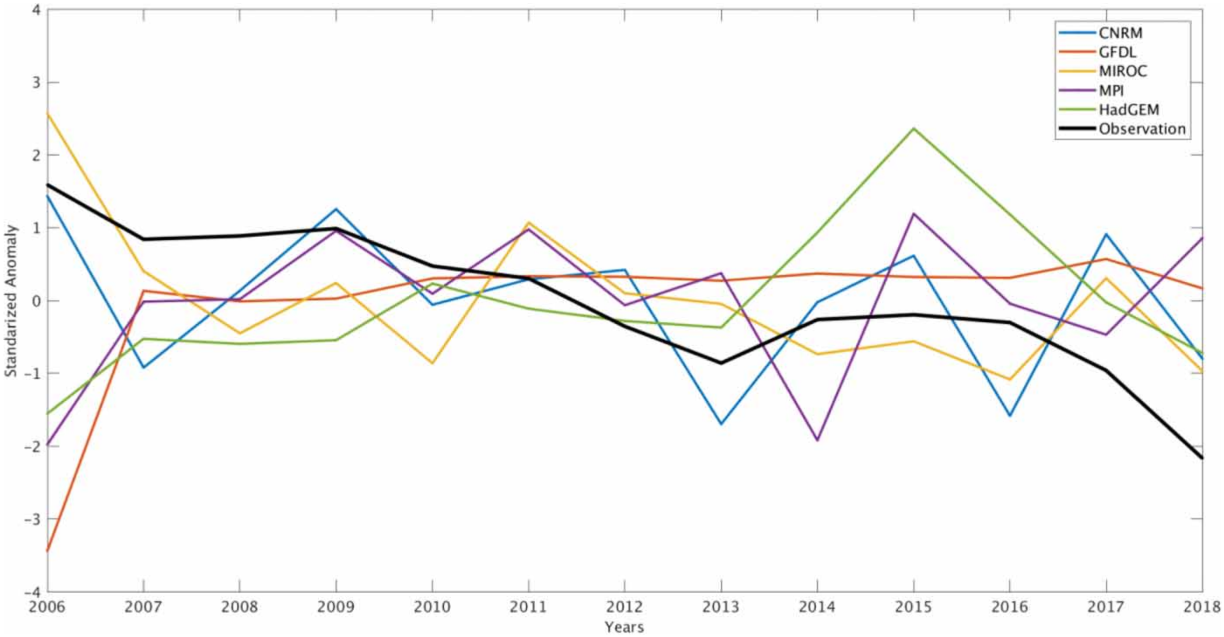

Figure 9 | Standardized anomaly of malaria cases over the Indian region for the years 2006–2018 corresponding to RCP8.5 run of CNRM-CM5, GFDL-CM3, MIROC-ESM, MPI-ESM-MR, and HadGEM2-ES models. The comparison is made with the corresponding anomaly computed using the data provided by the NVBDCP, Government of India (https://nvbdcp.gov.in/).

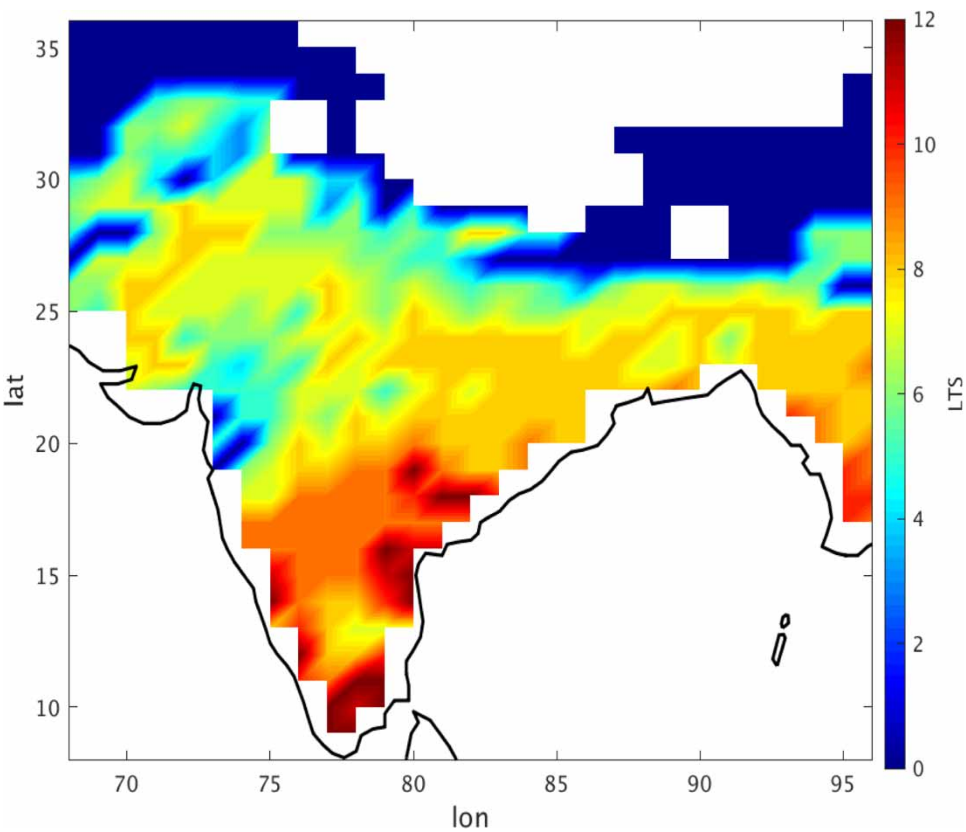

Figure 10 | LTS map of malaria computed from VECTRI simulation using the CNRM-CM5 data.

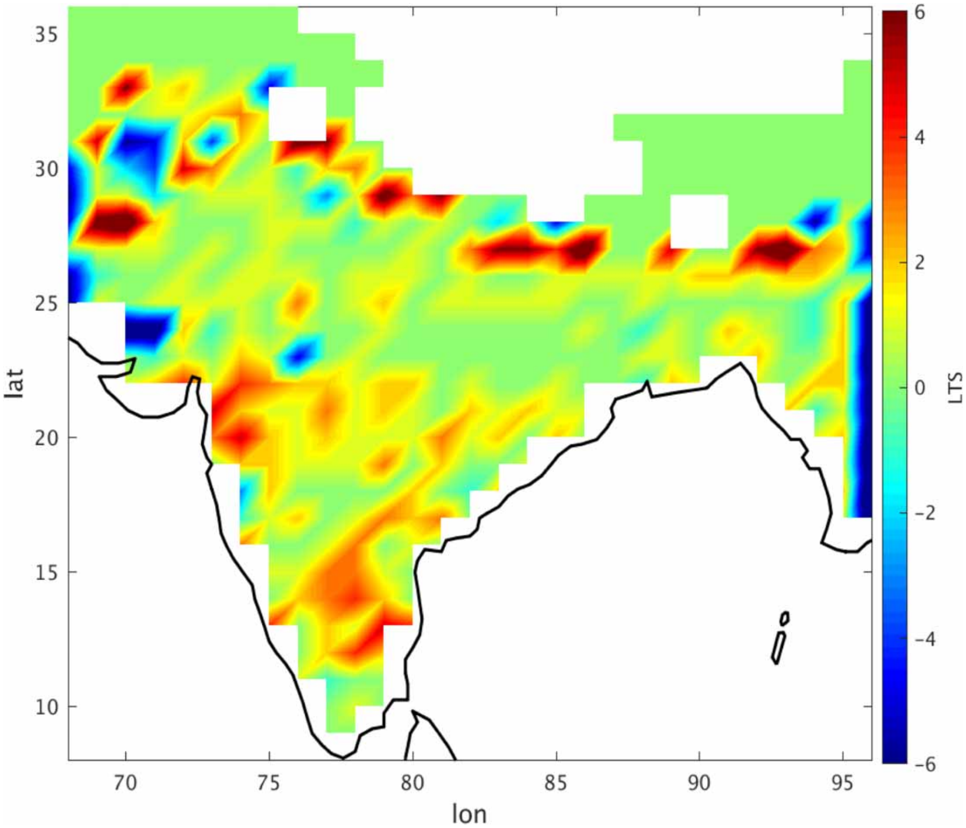

Figure 11 | Difference map of the LTS between RCP8.5 run (2006–2050) and historical run (1961–2005) for VECTRI simulation using the CNRM-CM5 data.

stable in the southern Indian states, intermediate (3–8) in central and eastern Indian states, and low unstable (<3) in parts of western and northern Indian states. The difference in the LTS between the VECTRI simulations using the RCP8.5 and historical data is shown in Figure 11. The LTS difference map clearly suggests even those regions that were less prone to malaria transmission will become susceptible to disease through climate change. For example, due to global warming, it is likely that the LTS will increase in the densely populated north central and western Indian states. In addition to these regions, the LTS is also likely to increase in the south and south central Indian states in a changing climate scenario.

CONCLUSION

In the present study, we try to assess the effect of climate change on malaria transmission over the Indian subcontinent using the VECTRI dynamical malaria model. This study suggests that temperature and precipitation play a dominant role in malaria transmission. The relationships between spatial patterns in malaria and climatological drivers of malaria varied greatly across India. The role of climate variability in influencing the malaria outbreaks in India is clearly seen under the climate change (seasonal shifts seen in the EIR and Larvae, for example). It is found that the malaria is endemic in the eastern and southeastern Indian regions of the country for the current climate. Applying the same criteria under the climate change conditions, it is projected that malaria is likely to persist in Western Ghats and north-eastern Indian regions. However, it may also shift from these regions to the southern Indian region in the month of November. The study carried out in the present manuscript uses the historical and future projection data of one of the five CMIP5 models. In future, it will be worthwhile to check the robustness of the results presented in the study by using multi-model mean and also by including more models from the CMIP6 output.

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