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Malaria risk map for India based on climate, ecology and geographical modelling

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Abstract

Mapping the malaria risk at various geographical levels is often undertaken considering climate suitability, infection rate and/or malaria vector distribution, while the ecological factors related to topography and vegetation cover are generally neglected. The present study abides a holistic approach to risk mapping by including topographic, climatic and vegetation components into the framework of malaria risk modelling. This work attempts to delineate the areas of *Plasmodium falciparum* and *Plasmodium vivax* malaria transmission risk in India using seven geo-ecological indicators: temperature, relative humidity, rainfall, forest cover, soil, slope, altitude and the normalized difference vegetation index using multi-criteria decision analysis based on geographical information system (GIS). The weight of the risk indicators was assigned by an analytical hierarchical process with the climate suitability (temperature and humidity) data generated using fuzzy logic. Model validation was done through both primary and secondary datasets. The spatio-ecological model was based on GIS to classify the country into five zones characterized by various levels of malaria transmission risk (very high; high; moderate; low; and very low. The study found that about 13% of the country is under very high malaria risk, which includes the malaria-endemic districts of the states of Chhattisgarh, Odisha, Jharkhand, Tripura, Assam, Meghalaya and Manipur. The study also showed that the transmission risk suitability for *P. vivax* is higher than that for *P. falciparum* in the Himalayan region. The field study corroborates the identified malaria risk zones and highlights that the low to moderate risk zones are outbreak-prone. It is expected that this information will help the National Vector Borne Disease Control Programme in India to undertake improved surveillance and conduct target based interventions.

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Introduction

In India, malaria affects more than a million people annually, a figure that amounts to about 4% of the global malaria burden (World Health Organization, 2018). With its extensive geographic and climatic diversity, the epidemiology of malaria ranges from endemic areas with perennial transmission to outbreak-prone, unstable areas. The situation is further complicated due to the presence of a wide distribution of anopheline vectors transmitting three major *Plasmodium* species: *Plasmodium falciparum*, *Plasmodium vivax*, and *Plasmodium malariae* (Kumar *et al*., 2007). Though the share of *P. falciparum* (66%) is more than *P. vivax* (34%) in the country, about 48% of the estimated global *vivax* malaria cases in 2017 occurred in India (World Health Organization, 2018). It is widely acknowledged that geo-ecological factors like climate, topography and vegetation characterize the habitat type of the malaria vectors leading to varying levels of malaria risk and transmission intensity (Craig *et al*., 2004; Lindsay *et al*., 2004; Kelly-Hope *et al*., 2009; Cottrell *et al*., 2012). In India, of the 36 states and union territories, the states of Odisha, Chhattisgarh, Madhya Pradesh and Jharkhand contribute 74.1% of the total malaria cases (Ghosh and Rahi, 2019), signalling the strong role of geo-ecological factors in malaria endemicity. To date the spatial distribution of malaria risk in India has been mapped either based on climate suitability, the number of malaria cases or the distribution of malaria vectors based on survey and expert opinion (Bhattacharya *et al*., 2006; Singh *et al*., 2013, 2017; Sharma *et al*., 2015; Srinivas, 2015), while the geo-ecological factors have so far been neglected with hotspots referred to as *tribal malaria* without further specification (Srivastava *et al*., 2009; Sharma *et al*., 2015).

Remote sensing, geographic information system (GIS) and other geospatial techniques have helped to analyse the epidemiological and ecological factors in the context of malaria (NASA, 1973; Hay *et al*., 1998; Mushinzimana *et al*., 2006; Shirayama *et al*., 2009; Yeshiwondim *et al*., 2009; Chikodzi, 2013; Gebreslasie, 2015). GIS combines spatial datasets with quantitative and qualitative databases and supports multi-criteria decision analysis (MCDA), which has the capability of transforming and integrating geographic data and expert knowledge to generate relevant information for decision-making (Eastman *et al*., 1995). MCDA, based on environmental and anthropogenic risk factors have been used in GIS environment in many countries to produce predictive malaria-indicative models (Kumi-Boateng *et al*., 2015). GIS-MCDA can thus be considered a process that transforms and integrates geospatial data and value judgments to obtain highly specific information. Weighted linear combination (WLC), a widely used MCDA method, involves standardization of attribute maps, assigning weights representing their relative importance of various environmental variables to obtain an overall score (Malczewski, 2004). In India, this approach is so far limited to only few micro level studies (Mutuwatte *et al*., 1997; Bhatt and Joshi, 2009), but has become a priority since knowledge of the malaria risk in the whole country is urgently needed.

The present work is an effort to delineate the areas of *P. falciparum* and *P. vivax* malaria transmission risk in India on the basis of defined risk categories related to the various climatic, topographic and ecological indicators in a GIS-MCDA environment. The report *Estimation of True Malaria Burden in India* by the National Malaria Research Institute (NIMR) (ICMR-NIMR, 2008) suggests that annual parasite incidence (API) generated from a routine surveillance system is not sufficient to map the malaria hotspots. The real burden of malaria in India is still not known (Kumar *et al*., 2007), and this jeopardizes the desirable outcomes in spite of extensive planning and resource allocation for malaria eradication. The study presented here is an attempt to address suspected under reporting of malaria cases in the neglected regions where the ecological malaria suitability is high, while case detection is low. The generated ecology-based geo-spatial malaria risk model should help the identification of hotspots and contribute to judicious planning and management of the malaria situation in all potentially endemic areas, which is of particular importance in the elimination phase.

Materials and Methods

Data

The climatic and environmental attributes/ indicators considered for malaria risk mapping in the study were temperature, relative humidity (RH), rainfall, forest cover, soil, slope, altitude and normalized difference vegetation index (NDVI). Table 1 summarizes the selected indicators.

For validation of the malaria risk map, both primary and secondary datasets were used. The annual malaria cases by district in India for 2010-1012 were procured from the National Vector Borne Disease Control Programme, while the reported malaria outbreak locations for 1981-2006 were obtained from the NIMR report *A Profile of National Malaria Research Institute* (unpublished).

Malaria risk model

The conceptual framework of the malaria risk model is given in Figure 1. The model was developed on the basis of the GIS-based MCDA, which included: i) identification of attributes as malaria risk indicators; ii) data processing and preparation; iii) risk characterization for relative risk scores; iv) weight assignments (degree of influence) of the risk indicators according to the Analytical Hierarchical Process (AHP); and v) combination of the weighted risk indicators to determine the risk zones.

Data preparation

Temperature and relative humidity

Previous studies (Gill, 1938; Russel *et al*., 1946) considered the influence of temperature and humidity on the mosquito to be inseparable. To understand malaria transmission dynamics, knowledge about the number of months suitable for malaria transmission

Table 1. Metadata for the indicators selected.

Indicator	Data description	Source
Temperature and relative humidity	Monthly averages (by district) for 1976-2005	CORDEX South Asia (domain WAS-44, WAS-44i) multi-model output data under the RCP 4.5 scenario*
Rainfall	Data for the homogeneous regions 1871-1990	Research Report No. RR-138 ESSO/IITM/STCVP/SR/02(2017)/189 (Kothawale and Rajeevan, 2017)°
Forest cover	Data by district for 2013	OGD Platform, India#
Soil	Soils of India map, 1983	European Digital Archive on Soil Maps§
Slope and altitude	SRTM^ 90 m DEM	CSI of the CGIAR$
NDVI	NDVI data (2012-2014)	Derived from OCM2 sensor of Oceansat-2, and the BHUVAN map service of the ISRO**

NDVI, normalized difference vegetation index; RCP, representative concentration pathways; OGD, Open Government Data; SRTM, Shuttle Radar Topography Mission; DEM, Digital Elevation Model; CSI, Consortium for Spatial Information; CGIAR, Consultative Group for International Agricultural Research; OCM2, Ocean Color Monitor; ISRO, Indian Space Research Organization. *https://sos.noaa.gov/datasets/climate-model-temperature-change-rcp-45-2006-2100/; °http://www.tropmet.res.in/; #http://data.gov.in; §http://eusoils.jrc.ec.europa.eu/esdb_archive/EuDASM/Asia/maps/IN1000_SOTO.htm; ^https://www2.jpl.nasa.gov/srtm/; $http://srtm.csi.cgiar.org/; **https://bhuvan.nrsc.gov.in/bhuvan_links.php windows (TWs) is essential as it governs the perennial risk. This can be done by fuzzy set theory, which attempts to generate a consistent representation of an inconsistent reality (Fisher and Unwin, 2005) by applying the fuzzy membership function, a curve that defines the degree of *belongingness* as varying between 0 and 1 (Zadeh, 1965). Vector capacity estimates for malaria (relying on temperature) have often been presented by Gaussian/binomial shapes (Martens *et al*., 1995; Mordecai *et al*., 2013). As this study considers *optimum/most suitable range* rather than the optimum point of temperature and RH, a sinusoidal membership function characterized by four scalar parameters: a, b, c and d was selected for the classification (Eq. 1):

$$\mu_F(x, a, b, c, d) = \begin{cases} 0 & \text{if } x<a \\ \frac{1}{2}\left(1-\cos\left(\pi\frac{x-a}{b-a}\right)\right) & \text{if } a \leq x \leq b \\ 1 & \text{if } b<x<c \\ \frac{1}{2}\left(1+\cos\left(\pi\frac{x-c}{d-c}\right)\right) & \text{if } c \leq x \leq d \\ 0 & \text{if } d<x \end{cases} \quad \text{Eq. 1}$$

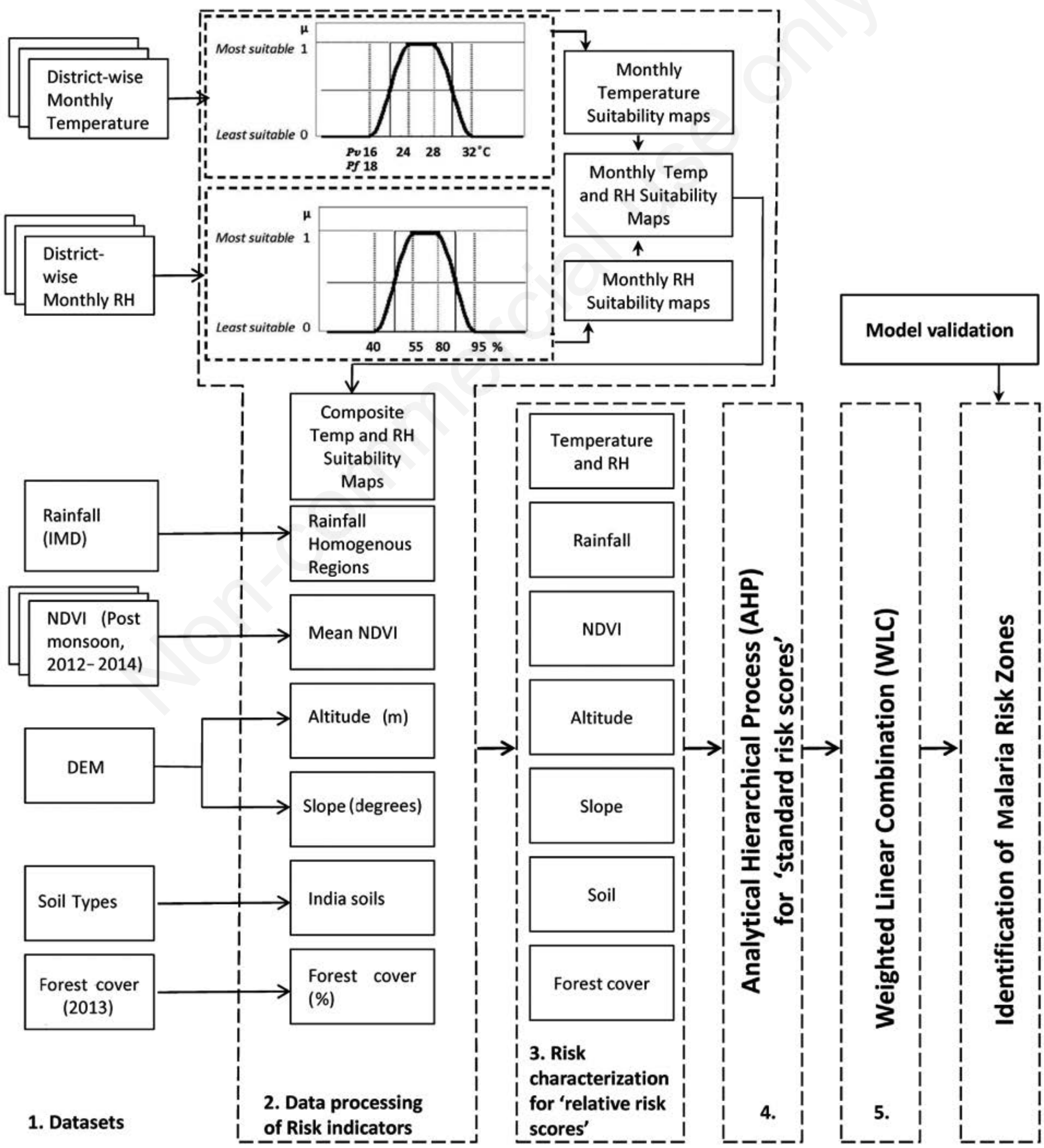

Figure 1. Conceptual framework of the malaria risk model. μ, mean; *Pv, Plasmodium vivax*; *Pf, Plasmodium falciparum*; RH, relative humidity; NDVI, normalized difference vegetation index; DEM, digital elevation model.

For the temperature index, ‘a’ represents the lower threshold (18°C for *P. falciparum* and 16°C for *P. vivax*), ‘d’ the upper threshold (32°C for both species) beyond which the membership function is 0 (unsuitable); whereas, ‘b’ and ‘c’ represents 24°C and 28°C, respectively. This range has been identified as the most suitable range for malaria transmission (Bhattacharya *et al*., 2006; Mordecai *et al*., 2013) and the membership function is thus 1. Similarly, the RH scalar parameters a, b, c and d are 40%, 55%, 80% and 95% humidity, respectively, where the membership function for range 55% and 80% is 1, *i.e.* the most suitable. As the value moves away from the range towards 40% or 95%, the membership function decreases to 0 representing the least suitable areas. The extreme limits for humidity was taken as 40% and 95% because vector survival is the least at humidity levels <40% (Bayoh, 2001; Yamana and Eltahir, 2013) and mosquito activity is suppressed at humidity levels >95% (Rudolfs, 1923; Platt *et al*., 1958).

Fuzzy-based analysis for temperature and RH was conducted to capture the gradual change in malaria transmission risk due to climatic factors and determine the TWs, which were generated in six stages as follows: i) generation of monthly interpolated temperature and RH maps; ii) determination of the fuzzy membership functions for both attributes; iii) creation of fuzzy-monthly temperature and RH transmission risk maps; iv) integration by month of temperature and RH transmission risk maps; v) generation of annual composite transmission suitability index; and vi) generation of spatial TWs in months.

On this basis, India was divided into four regions: i) >6 TWs; ii) 4-6 TWs; iii) 1-3 TWs and iv) 0 TWs.

Rainfall

A uniform hydrological threshold fails to capture the critical characteristics of malaria epidemiology. Under favourable temperature conditions, small quantities of stagnant water in potholes, dry river beds, tree holes, leaf axils, elephant hoof prints, discarded containers, coconut shells, *etc*. are sufficient for anopheline mosquito breeding (Sharma, 2014). Precipitation is related to the variations in the hydrological levels of a region (Olson *et al*., 2009; Stefani *et al*., 2011). In India, the annual summer monsoon rainfall varies between less than 50 cm in the west and more than 140 cm in the north-east and south-west. A region with moderate rainfall and low rainfall variability has a high probability for stable breeding habitats compared to a region characterized by high or extreme rainfall most of the time. The hydrological dynamics of a region, a contributor to the abundance and persistence of mosquito habitats, therefore, can be represented by rainfall variability. On the basis of the Mean, Standard Deviation and Coefficient of Variation computed for the period 1871-1990 accounting for the Southwest monsoon rainfall which takes place from June to September, Parthasarathy *et al*. (1995) divided India into five homogeneous regions i) the Northwest; ii) the West Central; iii) the Central Northeast; iv) the Northeast and v) the Peninsular (land area surrounded by water from three sides).

Forest cover

Vegetation influences the behaviour of the vector species both directly and indirectly (Singh *et al*., 1996; Gomez-Elipe *et al*., 2007). A strong relation between malaria prevalence and forest cover has been shown by several studies (Gunasekaran *et al*., 1989; Kondrashin *et al*., 1991; Yadav *et al*., 1997; Singh *et al*., 2013; Kar *et al*., 2014), emphasizing its significant role in malaria transmission. The forest cover has been assessed by the Forest Survey of India during 2013 using satellite-generated, remotely sensed data. The absolute forest acreage by district was converted to relative percentage for raster-based data compatibility when mapping the malaria risk. Accordingly, India was classified into five regions with respect to forest presence: i) >40%; ii) 30-40%; iii) 20-30%; iv) 10-20% and v) <10% cover.

Soil

Soil, in terms of its composition, texture and water-holding capacity, has a direct influence on breeding and emergence of adult mosquitoes and thus affects malaria transmission (Lindsay *et al*., 2004; Kankaew *et al*., 2005). Soils not only influence the vegetation character of the area but also foster malaria directly if it can hold surface water and therefore drains slowly. The major soil types in India, their characteristics and their suitability with regard to malaria are given in Table 2.

Table 2. Soil properties in relation with mosquito breeding.

Major soil type	Properties	Suitability for mosquito breeding habitat development
Alfisol (Udalf and Ustalf)	Soils of loamy properties and subsurface horizons of clay accumulation. Udalf soils remain moist in most time of the year and are well drained. However, Ustalf soils have limited moisture retention that regains during monsoon.	Good
Vertisol	Soils with high clays content that undergo considerable shrinkage by drying, which results in large and deep cracks which close only after prolonged wetting.	Temporarily good
Ultisol	Low-quality soils with subsurface layers of clay accumulation that do not hold water and are therefore vulnerable at high temperatures and rainfall with alternate wet and dry periods.	Barely useful
Aridisol	Dry and porous soils varying from silt made of fine clay loams to coarse sandy grains with limited water holding capacity that reach saturation much sooner than clay loams.	Temporarily good
Inceptisol	Soils that develop over geologically young sediments and where temporary flooding alters the soil profile that easily becomes saturated.	Barely useful

Slope and altitude

Several studies have shown an inverse relation between altitude and mosquito abundance (Hartman *et al*., 2002; Ermert *et al*., 2013). In contrast to temperature that presents a TW governed by certain levels (high or low), rain water influences in a general way by stagnation, infiltration and overflow with flat areas producing a higher risk of malaria due to water accumulation (Chikodzi, 2013). In the present study, definition of malaria risk due to slope and altitude was realized by using the GIS approach and overlaying API map, which shows that this measure decreases with increase in slope and altitude. Slope and altitude were extracted from the Shuttle Radar Topography Mission digital elevation model in ARC GRID, a raster GIS file format developed by ESRI (Redlands, CA, USA) projected in a latitude/longitude projection with the WGS84 horizontal datum and the EGM96 vertical datum.

The normalized difference vegetation index

NDVI is a measure of vegetation conditions that varies between +1.00 and −1.00; the higher the NDVI value, the denser the green vegetation. This index was used in this study as a quantitative proxy for the conditions favouring mosquito development with respect to water presence (both in vegetation and soil) and maintaining the RH for needed for mosquito survival. NDVI of a region exhibits the water table status of a region (Chen *et al*., 2006; Wang *et al*., 2011; Zhou *et al*., 2013) since a water table close to the surface in the absence of proper drainage during monsoon and post-monsoon tends to produce a better vegetation cover. Thus, a higher NDVI value can serve as an indicator of the suitability of areas for mosquito breeding (Dutt *et al*., 1980; Sharma and Srivastava, 1997). Owing to non-availability of water-level data at the district level, post-monsoon mean NDVI data were used as substitute for risk mapping of malaria transmission. The state-wise average NDVI for the post-monsoon period (November) and the water-level data (expressed in meters below the ground) available from the *Ground Water Year Book* for the November months of 2013-14 shows a significantly high negative correlation (correlation coefficient, r=-0.68, P<0.05).

The mean NDVI for the post-monsoon period was generated from 2012 to 2014 with the November NDVI values computed from Ocean Colour Monitor onboard the OCEANSAT-2 satellite (Chauhan and Navalgund, 2009) measuring the near infrared (ρ_{B8}) and Red (ρ_{B6}) bands (Eq. 2):

$$\mathrm{NDVI} = \frac{\rho_{B8} - \rho_{B6}}{\rho_{B8} + \rho_{B6}} \qquad \text{Eq. 2}$$

Risk characterization

Knowledge-based malaria risk characterization of the indicators given above was conducted after a thorough review of literature and also relying on an expert opinion survey. The relative risk scores were allotted with the logic that an indicator representing a higher risk of malaria be given a greater weight. The indicators were classified into five scores according to their relative risk, namely very high, high, moderate, low, and very low, which were given the weights 5, 4, 3, 2, and 1, respectively.

Hierarchical analysis

The AHP relies on the judgments by experts to derive priority scales and the approach rests on pair-wise indicator comparisons (Saaty, 2008). When determining the malaria risk, each identified ecological indicator has a certain degree of influence that needs to be scaled and prioritized for MCDA processing (Yalcin, 2008). In this study, AHP was conducted in three steps: formulation of pair-wise comparison for all risk indicators; establishment of the relative importance of each risk factor; and finally checking the consistency ratio of the pairing process. As recommended by Saaty (2008), experts were consulted during the construction of the pair-wise comparison matrix subsequently deriving the weights by normalizing the eigenvector of the square reciprocal matrix of these risk factor comparisons. Before accepting the final judgment on which weight (*i.e.* standard risk score) of each indicator to apply, the consistency ratio (CR) was calculated. The CR is a comparison between the consistency index (CI) and the random consistency index (RI) (Eqs. 3 and 4):

$$\mathrm{CR} = \mathrm{CI}/\mathrm{RI} \qquad \text{Eq. 3}$$

$$\mathrm{CI} = \frac{\lambda_{max} - n}{n-1} \qquad \text{Eq. 4}$$

where n is the dimension of the matrix (7 by 7 in this case) and λ_{max} the maximum eigenvalue of the comparison matrix.

If the CR turned out to be ≤10%, the inconsistency (for estimating weights in the AHP, the eigenvector yields is a way of measuring the consistency of the referee's preferences arranged in the comparison matrix. To represent the decision maker's judgements,

Table 3. Field survey schedule.

State/UTs	District surveyed	Survey months
Kerala	Palakkad, Kasargod, Mallappuram, Trivendrum and Kannur	August
Dadra and Nagar Haweli	Dadra and Nagar Haweli	March
Chhattisgarh	Dantewada	March
Odisha	Koraput	March
Rajasthan	Barmer, Jaisalmer, Bikaner, and Jodhpur	September
Uttarakhand	Nainital, Almora, Udham Singh Nagar	September
Punjab	Mansa and Bhatinda	June
Assam	Karbi-Anglong	June
Jharkhand	Ranchi	March

UT, Union territory.

the criterion of accepting/rejecting matrices depends upon the consistency/inconsistency of the referee's preferences) was accepted. Based on Saaty's table (Saaty, 1980) and n=7, we used a RI=1.32.

Determination of the risk zones

On generating the weights for each malaria risk indicator, all the indicators selected were combined to obtain the overall malaria transmission risk zone. Several techniques, such as Boolean intersection, WLC and ordered weighting average, can be used to combine the risk factors and determine the risk zone (Rafiee *et al*., 2011). In the present study, we applied the WLC method, which we found conveniently calculates the summation of the *relative risk score* of each risk indicator giving the percentage of influence (Eq. 5):

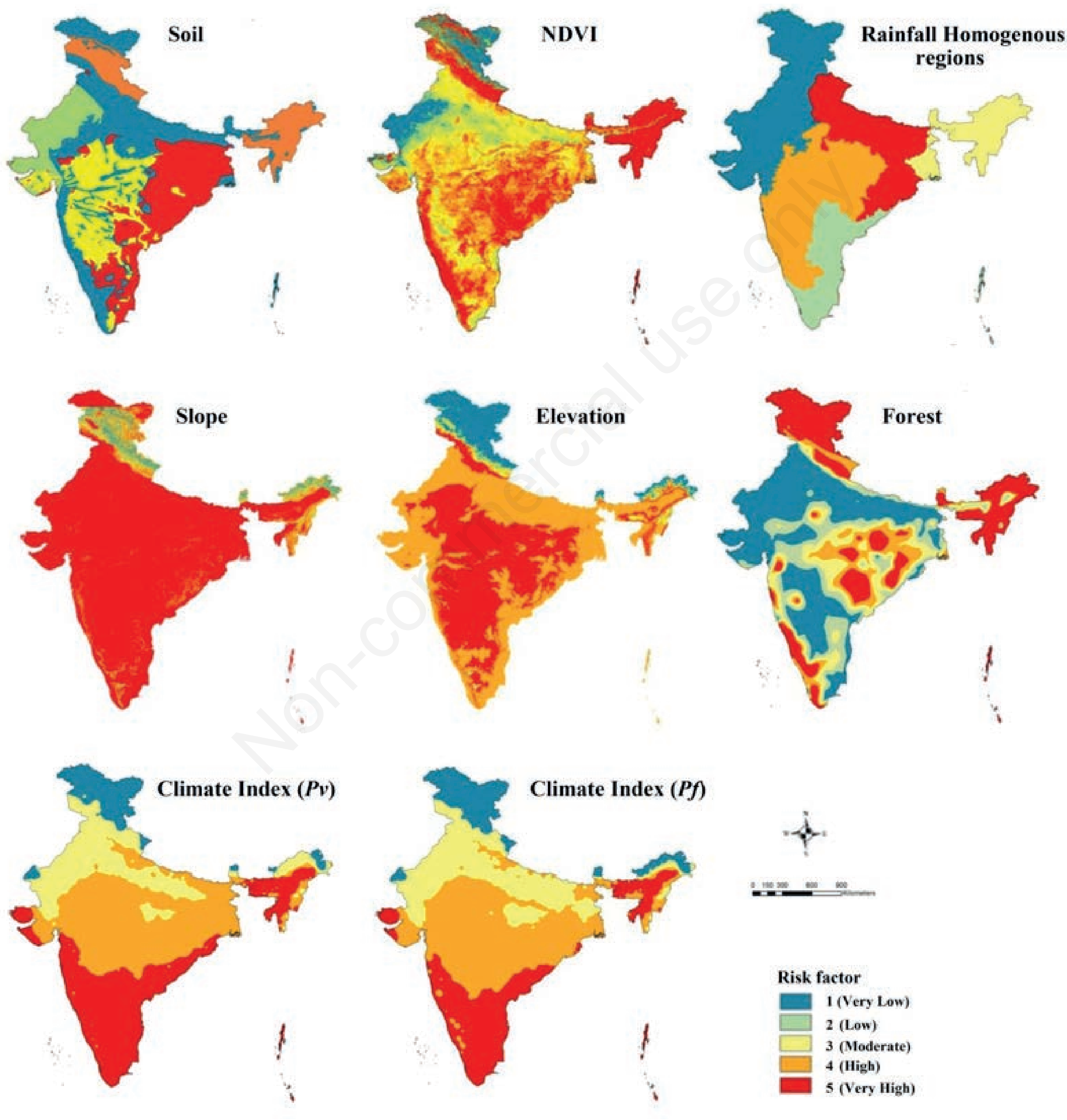

Figure 2. Classified malaria transmission risk indicators. NDVI, normalized difference vegetation index; *Pv, Plasmodium vivax; Pf, Plasmodium falciparum.*

$$S = \sum W_i X_{ij} \quad \text{Eq. 5}$$

where S is the spatial unit value on the output map (the malaria risk zone); W_i the weigh t of the i[th] indicator map (the malaria risk indicator map); and X_{ij} the i[th] spatial class (the malaria risk score) of the j[th] indicator map.

Model validation

The model was validated through both primary and secondary data sets. Considering the problem of underreporting malaria, we undertook a primary survey in randomly selected districts among the five identified risk zones except in the state of Rajasthan for the years 2012 and 2016 (Table 3) in addition to the secondary data sources (mean API by district for 2010-2012 and the districts experiencing malaria outbreak in the period 1981-2006). Furthermore, blood microscopy was carried out to assess the true malaria incidence and the results overlaid the mean API values for 2010-2012 and the malaria outbreak districts between 1981 and 2006.

Results

Characterization of the risk indicators

The spatial composite temperature and RH suitability for transmission showed maximum malaria TWs in the southern and eastern parts of India both for *P. vivax* and *P. falciparum*, while the TWs in the states in the West and North were shorter with the minimum reaching <4 months (Figure 2).

The vegetation components, *i.e.* forest cover and NDVI showed high to very high relative risks mainly concentrated in the Himalayan, western Ghat and eastern plateau regions, while there were lower values in the western arid states with negligible vegetation cover. The topographic components comprising soil, slope and elevation showed high to very high relative malaria risk in major parts of Peninsular India. Figure 2 provides a detailed spatial distribution of these relative risk scores ranging from 1(very low risk) to 5 (very high risk).

Malaria risk zone delineation

The *P. vivax* and *P. falciparum* risk maps (Figure 3), generated after combining all the physical and ecological risk indicators using the weighted sum function in the GIS environment (Tables 4 and 5), showed the complete spatial distribution of malaria risk in India. According to these findings, about 28% of the country is under high risk with as much as approximately 13% under very high risk, while nearly 40% of the area is under moderate risk and the rest under low to very low risk. This means that high and very high malaria transmission risk are common in the districts of the eastern states, including Chhattisgarh, Odisha and Jharkhand, and the north-eastern states, *i.e.* Tripura, Assam, Meghalaya and Manipur, while the districts of Madhya Pradesh, Maharashtra, Uttarakhand, Bihar, Karnataka, Telangana, Andhra Pradesh, Tamil Nadu, West Bengal and the rest of the north-eastern states are under moderate to high risk.

The states Uttar Pradesh, Himachal Pradesh, Jammu and Kashmir, Kerala, and Sikkim are under moderate malaria transmission risk, and remaining states, including Punjab, Haryana, Gujarat and Rajasthan, are characterized by low and very low risk for malaria. This inevitably shows that all these districts are vulnerable

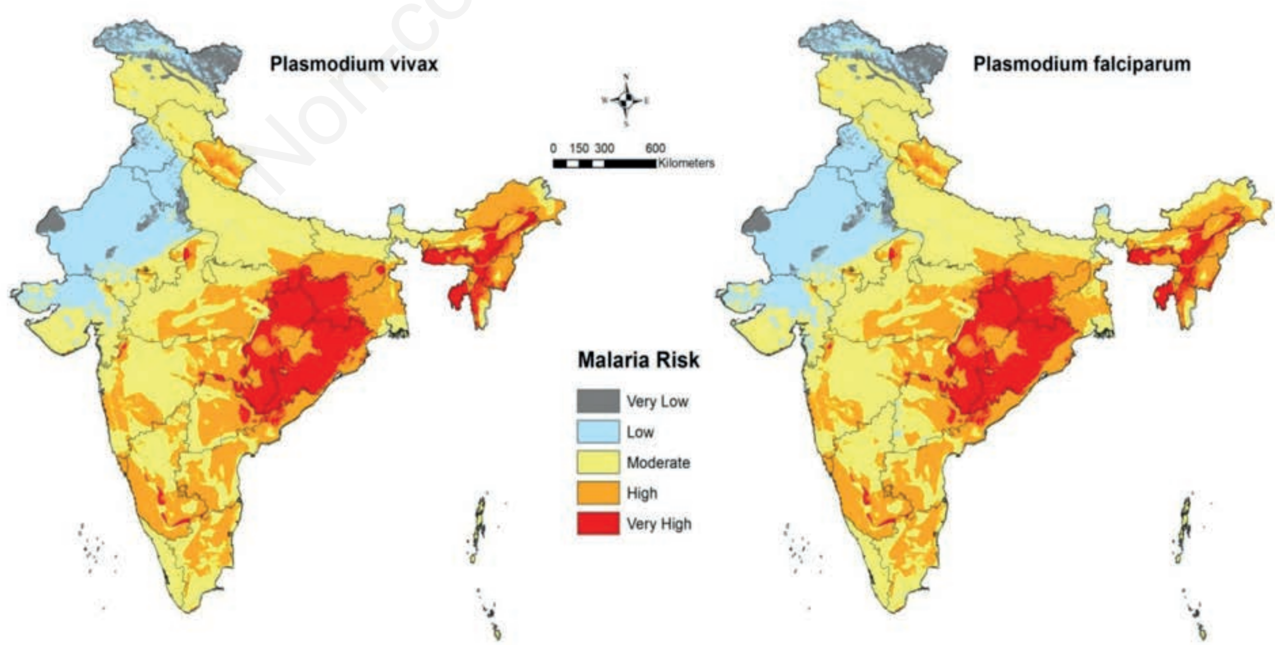

Figure 3. The overall malaria risk in India.

to malaria, though at different levels. *P. vivax* malaria transmission suitability was found to be more intensive than *P. falciparum* in Uttarakhand, Arunachal Pradesh, Meghalaya, Telangana and the interior of Karnataka.

In the Western Himalayan region, the Uttarakhand state is most ecologically suitable for *P. vivax* and *P. falciparum* transmission. In Eastern Himalayan region, most of the states are generally strongly ecologically suitable for perennial malaria transmission of both species. It should, however, be noted that *P. vivax* suitability is more pronounced than *P. falciparum* in Arunachal Pradesh. In

Table 4. Weights resulting from the Analytical Hierarchical Process (AHP) pair-wise comparison AHP.

Indicator	Soil	Forest	Temperature and RH	Rainfall	NDVI	Slope	Altitude	Weight
Soil	1	2.5	1	3	3	2	3	0.25
Forest	0.4	1	2	2	2	3	3	0.20
Temperature and RH	1	0.5	1	0.5	2	1.5	5	0.15
Rainfall	0.33	0.5	1	1	3	1.5	5	0.15
NDVI	0.33	1	0.5	0.33	1	2	2	0.10
Slope	0.5	0.33	0.67	0.2	2	1	2	0.10
Altitude	0.33	0.33	0.2	0.2	0.5	0.5	1	0.5
SUM	3.9	6.17	6.37	7.23	13.5	11.5	21	1.0

λ_{max}=7.7172; consistency index=0.1195; random consistency index=1.32 (for 7 indicators); consistency ratio=9.06 (≤10% - acceptable). RH, relative humidity; NDVI, normalized difference vegetation index.

Table 5. Weight determination of malaria risk indicators for multi-criteria analysis.

Sl. no.	Factor	Influence (% weight)	Classification or range	Rank	Degree of vulnerability
1	Soil (type)	25	Ustalf	5	Very high
			Udalf	4	High
			Vertisol	3	Moderate
			Aridisol	2	Low
			Ultisol	1	Very low
			Inceptisol	1	Very low
2	Forest (% distribution)	20	>40	5	Very high
			30-40	4	High
			20-30	3	Moderate
			10-20	2	Low
			<10	1	Very low
3	Climate suitability index (no. of months)	15	>6	5	Very high
			4-6	4	High
			1-3	3	Moderate
			0	1	Very low
			µ SD CV		
4	Rainfall (mm) Homogenous region	15	1002 112 11.2	5	Very high
			933 125 13.5	4	High
			1419 121 8.6	3	Moderate
			659 98 14.9	2	Low
			490 132 27.0	1	Very low
5	NDVI (post-monsoon, November)	10	>0.6	5	Very high
			0.5-0.6	4	High
			0.4-0.5	3	Moderate
			0.3-0.4	2	Low
			<0.3	1	Very low
6	Slope (degree per km^2)	10	0-5	5	Very high
			5-10	4	High
			10-15	3	Moderate
			15-20	2	Low
			>20	1	Very low
7	Elevation (m)	05	0-250	4	High
			250-750	5	Very high
			750-1250	4	High
			1250-1750	3	Moderate
			1750-2250	2	Low
			>2250	1	Very low

µ, mean; SD, standard deviation; CV, coefficient of variation; NDVI, normalized difference vegetation index.

the peninsular part of India, the prevailing climate makes the whole region highly suitable for stable malaria transmission; however, the east coast more so than west coast due to topographic characteristics. The interior peninsular region is characterized by moderate suitability, though Telangana suits *P. vivax* better than *P. falciparum*.

Model validation

The mean API for the years 2010-2012, the malaria outbreak districts over the 25-year period 1981-2006 and the positive rates of the microscopy survey support the resultant ecological risk map (Figures 4 and 5). The distribution of API isolines is mainly concentrated over the areas defined as having high to very high risk, while the outbreak sites were scattered over the low to moderate malaria risk regions. Similarly, analysis of field data suggests that Chhattisgarh and Assam, which are situated in high risk region, showed a >10% microscopy positivity rate, while a limited number of areas in the moderate risk region Odisha and Jharkhand had a 5-10% positivity rate; Kerala, Dadra and Nagar Haveli, Uttarakhand and Punjab in the region classified as moderate to low risk had a <5% positivity rate by microscopy. Exceptionally, the state of Rajasthan in the low risk region showed a positivity rate of nearly 10% and an average API of about 4.

Discussion

Our aim was to generate a spatial ecological malaria risk map for India. The GIS-based ecological modelling helped to classify the country at the district level into five transmission zones of varied risk, which were validated through both primary and secondary data sources to mark the relevance in context of the malaria elimination programme. The findings of the present study would also serve as a baseline for understanding the changing receptivity of malaria in view of climate change.

The zones representing the highest risk includes hotspots for endemic *P. vivax* and *P. falciparum* transmission. This risk zone was found to be spread over the districts in states of Chhattisgarh, Odisha, Jharkhand, Tripura, Assam, Meghalaya, and Mizoram, which is not surprising as these areas have perennially transmission of malaria throughout the year. These regions are characterized by forested areas with dense forest cover, warm climate and small streams to stagnant bodies of water, which encourages high vector density, longevity and hence high infection rates (Sahu *et al*., 1990; Nanda *et al*., 2000; Lindsay *et al*., 2004). According to the blood microscopy survey, parts of the states of Odisha and Jharkhand were categorized as moderate malaria risk areas though they are rather in the high-risk zone, which may be explained by the survey being undertaken in the month of March when malaria is not at its peak. High risk regions encompass areas within close proximity to the very high-risk regions, while the risk gradient decreases steeply towards the western states that are characterized by arid climatic conditions and dry sandy soil. Similarly, the northern most districts of Jammu and Kashmir also have very low risk because of high altitude and periglacial conditions. The reason of high slide positivity rate (10%) in the survey undertaken in Rajasthan may be attributed to most suitable month of survey, while in the states of Chhattisgarh, Jharkhand and Odisha, the surveys were undertaken in the month of March.

It should be noted that certain districts in the states of Uttarakhand, Himachal Pradesh, Bihar, Karnataka, and Nagaland

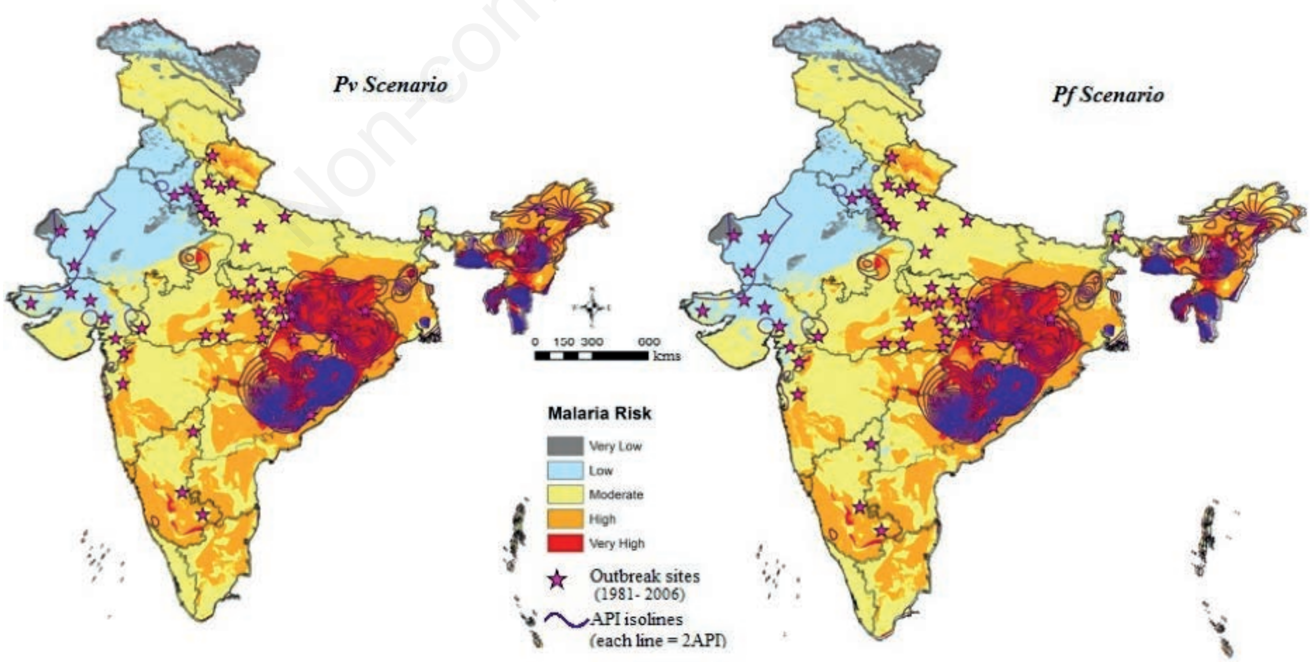

Figure 4. The malaria risk map with annual parasite incidence and outbreak values superimposed. ***Pv, Plasmodium vivax; Pf, Plasmodium falciparum*; API, annual parasite incidence.**

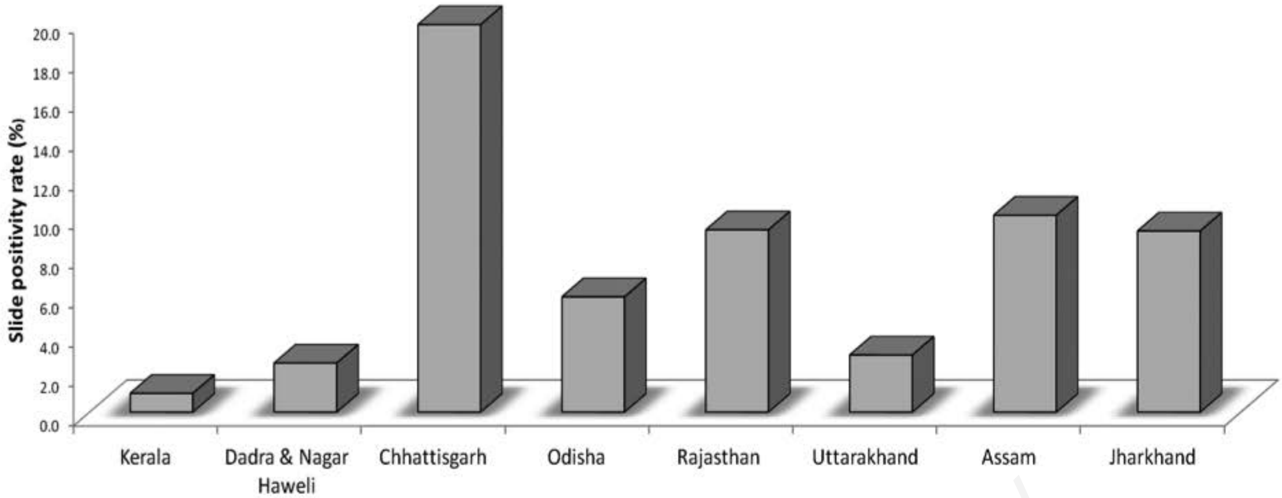

Figure 5. Malaria positivity rates by blood microscopy in selected field sites. Data from the survey shown in Table 3.

had a low API in spite of very high ecological suitability. This discrepancy may be due to underreporting, and the malaria eradication programme may have to intervene here to find out more.

The low to moderate risk zones, mainly spread over the northern, western and western-coastal states of India, needs a close analysis as these regions, *e.g.*, Kerala, Shimla and Rajasthan, have experienced some major malaria outbreaks in the recent past. Though these regions are not endemic due to one or more unsuitable ecological factor(s), they often face outbreaks due to external causes that may create new breeding habitats due to anthropogenic activities such as storage of water. Other reasons are unexpected heavy rainfall with stagnated water in its wake. Rajasthan falls under low malaria risk zone, because of less than 4 months of suitable climatic TWs. It has often faced outbreaks when receiving more than normal rainfall (Gupta, 1996; Akhtar and McMichael, 1996). The scenario is similar also in other states, for example Gujarat, west Maharashtra and north Karnataka. Outbreaks in Uttar Pradesh and Haryana have been reported due to heavy rainfall, disrupted surveillance and poor intervention (Dhiman *et al*., 2001; Shukla *et al*., 2002; Salve *et al*., 2014).

Conclusions

Understanding the patterns of malaria transmission risk is an essential component for a country like India, where resources are limited and elimination campaign has to be targeted cost-effectively. In this context, the presented spatio-ecological modelling, based on multi-criteria analysis in a GIS environment, has efficiently mapped the malaria risk zones in India at the district level. This should help the National Vector Borne Disease Control Programme to judiciously take decisions related to improved surveillance and conducting target based interventions.

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