Malaria Risk and Vulnerability of Communities Due to Climate Change in India

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Abstract

Background: Malaria is an erstwhile public health problem that is further compounded in India due to diverse climatic conditions, ecology, socio-developmental indicators and the imminent threat of climate change. Mapping of malaria risk using climatic and ecological factors has been assessed to some extent but the vulnerability by taking into consideration the human factors i.e. socio-economics and adaptive capacity, in climatically vulnerable areas is not known. The present communication deals with determining the risk and vulnerability at district level by taking into account the hazard due to climate change, population exposed, ecological sensitivity and the community's adaptive capacity.

Methods: Based on the IPCC framework, relevant indicators for the dimensions of risk (Hazard, Exposure, Sensitivity, Adaptive Capacity) were identified from literature and was used to develop indices. Data for each indicator was obtained through government websites. Weights for different indicators were assigned using principle component analysis and the indices were aggregated to develop a district wise risk and vulnerability profile of India.

Results: Malaria risk was found to be highest in Bihar (*Ri=0.7*) due to very low adaptive capacity coupled with high sensitivity. In some states with high climatic hazard and/or sensitivity for malaria, such as Tripura, Mizoram, Kerala and Tamil Nadu, high Adaptive capacity acted as a buffer, reducing the overall risk of malaria. Further, malaria risk is projected to be introduced for the first time in some districts of Himachal Pradesh and Arunachal Pradesh by 2030s due to the effects of climate change.

Conclusion: The results of the study highlight the importance of various socio-development indicators in representing a holistic view of malaria risk. Adaptive capacity emerged as an important index as it could help counter the effects of climate change on malaria by enabling the community to cope with the adverse effects.

Introduction

India is the third largest contributor to the global malaria burden after Nigeria and Democratic Republic of Congo, accounting for 6% of the global malaria cases [1]. In recent years, India has successfully reduced its malaria morbidity and mortality significantly, and is moving towards elimination. However, in a large country like India, there are diverse climatic conditions, ecology and socio-developmental indicators. In addition to this, climate change is posing a major threat by affecting the distribution of malaria [2–5].

Mapping of risk using climatic and ecological factors has been assessed to some extent and opening of new transmission windows in some parts of the Himalayan region as well as reduction in malaria intensity in hotter regions by 2030s has been projected [6, 7]. However, the vulnerability to malaria by taking into consideration the human factors i.e. socio-economics and adaptive capacity, in climatically vulnerable areas in India is not known. A comprehensive risk assessment should, therefore, incorporate all the socio-economic factors and demographic pressures that influence local vulnerability to malaria, such as the framework developed by the Intergovernmental Panel on Climate Change (IPCC) which identifies risk as a factor of the hazard, exposure and vulnerability [8–10].

The present study was, therefore, undertaken to assess the social impact of malaria taking into account the multitude of factors that shape malaria risk in India. The effect of future climate change (2030) on malaria, at present vulnerabilities was also assessed, to ascertain its impact in the future if present conditions are not alleviated. The malaria risk and vulnerability profile developed in the study can be used to develop appropriate adaptation measures that are based on local vulnerabilities tailored to each district.

Methodology

An indicator-based approach for risk assessment was used in the study. This approach combines a variety of different indicators of risk into meaningful indices. Such an approach incorporates all three dimensions of risk defined by the IPCC– hazard, exposure and vulnerability.

Risk Assessment Framework

The IPCC defines climate change risk as a product of probability of hazard due to climate change, the degree to which populations are exposed to the risk and vulnerability of the local communities.

Selection of Variables

An extensive literature survey of variables used in malaria risk and vulnerability assessment studies was conducted, and 18 indicators were shortlisted for the study. The variables selected represent the climatic and ecological risks to malaria, socio-economic well-being, health and nutritional status, education, infrastructure and demography. Data for each of these indicators was either available in the public domain or procured from various government organizations.

The shortlisted indicators were classified based on the definitions of hazard, exposure and vulnerability as described by the IPCC [12, 13]. A list of all the shortlisted indicators and their sources is given in Table 1.

Table 1
Variables selected for assessing risk and vulnerability

Indicators	Dimension	Source
Transmission Window (TW)	Hazard	[7]
Population Density	Exposure	Census 2011, Government of India [14]
% Children < 6 years	Exposure	Census 2011, Government of India [14]
% People > 60 years	Exposure	Census 2011, Government of India [14]
Annual Parasite Incidence (API)	Sensitivity	State Programme Officers District Malaria Officers
% HH with vulnerable material of wall	Sensitivity	Census 2011, Government of India [14]
% HH with vulnerable material of roof	Sensitivity	Census 2011, Government of India [14]
% Stunted Children under 5 years	Sensitivity	Ministry of Health and Family Welfare - National Family Health Survey, Government of India [15]
Livestock per 1000 HH	Sensitivity	Ministry of Agriculture – 19th Livestock Census, Government of India [16]
Forest Cover as percentage of land	Sensitivity	Forest Survey of India, Ministry of Environment, Forests and Climate Change [17]
NDVI	Sensitivity	NOAA CDR NDVI [18]
Net irrigated area	Sensitivity	Central Research Institute for Dryland Agriculture – District Agricultural Contingency Plans, Government of India [19]
Soil Moisture Content	Sensitivity	European Space Agency – Climate Change Initiative [20]
Literacy	Adaptive Capacity	Census 2011, Government of India [14]
Per Capita Income	Adaptive Capacity	[21]
Health Centre population burden	Adaptive Capacity	Rural Health Statistics, National Rural Health Mission, Government of India [22]
% HH with health insurance	Adaptive Capacity	Census 2011, Government of India [14]
% HH lacking essential assets	Adaptive Capacity	Census 2011, Government of India [14]

Transmission windows for malaria which have been determined in a recent study using the CORDEX model [6], were used as the indicator for hazard. Baseline and projected (2030) transmission windows of malaria at moderate climate change impacts (RCP 4.5) using temperature and relative humidity were used.

The indicators used to determine the degree of exposure to malaria risk were population density, percentage of children below 6 years and adults above 60 years, who are likely to have reduced immunity [23].

The vulnerability to malaria depends on the intrinsic sensitivity of the community and its ability to cope with and adapt to the changes. Sensitivity to malaria was further categorized into biological (API, malnutrition), ecological (forest cover, NDVI, soil moisture, net irrigated area) and demographic (material of wall and roof, livestock per 1000 people). The adaptive capacity of the communities was based on the socio-economic status (Literacy, per capita income), availability of resources (% households (HH) with health insurance, % households lacking essential assets) and robustness of health infrastructure (Health Centre population burden).

Data Processing

The raw data was analysed for missing information and potential outliers. Missing data were completed through interpolation and outliers were treated with 98% winsorization. The indicators were tested for multicollinearity through Pearson's correlation factor, with a value above 0.9 indicating high collinearity [24]. The indicators were then normalized using the standard formula for linear transformation: $X_s = (x - x_{min}) / (x_{max} - x_{min})$.

Assigning Weights

Principal component analysis (PCA) was used to assign weights to the indicators which reflect the largest variations. Kaiser-Meyer-Olkin (KMO) value of 0.762 indicated high usability of the PCA test (> 0.6). Weights were calculated by multiplying the square of the rotated factor loadings with the proportion of the explained variance for each component (Table 2) based on the method described by Organization for Economic Co-operation and Development (OECD [24].

Table 2
Weights assigned to each indicator

Dimension	Variables	Weightage
Hazard	TW	0.06
Exposure	Population Density	0.09
	Children < 6 yrs	0.09
	Population > 60 yrs	0.06
Sensitivity	API	0.04
	% HH with vulnerable material of wall	0.01
	% HH with vulnerable material of roof	0.06
	% Stunted Children < 6 yrs	0.08
	Livestock per 1000 HH	0.04
	Forest Cover	0.01
	NDVI	0.02
	Soil Moisture	0.05
	Net irrigated area	0.09
Adaptive Capacity	Literacy	0.09
	Per Capita Income	0.07
	% HH with health insurance	0.08
	Health Centre population burden	0.01
	% HH lacking essential assets	0.05

Composite Risk and Vulnerability Index

Hazard (baseline and projected), Exposure, Sensitivity and Adaptive Capacity indices were evaluated using linear summation: $\sum_i^n w_i x_i,$ where '*x*' is the indicator and '*w*' is the respective weight. The vulnerability index was calculated using the formula: $V_i = [S_i + (1 - A_i)]/2$, where V_i is the vulnerability index, S_i is the sensitivity index and A_i is the adaptive capacity index. Thereafter, the Risk index was calculated using geometric summation: $R_i = H_i \times E_i \times V_i$. Geometric summation was used for the final risk index in order to account for the fact that if the value any of the three dimensions of risk (Hazard, Exposure and Vulnerability) was 0, the overall risk will also be 0. All indices were transferred to ArcGIS 10.2.1 and district-wise raster surface was created for each index.

Results

Multicollinearities and Validation

Correlation between each of the 18 indicators was less than 0.9 indicating no multicollinearities. Furthermore, the Variance Inflation Factor (VIF) was below five which confirms that there were no errors due to multicollinearity.

Effect of Climate Change Hazard on Malaria

A recent study on the climatic suitability for malaria in India and the impacts of climate change projected an increase in malaria transmission by 2030s in the states of Rajasthan, Maharashtra, Assam, Meghalaya, Tripura and Mizoram and new foci of transmission in some districts of Himachal Pradesh and Arunachal Pradesh [6]. Climate suitability for malaria is projected to reduce in the states of Chhattisgarh, Gujarat, Madhya Pradesh and Bihar.

Degree of Exposure to Malaria

The results show that more population is exposed to malaria risk in the states of Chandigarh ($Ei = 0.9$), Delhi (0.85) and Bihar (0.61). When the indicators for exposure in these states were compared, it was found that in Delhi and Chandigarh population density was very high. On the other hand, Bihar had the highest proportion of children in the population (18.5%).

In the states of Sikkim, Telangana, Goa, Manipur, Himachal Pradesh and Arunachal Pradesh exposure is lowest (< 0.2). The indicators that contribute the most to low exposure in these states were found to be low population density (< 350 people per sq. km) and proportion of children (~ 10%) in the population.

Vulnerability of Communities to Malaria Risk

A large part of India, such as the states of Bihar ($Si = 0.79$), Uttar Pradesh (0.74), Jharkhand (0.62), Chhattisgarh (0.69), Haryana (0.64), Madhya Pradesh (0.61), Punjab (0.61), Meghalaya (0.70) and Arunachal Pradesh (0.65), are highly sensitive to malaria. These states were found to have high forest cover, NDVI and net irrigated area which contributed to high sensitivity. Kerala (0.21), Goa (0.18), Delhi (0.2) and Chandigarh (0.07) were found to be less sensitive to malaria risk with better housing conditions and low percentage of net irrigated area.

The results show that the states of Kerala ($ACi = 0.89$), Goa (0.89), Chandigarh (0.88), Puducherry (0.87), Delhi (0.86), Tamil Nadu (0.85), Punjab (0.65) and Himachal Pradesh (0.66) have the highest adaptive capacity. Examination of the role of each indicator revealed that Delhi and Chandigarh had the highest per capita income in the country (Rs. 1,00,050 and Rs. 74,720 per capita respectively), whereas in Arunachal Pradesh and Chhattisgarh a large percentage of the households had some form of health insurance (71.6% and 82.9%). The states of Bihar, Uttar Pradesh and Madhya Pradesh have the lowest overall adaptive capacity, corresponding with low level of literacy (41.5%, 50.8% & 51.1%) as well as low per capita income (Rs. 10,676, 19,085 & 17,085 per capita) in these states.

States, such as Bihar (*Vi* = 0.8), Uttar Pradesh (0.72), Meghalaya (0.61), and Jharkhand (0.66), which are highly sensitive with low adaptive capacity are the most vulnerable to malaria risk. In contrast, states that have high adaptive capacity and are less sensitive to malaria risk are the least vulnerable – Sikkim (0.25), Chandigarh (0.04), Himachal Pradesh (0.29), Goa (0.1), Delhi (0.1), Kerala (0.12). In Jammu & Kashmir and Rajasthan the sensitivity to malaria was relatively low (0.49 & 0.52 respectively), however, due to lack of adaptive capacity the overall vulnerability to malaria risk was high (0.6 and 0.56 respectively). In some states, such as Tripura (0.36), Puducherry (0.26) and Mizoram (0.35), both adaptive capacity and sensitivity were found to be high. Consequently, the vulnerability to malaria risk was found to be only moderate.

Composite Malaria Risk due to Climate Change

The results show that risk for malaria is highest in Bihar (*Ri* = 0.7), with almost all districts having a malaria risk index higher than 0.6, followed by the states of Meghalaya, Jharkhand, Assam and Odisha with more one district having very high malaria risk (> 0.6). Malaria risk is lowest in the states of Sikkim (0.01), Chandigarh (0.03), Himachal Pradesh (0.04), Goa (0.05), Delhi (0.08) and Kerala (0.09).

Climate change is projected to reduce malaria risk marginally in all the districts of Chhattisgarh, Andhra Pradesh and Haryana, as well as some districts of Gujarat, Rajasthan, Punjab, Jharkhand, Odisha, Madhya Pradesh, Uttar Pradesh and Uttarakhand by the 2030s. On the other hand, malaria risk is projected to increase significantly in the states of Meghalaya, Tripura and Manipur, and marginally in Rajasthan, Gujarat, Maharashtra, Himachal Pradesh, Telangana and West Bengal due to the effects of climate change by 2030s. In Odisha, malaria risk is projected to reduce in coastal districts and increase in districts away from the coast. Furthermore, in some districts such as Chamba in Himachal Pradesh and West Kameng in Arunachal Pradesh, that are presently malaria-free, climate change is projected to open new windows for transmission by 2030s. In the southern states such as Kerala and Tamil Nadu, malaria risk is projected to remain constant.

Discussion

Risk and vulnerability assessments have been used widely to determine the consequences of various stressors on the social and economic well-being of the communities exposed to the risk. Several studies have adopted this framework to evaluate the risk of climate change on farming communities [8, 25–27], coastal regions [28], disaster prone areas and health sector [29–31]. A few studies have also assessed the multi-factorial risk of malaria based on the risk and vulnerability assessment framework [32–34]. However, no study has adopted this approach to assess the social risk of malaria with respect to climate change in India.

The results of the study reveal that high malaria risk is found in the north-eastern and eastern parts of India as well as in some parts of the southern states of Maharashtra and Karnataka. High malaria risk in the north-eastern states can be attributed to high forest cover, poor housing materials, low per capita income, high burden of health centres and a large share of households that lack essential assets (such as telephone, computer, television etc.), which is coupled with a high climatic suitability for malaria. A risk and vulnerability assessment study undertaken in Rwanda also found that indicators such as poor housing wall materials, television ownership, poverty rate and clinic density had an excessive influence on the vulnerability index [32]. In the present study, malaria risk was found highest in the states of Bihar, Uttar Pradesh and Jharkhand, which was mostly a result of low adaptive capacity and high sensitivity to the climatic hazard of malaria in these states. The strong influence of adaptive capacity was also observed in the states of Rajasthan and Jammu and Kashmir where vulnerability is significantly high despite low sensitivity to malaria, as a result of low adaptive capacity. Previous research conducted in Tanzania similarly reported that regions of low adaptive capacity had high vulnerabilities even when susceptibility to malaria was low [34]. The southern states of Kerala and Tamil Nadu were found to have significantly low risk of malaria despite very high suitability. High adaptive capacity in this region acts as a buffer to high malaria hazard, thereby reducing the composite risk of malaria. This characteristic of the adaptive capacity dimension has been observed in a similar study undertaken in Rwanda, where high malaria suitability in the eastern lowlands was counter balanced by good socio-economic factors [35]. Climate change is projected to increase malaria risk by 2030s in the north-eastern states where adaptive capacity was low. On the other hand, in districts with high adaptive capacity, climate change had only a marginal or no impact on malaria risk.

Comparison of the malaria risk map with the map of malaria endemicity (Fig. 8) provides an insight into the implications of malaria risk. It can be observed that the study correctly identifies the north eastern and eastern regions of India to be at higher risk for malaria, albeit with a few minor deviations. Malaria risk has been found to be highest in the state of Bihar, even though it has an API less than 0.1. A Joint Monitoring Mission for vector borne diseases conducted by NVBDCP and the World Health Organization (WHO) in 2014 reported significant deficiency in malaria surveillance in Bihar due to a large number of vacancies in field and supervisory staff and an Annual Blood Examination Rate (ABER) less than 1 since 2003 (desired ABER = 10) [36]. This could be the reason for low API despite a very high malaria risk in Bihar. In Odisha, malaria risk appears to be understated in a few districts, when compared to the number of reported cases of malaria (Fig. 8). When observing the effect of individual factors, it is seen that low forest cover, low population density and high availability of essential assets could account for the lower risk in some districts of Odisha.

The results of the study are significantly dependent on the selection of suitable indicators due to which it is essential to discuss the relative importance of the indicators used. Most of the indicators used in the present study have also been used in similar risk and vulnerability assessments in the past [32–35, 37, 38]. One such study, conducted in East Africa, used elevation as a proxy indicator for immunity to malaria, and found that this resulted in high vulnerability in regions that are malaria free or have epidemic malaria [33]. However, this was not deemed as an important indicator in the present study. In another malaria risk and vulnerability assessment, undertaken in Tanzania, a notable similarity between the malaria risk and malaria hazard maps was observed [34]. This was attributed to the high weightage of the hazard variable used in the study (Entomological Inoculation Rate). However, such a similarity in the malaria hazard and malaria risk maps is not discernible in the present study even though the weight assigned to the hazard variable (Transmission window) was significantly high (0.25). For example, in the southern states of Kerala and Tamil Nadu very high malaria hazard does not lead to a significant malaria risk as it is offset by very high adaptive capacity. Therefore, adaptive capacity was found to bear greater influence on the composite malaria risk as opposed to the hazard dimension, which was more significant in previous research [34]. This may be attributed to the fact that most parts of Tanzania were found unsuitable for malaria, due to which malaria hazard served as a limiting factor for malaria risk. On the other hand, in India most of the regions are climatically suitable for malaria and adaptive capacity serves as a limiting factor for malaria risk. This has important implications for malaria elimination as it demonstrates that targeting these socio-economic factors can prove crucial in attaining as well as sustaining malaria elimination.

The study highlights the importance of considering social and economic indicators to present a holistic view of malaria risk. While the hazard and exposure dimensions of risk cannot be changed, vulnerability of the communities to the malaria risk are dependent on several demographic and socio-economic indicators that are controllable. This includes indicators of sensitivity and adaptive capacity such as material of roof and wall of houses, literacy rate, per capita income and Health Centre population burden. Elimination of malaria may pose a larger challenge in regions with lower adaptive capacity as compared to regions with higher adaptive capacity. Therefore, targeting these indicators will be crucial in order to eliminate malaria and prevent any possibility of resurgence

Conclusions

In this study a number of meaningful indicators for malaria were used to construct an index, based on the IPCC approach, to assess the impact of malaria on the social well-being of communities in India and the effects of climate change.

The results highlight the importance of adaptive capacity, which can act as a buffer to reduce malaria risk when climatic hazard and sensitivity is high. The converse is also observed i.e. moderate suitability for malaria could have adverse impacts on the community if the adaptive capacity is poor. Therefore, the social impact of malaria can be different to its epidemiology due to varying degrees of adaptive capacity. Furthermore, the risk and vulnerability assessment captured the high malaria risk in Bihar, which has been neglected due to poor surveillance. In regions where malaria risk is projected to be introduced by 2030s, targeting low performing indicators can help increase resilience and therefore, mitigate the impacts of climate change.

Abbreviations

ABER – Annual Blood Examination Rate

API – Annual Parasite Incidence

CORDEX – Coordinated Regional Downscaling Experiment

HH – Households

IPCC – Intergovernmental Panel on Climate Change

KMO – Kaiser-Meyer-Olken

NDVI – Normalized Difference Vegetation Index

OECD – Organization for Economic Co-operation and Development

PCA – Principle Component Analysis

TW – Transmission Window

VIF – Variance Inflation Factor

Declarations

Ethics Approval and Consent to Participate

Not Applicable.

Consent for Publication

Not Applicable.

Availability of data and materials

All datasets used in the study were obtained from the public domain. The vegetation index and soil moisture data that support the findings of the study are available in the NOAA Climate Data Record (https://doi.org/10.7289/V5ZG6QH9) [14] and the ESA Climate Change Initiative (https://doi.org/10.1016/j.rse.2017.07.001) [15] repositories respectively. Data on transmission windows for malaria was obtained from previous research [6] conducted in the same institute, while the malaria API data was collected from respective State Programme Officers and District Malaria Officers, and can be made available on reasonable request. The data for all other variables used in the study are available either in the 2011 Census of India (https://censusindia.gov.in/digitallibrary/TablesSeries2001.aspx), or in governmental and institutional reports that do not have a doi, the details of which are mentioned in Table 1.

Competing Interests

The authors declare that there are no competing interests.

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Authors' contribution

SSAH analysed data, performed statistical tests, developed relevant indicators and drafted the manuscript. PS contributed to data acquisition and drafting of the manuscript. RCD is the corresponding author and contributed to the concept and design of study, interpretation of results and revised manuscript for important intellectual content.

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References

1. World Health Organization. World malaria report. Geneva; 2018. http://www.who.int/malaria/media/world-malaria-report-2017/en/#Global and regional malaria trends in numbers. Accessed 25 Feb 2019.
2. Bhattacharya S, Sharma C, Dhiman RC, Mitra AP. Climate Change and Malaria in India. Curr Sci. 2006;90:369–75.
3. Dhiman RC, Pahwa S, Dash AP. Climate change and malaria in India: Interplay between temperatures and mosquitoes. Reg Heal Forum. 2008;12:27–31.
4. Garg A, Dhiman RC, Bhattacharya S, Shukla PR. Development, malaria and adaptation to climate change: A case study from India. Environ Manage. 2009;43:779–89.
5. Khormi HM, Kumar L. Future malaria spatial pattern based on the potential global warming impact in South and Southeast Asia. Geospat Health. 2016;11:416.
6. Sarkar S, Gangare V, Singh P, Dhiman RC. Shift in Potential Malaria Transmission Areas in India, Using the Fuzzy-Based Climate Suitability Malaria Transmission (FCSMT) Model under Changing Climatic Conditions. Int J Environ Res Public Health. 2019;16:3474.
7. Dhiman RC, Chavan L, Pant M, Pahwa S. National and regional impacts of climate change on malaria by 2030. Curr Sci. 2011;101:372–83.
8. O'Brien K, Leichenko R, Kelkar U, Venema H, Aandahl G, Tompkins H, et al. Mapping vulnerability to multiple stressors: Climate change and globalization in India. Glob Environ Chang. 2004;14:303–13.
9. Defiesta G, Rapera CL. Measuring Adaptive Capacity of Farmers to Climate Change and Variability: Application of a Composite Index to an Agricultural Community in the Philippines. J Environ Sci Manag. 2014;17:48–62.

10. Van Lieshout M, Kovats RS, Livermore MTJ, Martens P. Climate change and malaria: Analysis of the SRES climate and socio-economic scenarios. Glob Environ Chang. 2004;14:87–99.
11. Field CB, Barros VR, Dokken DJ, Mach KJ, Mastrandrea MD, Bilir TE, et al. Climate Change 2014 Impacts, Adaptation, and Vulnerability: Contribution of Working Group II to the Fifth Assessment Report of the IPCC. Cambridge Univ. Press. New York; 2014.
12. Füssel HM, Klein RJT. Climate change vulnerability assessments: An evolution of conceptual thinking. Clim. Change. 2006;301–29.
13. Wiréhn L, Danielsson Å, Neset T-SS. Assessment of composite index methods for agricultural vulnerability to climate change. J Environ Manage. 2015;156:70–80.
14. The Registrar General & Census Commissioner of India. Census India Library. Ministry of Home Affairs, Government of India. 2011. https://www.censusindia.gov.in/DigitalLibrary/TablesSeries2001.aspx. Accessed 26 Jan 2019.
15. International Institute for Population Sciences. National Family Health Survey - State Reports. Ministry of Health and Family Welfare, Government of India; 2016. http://rchiips.org/nfhs/NFHS-4Report.shtml. Accessed 2 Feb 2019
16. Department of Animal Husbandry Dairying and Fisheries. 19th Livestock Census - 2012 All India Report. New Delhi; 2012. http://dahd.nic.in/sites/default/filess/Livestock pdf. Accessed 12 Jan 2019.
17. Forest Survey of India. State of Forest Report - Forest and Tree Resources in States and Union Territories. Ministry of Environment Forests and Climate Change 2017. https://fsi.nic.in/forest-report-2017. Accessed 18 Jan 2019
18. Vermote E. NOAA CDR Program. (2019): NOAA Climate Data Record (CDR) of AVHRR Normalized Difference Vegetation Index (NDVI), Version 5. NOAA National Centers for Environmental information; 2019.
19. ICAR-Central Research Institute for Dryland Agriculture. District Agricultural Contingency Plans. Ministry of Agriculture and Farmers' Welfare, Government of India. http://www.crida.in/. Accessed 10 Mar 2019
20. Dorigo W, Wagner W, Albergel C, Albrecht F, Balsamo G, Brocca L, et al. ESA CCI Soil Moisture for improved Earth system understanding: State-of-the art and future directions. Remote Sens Environ. Elsevier Inc. 2017;203:185–215.
21. Hanagodimath S V. Regional Disparity in Per Capita Income in India: A Study on Inter-state and Intra-state Analysis. Dharwad; 2019.
22. National Rural Health Mission. Rural Health Statistics in India. New Delhi; 2012.
23. Bates I, Fenton C, Gruber J, Lalloo D, Lara AM, Squire SB, et al. Vulnerability to malaria, tuberculosis, and HIV/AIDS infection and disease. Part II: Determinants operating at environmental and institutional level. Lancet Infect Dis. 2004;4:368–75.
24. OECD. Handbook on Constructing Composite Indicators: Methodology and User Guide. Organization for economic co-operation and development; 2008.

25. Deressa T, Hassan RM, Ringler C. Measuring Ethiopian farmers' vulnerability to climate change across regional states. International Food Policy Research Institute; 2008.
26. Cochrane K, Young CD, Soto D, Bahri T. Climate change implications for fisheries and aquaculture: Overview of current scientific knowledge. Food and Agriculture Organization: Fisheries and Aquaculture. Rome; 2009.
27. Gbetibouo GA, Ringler C, Hassan R. Vulnerability of the South African farming sector to climate change and variability: An indicator approach. Nat Resour Forum. 2010;34:175–87.
28. Kumar KSK, Tholkappian S. Relative Vulnerability of Indian Coastal Districts to Sea-Level Rise and Climate Extremes. Int Rev Environ Strateg. 2006;6:3–22.
29. Malik SM, Awan H, Khan N. Mapping vulnerability to climate change and its repercussions on human health in Pakistan. Global Health. 2012;8:31
30. Yusuf AA, Francisco H. Climate Change Vulnerability Mapping for Southeast Asia. Economy and Environment Program for Southeast Asia. Singapore. 2009.
31. Heltber, R., Bonch-Osmolovskiy M. Mapping Vulnerability to Climate Change. The World Bank: Sustainable Development Network. 2011.
32. Bizimana JP, Kienberger S, Hagenlocher M, Twarabamenye E. Modelling homogeneous regions of social vulnerability to malaria in Rwanda. Geospat Health. 2016;11:129-146
33. Kienberger S, Hagenlocher M. Spatial-explicit modeling of social vulnerability to malaria in East Africa. Int J Health Geogr. 2014;13:29.
34. Hagenlocher M, Castro MC. Mapping malaria risk and vulnerability in the United Republic of Tanzania: A spatial explicit model. Popul Health Metr. 2015;13:1–14.
35. Bizimana J-P, Twarabamenye E, Kienberger S. Assessing the social vulnerability to malaria in Rwanda. Malar J. 2015;14:2.
36. Directorate General of Health Services. Joint Monitoring Mission 2014. New Delhi: World Health Organization/ National Vector Borne Disease Control Programme; 2014. https://apps.who.int/iris/handle/10665/208892. Accessed 21 Aug 2019.
37. Onyango EA, Sahin O, Awiti A, Chu C, Mackey B. An integrated risk and vulnerability assessment framework for climate change and malaria transmission in East Africa. Malar J. 2016;15:551.
38. Wandiga SO, Opondo M, Olago D, Githeko A, Githui F, Marshall M, et al. Vulnerability to epidemic malaria in the highlands of Lake Victoria basin : the role of climate change / variability , hydrology and socio-economic factors. Clim Chang. 2010;99:473–97.

Figures

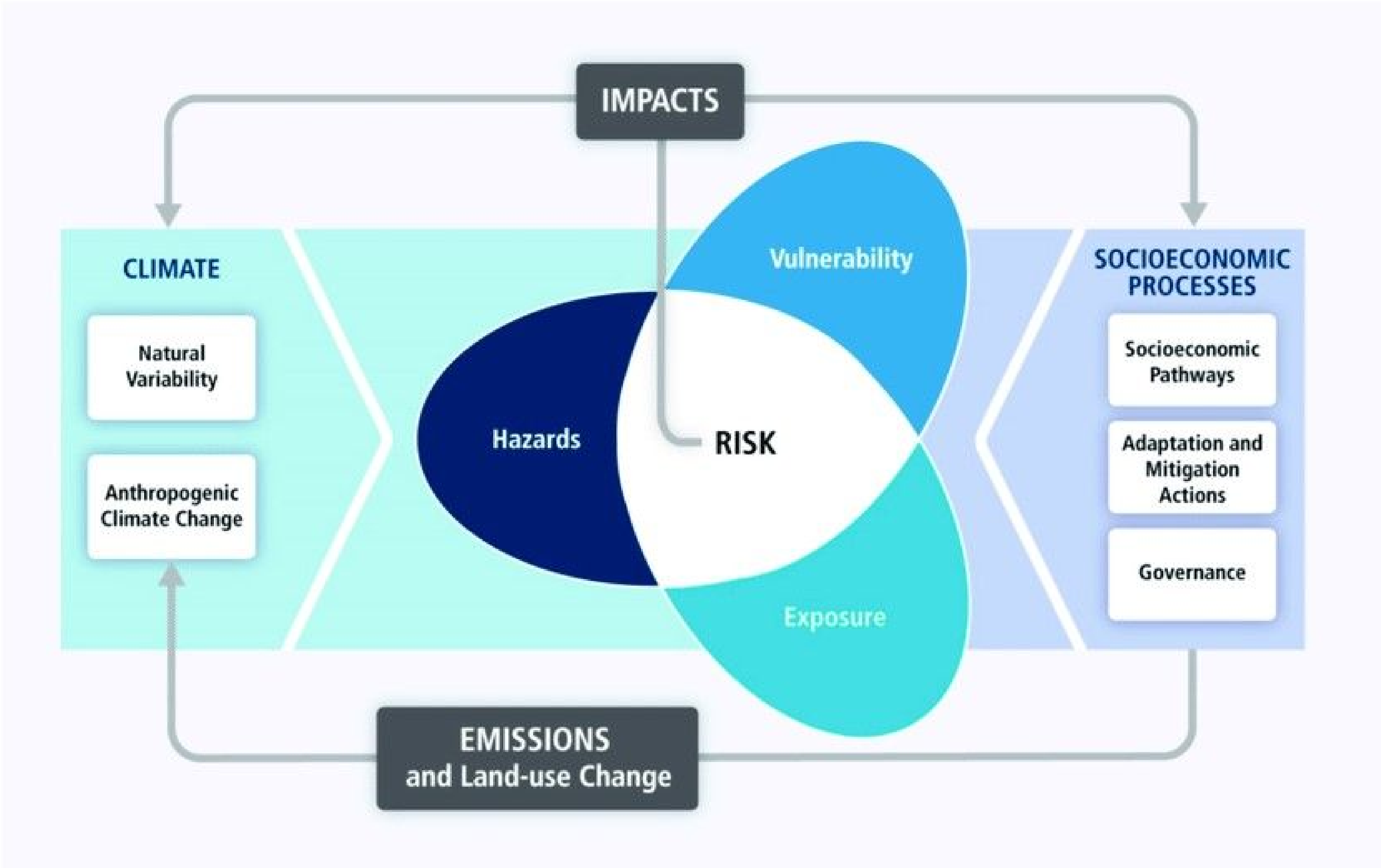

Figure 1

IPCC Risk assessment framework [11]

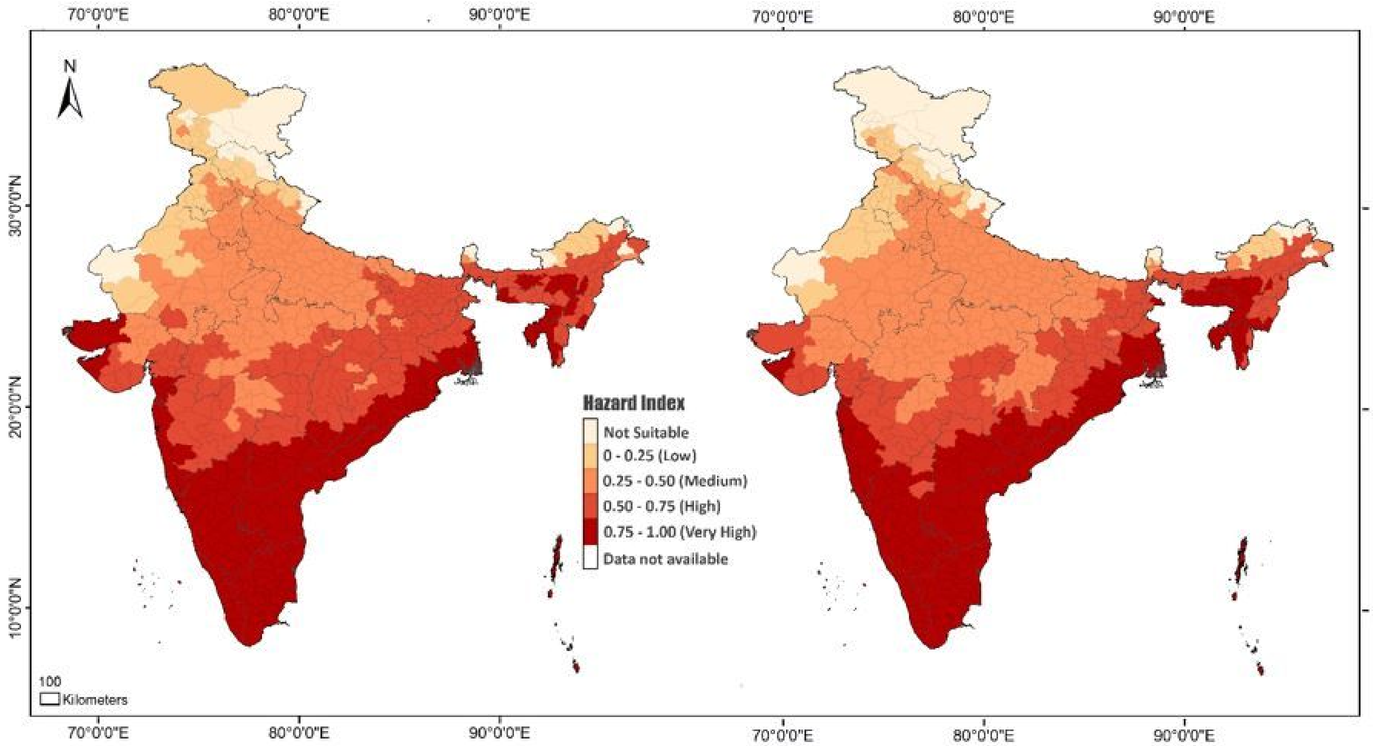

Figure 2

District-wise Hazard due to climate change based on Transmission Windows for malaria[6] Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

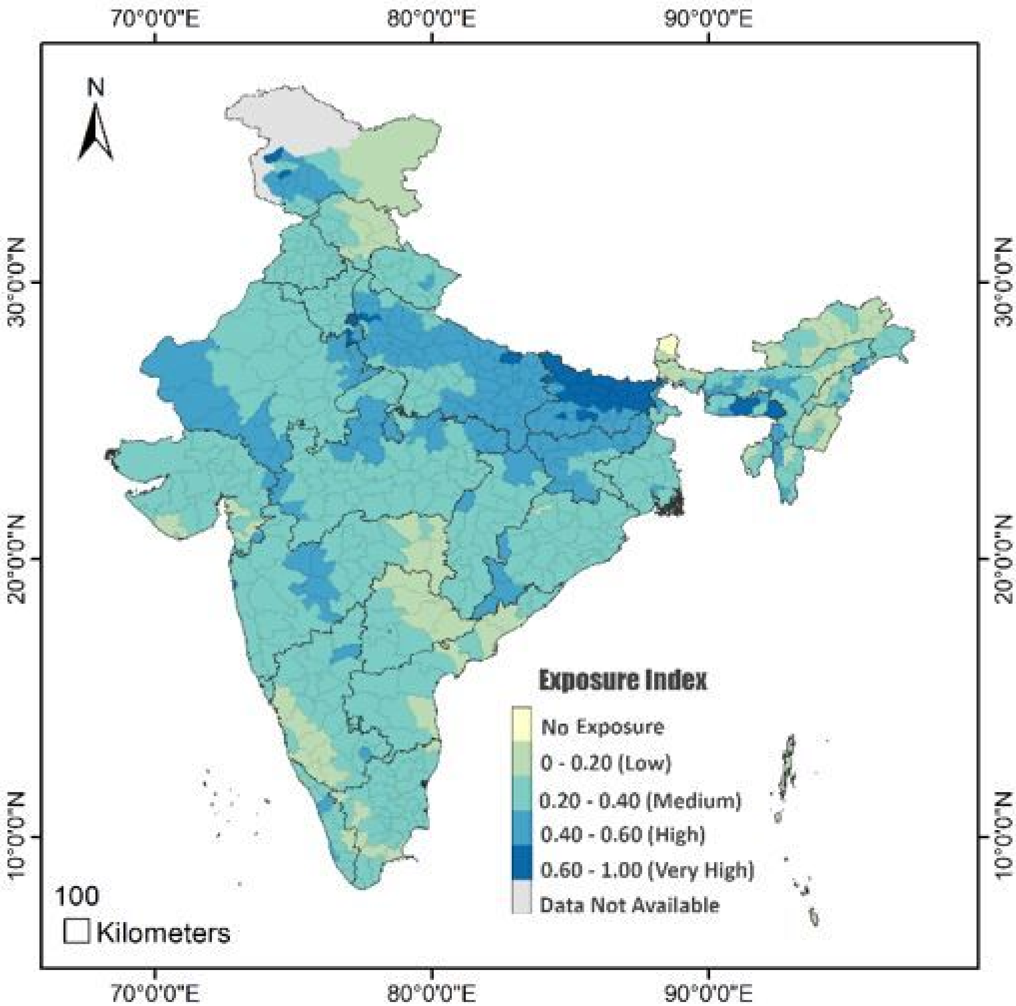

Figure 3

Degree of exposure to indicators of demography vis-à-vis malaria Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

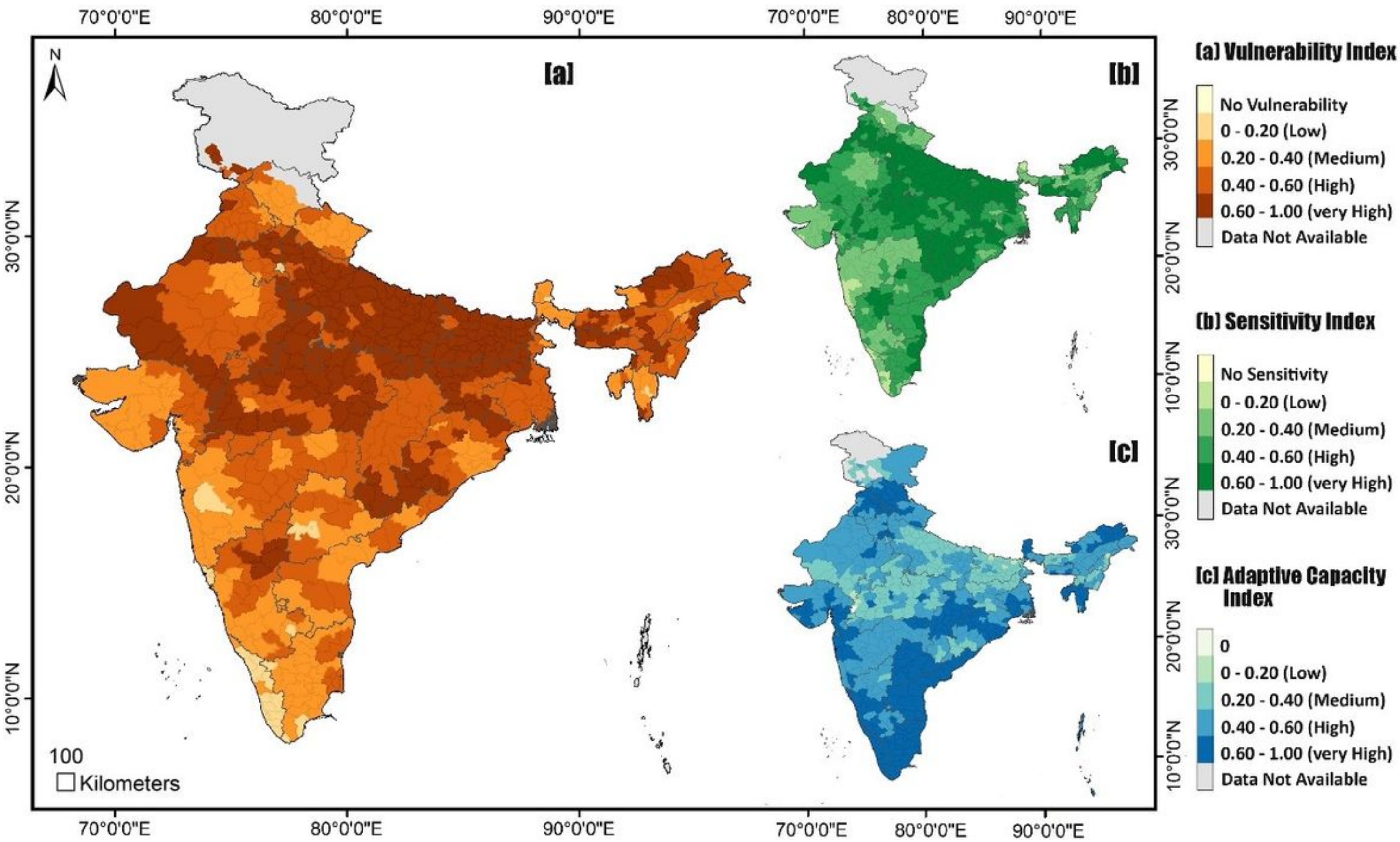

Figure 4

District wise (a) sensitivity to climate change impacts on malaria (b) adaptive capacity of communities and (c) vulnerability to malaria Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

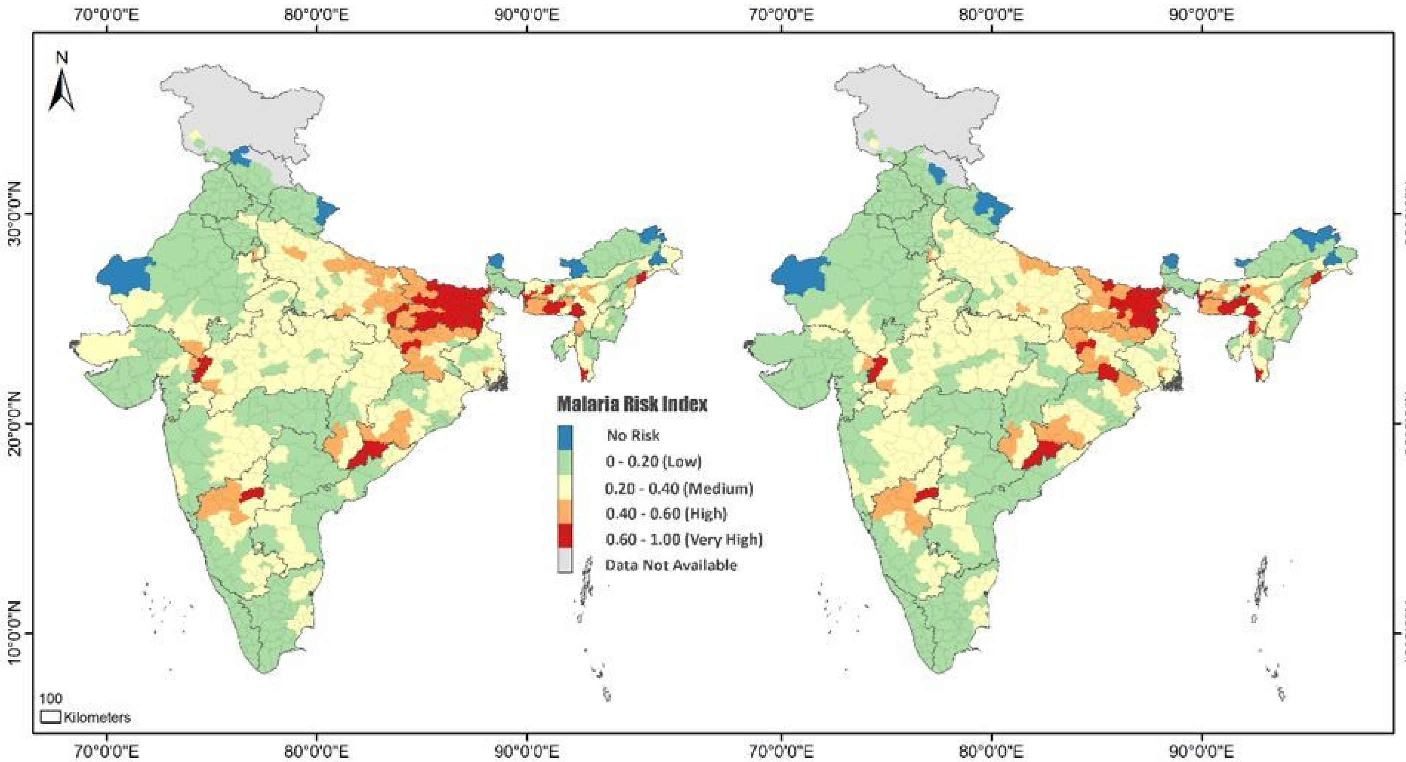

Figure 5

(a) Present risk of malaria and (b) impact of climate change on malaria risk by 2030s at present vulnerabilities Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

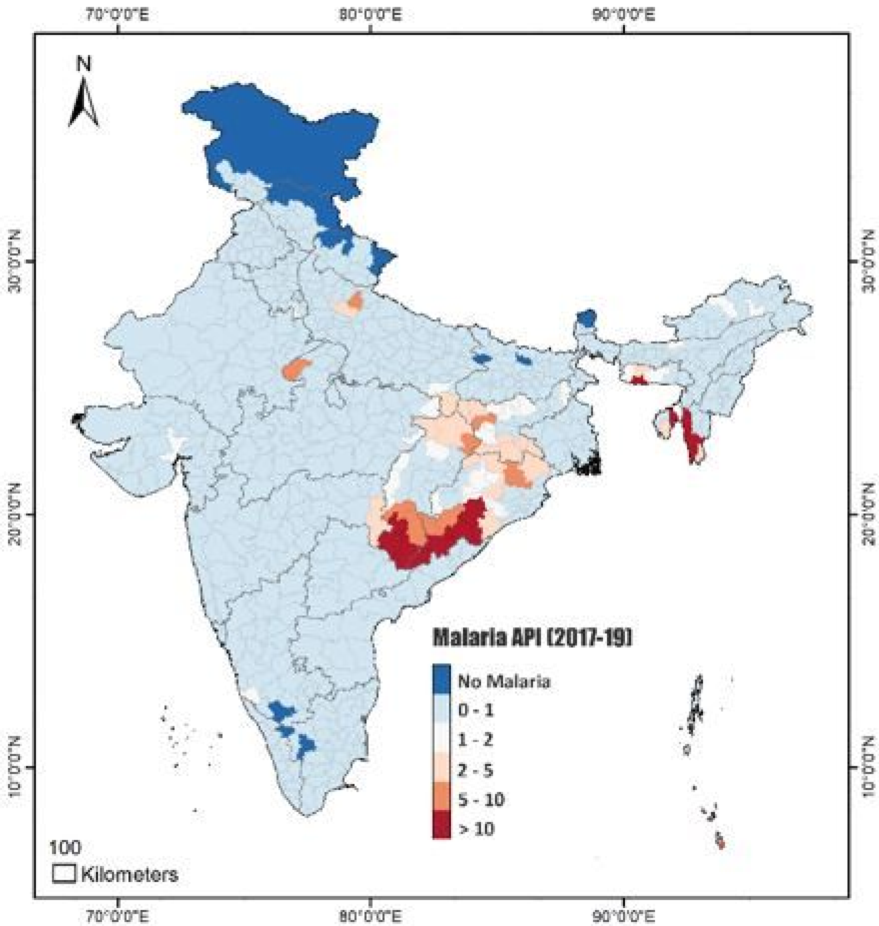

Figure 6

District wise malaria endemicity in India Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.