Ecological covariates based predictive model of malaria risk in the state of Chhattisgarh, India

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Abstract Malaria being an endemic disease in the state of Chhattisgarh and ecologically dependent mosquito-borne disease, the study is intended to identify the ecological covariates of malaria risk in districts of the state and to build a suitable predictive model based on those predictors which could assist developing a weather based early warning system. This secondary data based analysis used one month lagged district level malaria positive cases as response variable and ecological covariates as independent variables which were tested with fixed effect panelled negative binomial regression models. Interactions among the covariates were explored using two way factorial interaction in the model. Although malaria risk in the state possesses perennial characteristics, higher parasitic incidence was observed during the rainy and winter seasons. The univariate analysis indicated that the malaria incidence risk was statistically significant associated with rainfall, maximum humidity, minimum temperature, wind speed, and forest cover ($p < 0.05$). The efficient predictive model include the forest cover [IRR-1.033 (1.024–1.042)], maximum humidity [IRR-1.016 (1.013–1.018)], and two-way factorial interactions between district specific averaged monthly minimum temperature and monthly minimum temperature, monthly minimum temperature was

statistically significant [IRR-1.44 (1.231–1.695)] whereas the interaction term has a protective effect [IRR-0.982 (0.974–0.990)] against malaria infections. Forest cover, maximum humidity, minimum temperature and wind speed emerged as potential covariates to be used in predictive models for modelling the malaria risk in the state which could be efficiently used for early warning systems in the state.

Keywords Malaria · India · Ecological predictors · Forest · Humidity · Temperature · Wind speed · Negative binomial model

Introduction

Malaria is a vector (mosquito)-borne disease of human and animals caused by a parasitic protozoan, *Plasmodium*. In spite of 25% decline in global malaria incidence after year 2000, the world malaria report—2013 reported that 97 countries still have on-going transmission of malaria where 3.4 billion people were at risk and 1.2 billion people were at high transmission risk (more than one malaria case per 1000 population) during year 2012. The report estimated 207 million malaria cases, 0.627 million malaria deaths, and 0.482 million deaths of children under age of 5 years for year 2012 (WHO 2013). Along with the negative implications on global economy, it affects family income severely as it reduces family and individual income and thus push down the family into a financial malarial trap (Berthélemy et al. 2013). A study in Maldives estimated 19.82 dollars as a treatment cost for malaria for an individual from a low income household (Ettling et al. 1994).

In India as per “World Malaria Report-2013”, 0.272 billion people were under high transmission risk of malaria

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whereas 0.892 billion were under low transmission risk (0–1 cases per 1000 population) during the year 2012 (WHO 2013). The national Annual Parasitic Incidence (API) of malaria was 0.88 cases per 1000 population for the year 2012, whereas it was earlier 2.12 during the year 2000, this indicate a sharp decline in API throughout the years (NVBDCP 2014). In India, during the year 2007, estimated DALY for malaria was 1.86 million years loss and maximum DALY loss i.e. 53.25% was seen among the productive age group (15–44 years) (Kumar et al. 2007). The same study estimated loss of 8.96 person days to patient and 3.84 person day for their family members attributed to malaria infection. The state of Chhattisgarh is among the states which reported a higher number of malaria cases in India with an API of 4.7 which caused 89 deaths during year 2011–2012. The state reported 79.3% of the malaria positive cases were due to infection of *Plasmodium falciparum*. During the same year, 13 districts of the state were under high transmission risk of malaria whereas remaining 5 districts were under low transmission risk (NRHM 2013). Although integrated disease surveillance system is in implementation in India and the state, at present the state does not have a much effective disease surveillance system which would help in sending early warning for malaria to the districts. Given that malaria is a mosquito-borne disease which is largely dependent on the climate of a region, developing a weather-based early warning system would help the state and the districts in identifying the high risk areas for forthcoming probable epidemics. This could be achieved by developing a predictive model for malaria risk based on the weather forecast in space and time and thence it would assist planning and policy makers for mobilizing scarce resources for efficient control of malaria. The state is yet to have an evidence for a comprehensive predictive model and ecological covariates for the risk of malaria, which would have helped in developing early warning systems. In lieu of the above, this study intended to explore the distribution of malaria, its ecological correlates and the predictive model based on the district level ecological correlates.

Materials and methods

Study area

The state of Chhattisgarh, is the 10th largest state of India with a population share of 2.11% (25.6 million), spread over 135,192 km² (4.1% of national geographical areas) inhabits more than 40% of the scheduled populations (Office of The Registrar General & Census Commissioner, India, New Delhi 2011) (scheduled population are socio-economically disadvantaged social class which constitute

scheduled caste and scheduled tribes). Being a state in the proximity to the tropic of cancer, climate of the state is hot and humid. The state is mainly divided into three agro-climatic zones, which are Baster plateau (four southernmost districts), Chhattisgarh plain (central part of the state) and Northern Hills (three northernmost districts).

Data-set

District and month-wise reported confirmed malaria positive cases (Rapid Diagnostic Kits and/or slide testing) of the all 18 districts for 27 months (October 2011 to December 2013) were gathered from Department of health and family welfare, Government of Chhattisgarh, Raipur. Missing and underreported data were equally interpolated with mean of previous and following months (Manh et al. 2011). The monthly population of the districts for the 27 months were estimated using the annual population and decadal growth rate of each district as per census of India, 2011 (Office of The Registrar General & Census Commissioner, India, New Delhi 2011; Manh et al. 2011). The study used an ensemble of multi-model data forecasted by the Indian Meteorology Department (IMD) (Agricultural Meteorological Division, Indian Meteorological Department 2014). Forecasted meteorological data were used as the study expects to translate this model into forecasting model for predicting the malarial risks well in advance in the state to prevent its occurrence. IMD reports daily prediction of all meteorological variables (rainfall, maximum temperature, minimum temperature, maximum humidity, minimum humidity, wind speed, and cloud cover) for the five days in a row. There were some instances where IMD forecasted twice on subsequent days leading to duplication of forecasted information. In those conditions, the latest forecasted information was preferred. The daily forecasts were averaged to get mean monthly meteorological information. Missing information was equally interpolated based on the average of the previous five days' forecasts and the average of the subsequent 5 days' forecasts. IMD reports rainfall in millimetres, humidity in per cent, temperature in degrees Celsius, wind speed in kilometres per hour and cloud cover on the okta scale. Overall forest coverage of the districts for the year 2011 were gathered from report of Forest Survey of India (Forest Survey of India 2011).

Statistical methods

Data was summarized for the three agro-climatic zones and three seasons [summer (March to May), winter (November to January) and rainy (July to September)], using pivot table application of MS Excel 2010. Multi-collinearity among the explanatory variables was explored using

Pearson's correlation coefficients and thus accordingly the list of the explanatory variables was reduced and finally explanatory variables such as maximum humidity, minimum temperature, wind speed, cloud cover and Forest cover was used as possible covariates. Rainfall, being an important variable but collinear with maximum humidity, it was also tested separately after replacing maximum humidity in the previous set of explanatory variables. The response variable, district specific monthly total positive cases and corresponding monthly population were lagged by one month which was tested with panelled negative binomial regression model with fixed effect where districts were panelled and months were set as time variable for further analysis. The study considered one month time lag to adjust the duration between exposure of ecological covariates to the population and malarial incidence. The Negative Binomial regression model was used after confirmation of over dispersion of the outcome variable which was tested using Likelihood Ratio test of alpha ($p < 0.005$). Potential climatic variables were selected using a forward stepwise method where models were compared based on Akaike Information Criterion (AIC) value and a smaller AIC value was considered to be an indicator of an improved model. Two way factorial interaction with the district (study subject) and meteorological variables were also explored to review behaviour of the districts in the model. Thus, district specific mean of monthly maximum humidity, minimum temperature, rainfall and wind speed for the study duration (27 months) were calculated and tested with respective ecological variables using two-way factorial interactions with monthly maximum humidity, minimum temperature, rainfall and wind speed within the model. Coefficients are presented in the form of risk ratio and p value less than 5% was considered to be statistically significant. For regression analysis STATA 13.1 version was used.

Result

Malaria cases were reported throughout the months in all of the 18 districts indicating its perennial characteristics in the state. Minimum parasitic incidence of the disease in the state [1.19 cases per 1000 population for the study duration (27 months)] was observed during the summer season (March to May) whereas after the month of June, the incidence starts upswing and remains higher from the months of September to January, the monsoon and post monsoon season. The districts of the southern part of the state (Baster Plateau) have the highest annual parasitic incidence (20.75 cases per 1000 population for year 2013 and 14.79 cases per 1000 population for year 2012), and also have higher forest coverage and higher humidity, but

recorded lower temperature than the central part of the state. Monthly average rainfall was the highest in the Baster plateau. The highest parasitic incidence (19.66 cases per 1000 population for the study duration) was recorded in the winter season (November to January) of Baster plateau whereas least (0.53 cases per 1000 population) in summer of Chhattisgarh plain.

Under epidemiological analysis, univariate fixed effect panelled negative binomial regression model revealed a statistically significant association with rainfall [Incidence Rate Ratio (IRR)-1.026 (1.019–1.033)], maximum humidity [IRR-1.019 (1.016–1.022)], minimum temperature [IRR-1.011 (1.001–1.022)], wind speed [IRR-1.130 (1.089–1.172)], and forest cover [IRR-1.046 (1.038–1.055)] (Table 1). The final multiple regression model identified statistical significance of forest cover [IRR-1.033 (1.024–1.042)], maximum humidity [IRR-1.016 (1.013–1.018)], wind speed [IRR-1.086 (1.044–1.130)], two way factorial interaction between district specific averaged monthly minimum temperature and monthly minimum temperature with malaria incidence. In this model monthly minimum temperature was statistically significantly associated with the incidence risk of malaria [IRR-1.44 (1.231–1.695)] whereas the interaction with district specific minimum temperature had a statistically significant protective effect [IRR-0.982 (0.974–0.990)] with malaria risk. This interaction indicates that minimum temperature initially increases the malaria risk but in the districts where mean minimum temperature was higher, the malaria risk started decreasing after a certain rise in the malaria risk with increased temperature (Tables 2, 3). The model produced a smaller AIC value (5841.242) with comparison to another model where maximum humidity was replaced with rainfall {Rainfall [IRR-1.022 (1.014–1.029)], Forest Cover [IRR-1.047 (1.038–1.055)] and Wind Speed [IRR-1.066 (1.025–1.109)]} using the same type of model, fixed effect panelled multiple negative binomial regression (AIC = 6020.395) (Table 4). Thus, the previous model with smaller AIC value would be preferred as a model for malaria risk in the state.

Discussion

The finding of higher malaria risk in the southern and northern parts of the state is in agreement with previous studies in the state and adjoining districts of neighbouring states which documented higher prevalence of malaria in the region (Singh et al. 1996, 2003; Sharma et al. 2006; Nanda et al. 2012a). *An. fluviatilis* and *An. culicifacies* are often documented as main vectors of importance for malaria transmission in Chhattisgarh and adjoining states. Their coexistence in the state and the districts of adjoining states is often described in several publications (Nanda et al. 2000, 2012; Das et al. 1990; Kulkarni 1990; Subbarao

Table 1 Ecological covariates under univariate analysis

	Coefficients	IRR	<i>p</i> value	Lower 95% CI	Upper 95% CI	AIC
Maximum humidity	0.019	1.019	<0.001	1.016	1.022	6040.207
Rainfall	0.025	1.026	<0.001	1.019	1.033	6152.397
Minimum temperature	0.011	1.011	0.035	1.001	1.022	6192.230
Wind speed	0.122	1.130	<0.001	1.089	1.172	6157.178
Cloud cover	0.110	1.117	<0.001	1.094	1.140	6104.285
Forest cover	0.045	1.046	<0.001	1.038	1.055	6078.661

Table 2 Ecological covariates under final predictive model

	Coefficients	IRR	<i>p</i> value	Lower 95% CI	Upper 95% CI	AIC
Maximum humidity	0.016	1.016	<0.001	1.013	1.018	5841.242
Wind speed	0.082	1.086	<0.001	1.044	1.130	
Forest cover	0.033	1.033	<0.001	1.024	1.042	
Mean minimum temperature	−0.172	0.842	0.129	0.674	1.052	
Minimum temperature	0.368	1.444	<0.001	1.231	1.695	
Mean minimum temperature # minimum temperature	−0.018	0.982	<0.001	0.974	0.990	

Table 3 Model where maximum humidity is used as explanatory variables with other variables

Covariates	Model 1	Model 2	model 3	Model4
Maximum humidity	1.018	1.017	1.017	1.016
Forest cover	1.045	1.044	1.045	1.033
Wind speed		1.093	1.062	1.086
Minimum temperature			1.013	1.444
District specific averaged minimum temperature				0.842 [#]
Interaction between minimum temperature and district specific minimum temperature				0.982
AIC-value	5932.619	5905.246	5903.069	5841.242

[#] Statistically not significant at 95% CI

Table 4 Model where rainfall is used as explanatory variable with other variables

Covariates	Model 1	Model 2
Rain fall	1.027	1.022
Forest cover	1.048	1.047
Wind speed		1.067
AIC-value	6028.391	6020.395

[#] Statistically not significant at 95% CI

1988). However, forest areas of the state and districts of adjoining states have a predominant density of *An. fluviatilis* (Nanda et al. 2000, 2012; Singh et al. 1996; Kulkarani 1990) which is highly anthropophagic (Nanda et al. 2000; Parida et al. 2006) whereas *An. culicifacies* are more

in riverine, non-forested area which is more zoophilic however both species were infected with *Plasmodium* (Nanda et al. 2000; Kumari et al. 2009), in the region although *An. fluviatilis* has a higher rate of sporozoites (Pacholi 1993; Nanda et al. 2012b). Resistance towards insecticides among *An. culicifacies* has been documented in the region (Singh et al. 2003).

The perennial presence of malaria risk in Chhattisgarh is substantiated by many studies in the adjoining districts of the neighbouring states, Odisha and other parts of the country (Pacholi 1993; Sharma et al. 2006; Dev et al. 2010) which could be due to the presence of perennial slow moving streams, rivers, rivulets, water reservoirs, traditional ponds and other water sources in the forested state (Forest Department, Government of Chhattisgarh 2013)

which is perhaps a perennial breeding site of mosquitoes, especially for *An. fluviatilis* in the state (Sinka et al. 2011). Higher risk of malaria during the rainy and the winter seasons than in the summer season corroborates with a study in a north eastern state of India which explained higher presence of *An. culicifacies* during monsoon season whereas there is greater existence of *An. fluviatilis* during the post monsoon (Das et al. 2011). A higher density of anthropophagic *An. fluviatilis* with a higher rate of plasmodia was observed in the winter season of the southern forested part of the state (Nanda et al. 2012). Higher risk of malaria in the forest area in this study could be primarily due to *An. fluviatilis* (Sharma et al. 2006; Nanda et al. 2000).

Humidity appeared as one of the efficient predictor important covariates for malaria incidence in the districts of the state which is found to be consistent with studies in other parts of India (Nath and Mwchahary 2013) and China (Huang et al. 2011; Bi et al. 2013) whereas no such effect of humidity on malaria risk was reported in highlands of Bangladesh (Haque et al. 2010). In fact, generally higher humidity increases survival of *Anopheles* mosquito; maximum longevity of *Anopheles* mosquito was observed at 15 °C and 100% humidity (Bayoh 2001).

Minimum temperature is another positively associated predictor of the malaria risk in the state which is also evident in the publications (Bi et al. 2003; Li et al. 2013) whereas the neighbouring country of India, Bangladesh, reported no significant relationship between temperature and malaria in highland areas (Haque et al. 2010). The present study also describes the interaction between minimum temperature and specific district overall mean minimum temperature for the whole duration of study. As a result of interaction initially along with an increase in minimum temperature, the malaria risk increases but; later the interaction plays an important role when it starts to decrease malaria incidence with an increase in minimum temperature, whenever district has a higher specific overall mean temperature. Interaction is comparatively not much explored in the literature. In India, negative association of temperature and non-forest malaria risk is documented in the north eastern part of India which might be due to higher average temperature in non-forest areas (Nath and Mwchahary 2013) which uphold the findings of this study. Even though higher temperature shorten sporogonic cycle (Manguin et al. 2008; Paaijmans et al. 2012), reduction of vectorial capacity of the mosquito is seen at higher temperature (Paaijmans et al. 2012) which would be due to reduced longevity of both larvae and adults in extreme temperature (Bayoh 2001), thus finally, higher temperature reduces malaria risk in the districts with overall higher mean temperature.

This study provides evidence of increasing malarial incidence with an increase in wind speed in the state of Chhattisgarh. Few studies support the effect of wind speed on increase in malaria incidence in the African continent (Ayala et al. 2009; Omonijo and Matzarakis 2011) whereas in contrast to that, wind speed is cited to have either no effect on malarial risk (McReynolds and Hellenthal 2003) or to reduce malaria risk due to poor host seeking behaviour during high wind speeds which reduces ovi-position and reduced mosquito density (Service 1980; Cummins et al. 2012). However, as the state of Chhattisgarh lies in low or lower medium wind speed zone, perhaps increased wind speed favours host seeking flights of short flight ranged *An. fluviatilis* (0.8 km) (Pacholi 1993). This finding indicates an area of further study to explore the effect of wind speed on malaria and mosquito density in this area.

This study describes that a surge in rainfall is related to an increase in malaria incidence in the districts when rainfall was used as lone predictor in the model or with two other correlates, forest and wind speed. Findings on positive association of malarial occurrence and rainfall is supported by several publications in Asian countries (Bi et al. 2003; Devi and Jauhari 2006; Briet et al. 2008; Dev et al. 2010; Gao et al. 2012) however in contrast to that, other Asian and specifically Indian studies suggested there was no such relation seen in their studies (Nandi et al. 1996; Singh and Sharma 2002; Haque et al. 2010).

Humidity and temperature are widely used as covariates in many publications to develop models for malarial occurrence (Yé et al. 2007; Huang et al. 2011; Li et al. 2013; Yamana and Eltahir 2013), whereas many other studies found out that rainfall and temperature as are the most important covariates (Bi et al. 2003; Parham and Michael 2010). Rainfall has been shown to be a good predictor for malaria occurrence in Sri Lanka (Briet et al. 2008; Parham and Michael 2010) and based on this, a short term early warning system for malaria was developed in the country (Briet et al. 2008) whereas rainfall and temperature were used as correlates for predicting malaria risk in highland areas of Ethiopia (Abeku 2004). The present study revealed that the model with factors such as maximum humidity, minimum temperature, wind-speed and forest coverage in the state appeared to be better than a model based on rainfall, forest cover and wind speed in the state. The indoor resting behaviour of *An. fluviatilis* was not correlated with rainfall in the northern Part of West Bengal, India (Malakar et al. 1995) which also indicates a possible limited role of rainfall in the malaria risk in these geographical locations as *An. fluviatilis* is a predominate vector in the state of Chhattisgarh and adjoining forested parts of the state of Odisha. The presence of the interactions is suggestive of separate models with certain sets of geographic/climatic characteristics. Variation in type and

density of mosquitoes also demands area specific model building in different states of the country.

Conclusion

In conclusion, malaria is a perennial vector-borne disease in the state but the risk appears to higher in the rainy and winter seasons (August to January) and in the northern and southern part of the state. The intensity of malaria risk in the area largely depends on ecological variables such as forest cover, rainfall, humidity, temperature and wind speed. However, maximum humidity, minimum temperature, wind speed and forest coverage in the districts are the best set of predictors, significantly more important than rainfall, forest and wind speed in the state. The former set of correlates could be used for the prediction of malaria risk in the state. In the dataset, districts were used as clustering units, but were found to be confounders themselves. Thus, area-specific models would more precisely explain the malaria risk.

Compliance with ethical standards

Conflict of interest We declare that we have no any conflict of interest.

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