Exploring the Usefulness of Meteorological Data for Predicting Malaria Cases in Visakhapatnam, Andhra Pradesh

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(Manuscript received 15 February 2019, in final form 2 August 2019)

ABSTRACT

Malaria and dengue fever are among the most important vectorborne diseases in the tropics and subtropics. Average weekly meteorological parameters—specifically, minimum temperature, maximum temperature, humidity, and rainfall—were collected using data from 100 automated weather stations from the Indian Space Research Organization. We obtained district-level weekly reported malaria cases from the Integrated Disease Surveillance Program (IDSP), Department of Health and Family Welfare, Andhra Pradesh, India, for three years, 2014–16. We used a generalized linear model with Poisson distribution and default logarithm-link to estimate model parameters, and we used a quasi-Poisson method with a generalized additive model that uses nonparametric regression with smoothing splines. It appears that higher minimum temperatures (e.g., >24°C) tend to lead to higher malaria counts but lower values do not seem to have an impact on the malaria counts. On the other hand, higher values of maximum temperature (e.g., >32°C) seem to negatively affect the malaria counts. The relationships with rainfall and humidity appear to be not as strong once we account for smooth (weekly) trends and temperatures; both smooth curves seem to hover around zero across all of their values. We note that a rainfall amount between 40 and 50 mm seems to have a positive impact on malaria counts. Our analyses show that the incremental increase in meteorological parameters does not lead to an increase in reported malaria cases in the same manner for all of the districts within the same state. This suggests that other factors such as vegetation, elevation, and water index in the environment also influence disease occurrence.

1. Background

The World Health Organization (WHO) reports that in 2015 approximately 3.2 billion people—nearly one-half of the world's population—were at risk of malaria. Sub-Saharan Africa carries a disproportionately high share (90%) of malaria cases and deaths. India contributes 70% of malaria cases and 69% of malaria deaths in the Southeast Asia region (WHO Global Malaria Programme 2015). Malaria is transmitted through the bites of female *Anopheles* mosquitoes, which lay eggs in the water and thrive during rainy seasons of tropical countries (Climatenexus 2018).

Transmitted by bites from infected mosquitoes and other insects (vectors), vectorborne diseases (VBDs) are particularly dependent on climatic factors because insects have no internal control over their body temperature, and, as ambient temperatures rise, their distribution may expand through increased reproductive rate, biting behavior, and survival. Humidity and the availability of water for breeding also determine vector distribution, longevity, and behavior. However, the incubation period of pathogens within vectors is also temperature dependent and tends to become shorter in warmer conditions; human behavior is also likely to be affected by climate change, which may increase human interaction with vectors and the diseases they carry (WHO Western Pacific 2018).

Several researchers have explored the association of malaria prevalence with environmental conditions. Yacob and Swaroop (1944) used indicators such as rainfall to forecast a malaria outbreak in 1921 in Punjab, India.

Supplemental information related to this paper is available at the Journals Online website: https://doi.org/10.1175/WCAS-D-19-0029.s1.

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DOI: 10.1175/WCAS-D-19-0029.1

Hicks and Majid (1937) ascertained that high humidity, and not the total rainfall, was the key factor leading to a malaria epidemic. A similar negative correlation was observed between rainfall and malaria incidence in a 9-yr study on the Colombian Pacific coast (González et al. 1997). It has been observed that although malaria incidence is influenced by periods of heavy rainfall, excessive rainfall does not initiate an epidemic (de Zulueta et al. 1980). More recently, researchers have noted that in Madhya Pradesh, a weak correlation was observed between the number of rainy days and the incidence of malaria (Singh and Sharma 2002). Further, immature stages of the mosquito in water take about 10 days at optimum temperature to become adults, thus time duration is critical for predicting incidence of malaria.

Dhiman (2016) noted that temperature of two habitats affect mosquito development, that is, water bodies for development of immature stages and dwellings and/or resting places used by the adult mosquitoes after taking blood meal. Earlier studies have shown similar associations; a study conducted in hilly regions of India showed a higher positive correlation between monthly incidence of malaria and monthly minimum temperature, mean temperature, and rainfall with a one-month lag effect. The correlation coefficient for the association between monthly rainfall and monthly incidence of malaria was found to be greater than for the association between temperature and malaria incidence (Devi and Jauhari 2006). This indicates that rainfall plays a more important role in the transmission of the disease than temperature does. Several researchers reported a similar relationship of transmission with meteorological parameters (Bi et al. 2003; Greenwood and Pickering 1993; Ramasamy et al. 1992; Gupta 1996; Bouma et al. 1996). Furthermore, Zhou et al. (2004) has reported that the synergistic effect of temperature and rainfall on malaria transmission is much more pronounced than individual effects, and diurnal temperature range has been stated to be critical in the transmission of malaria (Paaijmans et al. 2010).

Researchers have reported on the influence of minimum temperature, humidity, and rainfall on malaria case occurrence in the community. Relative humidity, which is indirectly affected by rainfall at a given temperature, is critical for the life cycle of mosquitoes. For successful transmission of malaria, the infected vector species should survive for at least one week (Craig et al. 1999). If relative humidity is low, the infected vector species will die before the completion of sporogony (development of malaria parasite in the mosquito). Relative humidity of 60% or higher has been reported by several researchers as optimal for the development and survival of the mosquito vector and transmission of malaria (Bruce-Chwatt 1980; Craig et al. 1999; Grover-Kopec et al. 2006).

Other ecological variables have also been studied. McMichael and Martens (1995) noted that malaria incidence in both forest and nonforest areas was significantly correlated with rainfall in the first season of malaria. They recognized that nonforest areas developed breeding sites much sooner than the soil surface of forests. For this reason, the impact of high rainfall on malaria incidence is seen sooner in nonforest area. However, excessive rain counteracts mosquito development by flushing out their larvae. Other ecological determinants such as the soil type have been noted to influence the stagnation of water. Standing water makes a suitable breeding habitat for the mosquito vector; it depends on the type of soil and the amount of rain (Dhiman 2016).

Since a number of researchers have reported factors other than meteorological conditions that influence the occurrence of disease, we recommend that data such as satellite-derived built-up index, vegetation index, elevation, and soil type should be taken into consideration for better predictive models. Tay et al. (2012) emphasized simultaneous analysis of meteorological and parasitological data at different microepidemiological ecosystems at the local level is needed to assess the effects of climate on malaria cases.

This study offers an opportunity to explore the relationship of weather variables in an Indian state with distinctly different eco-epidemiological conditions across districts but with a common health information system and care structure. Furthermore, the availability of weekly data for the modeled parameters allowed us to capture the influence of meteorological variables such as relative humidity on the survival of the mosquito vector and transmission of malaria at short time intervals. The relevance of a short window of time has been noted earlier by Craig et al. (1999) and Tay et al. (2012).

Showcasing how the relationship of malaria occurrence varies with weather variables in different ecological conditions is important. These relationships determine if a prediction model developed in a certain ecological zone is applicable to another zone for forecasting malaria prevalence. Additionally, the data were available at small time intervals for all the districts of the state. This helped us to analyze the relationship of malaria cases with meteorological variables in different microepidemiological ecosystems.

Our choice of state has been determined by several factors: first, the state has districts with distinctly different climate, weather, vegetation, and soil. For instance, nine districts in the coastal region in Andhra

Pradesh are water abundant and four districts—namely, Anantapur, Chittoor, Kadapa, and Kurnool—are drought prone.

For this study, we procured the data from a number of sources. The average weekly meteorological parameters—specifically, minimum temperature, maximum temperature, humidity, and rainfall—were collected using data from 100 automated weather stations from the Indian Space Research Organization (ISRO; see the appendix for a list of this and other abbreviations). We obtained district-level weekly reported malaria cases from the Integrated Disease Surveillance Program (IDSP), Department of Health and Family Welfare, Andhra Pradesh, for three years, 2014–16. The IDSP is one of the major national health programs under the National Health Mission for all states and union territories in India. The key objective of the program is to strengthen and maintain a decentralized laboratory-based information-technology-enabled disease surveillance system for epidemic-prone diseases. The program is designed to monitor disease trends and to detect and respond to outbreaks in the early rising phase through a trained rapid response team. The data collection is a passive process and is based on rapid diagnostic tests for the detection of circulating parasite antigens (https://www.who.int/malaria/data/en/).

In India, *Plasmodium falciparum* and *Plasmodium vivax* are the most common species causing malaria; their proportion being around 50% each. *Plasmodium vivax* is more prevalent in the plain areas, while *Plasmodium falciparum* predominates in forested and hilly areas, hence the analysis focuses on these subtypes. According to Dhiman (2016), the advent of control measures in India was in the early 1950s, both by the central government and state governments. Nevertheless, malaria has become endemic in the central, southeastern, and northeastern parts of the country. However, with climate change, it is expected that the disease may spread to newer areas. Therefore, adaptation to climate change is very important. By 2100 it is estimated that average global temperatures will have risen by 1.0°–3.5°C, increasing the likelihood of many vectorborne diseases in new areas. The greatest effect of climate change on transmission is likely to be observed at the extremes of the range of temperatures at which transmission occurs. For many diseases, these lie in the range 14°–18°C at the lower end and about 35°–40°C at the upper end. Malaria and dengue fever are among the most important vectorborne diseases in the tropics and subtropics (Githeko et al. 2000).

Against this backdrop, the study team wanted to find out whether meteorological data can help to predict occurrence of malaria. With the inherent variability in physical characteristics within Indian states, can we predict areas of high risk based on climate variables? The inherent purpose was to develop knowledge that would help to prepare the health sector for the changing climate and identify areas that need to be strengthened and channels of information that need to be built.

2. Statistical models and estimation methods

For each of the 13 districts of Andhra Pradesh, a set of four plausible statistical models was developed with varying degrees of complexity for each model, and corresponding statistical model parameters were estimated using a maximum quasi-likelihood method based on either a fully parametric model or a semiparametric statistical model with smooth trends. The statistical model estimations were performed using the R software's base "glm" function (see https://www.statmethods.net/advstats/glm.html for a quick overview). In particular, we used a generalized linear model (GLM) with Poisson distribution and default logarithm-link to estimate model parameters, and we also used a quasi-Poisson method with generalized additive model (GAM) that uses nonparametric regression with smoothing splines. Before we fitted the models in R, missing values of some of the predictor variables (e.g., minimum temperature, maximum temperature, rainfall, and humidity) were imputed using median values of the available values for that variable across all years. Although more sophisticated imputation techniques such as predictive mean/median matching and more robust methods (e.g., random forest) could have been utilized (see e.g., R packages "mice" and "amelia"), our preliminary analyses suggested that, when values are missing completely at random (MCAR), predictive median matching techniques work relatively well.

For each of the four statistical models within a district, we assumed that the (weekly) malaria counts for three years 2014–16 (a total of 156 weeks) arise from a Poisson distribution in which the logarithm of the mean number of counts is assumed to follow different forms in the "glm" and "gam" functions in R:

(i) a basic Poisson regression model: glm[Malaria.Cases ~ Tmin + Tmax + rainfall + humidity, family = poisson(), data = imp.data],
(ii) a model with smoothly estimated week effects: gam[Malaria.Cases ~ s(Week) + Tmin + Tmax + rainfall + humidity, family = poisson(), data = imp.data],
(iii) a model allowing for monthly effects: glm [Malaria.Cases ~ Month + Tmin + Tmax + rainfall + humidity, family = poisson(), data = imp.data], and

(iv) a generalized additive model with smoothly estimated week, minimum temperature, maximum temperature, rainfall, and humidity: gam[Malaria. Cases ~ s(Week) + s(Tmin) + s(Tmax) + s(rainfall)+ s(humidity), family = poisson(), data = imp.data].

Each of the above four statistical models was then compared in terms of its goodness-of-fit statistic using adjusted R-squared (AdjR^2) values. We also used mean absolute relative error (MARE) to compare the predictive performance of the models based on one-week-ahead hold-out malaria counts by using at least two years of training data. Clearly, in terms of overall performance, a model with highest AdjR^2 and lowest MARE is preferred among the all plausible models. Once a model is found to be adequate by the above two overall measures, a more-detailed analysis that explores the extent of relationship between the malaria cases and the meteorological predictors was carried out using the estimated (possibly nonlinear) relations.

Note that a time series model [e.g., autoregressive moving average (ARMA)] might serve as a good candidate for capturing the weekly autocorrelations among the raw malaria counts. However, when we included time-dependent (in this case weekly) main effects or smooth trend, in addition to nonlinear trends with other temporally varying variables (e.g., temperature or humidity) within the GAM framework, the estimated (deviance) residuals were found to be not significantly autocorrelated by the standard Durbin–Watson test. For this reason, we have decided to report results based on the model that assumes uncorrelated (deviance) residuals. Moreover, the use of a generalized additive mixed model (GAMM; as described in Kohn et al. 2000) with an autoregressive (AR) model for the random intercept to account for possible temporal dependence did not significantly improve predictions for our data analyses. We agree, however, that such an extended analysis is worth doing, and we thank the reviewer for the suggestions.

3. Findings based on GLM and GAM models

To compare the predictive performance, in Fig. 1 we present the actual observed weekly malaria counts (solid black line) and predicted value of the malaria counts based on four different statistical models described in the previous section. For illustration, we present the detailed results only for the district of Visakhapatnam. Overall, the most complex model that takes into account all possible additive (smooth) nonlinear functional relationships between the malaria counts and the five predictors (including the smooth trend for weeks) seems to fit the data very well with 72% adjusted R squared, meaning that the fitted model accounts for 72% of the variation. Moreover, a MARE of 0.32 for model iv as described in the previous section indicates that, on average, the predicted counts are accurate with only 32% relative error. This means that if the predicted count is 100, on average, then the actual count is within the range of (68, 132).

In addition, we also computed the Spearman's rank correlation (Sp corr) between the malaria counts and each of the four predictor variables by each of the three years using weekly values. From Table 1 it appears that the relationship between the malaria counts and a specific predictor changes over time (here we are showing only annual variations, but monthly or, more generally, weekly variations can also be depicted using the smooth functions using model iv). In particular, notice that for 2014 humidity seems to be marginally strongly associated (Sp corr = 0.8072) with malaria counts among the four predictors, but for 2015 rainfall seems marginally strongly associated (Sp corr = 0.7131) and humidity seems least associated (with Sp corr = 0.3989) with malaria counts. This nonlinear temporal variability and association of malaria counts with different predictors partly justifies the need for more complex models such as statistical GAM model iv as described in the previous section. To illustrate the highly nonlinear nature of the relationship, we present below the smooth estimates of malaria counts as related to each of the five predictors (including weeks) (Fig. 2).

Consider the smooth trends that explain the relationships between malaria counts and each of the predictors that are allowed to vary smoothly with the respective values of the predictors. From Fig. 1 it is clear that the malaria counts for Visakhapatnam are expected rise around week 30 (i.e., during weeks of July) and then fall off during the winter months. However, such nonlinear relationships with meteorological variables (Tmin, Tmax, rainfall, and humidity) are not so clear-cut and vary significantly across various districts. Interestingly, it appears that higher minimum temperatures (e.g., >24°C) tend to lead to higher malaria counts but lower values do not seem to impact the malaria counts. On the other hand, higher values of maximum temperature (e.g., >32°C) seem to negatively impact the malaria counts. The relationships with rainfall and humidity appear to be not as strong once we account for smooth (weekly) trends and temperatures as both smooth curves seem to hover around zero across all of their values. Nonetheless, a rainfall amount between 40 and 50 mm seems to have a positive impact on malaria counts, and an excessive or a much lower amount of rainfall

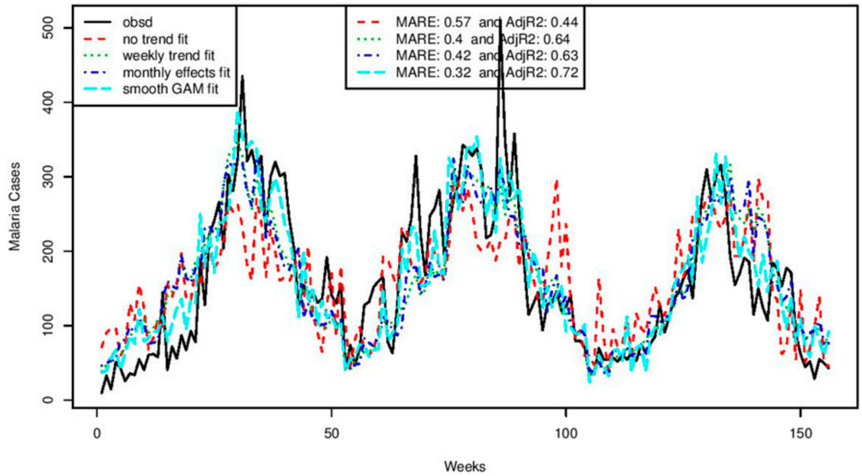

FIG. 1. Plot presenting predicted and reported cases of malaria for one of the districts of Andhra Pradesh.

seems to have very little effect on malaria counts. Also, the association of malaria counts with humidity appears even more precarious and relatively flat across almost all humidity levels. However, note that these (smooth nonlinear) relationships between malaria cases and predictors may change dramatically for other districts, and so we should not conclude and claim similar behavior of these predictors across all district levels. Detailed plots and analyses for the other districts (similar to Figs. 1 and 2) are available in the online supplemental material.

Results of all four models for all of the districts are available in Table S1 in the online supplemental material. We have described the incident rate ratio findings through an example of one of the districts of Andhra Pradesh: Visakhapatnam.

a. *Average of temperature*

The estimated ‘‘incident rate ratio’’ shows that a one-unit increase in minimum weekly temperature can lead to a 3%–6% increase [IRR = 1.041 with 95% confidence interval from 1.027 to 1.056] in weekly reported malaria cases, given that the other variables are held constant in the model. However, if the average maximum weekly temperature were to increase by one unit (1°), the rate ratio for weekly reported malaria cases would be expected to lead to a 7%–8% reduction (IRR = 0.924 with 95% CI of 0.916–0.932) in cases of malaria, while holding all other variables in the model constant.

b. *Average humidity*

From the estimated incident rate ratio, if the average humidity were to increase by one unit, it can lead to nearly a 1% decrease (0.996; 95% CI of 0.994–0.998) in weekly reported cases of malaria.

c. *Average rainfall*

From the estimated rate ratio, if the average rainfall were to increase by one unit, the rate ratio for malaria cases would be expected to increase by a factor of 1.0033 or 0.3% (95% CI of 1.003–1.004), while holding all other variables in the model constant (Table S1 in the online supplemental material).

The results for all of the districts of Andhra Pradesh summarized in Table S1 show that the adjusted R square varied from 34% to 72% (note that in Table S1 italics indicate where all IRR are less than 1 and show a significant negative relation and boldface type indicates where all IRR are above 1 and show a significant positive relation). The model shows that the districts of Anantapur, Chitoor, East Godavari, Kadapa, Krishna, and Kurnool present statistically significant increase in reported malaria cases with a one-unit increase in maximum temperature and humidity. The same model shows a statistically significant

TABLE 1. Spearman correlation of malaria cases with meteorological variables.

Year	Temperature min	Temperature max	Temperature mean	Humidity	Rainfall
2014	0.7674	0.6398	0.7213	0.8072	0.701
2015	0.7131	0.509	0.6301	0.3989	0.6318
2016	0.6392	0.3366	0.5726	0.559	0.7513

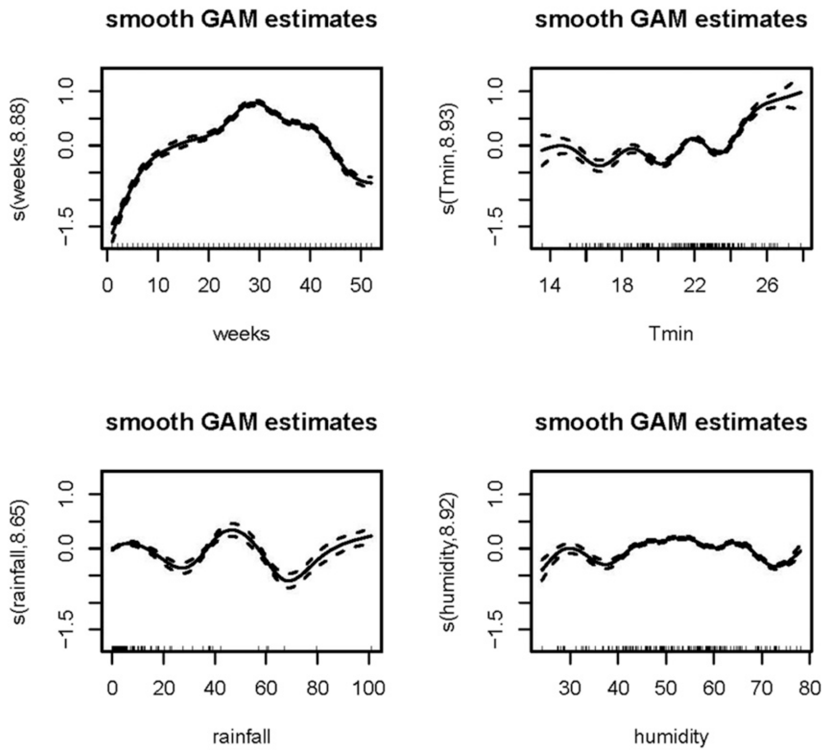

FIG. 2. GAM-based smooth estimates of malaria for Visakhapatnam, one of the districts of Andhra Pradesh.

reduction in cases of malaria in the districts of Nellore, Prakasam, Srikakulum, Visakhaptnam, and West Godavari with a one-unit increase in maximum temperature. Similarly, an increase in humidity did not show a trend in the same direction for all of the districts. Rainfall was not significantly associated with an increase in cases of malaria. On the basis of changes in meteorological conditions, we can predict cases for each district to some extent; these relationships can be viewed in a spatial map in Fig. 3.

Our analyses show that the incremental increase in meteorological parameters does not lead to an increase in malaria reported in the same manner for all of the districts within the same state. This result suggests that other factors in the environment also influence disease occurrence. Therefore, the research team plans to explore the influence of vegetation, elevation, and water index and report those results in a subsequent publication.

Identification and prediction of high-risk areas are useful to initiate prevention measures at the small-area level, such as a block, to minimize drug resistance and maximize control. The peaks in malaria cases can be prevented by a proactive approach such as predictive analyses. This would ensure timely communication designed for adopting preventive measures such as ensuring proper sanitation, preventing waterlogging, using long-lasting insecticide-treated bed nets, conducting indoor residential spraying, and ensuring complete antimalarial drug intake by positive cases. These tools can collectively help to prioritize resources, enhance investments, and establish effective initiatives.

4. Conclusions

For operational health agencies, the most pressing need is the strengthening of current disease-control efforts to bring down disease rates and manage short-term climate risks. Such planning will, in turn, increase development of processes designed for building resilience to long-term climate change.

National and state agencies need to work through a range of programs to (i) ensure political support and larger financial investment in preventive and curative interventions and tools to bring down current vector-borne disease burdens, (ii) promote a comprehensive approach to climate risk management to foster partnerships across departments of health, climate, and remote sensing for effective interventions, and (iii) support applied research through participation of local and national research departments and targeted initiatives on priority diseases and population groups.

5. Limitations

Better prediction may be achieved through a higher resolution of climate data and reported health cases at

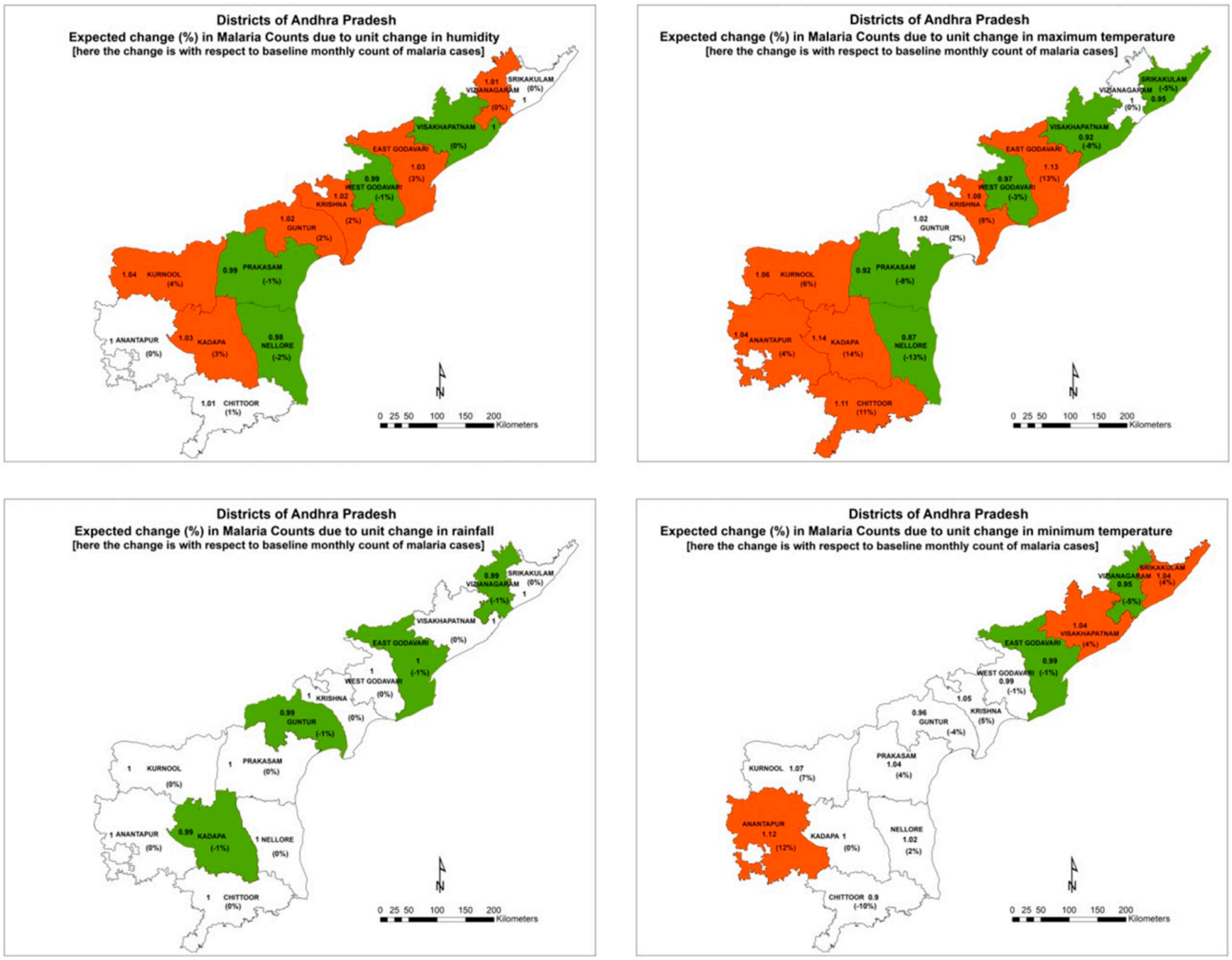

FIG. 3. Spatial display of district-specific incidence risk ratio based on Poisson regression.

the small-area level (block); inclusion of cases reported in private hospitals, population density, and type of built-up constructions may also improve prediction. This method also does not take into account indicators of human behavior, the economic profile of the community, or physical parameters such as moisture index or soil type. Many other additional explanatory variables could have been included that could potentially influence the spread of malaria; however, multiple-variable data collection over wider regions on a weekly basis for multiple years not only becomes time-consuming and expensive, it also introduces a lot of missing values. So, we focused on using those available variables that still could significantly explain the malaria epidemic. Also, we have not formally carried out a full hierarchical model to account for spatial patterns; computing rudimentary distance based on Moran's I for the estimated intercepts for different districts using the GLM (and not GAM) reveals no significant spatial association. However, admittedly a more thorough and complex model-based statistical analysis could be performed to find spatial patterns (if any) as a part of future analysis.

Acknowledgments. This work is supported by the U.S. Department of State and the National Oceanic and Atmospheric Administration as part of the U.S.–India Partnership for Climate Resilience. The authors declare no conflict of interest. The authors thank Dr. John Balbus of NIEHS for reviewing the analyses and suggesting new dimensions for analyses and Mr. Nehru Machineni, Mr. Kanwal N. Singh, and Mr. K. Venkatramana from TERI for preparing meteorological data for each district.

APPENDIX

List of Abbreviations

AdjR^2	Adjusted R-squared
GLM	Generalized linear model

GAM	Generalized additive model
GAMM	Generalized additive mixed model
IDSP	Integrated Disease Surveillance Program
ISRO	Indian Space Research Organization
MARE	Mean absolute relative error
MCAR	Missing completely at random
VBDs	Vectorborne diseases

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