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Geospatial-temporal Analysis of Dengue Fever Based on the Bayesian Spatiotemporal Model

Rong Zhao[1*] and Chen Liang[2,3]

[1]Vanke School of Public Health, Tsinghua University, Beijing 100084, China
[2]Beijing Institute of Surveying and Mapping, 60 Nanlishi Road, Beijing 100045, China
[3]Beijing Key Laboratory of Urban Spatial Information Engineering, 60 Nanlishi Road, Beijing 100045, China

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Dengue fever (DF) is one of the most rapidly spreading mosquito-borne viral diseases in the world. It can impose an enormous socioeconomic and disease burden on the world's population. The spatial and temporal distribution patterns of DF cases in China are heterogeneous. It is evident that further research is necessary to identify the high-risk areas of dengue occurrence and associated risk factors at a fine spatiotemporal scale. This will facilitate the prevention and control of DF transmission. With the rapid development of remote sensing (RS) and geographic information system (GIS) technology, RS and GIS technology have played an important role in monitoring, forecasting, and identifying influencing factors and formulating prevention and control strategies for DF. In China, the majority of dengue cases were clustered in Guangdong and Yunnan Provinces. In this study, Bayesian spatiotemporal models were fitted at the county level in order to quantify the relationships between environmental and socioeconomic factors and DF. Our findings indicate that both environmental and socioeconomic factors can affect the transmission of DF in Guangdong and Yunnan Provinces. However, the underlying drivers and the spatially clustered patterns observed in the two provinces appear to be different. The results indicate that elevated temperatures facilitate the transmission of DF, but it was found that the risk of DF begins to decrease when the temperature exceeds 27.6 ºC in Guangdong Province. There was a positive correlation between temperature and the incidence of DF, although no statistical significance was found in Yunnan Province. In Guangdong Province, the amount of precipitation did not significantly affect the incidence of DF. In Yunnan Province, the relationship between precipitation and DF is nonlinear. As the amount of precipitation increases, the risk of DF epidemics increases. In addition, vegetation cover can significantly affect the DF transmission, but the nonlinear relationships between vegetation cover and DF are diverse and complex in these two provinces. The incidence of DF was found to be positively correlated with the level of urbanization at the county level. The findings may prove beneficial to the governments of both provinces in the development of targeted strategies for the control of DF outbreaks at the county level.

*Corresponding author: e-mail: rongzhao1019@whu.edu.cn
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1. Introduction

Dengue fever (DF) is a systemic viral infection transmitted between humans by the vector Aedes mosquitoes, primarily *Aedes aegypti* and *Aedes albopictus*.(1) Mosquito-borne diseases are commonly prevalent in subtropical and tropical regions, because the larvae and eggs of mosquitoes are destroyed by low temperatures at high altitudes in winter.(2) According to the World Health Organization, the global incidence of dengue infection is currently increasing, and the geographical range of transmission has been steadily expanding over the past few decades. The number of dengue cases has increased from 505,430 in 2000 to 5.2 million in 2019 and resulted in a historic high of more than 6.5 million cases in 2023.(3) It is well established that the transmission of DF is affected by a combination of vegetation cover and meteorological, socioeconomic, and mobility factors.(4–9) Climate change has resulted in increased temperatures and high rainfall, as well as high humidity. Urbanization leads to increased human activities, economic and population growth, land cover changes, vegetation degradation, and biodiversity loss, which in turn affect mosquito breeding sites and human exposure to vectors, thereby promoting the spread of DF. Additionally, changes in the distribution of vectors have also been identified as influencing factors. Environmental conditions can directly affect the breeding, survival, and abundance of mosquitoes. Numerous reliable studies have already been conducted on the relationships among meteorological factors, vegetation cover, and the risk of DF.(4–7) Additionally, it has been documented that the incidence of DF is closely correlated with local socioeconomic conditions.(8–10) The world is currently experiencing a period of accelerated urbanization. The simultaneous occurrence of increased human activity, economic growth, population expansion, land cover alteration, vegetation deterioration, and biodiversity reduction is a phenomenon frequently observed in conjunction with urbanization.(11) The increased movement of goods and people, urbanization, and insufficient medical resources may also exacerbate the risk of DF transmission. Since the first reported DF outbreak in Guangdong Province in 1978, the affected areas in China have expanded from the southern to some inland regions.(12,13) In recent years, there has been a notable increase in the number of dengue cases in many provinces across mainland China. The outbreaks of DF may result in significant heavy social and economic burdens for individuals and countries. Clearly, DF has been a significant public health challenge in China. Appropriate strategies would enable citizens to deal with future risk and achieve the goals of reducing the impact of climate change, improving health outcomes for all, and developing resilient and sustainable cities.

A number of studies have been conducted to explore the characteristics of DF epidemics in mainland China and other countries.(5,9,12–16) The results of these studies have shown that meteorological factors, vegetation cover, and land cover are closely correlated with DF. However, the relationships between the influencing factors and DF were not consistent. and DF were not consistent. In particular, studies have demonstrated that the relationships between vegetation cover and DF can be either positive, negative, or nonlinear. These disparate findings can be attributed to different spatial scales of analysis, measures of influencing factors, and statistical techniques, and statistical techniques. Some studies indicated that the majority of the cases were concentrated in Guangdong and Yunnan Provinces.(13,14) The environmental conditions of

Guandong and Yunnan Provinces (e.g., high ambient temperature, abundant rainfall, and frequent trade between these provinces and neighboring countries) are appropriate for DF transmission. However, there are some shortcomings in the existing studies. These studies do not account for dependency structures of continuous time and between geographical units. The lack of fine-scale data on influencing factors weakens the credibility of the results. Therefore, to facilitate the optimal allocation of resources for the prevention and control of DF in China, it is critical to clarify the spatiotemporal patterns and potential factors of DF epidemics at the county level in areas with a high incidence of dengue. The investigation of trend patterns of DF epidemics and the estimation of spatial and temporal correlations simultaneously require further investigation. In addition, the advent of remote sensing and geographic information system technology has enabled the acquisition of high-resolution satellite data, which has facilitated the generation of more comprehensive and precise insights into environmental conditions, including population, vegetation cover, and urbanization level. Therefore, further studies can utilize high-precision remote sensing data to construct models.

The objective of this study was to utilize Bayesian spatiotemporal models to analyze the spatiotemporal pattern of DF epidemics in two high-risk regions of mainland China (Guangdong and Yunnan Provinces) and clarify the nonlinear effects of influencing factors on the occurrence of DF based on the records of DF cases from 2006 to 2020 in mainland China from the China Notifiable Disease Surveillance System and remote sensing data. The findings indicated that there are spatial and temporal disparities in the transmission of DF, which would provide important support for strengthening the prevention and control of DF outbreaks in Guangdong and Yunnan Provinces and raising the level of prevention of DF risk.

2. Materials and Methods

2.1 Study area

Guangdong Province (109°45′–117°20′E, 20°09′–25°31′N) is located in the southeastern part of China (Fig. 1). The province comprises 122 counties, with a permanent resident population of 127 million. Guangdong is one of the most urbanized regions in the world. In 2023, the gross domestic product per capita was approximately 106,985 yuan, as derived from the China Statistical Yearbook. The province has a humid subtropical monsoon climate, characterized by warm winter, hot summer, and abundant sunshine hours throughout the year.

Yunnan Province (97°31′–106°11′E, 21°8′–29°15′N) is situated in the southwest region of China and enjoys a tropical highland humid monsoon climate (Fig.1). The most notable climatic characteristics are minimal temperature fluctuations throughout the year and pronounced daily temperature variations. Next to the Southeast Asian countries Myanmar, Laos and Vietnam, Yunnan and these countries have frequent economic and trade exchanges. The total value of import and export between Yunnan and the Association of Southeast Asian Nations has demonstrated a notable increase over the past decade. In 2022, the total value reached 6515322 billion yuan, as derived from the National Development and Reform Commission.

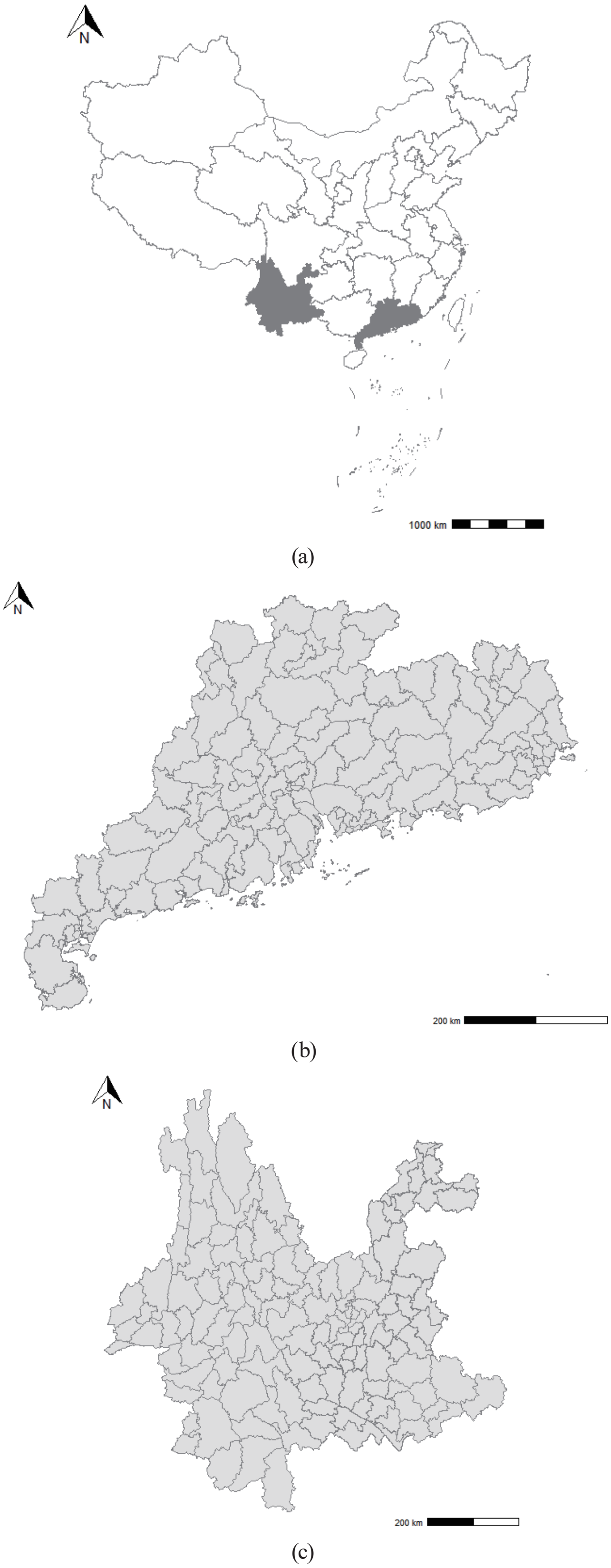


Fig. 1. Illustration of the study areas: (a) China, (b) Guangdong Province, and (c) Yunnan Province.

2.2 Data collection

2.2.1. DF data

Daily records of DF cases for 2006–2020 in mainland China at the county scale were directly obtained from the China Notifiable Disease Surveillance System. In our study, the number of monthly DF cases at the county scale was calculated.

2.2.2. Environmental data

In this study, environmental factors include meteorological factors and vegetation cover. Meteorological factors were considered in the form of the monthly mean temperature and precipitation. The data were obtained from the ERA5-Land (https://cds.climate.copernicus.eu/cdsapp#!/home), which can provide numerous meteorological variables.(17) Moreover, previous studies have indicated that vegetation cover is closely related to the survival and reproduction of mosquitoes.(18) The normalized difference vegetation index (*NDVI*) was incorporated into subsequent analyses. It is a commonly used indicator of vegetation coverage and can be measured by satellite remote sensors. Its value ranges from −1 to 1 with high values corresponding to a dense and active vegetation cover. The monthly *NDVI* data were obtained from MOD13A (https://search.earthdata.nasa.gov/search), which provides data with a spatial resolution of 1 km.

2.2.3 Socioeconomic data

Urbanization is a more complex social phenomenon. Three socioeconomic variables were considered in this study: population density, nighttime light (NTL), and the proportion of impervious surfaces. The process of urbanization is accompanied by an increase in population density and land use change.(19) The population was obtained from the LandScan database (https://landscan.ornl.gov/). In addition, many studies have shown that stable NTL data can reflect the extent and intensity of human socioeconomic activities and have been used to estimate the urbanization level.(20) NTL values were obtained from DMSP-OLS (2006–2011) and NPP-VIIRS(2012–2020) (https://www.ngdc.noaa.gov/eog). The expansion of impervious surfaces is frequently associated with the process of urbanization. Impervious surfaces may affect the ecological environment of the city, including the temperature distribution(21) and water cycle.(22) The land cover data (2006–2020) were downloaded from the Landsat-derived annual land cover product of China (CLCD) (https://zenodo.org/records/5816591).

2.3. Statistical analysis

In recent years, Bayesian spatiotemporal models have emerged as powerful tools for unravelling the intricacies of disease spread because of their ability to incorporate spatial and temporal dependences, uncertainties, and complex interactions.(23,24) In this study, we employed the Bayesian spatiotemporal models to explore the complex relationships between potential influencing factors and dengue incidence. The surveillance data appeared to be overdispersed and contained a considerable number of zeros at the county level. To address these issues, the monthly dengue case counts Y_{it} observed in county i and time t were modeled as a zero-inflated negative binomial process. The basic model for spatial data was as follows:

$$Y_{it} \sim ZIPNB\left(E_{it}\theta_{it}\right), \tag{1}$$

where E_{it} is the expected number of dengue cases in county i and time t, and θ_{it} is the relative risk (RR) in county i and time t. RR is used to measure the strength of the association between exposures and outcomes in epidemiology [25] Then, $\log\theta_{it}$ can be expressed as a sum of several components, including the effects of environmental and socioeconomic factors and spatial and temporal structures.

$$\log\theta_{it} = \beta_0 + \sum_{k}^{m}\beta_k C_k + \sum_{s}^{n} f_s\left(C_s\right) + \mu_i + v_i + \gamma_t + \varphi_t + \delta_{it} \tag{2}$$

Here, β_0 is the intercept and represents the overall risk in the study area, whereas $\{\beta_k\}$ and $\{f_s(.)\}$ denote the linear $\{C_k\}$ and nonlinear $\{C_s\}$ effects of covariates, respectively. In this study, covariates include meteorological factors, vegetation, land cover, and human activity. Among these factors, the relationships between temperature, precipitation, and dengue incidence were not found to be simply linear.[23] μ_i+v_i is the spatial random effect. μ_i denotes the structured spatial effect. It follows a conditional autoregressive (CAR) distribution, which smooths the data according to a certain neighborhood structure that specifies that two counties are neighbors if they share a common boundary. That means that outbreaks of infectious diseases in one area are always the source of outbreaks in nearby geographical neighbors. v_i denotes an unstructured spatial effect, which can address unobserved fluctuations unique to each county and is an independent and identically distributed normal variable. γ_t is the structured temporal random effect and can follow a random walk in time of first order (RW1) to capture the dependence between successive months. The outbreaks of infectious diseases are affected by adjacent time points, which can be called temporal correlation. φ_t denotes an unstructured temporal effect, which accounts for temporal heterogeneity and is modeled with an independent and identically distributed normal variable. δ_{it} refers to the interaction between space and time, which would explain differences in the time trend of outbreaks of DF for different areas. We assumed that the two unstructured effects v_i and φ_t interact. The deviance information criterion (DIC) of the models can be used to evaluate the competing models where a lower DIC indicates a better model. In addition, it is also important to detect multicollinearity before fitting the models. The most common method is to use the variance inflation factor (VIF) for each covariant. The covariant with the greater VIF value should be excluded. In this paper, the threshold for VIF is set at 10. In the context of Yunnan Province, the population density (VIF > 10) should be excluded. Subsequently, model selection was conducted to develop the baseline models for the following analysis.

In this study, the spatial data preprocessing was completed in ArcGIS 10.8, and all statistical analyses presented were performed using the statistical R software version 4.3.0 with the integrated nested Laplace approximation library.(26)

3. Results and Discussion

3.1. Temporal and spatial distributions of DF

Overall, the DF epidemic in China has occurred with considerable frequency, and the geographical range of transmission has spread. Furthermore, between 2006 and 2020, the total number of reported dengue cases in mainland China was 92104. The provinces in which dengue cases were reported each year and the transmission range was expanded further from the southeastern coastal areas to the southwestern, central, and northeastern areas.

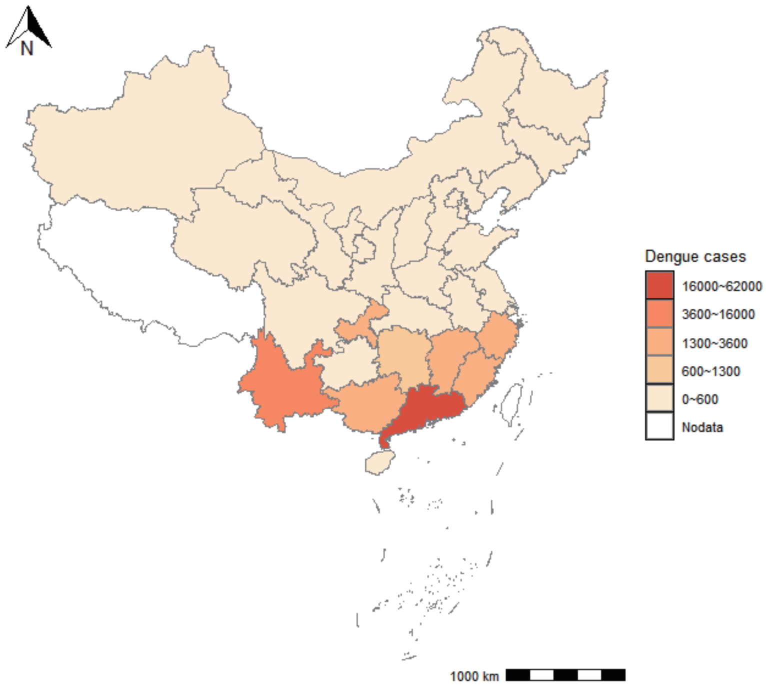
As illustrated in Figs. 2(a) and 2(b), from 2006 to 2020, the incidence of DF exhibited a pattern of clustering in specific geographical areas. Most dengue cases were reported in the southeastern coastal areas and southwestern regions. The incidences in Guangdong and Yunnan Provinces were particularly higher than those in other provinces. There were 59942 and 15472 dengue cases reported in Guangdong and Yunnan Provinces, respectively. Figure 3(a) shows that the monthly number of dengue cases exhibited an increasing trend. Furthermore, as illustrated in Figs. 3(b) and 3(c), there were seasonal characteristics observed from July to November for dengue cases. Additionally, a peak in dengue cases was reported in the mainland in 2014. A total of 44865 cases were reported, and Guangdong Province accounted for the majority (42673 cases, 95.11%).

3.2. Model evaluation and comparison

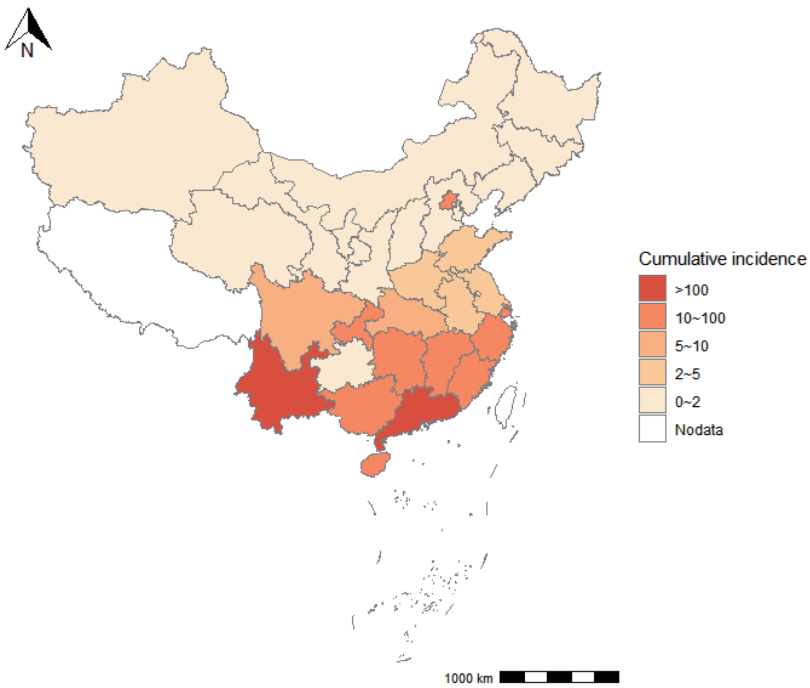
Table 1 shows the evaluation results of the four alternative spatiotemporal ZINB models. In Guangdong Province, the unstructured spatial and temporal effects do not significantly contribute to a reduction in DIC. Consequently, the optimal baseline model for Guangdong Province does not require the consideration of the unstructured spatial and temporal effects. In Yunnan Province, the unstructured temporal effect introduces complexity without a notable improvement in the model. Therefore, the baseline model should exclude the unstructured temporal effect. The final model still needs to include fixed effects of the proportion of the impervious surface, population density (log), and NTL (log), as well as nonlinear effects of temperature, precipitation, and *NDVI*.

3.3 Risk factors for DF in Guangdong and Yunnan Provinces

The exposure–response relationships between covariates and DF and their 95% confidence intervals (CIs) in Guangdong and Yunnan Provinces are presented in Figs. 4 and 5, respectively. The results indicated that the effects of covariates on DF exhibited slight differences between Guangdong and Yunnan Provinces. In Guangdong Province, the exposure–response

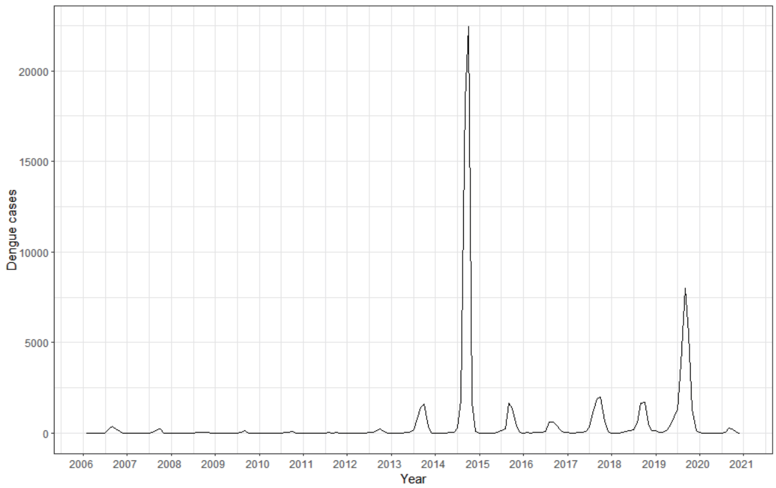


(a)

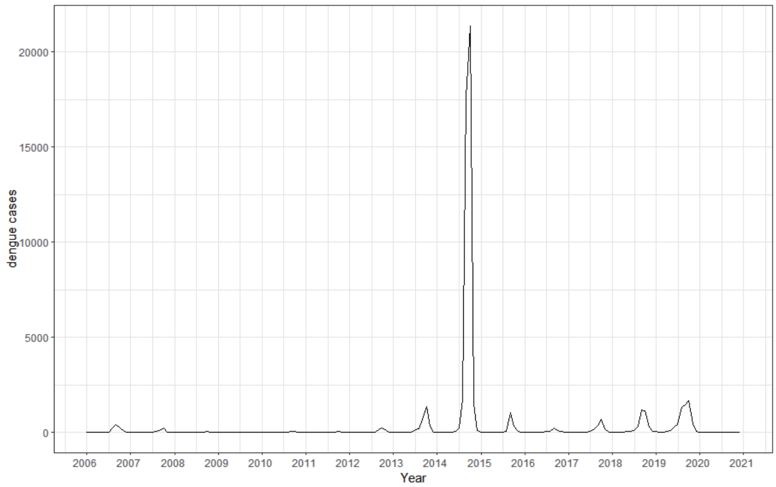


(b)

Fig. 2. (Color online) Spatial distribution of DF in China from 2006 to 2020. (a) Spatial distribution of dengue cases distinguished by color from high to low in each province. (b) Spatial distribution of the cumulative incidence of DF distinguished by color from high to low in each province.



(a)



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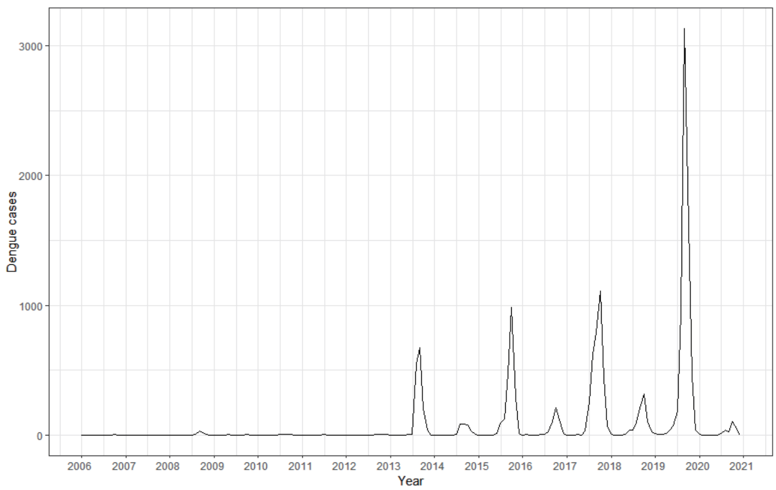

(c)

Fig. 3. Temporal distribution of dengue cases in China from 2006 to 2020. (a) Year-month temporal change in the number of DF cases in China. (b) Temporal distribution of dengue cases in Guangdong Province. (c) Temporal distribution of dengue cases in Yunnan Province.

Table 1
Evaluation results of four alternative spatiotemporal ZINB models.

Model	Random effects	DIC (Guangdong)	DIC (Yunnan)
Model 1	μ_i	23042.54	11030.30
Model 2	$\mu_i + v_i$	23040.21	9599.01
Model 3	$\mu_i + v_i + \gamma_t$	17278.49	7365.19
Model 4	$\mu_i + v_i + \gamma_t + \varphi_t$	17270.39	7362.26
Model 5	$\mu_i + v_i + \gamma_t + \varphi_t + \delta_{it}$	16109.05	7289.01

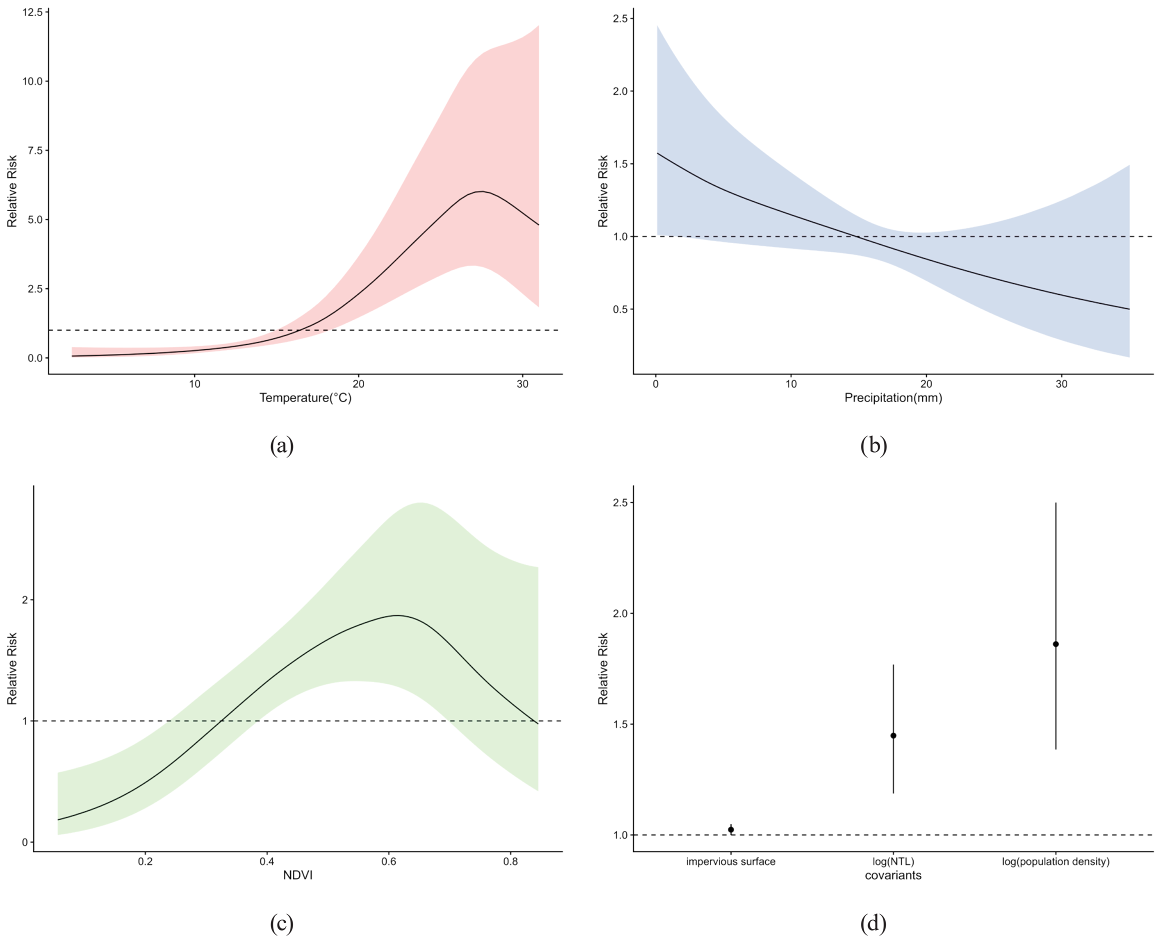

Fig. 4. (Color online) Effects of environmental and socioeconomic factors on county-level DF incidence in Guangdong Province. (a) Temperature. (b) Precipitation. (c) *NDVI*. (d) Socioeconomic variables. (The bold lines are the estimates of the relationships between factors and DF and the corresponding 95% confidence intervals).

relationships between DF and the monthly mean temperature indicated that low temperatures may be an important protective factor, whereas high temperatures may be a risk factor for DF. The incidence of DF was found to be more severe when temperatures exceeded 16.6 °C, with the peak *RR* reaching 6.01 (95% *CI*: 3.28–11.02) at 26.8 °C. A clear downward trend in risk was observed as the temperature exceeded 27.6 °C. As seen in Fig. 4(c), a clear nonlinear relationship between *NDVI* and DF was identified. In areas experiencing a relatively severe epidemic, the *NDVI* value was found to be between 0.38 and 0.70. It can be posited that *NDVI* may exert a

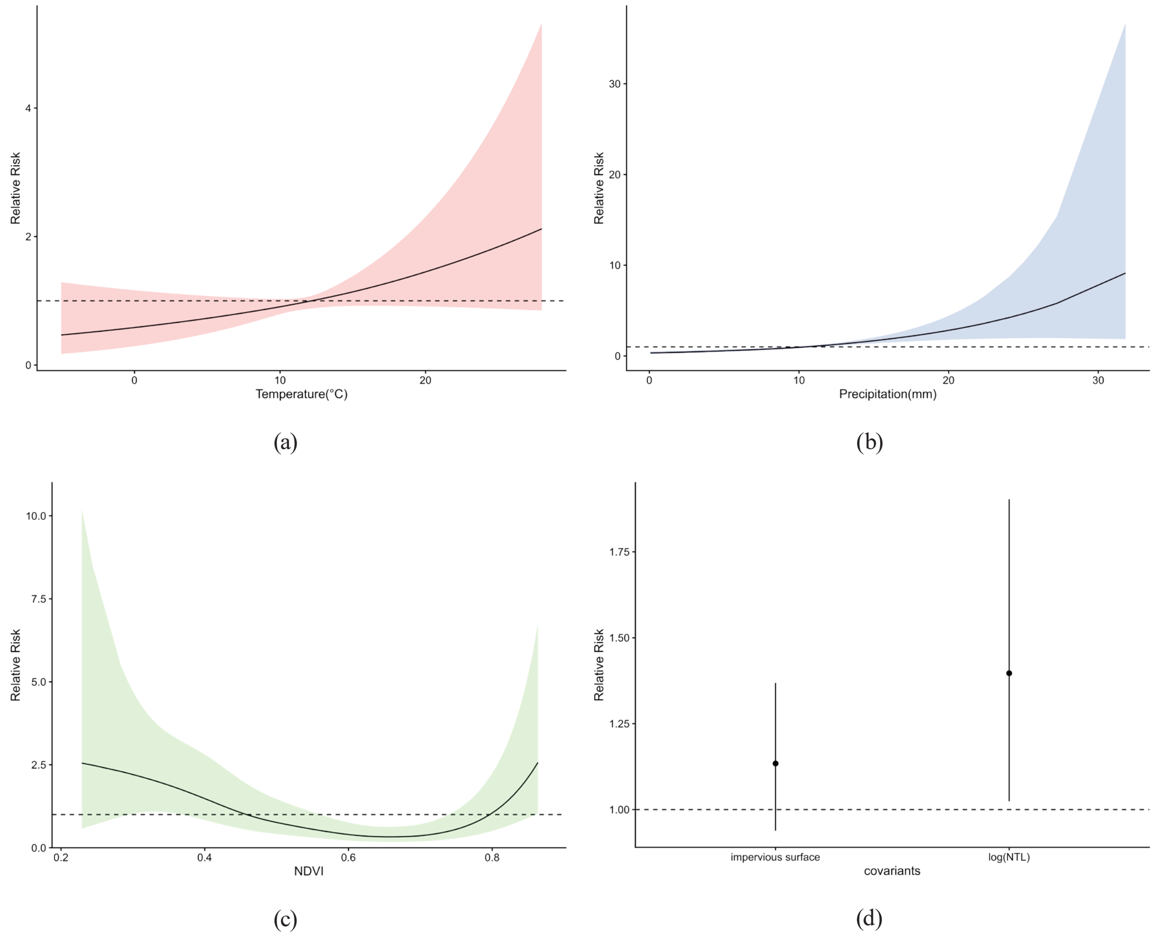

Fig. 5. (Color online) Effects of environmental and socioeconomic factors on county-level DF incidence in Yunnan Province. (a) Temperature. (b) Precipitation. (c) *NDVI*. (d) Socioeconomic variables. (The bold lines are the estimates of the relationships between factors and DF and the corresponding 95% confidence intervals).

protective effect on DF when the *NDVI* value is below 0.24. Nevertheless, the results of this study indicated that the monthly mean precipitation did not significantly affect the incidence of DF. In terms of socioeconomic factors, the DF epidemic is severe in the counties where the population is aggregated (*RR* = 1.86; 95% *CI*: 1.39, 2.50). The risk of DF epidemics was found to increase with the proportion of impervious surfaces (*RR* = 1.02; 95% *CI*: 1.01, 1.05) and the value of NTL (*RR* = 1.45; 95% *CI*: 1.87, 1.77).

In comparison with Guangdong Province, the relationships between monthly mean temperature and DF in Yunnan Province indicate that the risk of DF epidemic increases with temperature. Nevertheless, our study demonstrated that the impact of monthly mean temperature on DF was not statistically significant in Yunnan Province. Our study indicated that *RR* increased with the amount of monthly mean precipitation. Less precipitation may act as a protective factor (*RR* <1). The DF epidemic was relatively severe when the monthly mean precipitation exceeded 12.6 mm. *NDVI* may exert a protective effect on DF at a value of 0.57–0.74, while it may have a risk effect when it is greater than 0.29 and less than 0.36. The risk of DF epidemics was found to increase with the value of NTL (*RR* = 1.40; 95% *CI*: 1.02, 1.90). The impact of the proportion of the impervious surface on DF was found to be not statistically significant (*RR* = 1.13; 95% *CI*: 0.94, 1.37).

3.4 Temporal and spatial characteristics of the incidence of DF

Figure 6 shows the geographical distributions of *RR* across Guangdong and Yunnan Provinces. As seen in Fig. 6(a), the counties associated with higher *RR* (darker tones) are mainly situated at the center of Guangdong Province, i.e., the Pearl River Delta region. The high-risk regions of Yunnan Province were clustered in the southwestern border area [Fig. 6(b)].

A clear seasonal pattern was observed in the incidence of DF in Guangdong and Yunnan Provinces. As shown in Tables 2 and 3, the highest risk was observed in July, August, September, and October. Note that a high risk was observed in November in recent years.

4. Discussion

In this study, we employed the Bayesian spatiotemporal models to estimate the spread of and risk factors for DF epidemics in Guangdong and Yunnan Provinces at the county level. The results of this study indicate that the transmission of DF exhibits complex temporal and spatial characteristics, and that both environmental and socioeconomic factors may have played an important role in the transmission of DF. The different epidemiological characteristics of DF in Guangdong and Yunnan Provinces will provide important support for strengthening the targeted prevention and control of DF outbreaks and raising the level of prevention of DF risk.

Meteorological factors are the most important driving forces affecting the incidence of DF in mainland China. Specifically, according to previous studies, temperature can affect the survival and transmission of vector mosquitoes and dengue viruses. It has been demonstrated that higher temperatures can speed up the life cycle of mosquitoes and increase the biting rate of mosquitoes, which can subsequently lead to an increased incidence of dengue infections.(27,28) The results of this study were coincident with those of previous studies.(27,28) In Guangdong Province, the results indicated that the warm environment is conducive to the transmission of DF, but when the temperature exceeds a certain threshold, it is unable to increase the incidence of dengue infections. Temperature was positively correlated with the number of DF cases, although no statistical significance was found in Yunnan Province. Precipitation has also been identified as a factor contributing to the transmission of DF.(29) Our findings indicated that there is a clear nonlinear relationship between precipitation and DF in Yunnan Province. This is because mosquitoes lay their eggs on the surface of stagnant water, where the larvae develop and pupate before becoming mature adult mosquitoes.(29,30) An increase in precipitation can result in the creation of more potential breeding sites, which in turn can affect the life cycle of adult female mosquitoes and subsequently affect the number of mosquitoes. Different from Yunnan Province, our findings did not indicate a statistically significant impact of precipitation on the incidence of DF, which was consistent with previous studies(31–33) The possible explanation for this finding is that the effect of precipitation on the breeding of mosquitoes might be less important in urban

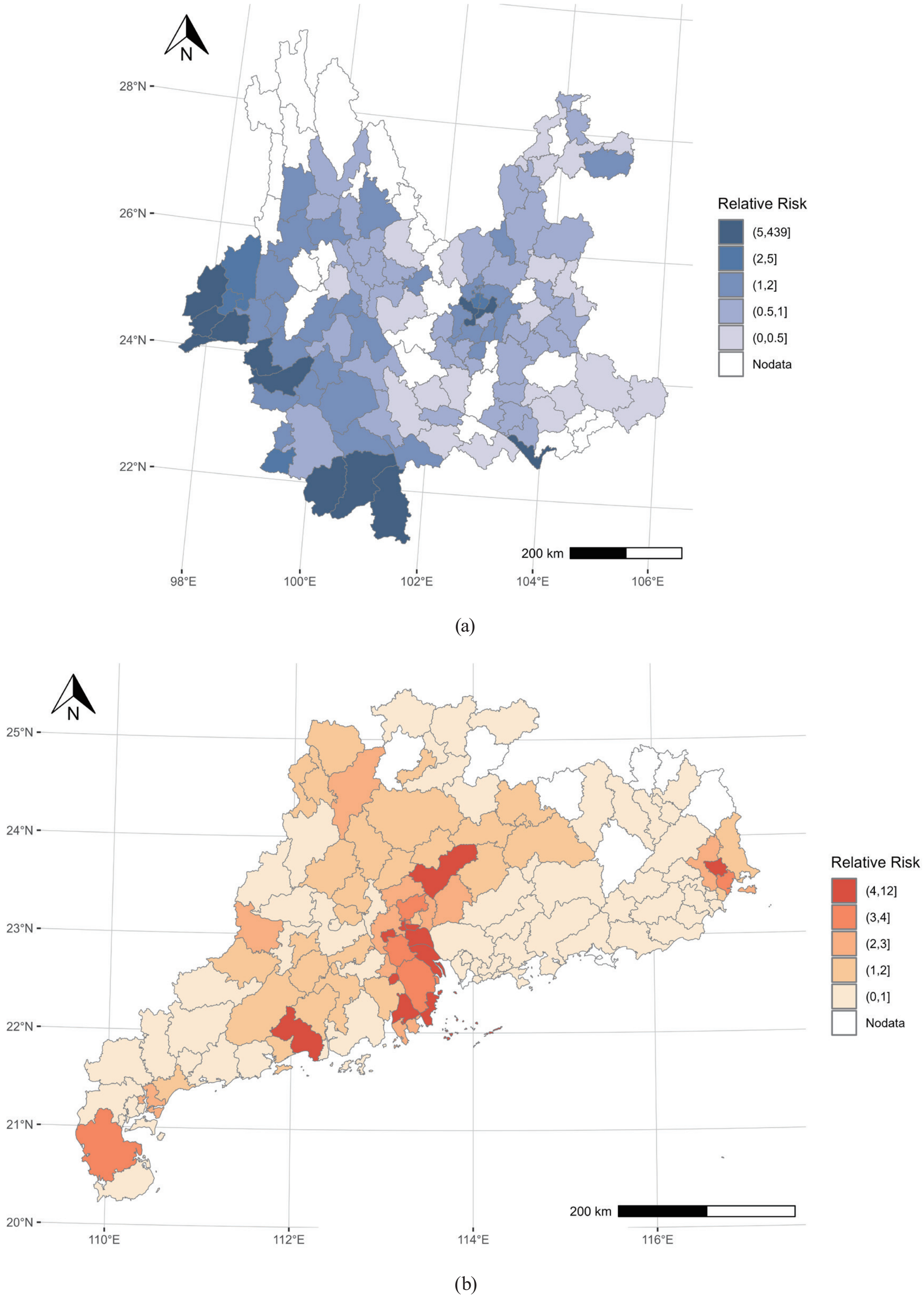

Fig. 6. (Color online) Risk map of DF at the county level in (a) Guangdong and (b) Yunnan Provinces, China, 2006–2020.

Table 2
Temporal risk of DF incidence in Guangdong Province from 2006 to 2020.

2006	*RR*	2007	*RR*	2008	*RR*	2009	*RR*	2010	*RR*
1	0.46 (0.12–1.69)	1	1.64 (0.56–4.77)	1	0.06 (0.01–0.37)	1	0.2 (0.04–0.95)	1	0.12 (0.02–0.6)
2	0.2 (0.05–0.83)	2	1.17 (0.43–3.15)	2	0.07 (0.01–0.53)	2	0.06 (0.01–0.3)	2	0.02 (0–0.14)
3	0.04 (0.01–0.23)	3	0.68 (0.21–2.2)	3	0.03 (0–0.18)	3	0.06 (0.01–0.28)	3	0.04 (0.01–0.19)
4	0.05 (0.01–0.23)	4	1.19 (0.46–3.06)	4	0.03 (0.01–0.16)	4	0.03 (0.01–0.16)	4	0.16 (0.04–0.56)
5	0.03 (0.01–0.17)	5	0.41 (0.14–1.17)	5	0.02 (0–0.12)	5	0.07 (0.02–0.27)	5	0.12 (0.03–0.44)
6	0.52 (0.19–1.43)	6	0.32 (0.11–0.93)	6	0.06 (0.01–0.3)	6	0.08 (0.02–0.31)	6	0.07 (0.02–0.27)
7	0.6 (0.24–1.47)	7	0.13 (0.04–0.44)	7	0.28 (0.1–0.79)	7	0.08 (0.02–0.31)	7	0.18 (0.06–0.54)
8	4.67 (2.41–9.12)	8	1.19 (0.55–2.61)	8	0.28 (0.1–0.8)	8	0.21 (0.07–0.61)	8	0.68 (0.29–1.63)
9	7.45 (4.2–13.3)	9	2.57 (1.31–5.1)	9	0.36 (0.14–0.98)	9	0.22 (0.07–0.63)	9	2.01 (0.94–4.31)
10	5.29 (2.88–9.73)	10	2.39 (1.21–4.75)	10	1.53 (0.74–3.18)	10	0.23 (0.08–0.65)	10	3.92 (2.09–7.4)
11	4.09 (1.99–8.42)	11	0.37 (0.12–1.15)	11	2.66 (1.24–5.7)	11	0.14 (0.03–0.56)	11	1.27 (0.55–2.93)
12	1.14 (0.39–3.36)	12	0.15 (0.03–0.65)	12	0.83 (0.27–2.54)	12	0.33 (0.09–1.28)	12	0.37 (0.11–.25)
2011	*RR*	2012	*RR*	2013	*RR*	2014	*RR*	2015	*RR*
1	0.06 (0.01–0.35)	1	0.28 (0.07–1.14)	1	0.21 (0.05–0.85)	1	0.48 (0.15–1.59)	1	4.57 (2.02–10.38)
2	0.03 (0–0.19)	2	0.28 (0.07–1.09)	2	0.52 (0.18–1.5)	2	0.15 (0.03–0.65)	2	1.28 (0.5–3.3)
3	0.04 (0.01–0.2)	3	0.31 (0.09–1.1)	3	0.38 (0.12–1.16)	3	0.18 (0.05–0.67)	3	0.91 (0.36–2.33)
4	0.13 (0.03–0.47)	4	0.15 (0.04–0.53)	4	0.4 (0.13–1.23)	4	0.54 (0.22–1.36)	4	0.39 (0.16–0.98)
5	0.1 (0.03–0.37)	5	0.14 (0.05–0.44)	5	0.5 (0.19–1.28)	5	0.35 (0.13–0.93)	5	1.07 (0.45–2.59)
6	0.24 (0.08–0.7)	6	0.18 (0.06–0.53)	6	0.86 (0.38–1.93)	6	1.17 (0.55–2.5)	6	0.48 (0.2–1.16)
7	0.21 (0.07–0.63)	7	0.55 (0.23–1.31)	7	1.37 (0.68–2.75)	7	3.38 (1.72–6.7)	7	1 (0.46–2.18)
8	0.33 (0.12–0.88)	8	0.92 (0.44–1.95)	8	5.9 (3.17–11.1)	8	21.39 (12.38–38.07)	8	2.42 (1.23–4.8)
9	0.48 (0.2–1.17)	9	2.07 (1.08–3.96)	9	15.42 (9.2–26.23)	9	320.2 (199.66–540.42)	9	9.07 (5.25–15.86)
10	1.17 (0.53–2.56)	10	3.61 (1.99–6.57)	10	21.6 (13.1–36.04)	10	777.26 (513.43–1219.82)	10	12.1 (7.39–19.88)
11	0.69 (0.28–1.73)	11	4.59 (2.4–8.8)	11	17.84 (10.31–31.31)	11	195.81 (129.1–302.14)	11	6.54 (3.69–11.65)
12	0.35 (0.1–1.27)	12	0.37 (0.11–1.28)	12	1.49 (0.54–4.08)	12	33.77 (17.91–64.91)	12	1.79 (0.74–4.37)

Table 2
(Continued) Temporal risk of DF incidence in Guangdong Province from 2006 to 2020.

2016	*RR*	2017	*RR*	2018	*RR*	2019	*RR*	2020	*RR*
1	2.61 (1.01–6.76)	1	1.47 (0.61–3.54)	1	0.8 (0.28–2.29)	1	13.66 (7.26–26.01)	1	2.09 (0.91–4.82)
2	4.27 (1.87–9.75)	2	1.02 (0.41–2.57)	2	0.71 (0.25–2.01)	2	4.14 (2.07–8.29)	2	0.72 (0.27–1.88)
3	2.19 (0.99–4.88)	3	1.08 (0.44–2.64)	3	0.36 (0.13–1.03)	3	3.24 (1.59–6.61)	3	0.24 (0.08–0.73)
4	1.03 (0.46–2.32)	4	1.24 (0.58–2.67)	4	0.83 (0.37–1.88)	4	7.72 (4.41–13.6)	4	0.05 (0.01–0.22)
5	1.07 (0.52–2.2)	5	0.8 (0.37–1.71)	5	1.33 (0.67–2.63)	5	13.06 (8.07–21.18)	5	0.03 (0.01–0.14)
6	1.05 (0.49–2.28)	6	1.75 (0.86–3.56)	6	2.46 (1.27–4.79)	6	33.98 (20.31–59.01)	6	0.09 (0.03–0.29)
7	1.95 (0.97–3.96)	7	2.4 (1.24–4.65)	7	5.78 (3.21–10.58)	7	71.08 (42.05–127.49)	7	0.25 (0.1–0.66)
8	3.6 (1.86–7.03)	8	9.43 (5.25–17.34)	8	32.49 (18.97–57.43)	8	168.93 (100.11–305.35)	8	0.23 (0.09–0.6)
9	7.22 (4.26–12.28)	9	16.91 (9.8–29.95)	9	82.72 (51.84–137.08)	9	182.93 (113.77–308.54)	9	0.34 (0.14–0.83)
10	5.03 (2.89–8.79)	10	32.63 (20.36–53.22)	10	105.85 (68–169.53)	10	168.26 (107–274.09)	10	0.53 (0.24–1.18)
11	4.59 (2.43–8.73)	11	21.52 (12.62–37.34)	11	45.93 (28.52–75.77)	11	96.62 (62.55–150.65)	11	0.29 (0.11–0.77)
12	0.8 (0.3–2.14)	12	3.6 (1.63–8)	12	9.73 (5.26–18.01)	12	14.75 (8.02–27.53)	12	0.23 (0.07–0.76)

Table 3
Temporal risk of DF incidence in Yunnan Province from 2006 to 2020.

2006	*RR*	2007	*RR*	2008	*RR*	2009	*RR*	2010	*RR*
1	0.43 (0.1–1.84)	1	2.23 (0.76–6.51)	1	0.41 (0.09–1.95)	1	0.2 (0.03–1.12)	1	0.26 (0.05–c1.2)
2	0.11 (0.02–0.59)	2	3.31 (1.23–8.78)	2	0.26 (0.05–1.31)	2	0.13 (0.02–0.8)	2	0.1 (0.02–0.59)
3	0.14 (0.03–0.71)	3	1.2 (0.4–3.63)	3	0.24 (0.05–1.16)	3	0.11 (0.02–0.67)	3	0.08 (0.01–0.46)
4	0.13 (0.02–0.71)	4	1.6 (0.55–4.57)	4	0.14 (0.03–0.72)	4	0.21 (0.05–0.96)	4	0.07 (0.01–0.42)
5	0.18 (0.04–0.83)	5	0.97 (0.33–2.88)	5	0.11 (0.02–0.59)	5	0.55 (0.18–1.73)	5	0.09 (0.02–0.46)
6	0.25 (0.06–1.07)	6	0.38 (0.11–1.34)	6	0.23 (0.05–0.92)	6	0.49 (0.16–1.55)	6	0.17 (0.04–0.67)
7	0.15 (0.04–0.58)	7	0.2 (0.05–0.8)	7	0.31 (0.09–1.09)	7	0.47 (0.15–1.5)	7	0.66 (0.23–1.91)
8	0.14 (0.04–0.53)	8	0.08 (0.02–0.39)	8	1.46 (0.6–3.56)	8	0.38 (0.12–1.19)	8	1.04 (0.41–2.66)
9	0.26 (0.07–0.91)	9	0.1 (0.02–0.46)	9	5.3 (2.62–10.74)	9	0.35 (0.11–1.13)	9	1.48 (0.62–3.54)
10	0.76 (0.26–2.27)	10	0.25 (0.07–0.94)	10	4.67 (2.22–9.82)	10	1.07 (0.37–3.05)	10	1.38 (0.55–3.52)
11	0.98 (0.3–3.19)	11	0.64 (0.18–2.27)	11	1.06 (0.35–3.22)	11	1.11 (0.37–3.39)	11	0.73 (0.22–2.45)
12	3.75 (1.3–10.75)	12	0.4 (0.09–1.79)	12	0.36 (0.08–1.67)	12	0.53 (0.14–2.03)	12	0.16 (0.03–0.82)

Table 3
(Continued) Temporal risk of DF incidence in Yunnan Province from 2006 to 2020.

2011	*RR*	2012	*RR*	2013	*RR*	2014	*RR*	2015	*RR*
1	0.14 (0.02–0.8)	1	0.45 (0.11–1.8)	1	0.7 (0.2–2.46)	1	0.78 (0.22–2.82)	1	0.79 (0.22–2.73)
2	0.16 (0.03–0.89)	2	0.83 (0.24–2.84)	2	0.45 (0.12–1.69)	2	0.73 (0.21–2.55)	2	0.84 (0.24–2.96)
3	0.26 (0.06–1.15)	3	0.35 (0.09–1.36)	3	0.32 (0.08–1.27)	3	0.39 (0.1–1.56)	3	0.43 (0.11–1.65)
4	0.28 (0.07–1.14)	4	0.15 (0.03–0.7)	4	0.2 (0.05–0.84)	4	0.64 (0.19–2.12)	4	0.47 (0.13–1.69)
5	0.62 (0.2–1.94)	5	0.09 (0.02–0.46)	5	0.22 (0.06–0.82)	5	0.71 (0.23–2.16)	5	0.63 (0.19–2.04)
6	0.64 (0.22–1.87)	6	0.09 (0.02–0.4)	6	0.42 (0.14–1.26)	6	0.43 (0.13–1.36)	6	1.44 (0.57–3.64)
7	0.55 (0.19–1.66)	7	0.15 (0.04–0.52)	7	0.94 (0.37–2.4)	7	0.87 (0.32–2.34)	7	4.36 (2.13–8.96)
8	0.27 (0.08–0.89)	8	0.19 (0.06–0.67)	8	3.5 (1.73–7.09)	8	1.15 (0.48–2.77)	8	5.94 (3.07–11.52)
9	0.28 (0.09–0.95)	9	0.49 (0.18–1.38)	9	9.23 (4.96–17.22)	9	1.79 (0.79–4.06)	9	9.42 (5.12–17.33)
10	0.18 (0.04–0.75)	10	0.79 (0.28–2.24)	10	8.35 (4.28–16.33)	10	8.12 (4.02–16.47)	10	30.15 (17.64–51.58)
11	0.16 (0.03–0.76)	11	1.03 (0.35–3.07)	11	5.19 (2.3–11.78)	11	6.8 (3.08–15.1)	11	20.41 (10.88–38.46)
12	0.22 (0.04–1.05)	12	1.26 (0.42–3.76)	12	1 (0.29–3.4)	12	2.09 (0.74–5.98)	12	6.61 (2.75–16.01)
2016	*RR*	2017	*RR*	2018	*RR*	2019	*RR*	2020	*RR*
1	2.35 (0.81–6.87)	1	1.12 (0.36–3.49)	1	3.75 (1.49–9.48)	1	9.94 (4.56–21.85)	1	3.4 (1.32–8.76)
2	1.89 (0.66–5.42)	2	0.99 (0.3–3.3)	2	1.04 (0.31–3.39)	2	3.76 (1.51–9.4)	2	0.78 (0.23–2.6)
3	0.71 (0.21–2.34)	3	1.35 (0.47–3.95)	3	0.59 (0.17–2.04)	3	3.46 (1.38–8.65)	3	0.4 (0.1–1.58)
4	0.55 (0.16–1.91)	4	2.16 (0.85–5.49)	4	0.44 (0.12–1.55)	4	6.94 (3.16–15.25)	4	0.16 (0.04–0.73)
5	0.5 (0.16–1.58)	5	1.32 (0.47–3.62)	5	0.89 (0.33–2.4)	5	24.91 (13.04–47.77)	5	0.12 (0.02–0.55)
6	0.82 (0.31–2.2)	6	3.53 (1.7–7.37)	6	2.93 (1.36–6.3)	6	24.85 (13.59–45.45)	6	0.14 (0.03–0.55)
7	0.74 (0.27–1.98)	7	7.17 (3.84–13.43)	7	4.27 (2.1–8.72)	7	20.11 (11.34–35.71)	7	0.35 (0.12–1.01)
8	1.21 (0.53–2.77)	8	13.25 (7.53–23.38)	8	5.2 (2.74–9.89)	8	31.46 (18.66–53.07)	8	0.41 (0.16–1.04)
9	2.99 (1.47–6.08)	9	25.12 (14.86–42.51)	9	8.87 (4.86–16.2)	9	82.76 (51.15–133.7)	9	0.45 (0.17–1.19)
10	7.41 (3.85–14.31)	10	37.1 (22.28–61.82)	10	12.44 (6.73–23.06)	10	225.43 (142.2–357.12)	10	1.06 (0.41–2.7)
11	9.34 (4.49–19.49)	11	57.46 (33–100.5)	11	32.65 (17.24–62.2)	11	189.8 (114.57–316.32)	11	1.29 (0.49–3.4)
12	2.75 (1.06–7.17)	12	22.59 (11.13–46.16)	12	11.2 (5.26–23.99)	12	24.1 (11.82–49.5)	12	0.31 (0.08–1.16)

areas. Mosquitoes typically breed in small containers, which can be filled with water either manually or by precipitation. Furthermore, heavy precipitation may even destroy existing breeding sites. Guangdong Province is a highly urbanized area, where the drainage system is in good condition. In addition, some studies indicated the relationship between precipitation and DF affected by precipitation patterns.(34) This may be the reason why precipitation exerts a limited effect on the breeding and survival of the vector mosquitoes and the transmission of DF. The meteorological conditions in the two provinces are suitable for the breeding and activity of mosquitoes, which is an important reason for the rapid and extensive spread of DF. Rising temperatures can increase the potential prevalence of DF. It is anticipated that global climate change will have a significant impact on the spatial and temporal distributions of DF in the future.

Green areas (e.g., urban parks and gardens) in metropolitan regions can regulate microclimatic conditions and provide ideal conditions for the activity and egg-laying of mosquitoes.(35–37) Moreover, cool green areas may increase the probability of contact between citizens and mosquitoes in summer, thereby increasing the risk of DF epidemics. However, the existing research studies have found a mixture of positive, negative, and nonlinear relationships between the vegetation coverage and the DF risk.(7) Our results indicated that vegetation coverage can significantly affect the DF transmission, but the nonlinear relationships between *NDVI* and DF are very diverse and complex. One possible explanation for this is that puddles or overgrown vegetation may increase the number of mosquito breeding sites and thus increase the risk of DF transmission if urban green space management is poor. Consequently, vegetation should not be ignored when proposing management strategies to reduce the risk of DF.

The results of this study are consistent with those of previous studies,(38,39) indicating that urbanization is an important factor in DF transmission. The incidence of DF was found to be positively correlated with the level of urbanization at the county level. Rapid urban development is associated with an increase in the proportion of impervious surfaces. This may increase the risk of DF transmission directly or indirectly. The expansion of impervious surfaces impairs the ability of water to infiltrate(40) and increase the number of potential breeding sites for mosquitoes. In addition, there is a significant positive correlation between the proportion of impervious surfaces and land surface temperature, which is known as the urban heat island effect.(21) The warmer environment may favor the survival and reproduction of mosquitoes, thereby accelerating the incidence of DF. In addition, population density is an important risk factor.(41) The population is relatively clustered in highly urbanized regions. The result of this study indicated that the population density is a significant contributing factor to the DF prevalence in Guangdong Province. In Guangdong and Yunnan Provinces, there are mass migration movements owing to their geographical locations. This condition provides a reasonable explanation for the relatively severe epidemic observed in these regions. Infected individuals were the fixed sources of pathogens. Local mosquitoes acquired the virus by feeding on the blood of infected individuals. Subsequently, mosquitoes infected with the dengue virus facilitate further spread of DF. The NTL was positively associated with the incidence of DF in Guangdong and Yunnan Provinces. This suggests that rapid urbanization can facilitate the transmission of DF. This is due to the fact that large populations reside in the rural-urban fringe, which is a common phenomenon in the process of rapid urbanization. The poor quality of housing conditions provides an attractive environment for mosquitoes.(42)

The county-level risk map of DF in this study showed that there were strong spatial clustering patterns of DF risk assessment in Guangdong and Yunnan Provinces. The DF cases in these two provinces are mainly clustered in the southwestern border of Yunnan and the Pearl River Delta region of Guangdong. According to the findings of this study, more dengue control resources should be placed in the Pearl River Delta of Guangdong and the southwestern border of Yunnan in the future. A clear seasonal pattern was observed in the incidence of DF in Guangdong and Yunnan Provinces. The highest risk was usually observed in summer and autumn.

There is a significant difference between Guangdong and Yunnan Provinces in terms of risk factors for DF incidence. In fact, there are large differences in urbanization level, attitude, human activities, and so forth. In addition, Guangdong Province has implemented some control measures (e.g., water retention and mosquito prevention) that can effectively reduce the risk of DF epidemics. This may be the reason for the differences.

5. Conclusions

DF is one of the most significant public health concerns. In this study, we not only identified the relationships between the risk factors and DF, but also provided valuable insights into the spatiotemporal distribution characteristics of DF. The findings suggest that the transmission of DF is affected by a combination of temperature, precipitation, vegetation cover, land cover, population density, and NTL. Specifically, the elevated temperature and precipitation facilitate the transmission of DF. However, there are some differences; for example, the incidence of DF will decrease when the temperature exceeds 27.6 °C in Guangdong Province. In Yunnan Province, the relationship between temperature and the incidence of DF was found to be positively correlated. In Guangdong Province, precipitation was found to have no significant impact on the incidence of DF. In Yunnan Province, the increase in the amount of precipitation can result in an increase in the risk of DF epidemics. Among these factors, vegetation cover can significantly affect the DF transmission in the two provinces, but the nonlinear relationships between *NDVI* and DF are diverse and complex. The relationship between the level of urbanization and the incidence of DF was found to be positively correlated. The counties identified as being at high risk are situated primarily in the central region of Guangdong and in the southwestern border area of Yunnan. The incidences of DF were predominantly observed during the months of July, August, September, and October. This information is crucial for governments to develop effective strategies to mitigate the impact of DF at the county level. By identifying the differences in specific risk factors and spatiotemporal transmission patterns among different counties, policymakers can target epidemic prevention and control measures. This targeted approach will ultimately lead to a more efficient allocation of resources and better outcomes in the process of disease prevention and control. In addition, in this study, we employed high-resolution remote sensing image data, which is a synthesis of geographic information and health statistics. The utilization of remote sensing data in this study has demonstrated considerable potential for application in the field of health.

However, some limitations should be taken into account when interpreting our results. First, our models were fitted without a careful analysis of the lagged temporal effect between DF and its risk factors. Second, the absence of more important potential factors, such as mosquito density, vegetation type, population immunity, and the effect of imported cases, may confound relationships between the covariates and DF. In addition, the data of influencing factors come from various remote sensing images. During the data processing stage, errors may occur at the machine or manual level, potentially leading to the partial distortion of the data. More accurate data should be employed in further study of the dengue epidemic.

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