Spatiotemporal Distribution Characteristics and Influencing Factors of Dengue Fever in China, 2004-2023

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Abstract

Background Dengue fever is one of the vector-borne infectious diseases with a rapidly increasing incidence among mosquito-borne diseases in China, and its epidemic range has rapidly spread to northern regions in recent years. Objective To analyze the disease burden, spatiotemporal distribution characteristics, and influencing factors of dengue fever in China from 2004 to 2023. Methods Data from the 2025 Global Burden of Disease (GBD) database, the China Public Health Science Data Center, the China Health Statistics Yearbook, National Data, and the Weather Post-Report Network database were used to analyze the estimated annual percentage change (EAPC) in dengue fever incidence and mortality in China. The temporal and geographical distribution and epidemic trends of dengue fever incidence were descriptively analyzed. Finally, after multicollinearity and spatial autocorrelation tests, a geographically and temporally weighted regression (GTWR) model was used to conduct a provincial-level analysis of regional heterogeneity in combination with influencing factors from four dimensions—economy, transportation, health care, and nature—from 2018 to 2020. Results From 2004 to 2023, the age-standardized incidence rate of dengue fever in China showed an upward trend (EAPC=5.51), while the age-standardized mortality rate showed a downward trend (EAPC=-5.16). The incidence of dengue fever in most provinces and municipalities in China showed an upward trend from 2004 to 2020, with the peak incidence occurring in September. The GTWR model constructed based on dengue fever incidence data in China from 2018 to 2020 had R2=0.739, Adjusted R2=0.719, and AICc=340.492, indicating that it could well explain the effects of independent variables on dengue fever incidence. The spatiotemporal distribution maps of the fitted coefficients for each variable showed that per capita disposable income of all residents (yuan) and passenger turnover (100 million person-kilometers) were negatively correlated with dengue fever incidence in all provinces and municipalities; international tourist arrivals (million person-times) and average temperature were positively correlated with dengue fever incidence in all provinces and municipalities; the number of health technicians per 1,000 population was positively correlated with dengue fever incidence only in economically developed eastern provinces; and average precipitation (mm) was mainly positively correlated with dengue fever incidence north of the Qinling-Huaihe Line in China, but mainly negatively correlated with dengue fever incidence south of the Qinling-Huaihe Line. Conclusion The incidence of dengue fever in most provinces and municipalities in China showed an upward trend from 2004 to 2020, with the peak incidence occurring in September. Per capita disposable income of all residents (yuan), passenger turnover (100 million person-kilometers), international tourist arrivals (million person-times), the number of health technicians per 1,000 population, average temperature, and average precipitation (mm) all have significant effects on the incidence of dengue fever in China, but strong regional heterogeneity exists. Therefore, targeted prevention and control measures should be formulated according to the specific conditions of each region.

Full Text

Epidemiological Research

Spatiotemporal Distribution Characteristics and Influencing Factors of Dengue Fever in China, 2004–2023

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Abstract Background Dengue fever is one of the vector-borne infectious diseases with the fastest-rising incidence in China, and its epidemic range has rapidly extended northward in recent years. **Objective** To analyze the disease burden, spatiotemporal distribution characteristics, and influencing factors of dengue fever in China from 2004 to 2023. **Methods** Data from the 2025 Global Burden of Disease (GBD) database, the Chinese Public Health Science Data Center, the *China Health Statistics Yearbook*, national statistical data, and meteorological-report network databases were used to analyze changes in the estimated annual percentage change (EAPC) of dengue morbidity and mortality in China. Descriptive analysis was performed to characterize the temporal and regional distribution and epidemic trends of dengue incidence. Finally, after tests for multicollinearity and spatial autocorrelation, a geographically and temporally weighted regression (GTWR) model was used to conduct provincial-level regional heterogeneity analysis of influencing factors across four dimensions—economy, transportation, medical and health services, and nature—for 2018–2020. **Results** From 2004 to 2023, the age-standardized incidence rate of dengue fever in China showed an upward trend (EAPC=5.51), while the age-standardized mortality rate showed a downward trend (EAPC=-5.16). In most provinces and municipalities in China, dengue incidence increased during 2004–2020, with the incidence peak occurring in September. The GTWR model constructed based on dengue incidence data in China from 2018 to 2020 had $R^2 = 0.739$, Adjusted $R^2 = 0.719$, and AICc=340.492, indicating that it could explain relatively well the effects of the independent variables on dengue incidence. Spatiotemporal distribution maps of the fitted coefficients for each variable showed that per capita disposable income of all residents (yuan) and passenger turnover (100 million person-kilometers) were negatively correlated with dengue incidence in all provinces and municipalities; the number of inbound international tourists received (million person-times) and average temperature were positively correlated with dengue incidence in all provinces and municipalities; the number of health technicians per 1 000 population was positively correlated with dengue incidence only in economically developed eastern provinces; and average precipitation (mm) was mainly positively correlated with dengue incidence north of the Qinling–Huaihe line in China, but mainly negatively correlated south of the Qinling–Huaihe line. **Conclusion** Dengue incidence in most provinces and municipalities in China increased during 2004–2020, with the incidence peak occurring in September. Per capita disposable income of all residents (yuan), passenger turnover (100 million person-kilometers), the number of inbound international tourists received (million person-times), the number of health technicians per 1 000 population, average temperature, and average precipitation (mm) all had significant effects on dengue incidence in China, but showed strong regional heterogeneity. Therefore, targeted prevention and control measures should be formulated according to local conditions.

[**Keywords**] Dengue fever; Incidence; Estimated annual percentage change; Spatiotemporal analysis; Geographically and temporally weighted regression; Influencing factors

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Spatiotemporal Patterns and Determinants of Dengue in China during 2004–2023

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Abstract Background Dengue is the fastest-rising mosquito-borne disease in China, with its prevalence rapidly

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expanding northward in recent years. **Objective** To analyze the disease burden, spatiotemporal patterns, and determinants of dengue in China from 2004 to 2023. **Methods** Data from the Global Burden of Disease Study 2024, the Chinese Public Health Science Data Center, the *China Health Statistics Yearbook*, National Statistics, and weather databases were used. The estimated annual percentage change (EAPC) in incidence and mortality was calculated. Spatiotemporal distributions and trends were described. After addressing multicollinearity and spatial autocorrelation, a geographically and temporally weighted regression (GTWR) model was applied to assess the heterogeneous effects of economic, transportation, healthcare, and natural factors (2018–2020). **Results** From 2004 to 2023, the age-standardized incidence rate increased (EAPC=5.51), whereas age-standardized mortality declined (EAPC=−5.16). The dengue incidence rate rose nationwide and peaked in September. The GTWR model demonstrated strong explanatory power (R^2=0.739, adjusted R^2=0.719, AICc=340.492). Based on the spatiotemporal distribution of fitted coefficients, per capita disposable income and passenger turnover were negatively correlated with dengue incidence across provinces. International tourist arrivals and average temperature showed positive correlations nationwide. The number of health personnel per 1,000 population was positively correlated only in developed eastern provinces. Average precipitation was positively correlated north of the Qinling–Huaihe Line but negatively correlated south of it. **Conclusion** The incidence of dengue in most provinces and municipalities in China increased from 2004 to 2020, with the disease peaking in September. These determinants significantly influence dengue transmission but exhibit marked spatial heterogeneity, necessitating region-specific prevention and control measures.

【Key words】 Dengue; Incidence; Estimated annual percentage change; Spatiotemporal analysis; Geographically and temporally weighted regression; Influencing factors

Dengue is an acute vector-borne infectious disease transmitted mainly by *Aedes* mosquitoes (*Aedes aegypti* or *Aedes albopictus*). Its pathogen is dengue virus, and its main epidemic season is the rainy season in summer and autumn; it is prevalent primarily in urban and suburban areas. According to the WHO report *Dengue—Global Situation (2024-05-30)*, as of 2024-04-30, more than 7.6 million dengue cases had been reported worldwide, including 16,000 severe cases and more than 3,000 deaths, showing a sharp upward trend for five consecutive years. The current dengue epidemic is most severe in the Americas and Southeast Asia[1]. Moreover, because testing and reporting mechanisms remain incomplete in many endemic countries, the disease burden caused by dengue is underestimated. The incidence of dengue in China has been increasing year by year; however, because natural climate and economic conditions vary greatly among provinces, it has very strong spatiotemporal distribution specificity[2]. Dengue has four serotypes (DENV-1, DENV-2, DENV-3, DENV-4), all of which have the capacity for vertical transmission to offspring. Infection with one serotype confers long-term immunity only to that serotype; once secondary infection with another dengue virus serotype occurs, the risk of severe dengue is significantly increased. At present, however, there is still no specific treatment[3]. Previous studies have shown that the epidemiology of dengue is influenced by local population characteristics, socioeconomic conditions[4], and the natural environment[5]. Therefore, this study intends to extract relevant data from the 2025 Global Burden of Disease (GBD) database, the Chinese Public Health Science Data Center, the *China Health Statistics Yearbook* 2022, National Data, and the Weather Post-Report Network for multidimensional analysis, in order to clarify the spatiotemporal distribution characteristics of dengue in China and the contributions of various influencing factors, thereby providing data support for formulating more precise prevention and control policies.

1 Data and Methods

1.1 Data and Data Sources

Through the Global Health Data Exchange query tool (GHDx) (http://ghdx.healthdata.org), annual data for overall dengue cases, age-standardized incidence rate, deaths, and age-standardized mortality rate in China from 2004 to 2023 were obtained. Age standardization refers to a method of processing demographic data according to the same standard age structure[6]. Data on dengue cases and incidence rates (i.e., crude incidence rates) in Chinese provinces from 2004 to 2020 (excluding Hong Kong, Macao, and Taiwan) were obtained from the Chinese Public Health Science Data Center (https://www.phsciencedata.cn/Share/). Data on beds in medical and health institutions per 1,000 population and health technicians per 1,000 population were obtained from the *China Health Statistics Yearbook* 2022[7]. Data on per capita GDP (yuan), per capita disposable income of all residents (yuan), passenger turnover (100 million person-kilometers), and international tourist arrivals received (million person-times) were obtained from National Data (https://data.stats.gov.cn/index.htm). Data on average precipitation (mm) and average temperature (℃) were obtained from the Weather Post-Report Network (http://tianqihoubao.com/). All data in this study were derived from public databases; therefore, ethics review was not applicable.

1.2 Study Methods

1.2.1 Descriptive Statistical Analysis Based on dengue data for China from 2004 to 2023 in the GHDx database, the percentage change in the number of cases, uncertainty intervals (UIs) (defined as the 2.5th and 97.5th percentiles of the posterior distribution), and the estimated annual percentage change (EAPC) (used to measure trends in the age-standardized incidence rate and age-standardized mortality rate over a specified time interval)[8] were used to describe dengue incidence and mortality indicators, and data visualization was performed for the spatiotemporal epidemic trends in incidence.

1.2.2 Correlation Analysis Considering that completeness in the number of reporting years differed among provinces, to ensure the robustness of trend analysis, for provinces with a number of reporting years $ $10, the data formed time series of a certain length; therefore, the Mann–Kendall test, which is specifically used for detecting trends in time series, was adopted[9]. For the

For provinces with fewer than 10 reporting years, the data points were relatively few and possibly discontinuous, and were more similar to independent observations. Therefore, Spearman rank correlation, which has more relaxed sample-size requirements and a broader range of applicability, was used to analyze the correlation between incidence and year.

1.2.3 Multicollinearity This was used to analyze the correlations among the independent variables intended for inclusion in the model. When the variance inflation factor (VIF) was between 0 and 10, it was considered that there was no high collinearity between that independent variable and the other independent variables, and it could be included in the model. Conversely, when VIF > 10, it was considered that there might be a high degree of collinearity between that independent variable and the other independent variables, and it was removed from the model.

1.2.4 Spatial autocorrelation analysis Based on dengue data for provinces and municipalities in China from 2004 to 2020 obtained from the Chinese Center for Disease Control and Prevention’ s Public Health Science Data Center, the spatial distribution characteristics of dengue in China were analyzed. A distance-based spatial weight (K-nearest-neighbor) matrix was established. The results of global autocorrelation were used to evaluate spatial clustering and were expressed using Moran’s I index, with a value range of -1 to 1. When Moran’s I $>$ 0, stronger spatial correlation is indicated; when Moran’ s I < 0, greater spatial heterogeneity is indicated; and when Moran’ s I $= 0$, the spatial distribution is random

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1.2.5 Geographically and temporally weighted regression (GTWR) model analysis On the basis of the geographically weighted regression (GWR) model, the influence of temporal changes on the relationship between the independent variables and the dependent variable was considered. The GTWR model, proposed by HUANG et al.

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to explain spatiotemporal variation in the spatial dependence between independent and dependent variables, is a type of spatial local regression analysis. It can detect nonstationarity in the data across space and time, thereby avoiding the masking of interregional differences by global analysis results.

In this study, the spatial matrix was determined using leave-one-out cross-validation (CV), a Gaussian kernel function, and Euclidean distance. Specifically, the grid-search method was used to traverse the parameter space of the preset bandwidth, and then, for each candidate bandwidth combination, the corresponding cross-validation (CV) error was calculated. The bandwidth group that minimized the CV error was ultimately selected as the optimal parameter to ensure optimal smoothing of the model in the spatiotemporal dimension. In terms of model-performance evaluation, corrected Akaike information criterion (AICc) and R^2 were used for assessment. A smaller AICc value and a larger R^2 indicated stronger explanatory power of the independent variables for the dependent variable.

The natural breaks method was used to group data with relatively high similarity, with “0” set as the interval value to distinguish positive and negative coefficients. When the fitted coefficient was positive, it indicated that the independent variable had a promoting effect on the dependent variable; when the fitted coefficient was negative, it indicated that the independent variable had an inhibitory effect on the dependent variable. Moreover, the greater the absolute value of the fitted coefficient, the greater the magnitude of the effect.

1.3 Statistical analysis

Excel 2024 was used to establish a spatiotemporal distribution database of dengue, R 4.2.0 was used for descriptive statistics, correlation analysis, and multicollinearity analysis, and ArcMap 10.8 was used for spatial autocorrelation, spatial regression analysis, and map visualization. The spatiotemporal distribution maps of the fitted coefficients of each variable were drawn according to the average regression coefficients of each province from 2018 to 2020. The test level was $\alpha = 0.05$, and $P < 0.05$ was considered statistically significant.

2 Results

2.1 Trends in dengue incidence, death, and disease burden in China from 2004 to 2023

In 2023, the number of dengue cases and the age-standardized incidence rate in China were 2,800 cases (95% UI = 1,735-4,231) and 0.21 per 100,000 (95% UI = 0.13-0.31 per 100,000), respectively; the number of deaths and the age-standardized mortality rate were 8 cases (95% UI = 4-15) and 0 per 100,000 (95% UI = 0.00-0.00), respectively. From 2004 to 2023, the age-standardized incidence rate of dengue in China showed an upward trend, with an EAPC of 5.51% (95% CI = 1.53%-9.64%); the age-standardized mortality rate showed a downward trend, with an EAPC of −5.16% (95% CI = −5.92% to −4.40%) (Table 1).

2.2 Spatiotemporal distribution of dengue incidence in China from 2004 to 2020

From 2004 to 2020, dengue incidence in China showed clear seasonality, with the peak incidence occurring from July to November and reaching its maximum in September (Figure 1). Further analysis of incidence rates by province and municipality showed that the provinces with relatively high annual average incidence rates were, in order, Guangdong Province (3.497 per 100,000), Yunnan Province (1.745 per 100,000), Fujian Province (0.540 per 100,000), and Jiangxi Province (0.451 per 100,000). Those with relatively low incidence rates were, in order, Inner Mongolia Autonomous Region (0.003 per 100,000), Xinjiang Uygur Autonomous Region (0.003 per 100,000), Shanxi Province (0.009 per 100,000), and Heilongjiang Province (0.009 per 100,000) (Tibet Autonomous Region was not included because no data were reported) (Figure 2). Because the number of reports from Inner Mongolia Autonomous Region, Xinjiang Uygur Autonomous Region, Qinghai Province, Shanxi Province, Jilin Province, Gansu Province, Tianjin Municipality, Ningxia, and Guizhou Province was fewer than 10, Spearman rank correlation was used; for other provinces, the Mann-Kendall trend test was used. The results showed that the incidence rates in Liaoning Province, Jiangsu Province, Zhejiang Province, Anhui Province, Fujian Province, Jiangxi Province, Shandong Province, Hubei Province, Guangdong Province, Sichuan Province, Yunnan Province, Shaanxi Province, Guangxi Zhuang Autonomous

Region, Beijing Municipality, Shanghai Municipality, and Chongqing Municipality showed upward trends over time (all $P < 0.05$).

Table 1. Disease burden and trends of dengue in China, 2004-2023

Year	Incidence status (95% UI): cases (cases)	Incidence status (95% UI): age-standardized rate (1/10^5)	Death status (95% UI): deaths (cases)	Death status (95% UI): age-standardized rate (1/10^5)
2004	1,399 (927-1,930)	0.11 (0.08-0.15)	19 (13-29)	0.00 (0.00-0.00)a
2023	2,800 (1,735-4,231)	0.21 (0.13-0.31)	8 (4-15)	0.00 (0.00-0.00)a
EAPC (95% CI)		5.51 (1.53-9.64)		−5.16 (−5.92-−4.40)

Note: a indicates that the data are too small, but not 0.

Note: A represents 2004-2007, B represents 2008-2011, C represents 2012-2015, and D represents 2016-2020.

Figure 1 Temporal distribution of dengue cases by province in China, 2004-2020

Figure 2 Incidence rate of dengue by province in China, 2004-2020

2.3 Spatial distribution characteristics and influencing factors of dengue fever in China

A global spatial autocorrelation analysis was performed on dengue incidence data for each province in China from 2004 to 2020. The results showed that, except for 2006, 2009, 2012, 2014, and 2017, when the spatial pattern was randomly distributed, all other years exhibited clustering (all Moran' s $I > 0$, $P > 0.05$); see Table 2. When constructing the GTWR model, a total of 8 variables were included, covering four dimensions: economic, transportation, medical and health, and natural factors. After excluding two variables with strong collinearity—number of beds in medical and health institutions per 1 000 population and per capita GDP (yuan) (both VIF>10)—the model was constructed using the number of health technicians per 1 000 population, per capita disposable income of all residents (yuan), passenger turnover (100 million person-kilometers), number of international tourists received (million person-times), average precipitation (mm), and average temperature (°C). First, incidence rates from 2004 to 2020 were selected for modeling. The results showed $R^2 = 0.176$, adjusted $R^2 = 0.167$, and AICc=2189.671, indicating poor goodness of fit. Incidence data from 2015 to 2020 were then selected as far as possible for modeling. The results showed $R^2 = 0.505$, adjusted $R^2 = 0.489$, and AICc=597.962, also indicating poor goodness of fit. This was considered to be due to missing data in some years and random spatial distribution. Therefore, based on comprehensive consideration of the spatial clustering of dengue incidence in each year, data continuity, and timeliness, incidence data from 2018 to 2020 were used to construct the regression model. The results showed $R^2 = 0.739$, adjusted $R^2 = 0.719$, and AICc=340.492, indicating that the model had relatively high goodness of fit. Furthermore, spatiotemporal distribution maps were drawn based on the mean regression coefficients of each independent variable (excluding data from Hong Kong, Macao, and Taiwan, and the unreported Xinjiang and Xi

hidden data), the results show that the fitted coefficients for per capita disposable income of all residents (yuan) and passenger turnover (100 million person-kilometers) were negative across all provinces and municipalities, while the fitted coefficients for international tourist arrivals (million person-times) and mean temperature were positive across all provinces and municipalities. For the number of health technicians per 1,000 population, the fitted coefficients were positive in most economically developed eastern provinces of China, whereas they were negative in the remaining provinces. For mean precipitation (mm), the fitted coefficients were mainly positive north of the Qinling–Huaihe Line and mainly negative south of the Qinling–Huaihe Line; see Figure 3.

Table 2 Global autocorrelation analysis of Dengue incidence in China, 2004–2020

Year	Moran' s I	Z value	P value	Spatial clustering (Yes/No)
2004	0.176	3.114	0.011	Yes
2005	0.161	2.764	0.018	Yes
2006	−0.022	0.504	0.302	No
2007	0.050	2.297	0.028	Yes
2008	0.143	3.096	0.009	Yes
2009	−0.010	0.827	0.204	No
2010	0.051	2.968	0.005	Yes
2011	0.132	3.740	0.004	Yes
2012	−0.002	1.692	0.052	No
2013	0.086	2.336	0.042	Yes
2014	−0.017	0.896	0.232	No
2015	0.107	2.326	0.042	Yes
2016	0.116	2.537	0.023	Yes
2017	0.048	1.260	0.107	No
2018	0.054	2.658	0.020	Yes
2019	0.236	4.223	0.002	Yes
2020	0.155	3.345	0.002	Yes

3 Discussion

To use relatively comprehensive data as much as possible to characterize the overall dengue burden in China, this study selected dengue data for China from the GHDx database for 2004-2023 to analyze trends in disease burden; selected dengue data for provinces and municipalities in China from the China Public Health Science Data Center for 2004-2020 to analyze spatiotemporal distributions at the overall and provincial scales; and, finally, at the stage of constructing the GTWR model, after analyzing the sensitivity of data from different time windows, selected data from 2018-2020 for modeling by considering the spatial clustering of dengue incidence in each year, data continuity, and timeliness.

The occurrence of dengue fever is closely related to natural, economic, transportation, medical and health, and other factors. China has a vast territory, and therefore the epidemic situation of dengue fever varies greatly across regions. However, systematic studies of the effects of comprehensive influencing factors on dengue incidence in each province are still lacking. Accordingly, this study conducted a retrospective

Note: A indicates the spatiotemporal distribution map of the fitted coefficient for per capita disposable income of all residents (yuan); B indicates the spatiotemporal distribution map of the fitted coefficient for the number of health technicians per 1,000 population; C indicates the spatiotemporal distribution map of the fitted coefficient for mean temperature (℃); D indicates the spatiotemporal distribution map of the fitted coefficient for mean precipitation (mm); E indicates the spatiotemporal distribution map of the fitted coefficient for international tourist arrivals (million person-times); and F indicates the spatiotemporal distribution map of the fitted coefficient for passenger turnover (100 million person-kilometers). The maps were produced based on the standard map from the National Platform for Common Geospatial Information Services; map approval number: GS(2020)4621. The boundaries of the base map were not modified.

Figure 3 Spatiotemporal distribution of fitted coefficients for variables in Chinese provinces, 2018-2020.

analysis. The results showed that, overall, the incidence of dengue fever in China showed an upward trend (EAPC = 5.51), consistent with the global trend of dengue cases surging for five consecutive years[11]. However, mortality (EAPC = -5.16) showed a downward trend, which may have benefited from improved capacity for early case identification, advances in the treatment of severe cases, and strengthened public health interventions[12].

Further analysis of the spatiotemporal distribution of dengue fever in China showed that cases were mainly concentrated from July to November, peaking in September. This lagged behind the peak activity period of the vector *Aedes* mosquitoes, which is from June to September. This is because dengue transmission results from complex interactions among virus, vector, host, and environment. As the vector of dengue fever, *Aedes* mosquitoes require about 15 d to develop from egg to emergence, and adult mosquitoes can survive for 1-3 months. Under the influence of high temperature and high humidity from June to August, their density increases markedly. The expansion of local outbreaks requires the process by which the index case gives rise, through the vector, to second- and third-generation cases; therefore, September readily becomes a high-incidence period for dengue fever[13]. This suggests that before the peak incidence period—namely in May and June—efforts should be made to clear *Aedes* breeding sites and conduct baseline investigations of dengue virus carriage, thereby supporting the advancement of dengue prevention and control to earlier stages and facilitating risk assessment. In terms of geographic distribution, dengue incidence in China showed the characteristic of being "higher in the south and lower in the north." A trend test of incidence by year showed that incidence increased in 16 provinces and municipalities. Taking the Qinling Mountains-Huaihe River line as the north-south dividing line of China, Liaoning Province, Shandong Province, Shaanxi Province, and Beijing also showed upward trends. This is consistent with the findings of Zhao Jin et al.[14], indicating that dengue fever in China has already shown a trend of rapid northward spread, and suggesting that northern provinces and municipalities in China should strengthen awareness and measures for dengue prevention and control.

Finally, regional heterogeneity in dengue incidence in China was analyzed. The spatial autocorrelation analysis showed that, except for 2006, 2009, 2012, 2014, and 2017, when the spatial distribution was random, all other years showed clustering, consistent with the results of Yang Huixin et al.[5]. The GTWR model constructed using data from 2018 to 2020 had a relatively high goodness of fit ($R^2 = 0.739$, Adjusted $R^2 = 0.719$, AICc $= 340.492$). Among the variables, per capita disposable income of all residents (yuan) and passenger turnover (100 million person-kilometers) were negatively correlated with dengue incidence across provinces and municipalities, and the strength of this relationship gradually decreased from southwest to northeast. The reason may be that higher economic levels and passenger turnover are associated with better urban infrastructure, health awareness among residents, and prevention and control capacity. Relevant studies have shown that *Aedes* larva-positive water bodies are mostly idle containers, such as bowls, bottles, jars, and cans. Better urban infrastructure often means a more complete waste collection and treatment system, which can significantly reduce the number of *Aedes* breeding sites[15]. Better health awareness helps improve mosquito protection, protects susceptible populations, and has a protective effect in the prevention and control of both imported and local dengue cases[16].

The coefficient for the number of health technicians per 1,000 population crossed zero across different regions of the country, indicating that this indicator has different effects in different provinces. As a key indicator for evaluating local economic development and the level of medical security, an increase in this indicator is conducive to dengue identification and treatment[17]. Therefore, in most provinces of China it was negatively correlated with dengue incidence;

however, in most economically developed eastern provinces of China it was positively correlated with dengue incidence. This is presumed to be related to higher population density and stronger capacity for dengue identification. Relevant studies have shown that the concentration of health resources in China is basically consistent with population density[18]. As interprovincial population mobility has intensified, population density in the southeastern coastal region has become significantly higher than in other regions[19]. Relevant studies have shown that dengue cases are mostly concentrated in urban central areas. Because *Aedes* mosquitoes have limited flight capacity, among dengue cases living within 200 m of each other, 60% originate from the same transmission chain, whereas in areas 1–5 km apart, only 3% of dengue cases originate from the same transmission chain. In other words, population density is significantly associated with the transmission efficiency of dengue outbreaks[20]. In addition, this indicator also reflects the more complete medical and health service systems in economically developed eastern provinces, as well as their stronger capacity for surveillance and identification of dengue cases[21]. There may be a "detection-rate bias," meaning that this indicator carries a triple signal of "protective effect," "population density," and "surveillance intensity." Therefore, all regions of the country should further improve active surveillance and early-warning capacity for dengue fever. In densely populated areas of economically developed eastern provinces, a three-dimensional dengue prevention and control system involving the government, disease control institutions, and the three-tier medical and health system should be further established to prevent large-scale local dengue outbreaks.

The coefficients for international tourist arrivals received (million person-times) were positive across all provinces and municipalities, indicating a positive association with dengue incidence, and the fitted coefficient was the highest among all variables. This is mainly because receiving more international travelers often implies a higher risk of importation. Relevant studies have shown that from 2005 to 2023, there were 14,376 imported dengue cases in China, accounting for 12.54% of all cases; among them, 97.68% came from Southeast Asia, mainly Myanmar, Cambodia, Thailand, the Philippines, and Malaysia. The main destinations of importation were Yunnan Province, Guangdong Province, Fujian Province, and Zhejiang Province, which readily led to local transmission[22]. In addition, the provinces where international tourist arrivals had the greatest effect on dengue incidence were Qinghai Province, Sichuan Province, and Hainan Province, indicating that dengue incidence in these provinces was most sensitive to changes in this variable. This may be because these provinces are popular tourist destinations for international visitors but are not traditional high-incidence provinces for dengue fever, and most cases are imported dengue cases. This suggests that all provinces in China should continue to strengthen health monitoring of inbound travelers from Southeast Asia and other countries with high dengue incidence, improve the ability to identify and diagnose dengue cases, prevent imported cases from causing local outbreaks, and formulate emergency prevention and control plans for imported dengue cases so as to achieve dynamic zero transmission.

The coefficients for average temperature were positive across all provinces and municipalities, indicating a positive correlation with dengue incidence. Relevant studies have shown that north of 30°N, overwintering occurs mainly in the form of eggs; in the boundary areas between subtropical and tropical zones, overwintering occurs as both eggs and larvae; and in tropical regions, *Aedes albopictus* can breed and develop throughout the year[23]. The developmental threshold temperature is 10–11 ℃. Within the range of 16–31 ℃, the larval growth rates of the two *Aedes* species increase as temperature rises[24], and mosquito eggs can overwinter under dry room-temperature conditions while preserving dengue virus[25]. Therefore, for all provinces in China, especially southern regions, cleanup activities should be carried out before temperatures rebound, according to the overwintering mode of *Aedes* mosquitoes: the inner walls or bottoms of water-holding containers should be treated where overwintering occurs as eggs, and warm sheltered places such as air-raid shelters, basements, sewers, and bridge openings should be cleaned where adult mosquitoes overwinter, targeting breeding sites and harborages so as to effectively control *Aedes* density.

Average precipitation was mainly positively correlated with dengue incidence north of the Qinling Mountains–Huaihe River line in China, presumably because rainfall creates outdoor *Aedes* breeding sites.

This increase is related to the fact that, in northern regions with relatively low annual precipitation, residents often use water-storage containers to store water for irrigation, thereby providing oviposition sites for *Aedes* mosquitoes

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. Therefore, increased precipitation in northern regions often promotes the breeding of *Aedes* mosquitoes and thus increases the incidence of dengue fever. This suggests that, once precipitation increases in northern regions, potential *Aedes* breeding sites such as discarded tires, abandoned bottles and cans, and piles of debris should be cleaned up promptly. South of the Qinling–Huaihe line, the main manifestation is a reduction in dengue incidence, which is presumed to be closely related to temperature

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. Nationwide, regions with higher mean annual temperature have air that can hold more water vapor, and therefore also have higher mean annual precipitation. However, within the same region, a decrease in temperature can promote condensation of water vapor in the air and cause rainfall. Thus, a high amount of rainfall in a given year indicates more low-temperature weather compared with other years

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, which is unfavorable for the rapid breeding of *Aedes* mosquitoes

and helps reduce the incidence of dengue fever.

4 Conclusion

Using databases including GHDx, the China Public Health Science Data Center, the *China Health Statistics Yearbook*, National Data, and the Weather Houbao website, this study comprehensively analyzed trends in the burden of dengue fever and its spatiotemporal distribution characteristics. For the first time, a GTWR model was applied to conduct regional heterogeneity analysis by integrating influencing factors from four dimensions—economy, transportation, medical and health services, and nature—thereby constructing a statistical association among "macro-social factors-climatic variables-reported dengue incidence." Compared with the traditional GWR model, the GTWR model incorporates the temporal dimension and forms three-dimensional spatiotemporal coordinates, enabling it to better handle indicators such as dengue fever that are associated with temporal change, explain patterns of dengue incidence varying across time and space in different regions, and provide data support for provinces and municipalities in formulating targeted dengue prevention and control measures. Nevertheless, the study still has the following limitations: (1) because data on dengue pathogens, vector *Aedes* density, and population immunity levels in each province and municipality were unavailable, these factors were not included as variables in the model, which limited interpretation of the dengue pathogenesis mechanism using the classic "source of infection–vector–susceptible population" model. (2) Because the selected indicators had relatively strong collinearity, model stability may have been reduced; therefore, subsequent studies should include datasets covering more years for validation. (3) Dengue fever has strong seasonality, but the data used in this study were annual statistics; future analyses may consider using monthly data. (4) During model construction, constrained by factors such as the cutoff year of the data, the spatial clustering of existing incidence rates, and the continuity and timeliness of the data, only relevant data from 2018 to 2020 were included to build the regression model, which limited the model' s explanatory power regarding the spatiotemporal evolution of dengue fever over the past nearly 20 years. In the next step, dengue incidence data from recent years should continue to be collected to optimize the model parameters.

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Note: Figure translations are in progress. See original paper for figures.