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Assessment of the Impact of Climatic Factors on the Transmission of Dengue Fever in China -- Empirical Analysis Based on National Annual Data and Interpretation of Insignificant Results

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Abstract. Dengue fever outbreaks have occurred repeatedly in China in recent years. This study systematically evaluated the effects of temperature, precipitation and extreme weather on the spread of dengue fever using China's national annual health data and climate reports. Through the construction of a bidirectional fixed-effect model and multiple robustness tests, the empirical analysis found that the impact of climate variables on the incidence of dengue fever in China was not statistically significant at the annual data scale. This "insignificant" result may stem from the smoothing effect of the annual data on seasonal signals, the "buffering" effect of strong public health interventions, and the high collinearity among the variables. The findings suggest that in countries with an effective prevention and control system, it may be difficult to capture the direct link between climate and dengue spread based on macro annual data, and future research will need higher-resolution data and more refined models to reveal the complex mechanism.

Keywords: Dengue fever, Climate factors, Annual data, Macro analysis, Public health interventions

1. Introduction

Dengue fever, one of the world's fastest-spreading mosquito-borne diseases, has become a major challenge in the field of international public health. In the context of climate change, rising global temperatures, changing precipitation patterns and frequent extreme weather events have created new ecological conditions for the breeding of vector mosquitoes and the spread of viruses.

China, as a typical example of the spread of dengue fever from traditional endemic areas to new outbreak areas, shows significant spatiotemporal heterogeneity in its epidemic dynamics. However, existing research on the climate drivers of dengue fever in China has obvious limitations: a focus mostly on single-province or short-term epidemic analysis, the lack of systematic integration of meteorological variables with extreme weather indicators, and insufficient exploration of the spatiotemporal heterogeneity of the association between climate factors and dengue fever.

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This study systematically examines the mechanisms through which temperature, precipitation, and extreme weather events affect dengue incidence at the national scale in China. The study employs multi-year nationwide data, integrating dengue case data with meteorological indicators and constructing statistical models for empirical testing. This research provides a predictive basis for future trends in dengue transmission under the context of climate change.

2. Literature review

A large number of global studies indicate that climate factors, particularly temperature and precipitation, are key environmental variables driving the spatiotemporal dynamics of dengue fever transmission. Temperature directly affects the survival and reproduction cycle of the vector Aedes mosquitoes, the frequency of bites, and the external latency period of the dengue virus in mosquitoes [1,2]. Precipitation impacts are complex; moderate rainfall increases breeding sites, while extreme weather can disrupt local transmission patterns. In addition, extreme weather events such as heat waves and floods have been proven to be important drivers of local outbreaks that can disrupt the original local transmission balance [3]. mathematical models predict that climate change will lead to the expansion of dengue fever transmission areas to higher latitudes and altitudes, exposing more populations to risk [4-6].

In China, research on the association between climate and dengue fever shows a distinct regional variations, particularly from 2020 to 2022, with outbreaks mainly concentrated in southern provinces such as Guangdong and Yunnan. The spatial aggregation was closely related to environmental factors such as temperature and precipitation [7]. At the regional scale,, the study in South China found that the increase in temperature was linked with a higher incidence rate and earlier epidemic onset [8]. An in-depth analysis of Guangdong Province further revealed the non-linear effects of climate influence. There are distinct thresholds for temperature and precipitation that form an inverted "U" relationship, where extreme values hinder transmission peaks [9].

However, existing studies in China have mostly focused on the southern provinces where the epidemic is prevalent, and have mainly used monthly or seasonal data for analysis [10-11]. Climate impact assessments based on annual data remain scarce nationwide, especially in low-prevalence or newly emerging areas.

3. Empirical design

3.1. Research hypotheses

H1: Climate-driven factors

H1a: The average annual temperature is positively correlated with the annual incidence of dengue fever. It is expected that this association will be more likely to be observed in the southern regions where the annual average temperature is higher.

H1b: There is a non-linear association between total annual precipitation and morbidity, and there is an appropriate risk range. Too high or too low annual precipitation may be detrimental to the maintenance of stable mosquito populations by causing floods or droughts respectively.

H1c: The number of extremely hot days in a year and the frequency of heavy precipitation events in a year are positively correlated with the risk of interannual fluctuations in dengue fever. Extreme weather events may drive the peak of the epidemic at the annual level by expanding vector breeding grounds, affecting human exposure behavior, or impacting control systems.

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H2: The statistical association between climate variables (annual temperature, annual precipitation) and annual dengue morbidity will weaken or disappear in regions with strong vector control measures and high public health response capacity.

H3: Using annual data will smooth out key seasonal climate-driven signals of dengue transmission, diluting statistical correlations and making significant results difficult to detect.

3.2. Empirical model design

This study uses a panel data regression model to assess the impact of temperature, precipitation, and extreme weather on the transmission of dengue fever. Given that the occurrence of dengue fever may be interfered by region-specific factors and temporal trends, the model will incorporate region-fixed effects and temporal fixed effects to control for regional characteristics that do not change over time and common temporal shocks. The base model is set as a bidirectional fixed-effect model, which is generally in the form of:

$$Y_{it} = \beta_0 + \beta_1 T_{it} + \beta_2 P_{it} + \beta_3 E_{it} + \gamma X_{it} + \mu_i + \lambda_t + \epsilon_{it} \quad (1)$$

Where represents the Y_{it}it incidence of dengue fever in the region over time; T_{it} And, respectively, represent the core independent variables of temperature, precipitation and extreme weather; $P_{it}E_{it}X_{it}$ It is a set of control variables; μ_i And respectively represent regional fixed effects and time fixed effects; $\lambda_t\epsilon_{it}$ For random error terms. The model allows for estimating the net impact of climate variables on dengue fever while controlling for potential confounding factors.

3.3. Variable settings

The dependent variable is the intensity of dengue transmission, operationalized as the monthly or annual dengue incidence rate in the region, that is, the number of dengue cases per 100,000 people. Case data should cover both clinical diagnoses and laboratory-confirmed cases to ensure the accuracy of the indicator.

Core independent variables include three types of climate indicators. The temperature variable uses average air temperature or cumulative heat units to capture the thermal conditions for mosquito breeding and virus transmission. The precipitation variable uses cumulative precipitation or precipitation days to reflect the water environment required for mosquito breeding. Extreme weather variables are measured by composite indices such as the number of extreme hot days, the frequency of extreme precipitation events, or standardized climate indices, designed to quantify the impact of climate anomalies.

Control variables are used to rule out other factors that could affect the spread of dengue fever. These variables include population density, GDP per capita, healthcare resource density such as the number of doctors per thousand people, and urbanization rate. In addition, considering the lag effect of dengue transmission, the model can introduce a lag term of the climate variable for robustness testing.

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4. Empirical analysis results

4.1. Dengue fever incidence and climate time trend chart

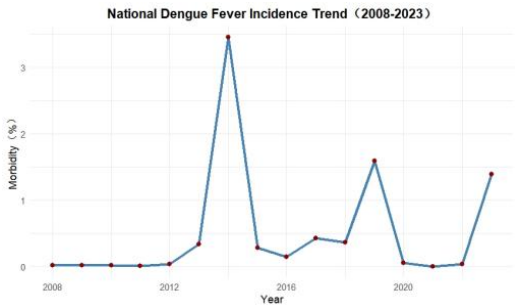


Figure 1. Annual trend chart of dengue fever incidence

Figure 1 depicts the interannual fluctuations in the incidence of dengue fever in China from 2008 to 2023. The overall trend shows that the incidence rate has remained at a low baseline level over the long term (less than 0.5 per 100,000 in most years), but has shown intermittent and irregular outbreak characteristics. The most prominent peak occurred in 2015, when the incidence soared to 3.45 per 100,000, forming the highest point of the study period; There were also more significant increases in 2019 and 2023.

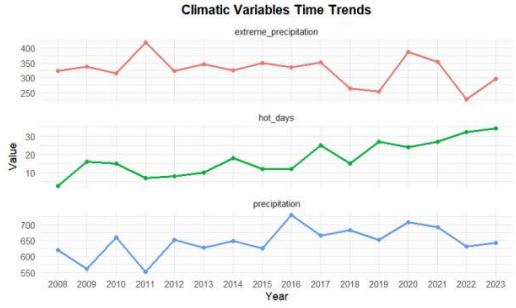


Figure 2. Time trend chart of climate variables

Figure 2 presents the annual changes of three key climate indicators - the number of hot days, extreme precipitation and total annual precipitation - from 2008 to 2022. It shows the following characteristics. The number of hot days showed an overall upward trend in fluctuations, especially after 2016, when the number of hot days remained at a relatively high level, in line with the context of global and regional warming. The curve of extreme precipitation versus total annual precipitation fluctuated sharply, but did not show a clear long-term trend like the number of high-temperature days, and the interannual fluctuation was more prominent. The synergistic changes among the three curves are not consistent. For example, in some years (such as 2015), the number of hot days reached a stage high, but the precipitation was not at a high level simultaneously; In other years, such as 2020-2021, precipitation indicators were high while the number of hot days was relatively low.

4.2. Descriptive statistics of variables

Table 1 shows the descriptive statistics of the main variables. The national average annual dengue fever incidence rate was 0.51 per 100,000, but the standard deviation (0.92) was larger and the

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median (0.10) was much lower than the mean, indicating a highly right-skewed distribution of the epidemic, with outbreaks in a few years or regions pushing up the overall mean.

Table 1. Descriptive statistics of major variables (N=16)

Variables	Mean	Standard deviation	Minimum value	Maximum	Median	IQR
Incidence (1 in 100,000)	0.51	0.92	0.01	3.46	0.10	0.36
Precipitation (mm	646.42	46.76	551.32	730.00	649.82	42.75
Number of hot days (days)	17.81	9.32	3.00	34.00	15.50	14.00
Extreme precipitation (mm)	325.31	48.41	226.00	419.00	330.00	40.00
Per capita GDP (yuan)	55752.21	21568.30	24483.19	91746.12	52880.54	32387.17
Population density (people per square kilometer)	2474.41	263.36	2080.00	2894.62	2413.50	367.26
Urbanization rate (%)	0.58	0.06	0.47	0.66	0.58	0.10
Health technicians (person-thousand)	6.12	1.56	3.90	8.87	5.98	2.49
Per capita health expenses (yuan)	3412.46	1738.24	1094.52	6425.32	3145.40	2777.39

4.3. Regression results from multiple models

Table 2 summarizes the regression results of the three core models. In all models, the coefficients of the climate variable did not pass the statistical significance test (p values were much greater than 0.1).

Table 2. Comparison of core regression model results

Variables	Simple OLS Model	With a time trend model	Logarithmic model
	Coefficients (standard deviation)	Coefficient (standard deviation	Coefficient (standard deviation)
Constant term	-71.96 (66.455)	6064.82 (7765.109)	-117.26 (115.071)
Precipitation	0.002 (0.010)	0.003 (0.010)	0.008 (0.018)
Number of hot days	0.086 (0.077)	0.089 (0.079)	0.100 (0.134)
Extreme precipitation	-0.001 (0.008)	-0.002 (0.008)	-0.001 (0.014)
Population density	-0.004 (0.008)	-0.003 (0.008)	-0.022 (0.014)
ln(GDP per capita)	13.96 (12.459)	14.34 (12.817)	15.26 (21.574)
Urbanization rate	-8.45 (164.400)	20.55 (172.931)	-162.62 (284.671)
Health technicians	-0.102 (2.345)	4.956 (6.838)	2.567 (4.060)

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Table 2. (continued)

ln(Health cost per capita)	-8.24 (19.493)	0.094 (22.642)	9.410 (33.754)
Year	-	-3.10 (3.929)	-
Number of observations	16	16	16
Adjusted R^2	0.544	0.631	0.084

In the OLS model, the influence coefficients of precipitation, the number of hot days, and extreme precipitation on morbidity were all close to zero, with extremely high p-values (0.85, 0.30, 0.91). In the model with time trend, the size and significance of the variable coefficients did not change essentially after the year variable was added, but the R^2 performed better after the time trend was added, increasing to 0.631. Furthermore, the results of the logarithmic model showed that the results were still not significant when the explanatory variable was replaced with the logarithmic incidence rate, and the model had weak explanatory power (adjusted $R^2 = 0.084$).

5. Conclusion

This research revealed that there was no statistically significant association between temperature, precipitation, and extreme weather events and the incidence of dengue fever at the national macro annual scale. The p-values of climate variables in all regression models were much higher than the conventional significance level. The findings strongly support the prevention and control buffer hypothesis (H_2). The systematic surveillance and vector control measures established and continuously implemented in key dengue epidemic areas in China likely effectively blocked the transformation path from favorable climatic conditions to large-scale outbreaks. What is captured by macro annual data may be the performance of risks that have been "smoothed" and "hedged" by public health interventions. This reflects, in one aspect, the potential effectiveness of China's public health system in responding to climate-sensitive infectious diseases. The findings also highlight the rationality of the data and methodology limitation hypothesis (H_3). The transmission of dengue fever is highly seasonal, and aggregated analysis using annual data inevitably dilutes key monthly or quarterly climate-driven signals, resulting in weakened statistical correlations.

Therefore, the conclusions suggest that in future assessments of the impact of climate on seasonal infectious diseases such as dengue fever, higher-resolution (such as monthly) data should be prioritized, and refined models that can separate climate effects, socio-economic effects, and the effects of prevention and control interventions should be constructed to more precisely assess the health risks of climate change and the effectiveness of prevention and control strategies.

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