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Exploring the influencing factors of scrub typhus in Gannan region, China, based on spatial regression modelling and geographical detector

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A B S T R A C T

Scrub typhus is a significant public health issue with a wide distribution and is influenced by various determinants. However, in order to effectively eradicate scrub typhus, it is crucial to identify the specific factors that contribute to its incidence at a detailed level. Therefore, the objective of our study is to identify these influencing factors, examine the spatial variations in incidence, and analyze the interplay of two factors on scrub typhus incidence, so as to provide valuable experience for the prevention and treatment of scrub typhus in Gannan and to alleviate the economic burden of the local population.This study employed spatial autocorrelation analyses to examine the dependent variable and ordinary least squares model residuals. Additionally, spatial regression modelling and geographical detector were used to analyze the factors influencing the annual mean 14-year incidence of scrub typhus in the streets/townships of Gannan region from 2008 to 2021. The results of spatial[1] autocorrelation analyses indicated the presence of spatial correlation. Among the global spatial regression models, the spatial lag model was found to be the best fitting model (log likelihood ratio = −319.3029, AIC = 666.6059). The results from the SLM analysis indicated that DEM, mean temperature, and mean wind speed were the primary factors influencing the occurrence of scrub typhus. For the local spatial regression models, the multiscale geographically weighted regression was determined to be the best fitting model (adjusted $R^2 = 0.443$, AICc = 726.489). Further analysis using the MGWR model revealed that DEM had a greater impact in Xinfeng and Longnan, while the southern region was found to be more susceptible to scrub typhus due to mean wind speed. The geographical detector results revealed that the incidence of scrub typhus was primarily influenced by annual average normalized difference vegetation index. Additionally, the interaction between GDP and the percentage of grassland area had a significant impact on the incidence of scrub typhus ($q = 0.357$). This study illustrated the individual and interactive effects of natural environmental factors and socio-economic factors on the incidence of scrub typhus; and elucidated the specific factors affecting the incidence of scrub typhus in various streets/townships. The findings of this study can be used to develop effective interventions for the prevention and control of scrub typhus.

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1. Introduction

Scrub typhus is a febrile natural epidemic disease caused by Orientia tsutsugamushi. The disease is transmitted through the bite of scrub typhus larvae, with rodents serving as the source of infection (Sun et al., 2017). Common clinical manifestations include high fever, chills, and crusting. If left untreated, scrub typhus can lead to complications such as myocarditis, meningitis, and even death (Cracco et al., 2000; Paris et al., 2013). The mortality rates for untreated patients range from 0% to 70% (with a median of 6%), while treated patients have a mortality rate of 1.4%. Currently, there is no vaccine available for scrub typhus. With 1 million cases reported annually and 1 billion people at risk of infection, scrub typhus poses a significant threat to global public health, leading to a substantial economic and social burden (Bonell et al., 2017; Taylor et al., 2015; Varghese et al., 2006).

The prevalence of scrub typhus is influenced by the proximity of breeding sites for vector chiggers to human settlements or the overlap of their habitats with human activities (Zhou et al., 2021). Extensive research has demonstrated a significant correlation between scrub typhus occurrence and various environmental factors such as temperature, rainfall, sunshine, humidity, altitude, and vegetation cover (Acharya et al., 2019; Roberts et al., 2021; Wei et al., 2017; Yao et al., 2019; Zheng et al., 2019). The occurrence of scrub typhus is influenced by both natural environmental factors and socio-economic factors. As the national economy continues to develop and urbanization accelerates, people's lives are becoming more convenient, leading to an increase in outdoor tourism and leisure activities. These changes have indirectly impacted the spread of the disease, resulting in a rise in the number of scrub typhus cases each year. Previous studies have indicated a strong correlation between the occurrence of scrub typhus and various factors, including the percentage of land use type area, urbanization, level of education, knowledge about the disease, GDP, living environment, and place of labor (Devamani et al., 2020; Kuo et al., 2011; Li et al., 2020; Ma et al., 2017; Park et al., 2015; Tran et al., 2021).

However, previous studies have predominantly utilized methods such as multiple linear regression, negative binomial regression, generalized additive Poisson models, one-way correlation, or regression models. These studies have often overlooked the spatial and temporal dimensions of onset, potentially resulting in a loss of valuable information pertaining to temporal and spatial heterogeneity. Consequently, this oversight may lead to divergent conclusions. In addition, most of the existing literature only focuses on analyzing the individual effects of single factors on the incidence of scrub typhus. However, it is crucial to explore the interaction between natural environmental factors and socio-economic factors in order to better understand scrub typhus. Additionally, analyzing the spatial heterogeneity of scrub typhus incidence and identifying the dominant factors contributing to its occurrence are important for effective prevention and control measures in the local context. Therefore, from 2006 to 2012, there was a yearly increase in both the number and occurrence of scrub typhus in Jiangxi Province (Yu et al., 2014). Additionally, between 2006 and 2018, over 5000 cases of scrub typhus were reported across eight provinces in mainland China, with Jiangxi Province being among them (Luo et al., 2022). Following the initial documented case of scrub typhus in Gannan in 2006, there has been a significant increase in its spread, leading to Gannan becoming a region of high prevalence for this disease within Jiangxi Province. Furthermore, from 2006 to 2017, the Gannan area held the highest position in Jiangxi Province regarding both the total number of cases and their incidence (Liao et al., 2019). Therefore, this research employed spatial regression modeling and geographic detectors to pinpoint the primary factors contributing to the incidence of scrub typhus. By examining the interactions and the spatial and temporal variability of the critical factors linked to scrub typhus occurrence, the study utilized the streets and townships of the Gannan region as the unit of analysis. The objective was to offer valuable insights and lessons for the prevention and control of scrub typhus in Gannan, aiming to reduce the economic burden on its residents and ensure their safety in terms of life and property.

2. Methods

2.1. Data on scrub typhus cases

The dependent variable for this study was the annual average 14-year incidence of scrub typhus from 2008 to 2021. The case information was obtained from the National Disease Surveillance Information Management System (NDSIMS), and the number of scrub typhus cases collected in this study adhered to the diagnostic criteria throughout the study period(https://www.chinacdc.cn/).

2.2. Explanatory variables

The study focused on two categories of influencing factors: natural environment factors and socio-economic factors. Natural environment factors included DEM, NDVI, and meteorological factors such as temperature, humidity, sunshine, and wind speed. Due to the challenges in obtaining socio-economic factors at the township level and the limited changes observed over a short period of time, the data collected in this study focused on GDP and the distribution of land use types for the years 2010, 2015, and 2020 (Supplementary Table 1). Considering that the meteorological data is sourced from various meteorological stations, it is impractical to extract specific meteorological values for each street or township within the Gannan region. Consequently, it is essential to rasterize the station data by employing kriging interpolation. Furthermore, the remaining impact factor data are represented as raster data. Therefore, in this study, we calculated the mean values of the impact factors for each street and township in the Gannan region over a 14-year period, from 2008 to 2021, utilizing the zonal statistics method and raster calculator. All aforementioned processes were executed using ArcGIS 10.8.

In order to avoid multicollinearity in the independent variables, this study used SPSS 25.0 to diagnose collinearity in the data, and Spearman correlation coefficient <0.75, variance inflation factor (VIF) < 10, and tolerance (TOL) > 0.1 indicated that the model was free from collinearity problems.

2.3. Global spatial autocorrelation

Global spatial autocorrelation describes whether or not the study object is correlated on an overall scale, and a commonly used test is *Moran's I* statistic.

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} Z_i Z_j}{S_0 \sum_{i=1}^{n} z_i^2} \tag{1}$$

N: total number of space units; Z_i and Z_j are the off−mean deviations $(x_i - \overline{X})$ and $(x_j - \overline{X})$ of the observations of this variable in the ith and jth spatial cells, respectively; W_{ij}: weights between the ith and jth spatial units; S_0: sum of spatial weights for each spatial cell. Use the Z-test to determine if Moran's I value is equal to 0.

$$Z = \frac{I - E(I)}{\sqrt{Var(I)}} \tag{2}$$

$E(I)$: expected value of *Moran's I*; $Var(I)$: variances;$P < 0.05$, indicating a spatial correlation.

2.4. Local spatial autocorrelation

Global spatial autocorrelation primarily examines the overall spatial relationship of the research object, whereas local spatial autocorrelation is commonly employed to investigate the local spatial distribution characteristics. By analyzing the incidence of scrub typhus, local spatial autocorrelation can identify spatial clustering patterns, thereby compensating for the limitations of global spatial autocorrelation. There are four types of aggregation for local spatial autocorrelation: high-high aggregation, high-low aggregation, low-high aggregation, and low-low aggregation. Anselin's Local Moran's I statistic is the commonly used test.

$$I_i = \frac{x_i - \overline{X}}{S_i^2} \sum_{j=1, j \neq i}^{n} w_{i,j} (x_j - \overline{X}) \tag{3}$$

$$S_i^2 = \frac{\sum_{j=1, j \neq i}^{n} (x_j - \overline{X})^2}{n-1} - \overline{X}^2 \tag{4}$$

x_i and x_j: are the observations of the variable in the ith and jth spatial cells, respectively; $\overline{X}$: the average of the values taken by this variable in all spatial cells.

2.5. Global spatial regression models

Ordinary least square (OLS) is one of the global spatial regression models that assumes that the dependent variables are independent of each other and not correlated.

A spatial lag model (SLM) is characterized by the spatial autocorrelation of variables being primarily reflected in the spatial lag term of the dependent variable. The expression is:

$$y = \rho W y + x\beta + \mu \tag{5}$$

y: dependent variable; x: n × k matrix of independent variables; ρ: spatial regression coefficient; β: a k × 1 vector of parameters associated with the independent variables; Wy: n × n order spatial weight matrix; μ: vector of random error terms.

A spatial error model(SEM) is characterized by the spatial autocorrelation of a variable being primarily reflected in the error term. The expression for a spatial error model is:

$$\begin{aligned} y &= x\beta + \varepsilon \\ \varepsilon &= \lambda W\varepsilon + \mu \end{aligned} \tag{6}$$

λ: spatial error coefficients for n × 1 vectors of cross-sectional dependent variables; $W\varepsilon$: spatial lag of the error term.

2.6. Local spatial regression models

Geographic Weighted Regression Model (GWR) is a spatial statistical method proposed by Fotheringham to solve the problem of spatial heterogeneity (Stewart Fotheringham et al., 1996). Its expression is:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i)x_{ik} + \varepsilon_i \tag{7}$$

y_i with x_{i1}, x_{i2} …, x_{ip} are respectively the dependent variable y and the independent variables x_1, x_2 …, x_p observations at sample point $i(u_i, v_i)$; β_0 (u_i, v_i): constant term for the ith sample point; β_k (u_i, v_i): regression coefficient of the independent variable k at sample point i; ε_i: random error.

Multiscale Geographically Weighted Regression(MGWR) is an extension of GWR that matches each explanatory variable to its unique bandwidth. The differences in bandwidth reflect differences in spatial scale. By capturing the effect of scale on spatial processes, MGWR is able to accurately capture spatial heterogeneity (Yu et al., 2020). The expression of MGWR is:

$$y_i = \beta_{bw0}(u_i, v_i) + \sum_{k=1}^{p} \beta_{bwk}(u_i, v_i)x_{ik} + \varepsilon_i \tag{8}$$

$\beta_{bw0}(u_i,v_i)$: the constant term at sample point i, the intercept at the optimal bandwidth; $\beta_{bwk}(u_i,v_i)$: regression coefficient of the independent variable k at sample point i; bwk: Bandwidth used for the regression coefficients of the independent variable k; ε_i: random errors.

2.7. Geographical detector

Geographical detector is tools used to detect and exploit spatially stratified heterogeneity. They consist of four components: factor detector, risk detector, ecological detector, and interaction detector. In this study, we primarily utilized the factor detector and interaction detector of the geographical detector to examine the individual impact of natural environmental factors and socio-economic factors on the incidence of scrub typhus. Additionally, we explored the interaction between these two factors.

2.8. Modelling elaboration

This study conducted a comprehensive analysis of the spatial correlation, spatial regional heterogeneity, and spatial stratified heterogeneity between the 14-year annual average incidence of scrub typhus and its determinants in Gannan region. Various global spatial regression models were employed, including OLS, SLM, and SEM. Additionally, local spatial regression models such as GWR and MGWR were utilized. The study also incorporated geographical detector, specifically factor detectors and interaction detectors. To address the issue of heteroskedasticity in the model and to achieve a normal distribution for the dependent variable, the incidence of scrub typhus was log-transformed after adding 1 to the overall value (Bosse et al., 2023). In this study, we conducted global spatial regression modeling using Stata 16. The first-order Queens neighborhood weight matrix was selected for analysis. We employed the LM test, Robust-LM test, AIC, BIC, and LLR to identify the most suitable model. The local spatial regression model was conducted using the open source software MGWR 2.2.1. The best model was selected based on adjusted R^2 and residual sum of squares, and the bandwidth was optimized using the modified Akaike Information Criterion (AICc) and a fixed Gaussian kernel (Chen et al., 2022; Liu et al., 2021). Additionally, we performed geographical detector analysis using the 'GD' package in R 4.2.3 software.

3. Results

3.1. Descriptive analysis of the average 14-year incidence of scrub typhus and influencing factors

This study encompassed 308 townships/streets across 18 counties and districts within Gannan region, documenting a total of 5942 cases of scrub typhus. Furthermore, the trend of the incidence rate in Longnan City from 2008 to 2021 exhibited an 'N' shape, with the incidence rate in 2021 recorded at 76.75 per 100,000 persons. In 2019, the incidence rate of scrub typhus in Xunwu County peaked at 89.69 per 100,000 people (Supplementary Fig. 1). The focus of the study was to describe the distribution of the 14-year mean of each explanatory variable across the 308 streets/towns. By using the 14-year mean, the study aimed to eliminate the trend of the variable over time. Supplementary Table 2 provides information on the annual mean 14-year incidence rate and its influencing factors. The median annual mean 14-year incidence rate was 3.02. The corresponding values for DEM, mean temperature, and mean wind speed were 325.93, 19.21, and 1.61, respectively.

In this study, we conducted Spearman, tolerance, and variance inflation factor analyses on the influential factors (Supplementary Table 2 and Supplementary Fig. 2). The findings revealed a strong correlation between DEM and NDNI ($rs = 0.840$). Furthermore, the VIF values for percentage of forested land area and percentage of land area of settlements exceeded 10, while their tolerance values were below 0.1. In order to avoid multicollinearity among the independent variables, this study considered several variables for the subsequent analysis. These variables included DEM, population density, GDP, average temperature, average wind speed, average humidity, average sunshine, percentage of cultivated land area, percentage of grassland area, percentage of water area, and percentage of unutilised land area.

3.2. Exploratory data analysis

Global spatial autocorrelation analyses were conducted to examine the presence of a global spatial autocorrelation pattern in the annual mean 14-year incidence of scrub typhus in Gannan region. The results revealed a significant Moran's I statistic of 0.482 at the 5% level, indicating the existence of positive spatial autocorrelation. These findings suggested that the annual mean 14-year incidence of scrub typhus is not randomly distributed, but rather exhibits significant spatial aggregation. In this study, a local spatial autocorrelation analysis of incidence was conducted to identify specific areas of aggregated distribution. Anselin's local Moran's indicated the presence of core clustering in the occurrence of scrub typhus, including high-high, low-high, high-low, and low-low areas (Supplementary Fig. 3).

3.3. Global spatial regression models

The OLS model was subjected to White and Jarque-Bera tests, which revealed heteroskedasticity and non-stationarity ($P < 0.05$), along with a normal distribution of residuals. Furthermore, significant Moran's I scores indicated a strong presence of spatial autocorrelation ($P < 0.001$) among the residuals. These findings suggested the existence of spatial autocorrelation and heterogeneity in the variables. However, the OLS model failed to account for spatiality. Therefore, this study incorporated other global and local spatial regression models to enhance the model's fit. In this study, further observation of robust lagrange multiplier was required as the lagrange multiplier of both the SLM and SEM models were statistically significant. The Robust-LM of the SLM model was statistically significant, while the Robust-LM of the SEM model was not statistically significant. Therefore, the SLM model was chosen for the global spatial regression in this study (Table 1).

The AIC and BIC values of the SLM model were 666.6059 and 718.8273, respectively, which were significantly smaller than those of the SEM and OLS models. Furthermore, the absolute value of LLR for the SLM model was smaller than the absolute value of LLR for the SEM and OLS models. This suggested that the slm model was a better fit in the global regression model. In the OLS regression model, the DEM and mean temperature showed a strong association with the incidence of scrub typhus. Similarly, in the SLM and SEM models, DEM, mean temperature, and mean wind speed were positively correlated with the incidence of scrub typhus. This suggested that higher DEM, mean temperature, and mean wind speed were associated with an increased risk of scrub typhus. Despite the better fit of the SLM model, its residuals still exhibited spatial autocorrelation ($P < 0.001$) (Supplementary Table 3). Therefore, this study aims to utilize the local spatial regression models, such as GWR and MGWR, along with geographical detector analysis. The objective is to gain insights into the spatial heterogeneity of variables,

Table 1
LM and Robust-LM tests.

Test	Statistic	*Df*	*P-value*
Spatial error:			
Moran's I	10.420	1	0.000
Lagrange multiplier	97.109	1	0.000
Robust Lagrange multiplier	0.014	1	0.904
Spatial lag:			
Lagrange multiplier	110.850	1	0.000
Robust Lagrange multiplier	13.756	1	0.000

Table 2
Q-values and P-values of factor detector results.

Variable	*Q-value*	*P-value*
DEM	0.112555	0.001625
Population density	0.113290	0.000069
GDP	0.091905	0.000370
NDVI	0.169980	0.000000
Average temperature	0.041142	0.523173
Average wind speed	0.057037	0.064390
Average humidity	0.037706	0.171934
Average sunshine	0.027858	0.704246
Percentage of cultivated land area	0.061430	0.021772
Percentage of forested land area	0.144862	0.000006
Percentage of grassland area	0.058487	0.029321
Percentage of water area	0.040857	0.256948
Percentage of land area of settlements	0.086962	0.003255
Percentage of unutilised land area	0.006994	0.999725

examine the distribution of influencing factors across different regions, investigate the impact of various factors on the incidence of scrub typhus, and address the previously mentioned issue of spatial autocorrelation.

3.4. Geographical detector

Table 2 presents the q-values and corresponding p-values acquired through the factor detector. From the results, it can be inferred that the DEM, population density, GDP, NDVI, percentage of cultivated land area, percentage of forested land area, percentage of grassland area, and percentage of land area of settlements exhibit statistical significance. In addition, meaningful indicators were screened based on p-values and ranked in order of q-value. The results showed that NDVI had the largest q-value, indicating that it has the greatest influence on the incidence of scrub typhus. The percentage of forested land area and population density were also found to have a significant impact (Fig. 1) .

Fig. 2 shows the interaction of natural environmental factors and socio-economic factors on the 14-year annual average incidence rate. With the exception of the interactions between NDVI and percentage of water area, NDVI and percentage of land area of settlements, and percentage of forested land area and percentage of land area of settlements on the incidence of scrub typhus, which demonstrated a unilaterally nonlinearly weakened, the explanatory power of any two of the remaining independent factors was improved by the interactions. These interactions either bilaterally enhanced or nonlinearly enhanced the explanatory power. This study suggested that the interactions between the two factors had a greater impact on the incidence of scrub typhus compared to individual factors. The highest interaction values were observed for GDP and the percentage of grassland area ($q = 0.357$). This was followed by mean wind speed and the percentage of forested land area, as well as NDVI and mean temperature ($q = 0.356$, $q = 0.328$).

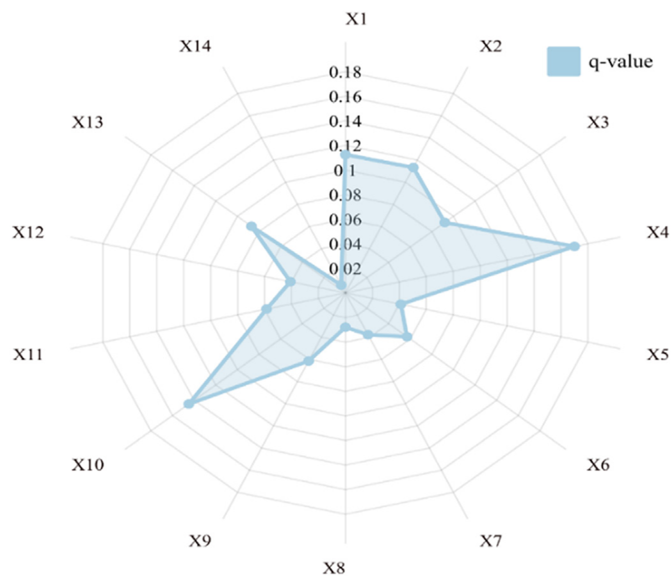

Fig. 1. Q-value results for the factor detector.

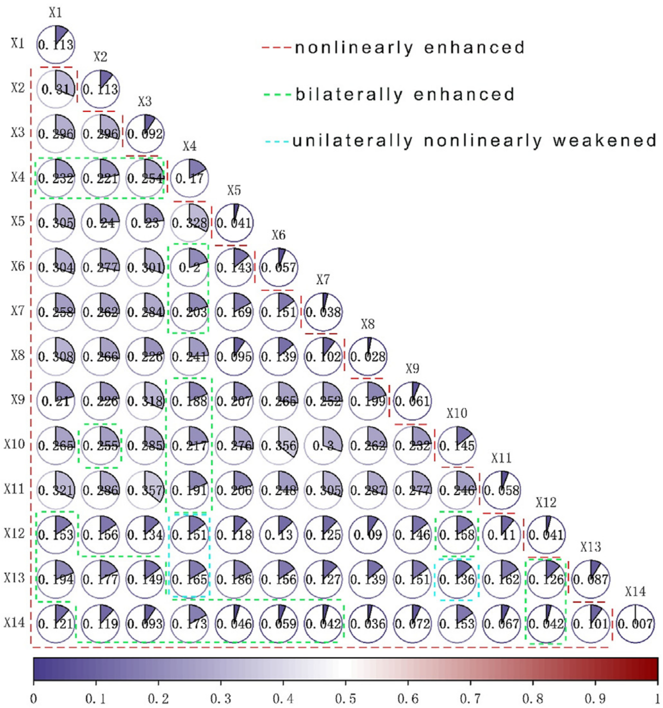

Fig. 2. Interaction analysis between explanatory variables on 14-year average annual incidence of scrub typhus.

3.5. Local spatial regression models

The Global Regression model had the lowest adjusted R^2 value of 0.200. In contrast, the local model had a significantly higher adjusted R^2 value. Specifically, the adjusted R^2 value of GWR was 0.433, indicating a substantial improvement in its explanatory power. However, MGWR outperformed all other models with the highest adjusted R^2 value of 0.443, the lowest AICc value of 726.489, and the lowest Residual sum of squares of 156.713. These results suggested that MGWR was the most effective model in local spatial regression, explaining 44.3% of the variations in the incidence of scrub typhus (Table 3). Although the fit of MGWR was weaker than SLM (the AIC value of MGWR was larger than SLM), MGWR took into account the spatial heterogeneity of parameter estimates. Furthermore, this paper conducted a Moran's I test ($I = 0.070$, $Z = 1.847$, $P = 0.065$) on the residuals of the MGWR, which indicated that the residual was not spatially autocorrelated.

In the MGWR analysis, the regression coefficients for DEM and mean wind speed were found to be statistically significant. However, the coefficients for mean temperature did not show significant results. The maximum value of DEM was 0.262 (Table 4).

Fig. 3 demonstrates the impact of the MGWR model test and the visualization of the coefficients of the explanatory variables. The regression coefficients of the independent variables provided a visual representation of the spatial heterogeneity among the variables in each township/street. Areas with brighter colors indicated larger regression coefficients, indicating a greater impact of the explanatory variable on the incidence of scrub typhus in that particular area. Conversely, areas with lighter colors represented smaller regression coefficients, indicating a smaller impact of the explanatory variables on the incidence of scrub typhus in that area.

Fig. 3a presents the spatial distribution of local R^2 in MGWR. The results indicated that the southeastern region of Gannan exhibited higher adaptability, as reflected by the higher local R^2 values. Moving towards both ends from the central region, the local R^2 gradually decreased, indicating poorer model performance. The maximum local R^2 value was 0.50, and 39.94% (123/308) of the local R^2 values exceed 0.30.

Fig. 3b illustrates the spatial distribution of the residuals of the MGWR model, which measured the difference between the observed and predicted values of scrub typhus incidence. This was an important indicator of the model's performance. The residuals exhibited a random spatial distribution, with values less than 2.5. Furthermore, 87% of the regions (268 out of 308) had residuals between −1 and 1.

Fig. 3c presents the distribution of DEM regression coefficients under the MGWR model. The positive DEM coefficients indicated a positive correlation between DEM and the incidence of scrub typhus. Furthermore, The distribution of larger DEM coefficients was primarily observed in Xiaojiang and Tieshikou townships in Xinfeng County, as well as Liren and Guanxi townships in Longnan. This indicated that Xinfeng and Longnan were more vulnerable to scrub typhus infection due to the influence of DEM. Fig. 3d illustrates the distribution of regression coefficients for mean wind speed under the MGWR model.

Table 3
Effectiveness tests of the basic and local spatial regression models.

	Global Regression model	GWR	MGWR
R-squared	0.207	0.478	0.491
Adjusted R-squared	0.200	0.433	0.443
Residual sum of squares	244.117	160.631	156.713
Log Likelihood	−401.235	−336.781	−332.977
AICc	812.669	729.278	726.489

Table 4
Statistical description of MGWR model parameters.

Variable	Mean	SD	Min	Median	Max
Intercept	−0.007	0.555	−0.897	0.078	1.179
DEM	0.110	0.061	0.026	0.097	0.262
Average wind speed	0.124	0.073	0.024	0.110	0.273

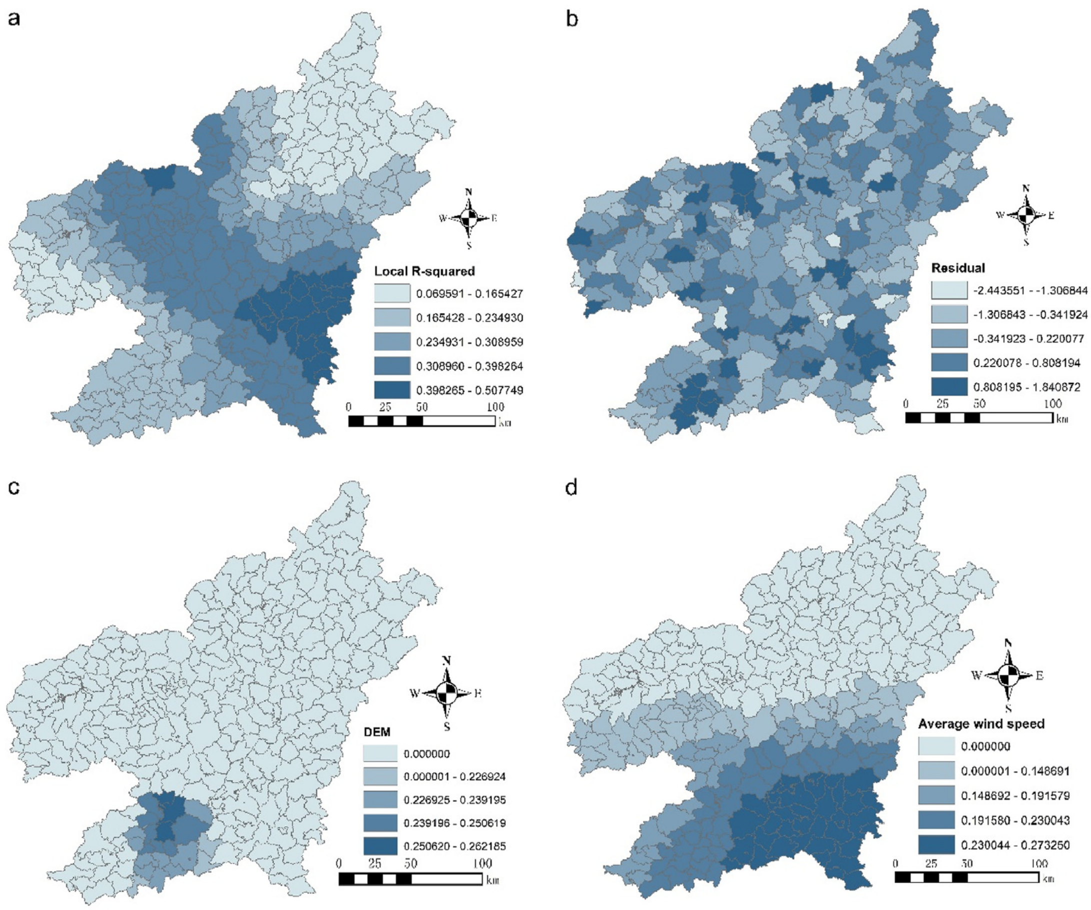

Fig. 3. Local R^2, standardised residuals and regression coefficients of explanatory variables for the MGWR model.

The positive coefficient for mean wind speed indicated a positive correlation between mean wind speed and the incidence of scrub typhus. Furthermore, the coefficient of mean wind speed decreased from south to north, suggesting that the impact of mean wind speed was greater in the southern region. This implied that the southern region had a higher likelihood of being infected with scrub typhus due to the influence of mean wind speed. The distribution of regression coefficients for two explanatory variables indicated that the southern region of Gannan was more susceptible to scrub typhus and could be considered a high incidence area.

4. Discussion

In recent years, scrub typhus has become a significant public health concern in Gannan region. This study aimed to investigate the spatial distribution pattern of scrub typhus incidence and analyze the relationship between natural environmental and socio-economic factors and the annual mean 14-year incidence rate of scrub typhus. We utilized a geographical detector and five spatial regression models to quantitatively and systematically examine these factors.

The occurrence of scrub typhus is commonly influenced by various natural environmental factors and socio-economic factors. These factors include temperature, wind speed, sunshine, altitude, rainfall, relative humidity, type of land use, GDP, and educational attainment (Acharya et al., 2019; Bhopdhornangkul et al., 2021; Devamani et al., 2020; Li et al., 2020; Lu et al., 2021; Shah et al., 2019; Xiang et al., 2017). Similar results were obtained in this study through the use of spatial regression modelling and factor detectors. The study found that four natural environmental factors (mean temperature, mean wind speed, NDVI, and DEM) and six socio-economic factors (GDP, population density, percentage of cultivated land area, percentage of forested land area, percentage of grassland area, and percentage of land area of settlements) had a significant impact on the spatial differentiation of the annual mean 14-year incidence of scrub typhus. Notably, most of these factors exhibited a positive correlation with the incidence of scrub typhus. This suggested that residents of Gannan should minimize travel to areas characterized by high altitudes and dense vegetation during warmer temperatures and windy conditions. Furthermore, residents should enhance their awareness of personal protection measures, such as wearing long-sleeved clothing, tall boots, and gloves to prevent chigger bites, thereby reducing the risk of chigger-related infections.

In Gannan, scrub typhus was predominantly located in the south-central region, which included Xinfeng County, Longnan City, and Xunwu County. This area is characterized by a subtropical monsoon humid climate, featuring warm and humid conditions, substantial rainfall, and sufficient sunlight. These climatic factors collectively created a conducive environment for the proliferation of chiggers and the breeding of rodents (Wei et al., 2022). Additionally, navel oranges were extensively cultivated in the region, leading farmers to inevitably increase their exposure to chiggers during the planting and harvesting processes. This heightened exposure subsequently elevated the risk of chigger infestations(Liao et al., 2014).

The incidence of scrub typhus was observed to increase with altitude, although at a decreasing rate. This may be due to the fact that as the altitude increases, the vegetation grows denser and the relative humidity becomes higher, and this vegetation is less likely to be damaged by humans, which provides favorable conditions for the growth and development of hosts and chiggers (Wardrop et al., 2013). However, as the altitude increases beyond a certain point, the density of vegetation decreases and is difficult for humans to reach. This unfavorable condition hinders the growth of chiggers and also lacks a transmission route for their spread (Li et al., 2023).

Temperature has a significant impact on the development of scrub typhus as it affects the host, chiggers, and human activities (Van Peenen et al., 1976). Our study in Gannan region revealed a positive correlation between the average temperature and the incidence of scrub typhus, which aligns with previous research (Dorji et al., 2019; Wei et al., 2017). These studies have indicated that temperature plays a facilitating role in the transmission of scrub typhus. The rise in temperatures leads to an increase in the abundance of pathogens and hosts, resulting in the proliferation of chiggers. Additionally, humans tend to spend more time outdoors. These factors collectively contribute to a higher likelihood of human exposure to chiggers, consequently increasing the probability of human infection with scrub typhus (Lu et al., 2021; Yu et al., 2018). However, contrary to expectations, reports from India and Korea have indicated a negative correlation between temperature and the incidence of scrub typhus (Bang et al., 2008; Mathai et al., 2003). This discrepancy may be attributed to regional variations in dominant strains and meteorological conditions (Wei et al., 2017).

Previous studies have conducted limited research on the correlation between wind speed and scrub typhus, with some indicating a positive relationship (Lu et al., 2021). Our findings align with these previous studies; however, the impact of wind speed on the chiggers' life cycle and the mechanisms underlying infection remain unclear. Higher wind speeds may enhance the survival and development of chiggers, as their eggs can be carried into habitats that are conducive to mite growth until they reach adulthood. A Korean study has shown a significant correlation between chiggers and average wind speed, although the impact of wind speed on the epidemiology and ecology of chiggers was not analyzed in this particular study (Kwak et al., 2015). Consequently, future research should delve into the relationship between wind speed and the ecology and life cycle of scrub typhus, as well as the infection mechanism of this disease. This study concluded that the southern area was more susceptible to scrub typhus infections due to the average wind speed. Consequently, it was crucial for residents of this street/township to minimize travel during windy weather. This finding also facilitated relevant authorities in proactively informing local residents to adopt protective measures.

The development of scrub typhus is influenced by multiple factors, and the explanatory effect is significantly enhanced by two-by-two interactions compared to single variables (Cao et al., 2017; Tian et al., 2021). Traditional epidemiological methods struggle to assess and interpret interactions when there are numerous influencing factors. However, in this study, an interaction detector was used to explore interaction effects by overlaying spatial patterns of risk factors and quantifying them using q-values. The results demonstrated that the relationship between GDP and the percentage of grassland area played a significant role in the occurrence of scrub typhus in Gannan region. Scrub typhus is an epidemic disease transmitted by insects, with its hosts or chigger larvae primarily found in woodlands or grasslands with dense vegetation cover (Kweon et al., 2009). The higher the percentage of grassland area, the more favorable it becomes for chiggers and hosts to congregate. As GDP per capita increases, a greater number of residents opt for outdoor travel, thereby increasing the likelihood of chigger exposure (Vallée et al., 2010). The increase in GDP and the percentage of grassland area have been found to positively affect host survival, reproduction, and chigger biting. This could potentially lead to a future increase in the incidence of scrub typhus. Therefore, it is recommended that relevant authorities prioritize these two aspects and take appropriate measures to reduce the chances of another outbreak of scrub typhus in Gannan region.

The strengths of this study can be divided into the following points: Firstly, the study comprehensively analyzed the natural environmental factors and socio-economic factors that affect the incidence of scrub typhus. Secondly, global spatial regression models and local spatial regression models were utilized to explore the spatial correlation and spatio-temporal heterogeneity of the influencing factors. This helped to identify the specific influencing factors in each street/township. Thirdly, This study utilized the factor detector and interaction detector in the geographical detector to examine the specific impact of individual factors on the incidence of scrub typhus, as well as the interaction between two factors. Additionally, three methods (correlation coefficient, variance inflation factor, and tolerance) were employed to assess the multicollinearity of independent variables, thereby reducing the likelihood of collinearity. Finally, in this study, the average of each variable over a 14-year period was chosen to reduce error. This approach allows for a better representation of the actual situation in the region. Furthermore, previous research has indicated that regression on the mean value in ecological studies can help mitigate the ecological fallacy (Ben-Shlomo, 2005; Li et al., 2014).

This study also has certain limitations and shortcomings. Firstly, the cases were obtained passively, and factors such as the residents' perception of seeking medical advice, the accuracy of medical diagnosis, and the reporting practices of relevant units may have led to an underestimation of the incidence level of scrub typhus. This could result in cases being underdiagnosed or misdiagnosed. Secondly, the incidence of scrub typhus is also influenced by factors such as the level of urbanisation and the level of education of the population. However, obtaining data on these factors is challenging, and therefore, they were not considered in the analyses of this study. Finally, the results of this research cannot be easily generalized to other regions due to variations in climatic and geographical conditions.

5. Conclusions

In this study, spatial regression modelling indicated positive associations between scrub typhus incidence and DEM, mean temperature, and mean wind speed. The south-western region was found to be more susceptible to scrub typhus due to DEM. Similarly, the southern region had a higher likelihood of scrub typhus infection due to mean wind speed. Moreover, the interaction between GDP and the percentage of grassland area had the greatest impact on scrub typhus incidence. This study presents evidence suggesting that the onset of scrub typhus is influenced by both natural environmental factors and socio-economic factors. Consequently, researchers can utilize these factors as early warning predictive signals to effectively prevent and control the occurrence of scrub typhus.

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Availability of data and materials

All relevant data are within the manuscript and its Supporting Information files.

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare no conflicts of interest.

CRediT authorship contribution statement

Kailun Pan: Writing – review & editing, Writing – original draft, Validation, Software, Investigation, Data curation, Conceptualization. **Fen Lin:** Writing – original draft, Validation, Project administration, Data curation, Conceptualization. **Hua Xue:** Validation, Software, Methodology, Data curation. **Qingfeng Cai:** Validation, Software, Methodology, Data curation. **Renfa Huang:** Validation, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.idm.2024.09.003.

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