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Research on the Resilience and Impact Mechanism of Urban waterlogging in the Chengdu Chongqing Economic Circle Urban Agglomeration

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Abstract： Urban waterlogging resilience is one of the core indicators of urban sustainable development. This study is based on sample data from 16 prefecture-level cities within the Chengdu-Chongqing Economic Circle urban agglomeration from 2000 to 2023. Using ArcGIS and other software tools, the study employs methods such as the entropy weight method, the PSR model, and the spatial Durbin model to empirically analyze the spatiotemporal evolution and impact mechanisms of urban waterlogging resilience. The findings reveal the following: (1) From 2000 to 2023, the average resilience of urban agglomerations to waterlogging increased from 0.158 to 0.525, exhibiting a general upward trend characterized by "stable fluctuations and high-speed growth". Chengdu experienced the most significant increase, rising by a factor of 3.25, while Ya'an saw the smallest increase, with a factor of 1.07. (2) The resilience of urban waterlogging within the Chengdu-Chongqing Economic Circle exhibits a spatial pattern of "high in the east and west, low in the center". Both Chengdu and Chongqing have consistently remained in high-resilience areas, with surrounding cities gradually showing clustering trends. (3) The analysis of the driving mechanism reveals that per capita GDP exhibits a negative spillover effect, known as the "siphon effect," in economically adjacent areas, while the road network and drainage network show a positive synergistic effect; The monthly average rainfall generates a positive local effect by forcing facility upgrades; The effect of urban green space ratio and drainage network coefficient is constrained by spatial correlation and extreme scenarios. Based on this, the study proposes a path to strengthen the coupling of grey and green facilities and cross regional collaborative governance, providing theoretical support and scientific basis for the collaborative governance and resilience improvement of waterlogging in the Chengdu Chongqing urban agglomeration.

Keywords: urban waterlogging resilience；Pressure–State–Response (PSR) model；spatial Durbin model；Chengdu–Chongqing urban agglomeration.

1. Introduction

The concept of urban waterlogging resilience refers to the comprehensive ability of urban systems to resist, absorb, adapt, and restore core functions when subjected to waterlogging disturbances caused by extreme rainfall[1], It has become an important

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issue in the current field of urban safety and sustainable development[2]. Under the dual pressures of global climate change and rapid urbanization, many highly urbanized regions, including the Tokyo Metropolitan Area in Japan, the National Capital Region of Delhi in India, the São Paulo Metropolitan Area in Brazil, and Beijing in China, frequently face the challenge of waterlogging disasters[3]. These disasters not only seriously affect residents' normal lives but also impact the stable operation of urban socio-economic systems[4]. The traditional engineering defense system, dominated by gray infrastructure, gradually reveals the limitations of its static prevention and control mode in the face of increasingly frequent and intense extreme rainfall events. There is an urgent need to construct a more adaptable urban waterlogging governance path from the perspective of system resilience[5]. In China, with the frequent occurrence of extreme rainfall and the continuous advancement of urbanization, urban waterlogging prevention and control have become key tasks in the construction of the national disaster prevention and mitigation system[6]. As a core area of the national major regional development strategy, the Chengdu-Chongqing urban agglomeration, with its high level of urbanization, population agglomeration, economic vitality, and complex geographical conditions, stands out as a typical region with the most prominent waterlogging risk and resilience contradiction in western China[7]. Therefore, systematically assessing the level of waterlogging resilience in this region and deeply analyzing its spatiotemporal evolution patterns and spatial driving mechanisms are of great practical significance for promoting the safety and sustainable development of urban systems.

In terms of urban waterlogging resilience assessment, scholars both domestically and internationally have established a relatively rich theoretical system and technical approach[8-9], This mainly encompasses two types of research methods[10]. One is based on hydrodynamic models, such as the SWMM model and the InfoWorks ICM model[11], which assess urban waterlogging resilience by simulating the entire process of urban waterlogging[12-14]. This method has a clear mechanism, but it requires high data accuracy and is difficult to apply to large-scale, long-time series analysis at the urban agglomeration level. The second is a comprehensive assessment method based on

multi-dimensional indicators, which conducts quantitative assessment by constructing an evaluation index system[15], such as the Analytic Hierarchy Process (AHP), the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) evaluation method, and the widely used Pressure-State-Response (PSR) model. The PSR model can clearly depict the causal relationship of "external climate pressure - urban system state - socio-human response", providing effective support for constructing a structured evaluation index framework[16-17]. For example, Yuan Donghai et al[18]. established a quantitative assessment model for urban waterlogging toughness under rainstorm conditions based on the PSR model, and conducted an empirical study on Haikou City. Scholars such as Chen Junfei[19] also used this model to analyze the spatiotemporal evolution characteristics of urban flood resilience in the Yangtze River Delta region.

Despite certain achievements in urban waterlogging resilience research[20], there are still several aspects that merit further exploration. Firstly, existing research often focuses on a single time slice or the eastern coastal urban agglomeration[21], with insufficient attention paid to the long-term evolution of waterlogging resilience in rapidly developing inland urban agglomerations such as the Chengdu-Chongqing region. Secondly, in the selection of indicator systems, there is a preference for socioeconomic and ecological dimensions[22], while engineering response indicators are often overlooked, affecting the comprehensive evaluation of urban waterlogging response capabilities. Furthermore, traditional methods often assume that urban units are independent of each other[23], ignoring the spatial correlation of resilience, making it difficult to reveal the interactions within the urban agglomeration and not conducive to the formulation of regional collaborative governance strategies. Based on this, this study takes the Chengdu-Chongqing urban agglomeration as the research object, constructs an urban waterlogging resilience evaluation system integrating socioeconomic, ecological background, and engineering facilities based on the PSR theoretical framework, and systematically analyzes the spatiotemporal evolution characteristics of waterlogging resilience in the study area from 2000 to 2023. Combining the spatial Durbin model (SDM), this study identifies key driving factors and analyzes spatial spillover effects, revealing the trade-off-synergy relationship of

resilience within the urban agglomeration. It proposes targeted paths for enhancing urban waterlogging resilience and cross-regional collaborative governance, providing theoretical references for urban waterlogging prevention and control as well as adaptive planning in the urban agglomeration.

2. Research Area and Data Source

2.1. Overview of the Study Area

This study focuses on the Chengdu-Chongqing Urban Agglomeration Development Plan as the research area, which spans from 101°56′E to 110°11′E longitude and from 28°05′N to 33°16′N latitude. The total area covers 189,600 square kilometers and includes 15 cities in Chongqing and Sichuan Province (Figure 1). This region is situated in the southwestern hinterland of China and is the most developed and growth-potential urban agglomeration in western China, recognized at the national level. Notably, it plays a prominent ecological role as the core area for ecological security within the Three Gorges Reservoir and falls within the subtropical monsoon climate zone. The region experiences an annual average temperature of 16–18°C, with annual precipitation ranging from 800 to 1300 mm, primarily concentrated between May and September. The concentration of heavy precipitation and frequent extreme rainstorms make the Chengdu-Chongqing urban agglomeration particularly susceptible to rainstorm and waterlogging disasters. The broad span of geographical coordinates and the variation in rainfall and climatic conditions directly influence urban waterlogging resilience, infrastructure adaptability, and the sustainable development of urban construction.

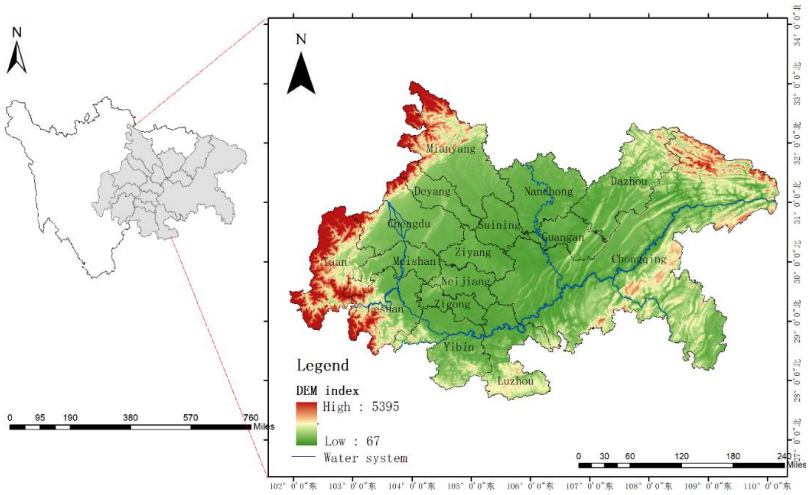


Fig.1 Location of the research area and administrative division

2.2. Data Sources

The primary data used in this study consists of geographic spatial data for the research area covering the period from 2000 to 2023. The original data were obtained from China's Geographic Spatial Data Cloud (http://www.gscloud.cn/). Remote sensing images from the Landsat series have a spatial resolution of 30 meters. Based on the nature of the indicator factors, all indicators are classified into two categories: statistical and computational. Statistical indicators, including annual rainfall data, were sourced from the National Environmental Information Center (NCEI) of the National Oceanic and Atmospheric Administration (NOAA) in the United States, covering the period from 2000 to 2023. NDVI data were obtained from the MOD13A3 dataset, regularly released by NASA's Earth Science Data program (https://www.earthdata.nasa.gov/). The data for this study, including population density, urban built-up area, per capita road area, green coverage rate of built-up areas, drainage pipe network length, number of health institution beds per 10,000 people, proportion of the tertiary industry, per capita regional GDP, per capita green space area, and the proportion of personnel in public management, social security, and social organizations, were all sourced from the construction statistical yearbooks of various prefecture-level cities. Computational data include elevation data from geographic spatial data cloud platforms, combined with quantitative calculations. Runoff depth data were calculated using the SCS-CN method, with rainfall data from P1 replacing the original rainfall data in the SCS-CN formula.

Data on road network density, per capita social security and employment expenditure, and per capita GDP of urban secondary and tertiary industries were calculated based on information in the urban statistical yearbooks. The density of meteorological stations was calculated using data from the China Resources and Environment Science and Data Platform.

3. Methods

Based on the natural geographical and socio-economic characteristics of the research area mentioned above, this study uses the "pressure state response" (PSR) model framework to consider the resilience process as the three stages before, during, and after disturbance, corresponding to the three stages of pressure, state, and response in the PSR model. The pressure dimension represents the disturbance before disturbance, that is, the disturbance that the system is subjected to, such as extreme rainfall risk. The state dimension represents the impact and changes of the urban system during disturbance. The response dimension represents the ability of the urban system to recover after disturbance and make adjustments to adapt to the environment. The three together constitute the core connotation of urban waterlogging resilience[24].

3.1. Constructing an indicator model for assessing urban waterlogging resilience

This study is grounded in the PSR theoretical framework and, considering the actual environmental conditions of the Chengdu-Chongqing economic circle urban agglomeration, develops a resilience assessment index system for urban waterlogging, consisting of 19 indicators across three dimensions: Pressure, State, and Response. Using data on the natural ecology, socioeconomics, and infrastructure of the urban agglomeration from 2000 to 2023, the weights for each indicator were calculated to establish an evaluation model for urban waterlogging.

Weight denotes the significance of a specific indicator within the evaluation framework. To ensure the objectivity and accuracy of the results, this study employs

the global entropy method to calculate the weights of indicators in the P, S, and R systems, as illustrated in Table 1[25]. The calculation steps are as follows:

（1） Indicator Definition

n cities, *m* evaluation indicators, *T* years, *m* variables of *n* cities in *t* years are set for evaluation, and together they form the initial global evaluation matrix.

$$X = (X1, X2, X3, \ldots Xt)nt * m \tag{1}$$

where *Xijt* represents the original value of the *i* city in the *t* year on the *j* index.

（2） Data Standardization

Due to the different dimensions of the indicators, direct comparison is not possible. To ensure comparability of the indicator data, a standardization process is implemented. The indicators are categorized into positive and negative indicators, and standardization is carried out using specific formulas for each category. The formulas are as follows:

Positive Indicators:

$$Y_{ijt} = \frac{X_{ijt} - min(X_j)}{max(X_j) - min(X_j)} \tag{2}$$

Negative indicators:

$$Y_{ijt} = \frac{max(X_j) - X_{ijt}}{max(X_j) - min(X_j)} \tag{3}$$

In the formula: *i=1, 2, ..., n; j=1, 2, ..., m.* Y_{ijt} represents the standardized value of the *j* indicator for the *i* city in the year t; $max(X_j)$ denotes the maximum value of the indicator; $min(X_j)$ denotes the minimum value of the indicator; *j* indicates the sequence number of the indicator, used to differentiate between different evaluation indicators; *i* indicates the sequence number of the sample, used to distinguish between different evaluated subjects.

（3） Calculate the specific gravity

After data normalization, calculate the proportion of each sample under each indicator using the following formula:

$$P_{ijt} = \frac{Y_{ijt}}{\sum_{t=1}^{T}\sum_{i=1}^{n} Y_{ijt}} \tag{4}$$

In the equation, P_{ijt} represents the weight of the i sample under the j indicator at time t.

（4） Calculate the entropy values of each indicator

$$E_j = -k \sum_{t=1}^{T} \sum_{i=1}^{n} \left(P_{ijt} \, ln\left(P_{ijt}\right) \right) \quad (5)$$

Among them, E_j represents the global entropy value of the j indicator, where $0 \leq ej \leq 1$; $k = 1/\ln(nT)$, with n being the sample size.

（5） Calculate the coefficient of variation for each indicator

Calculate the coefficient of variation to reflect the relative importance of each indicator. The larger the coefficient of variation, the higher the relative importance of that indicator in the evaluation. The formula is as follows.

$$g_j = 1 - E_j \quad (6)$$

（6） Calculate the weights of each indicator

$$W_j = \frac{g_j}{\sum_{j=1}^{m} g_j} \quad (7)$$

Among them, m represents the number of indicators, and W_j denotes the weight of the j indicator.

Table 1 Evaluation Indicators and Weights for Urban Waterlogging Resilience in the Chengdu-Chongqing economic circle urban agglomeration.

Target Level	Standards Level	Weight at the criteria level	Indicator Level	Nature of the indicator	Weight of Indicator Layer
Urban Waterlogging Resilience	Stress P	0.0750	Annual rainfall /mm	P1（-）	0.0134
			Elevation /m	P2（-）	0.0320
			Population density /(people/km2)	P3（-）	0.0165
			Runoff depth /mm	P4（-）	0.0131
	State S	0.0823	Urban built-up area size /km2	S1（-）	0.0051
			Per capita road	S2（-）	0.0051

			area/(m2/people)		
			Vegetation coverage rate（NDVI）/%	S3（+）	0.0252
			Green coverage rate of the built-up area. /%	S4（+）	0.0090
			The GDP of the secondary and tertiary industries per capita in urban areas(billion yuan/km²)	S5（-）	0.0095
			Wastewater treatment rate /%	S6（+）	0.0284
			Length of the drainage pipeline network /km	R1（+）	0.1962
			Health Institution Beds per 10,000 Population/(Beds/10,000 people)	R2（+）	0.0385
	Response R	0.8190	Personnel in Public Administration, Social Security, and Social Organizations/（10,000 persons）	R3（+）	0.1314
			Proportion of the tertiary industry/%	R4（+）	0.0400
			Gross Regional Product (GRP) per Capita/ (10^4 yuan/person)	R5（+）	0.0752
			Green space area in the built-up area /km2	R6（+）	0.1785
			Per capita social security and	R7（+）	0.0741

	employment expenditure /(Yuan)		
	Density of meteorological stations (units/km²)	R8（+）	0.0855
	Road network density / (km/km²)	R9（+）	0.0235

presents the weight values of various indicators in the urban waterlogging resilience evaluation system for the Chengdu-Chongqing economic circle. This study utilizes the composite index method, based on the identified indicators and their corresponding weight values, to assess urban waterlogging resilience[26]. The composite index method is widely recognized for its computational efficiency and is primarily based on the weighted sum of standardized indicators, multiplied by their respective weights. This method calculates evaluation indices at different criterion levels and the urban waterlogging resilience evaluation values for the study area. The formula is as follows:

$$RI = \frac{R}{P + S} \tag{8}$$

$$P = \sum_{j=1}^{np} W_j \times Y_{ijt} \tag{9}$$

$$S = \sum_{j=1}^{ns} W_j \times Y_{ijt} \tag{10}$$

$$R = \sum_{j=1}^{nr} W_j \times Y_{ijt} \tag{11}$$

In the formula, *RI* represents the urban waterlogging resilience level; Y_{ijt} denotes the standardized value of the indicators; *P, S*, and *R* represent the evaluation indices of the pressure layer, state layer, and response layer, respectively; W_{pi}、W_{pi}、W_{pi} signify the weights of each indicator. The pressure (P) and state (S) have a negative correlation with urban waterlogging resilience, meaning that as the index for pressure and state increases, the urban waterlogging resilience index decreases; conversely, the response

(R) has a positive correlation with urban waterlogging resilience, indicating that as the index increases, the urban waterlogging resilience index also increases.

3.2. Spatial autocorrelation model

Spatial autocorrelation is one of the important methods for measuring geographic spatial association, mainly including global spatial autocorrelation statistics and local spatial autocorrelation[27]. This article employs Stata software to calculate the global Moran's I index to analyze the spatial autocorrelation of urban waterlogging resilience in the Chengdu-Chongqing economic circle urban agglomeration, and to compute the local Moran's I to present the distribution state of spatial aggregation. The specific formula is as follows:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - x^-)(x_j - x^-)}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\sum_{i=1}^{n}(x_i - x^-)} \tag{12}$$

$$I_i = \frac{(x_i - x^-)}{S^2}\sum_{j=1}^{n} W_{ij}\left(x_j - x^-\right) \tag{13}$$

where I is the global Moran's I, and I_i is the local Moran's I; X_i and X_j are the spatial sequences of the data of the i and j cities. x^- is the average of the unit observations; W_{ij} is the element value of the spatial weight matrix, and the economic geospatial weight matrix is used based on the research of Peng Wenbin et al.[28].

3.3. Space Measurement Model

When studying the influencing factors of urban waterlogging resilience, one cannot overlook the spatial correlation. Therefore, a spatial panel model is employed to identify the influencing factors[29-31]. The Spatial Durbin Model (SDM) combines the Spatial Autoregressive Model (SAR) and the Spatial Error Autoregressive Model (SEM) [32], allowing for a more comprehensive understanding of the spatial correlation between different systems. The formula for the Spatial Durbin Model is as follows:

$$Y_t = \rho W Y_t + \beta X_t + W X_t \theta + \varepsilon \tag{14}$$

In the equation: Y represents the dependent variable, which is urban waterlogging resilience; X represents the factors influencing waterlogging resilience; W is the spatial

weight matrix; ρ is the coefficient for the spatial lag term of y; β is the estimated coefficient of the independent variable X, indicating the direct effect of the independent variable on the dependent variable; and θ is the vector of spatial spillover coefficients of the independent variable X.

4. Results

4.1. Analysis of the Results of the Temporal Evolution of Urban Waterlogging Resilience

4.1.1. Comprehensive Temporal Difference Analysis of Urban Waterlogging Resilience

The temporal evolution of urban waterlogging resilience in the Chengdu-Chongqing urban agglomeration from 2000 to 2023 can be characterized by a three-stage pattern: "stable development, fluctuating changes, and steady growth" (Figure 2). The average waterlogging resilience across various cities increased from 0.1579 to 0.5251, showing particularly significant growth after 2016, corresponding to an overall increase of 232.51%. This change can be attributed to the proactive promotion of ecological civilization construction and the establishment of waterlogging control resilience systems in the Chengdu-Chongqing region. Key initiatives include provincial-level reforms in ecological civilization systems and water security guarantee plans, which have collectively contributed to improving waterlogging resilience and enhancing the collaborative resilience of urban agglomerations to extreme precipitation events. The evolution of waterlogging resilience can be divided into three stages: in the first stage (2000-2013), the resilience index remained relatively stable; in the second stage (2013-2016), it exhibited a steady upward trend; in the third stage (2016-2023), it showed significant growth.

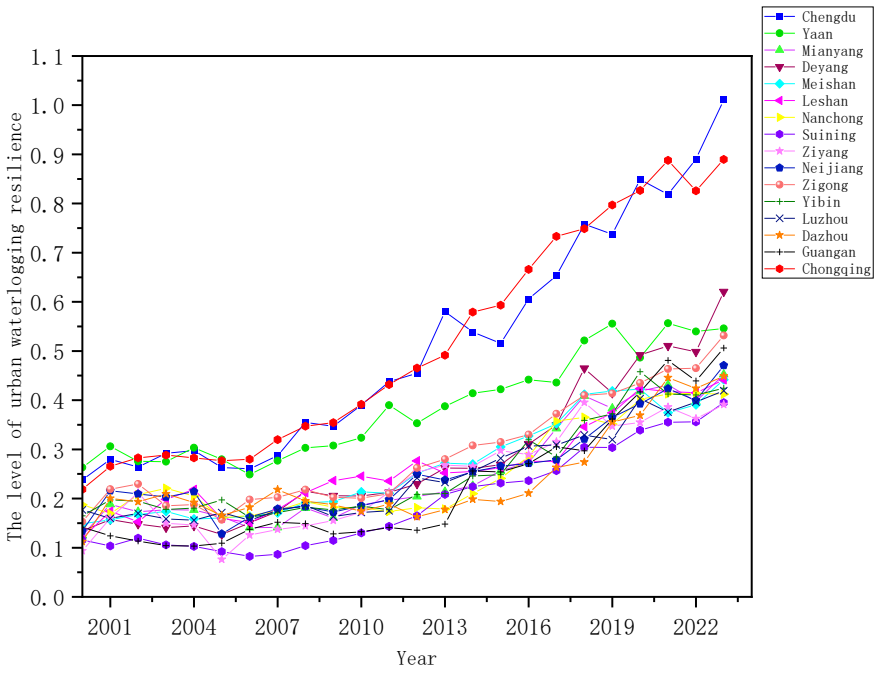


Fig.2 Temporal changes of urban waterlogging resilience from 2000 to 2023

During this period, Chengdu and Chongqing consistently exhibited the highest urban waterlogging resilience, reaching 0.951 and 0.818 respectively in 2023 (Figure 3). This can be primarily attributed to enhancements in urban waterlogging prevention systems and infrastructure, including drainage pipe network length, per capita regional GDP, and built-up green space. Ya'an City exhibits higher waterlogging resilience and lower pressure on its urban waterlogging control system, owing to its high altitude and low population density. From 2017 to 2019, Mianyang and Deyang Cities experienced significant improvements in waterlogging resilience. The improvement in Mianyang City is primarily attributed to ecological initiatives, including the expansion of urban green spaces, whereas Deyang City's resilience increase resulted from rapid expansion of drainage networks and per capita regional GDP. Dazhou, Guang'an, Meishan, Leshan, Neijiang, and Zigong Cities exhibit moderate urban waterlogging resilience, yet their developmental trajectories differ markedly. Specifically, Dazhou City experienced a slight continuous decline post-2008, followed by a substantial increase in 2016, whereas Guang'an City underwent significant improvements from 2013 to 2015 and continued to rise, both attributed to gradual enhancements in infrastructure. The marked decline in Neijiang City in 2005 was attributed to unusually high rainfall, which

increased urban runoff and exerted additional stress on the city, thereby reducing its waterlogging resilience. Although Nanchong, Suining, Ziyang, Yibin, and Luzhou Cities currently have relatively low waterlogging resilience, an upward trend is evident. This improvement is attributable to the progressive enhancement of infrastructure in these cities.

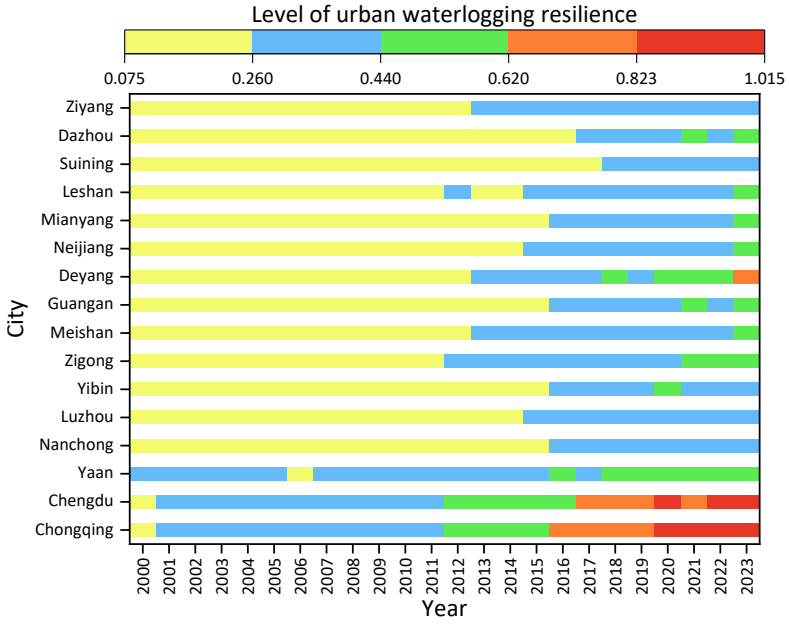


Fig. 3 The Comprehensive Level of Urban Waterlogging Resilience in the Chengdu-Chongqing City Cluster

4.1.2. Analysis of Internal Differences in the Temporal Evolution of Urban Waterlogging Resilience

The waterlogging resilience of the Chengdu Chongqing urban agglomeration shows an upward trend from 2000 to 2023, with an average increase from 0.1579 to 0.5251, and both the minimum and maximum values show an increasing trend year by year. To investigate the temporal evolution and internal differences of urban waterlogging resilience in the Chengdu Chongqing urban agglomeration, based on two dimensions of distribution characteristics and dispersion degree, skewness coefficient, kurtosis coefficient, IQR (interquartile range), and coefficient of variation (CV) are used to reflect it. The results showed that the waterlogging resilience values of Chengdu, Chongqing, and Ya'an were significantly higher than those of other cities, resulting in

316 higher skewness and kurtosis coefficients for the entire urban agglomeration, and the
317 data distribution showed a right skewed pattern. To accurately describe the distribution
318 characteristics of each city, the data was divided into two groups and calculated
319 separately (Table 2).

320 **Table 2** Descriptive statistics of the urban waterlogging resilience levels in the
321 Chengdu-Chongqing economic circle urban agglomeration

Year	High-value urban agglomerations		Main urban agglomerations		CV	IQR
	Skewness coefficient	IQR	Skewness coefficient	Kurtosis		
2000	0.3902	0.0222	0.2718	0.4340	0.3037	0.0562
2001	0.8578	0.0202	0.4623	0.0068	0.2857	0.0577
2002	0.6694	0.0093	0.3978	0.7073	0.2621	0.0526
2003	1.4613	0.0084	0.6148	0.3822	0.2984	0.0558
2004	1.2152	0.0102	0.5165	0.4979	0.3190	0.0616
2005	1.5498	0.0083	0.6766	0.2264	0.3620	0.0501
2006	0.7559	0.0157	1.0449	2.6604	0.2984	0.0379
2007	1.3257	0.0215	1.0323	2.4043	0.3147	0.0405
2008	1.5854	0.0259	1.2597	1.6643	0.3287	0.0336
2009	1.5526	0.0234	0.1591	0.3475	0.3487	0.0508
2010	1.7293	0.0340	0.0180	0.8283	0.3704	0.0478
2011	1.6269	0.0240	0.4699	0.2373	0.4122	0.0421
2012	1.6742	0.0561	0.5012	0.9973	0.3723	0.0675
2013	0.2367	0.0964	0.4590	0.7446	0.4241	0.0641
2014	1.3161	0.0826	0.0883	0.6561	0.3804	0.0388
2015	0.2745	0.0855	0.3556	0.5773	0.3501	0.0548
2016	1.2290	0.1122	0.7039	0.3029	0.3739	0.0550
2017	1.2237	0.1486	0.0682	1.4810	0.3700	0.0782

2018	1.7233	0.1182	0.2141	0.6740	0.3456	0.0979
2019	1.3097	0.1207	0.1311	0.2920	0.3347	0.0610
2020	1.7081	0.1813	0.1439	0.3530	0.3209	0.0657
2021	1.4280	0.1656	0.4526	0.2281	0.3170	0.0825
2022	1.5038	0.1753	0.7702	0.9724	0.3285	0.0764
2023	1.2518	0.2325	1.5675	2.7162	0.3393	0.1123

From Table 2, the interquartile range (IQR) of high-value urban agglomerations has exhibited an upward trend since 2020, suggesting the emergence of "super cities" characterized by waterlogging resilience. Since 2020, the waterlogging resilience has significantly improved, accompanied by an increasing disparity between cities. Around 2010, the primary urban agglomeration shifted from a positively skewed distribution to a negatively skewed one, signifying a reduction in low-resilience cities and a rise in medium-resilience cities. The kurtosis coefficients all exceed 0. Between 2006 and 2008, the resilience values were highly concentrated, but the distribution exhibited a thick tail. In 2023, a sharp peak emerged once again, indicating that several cities experienced severe waterlogging, contributing to a widening development gap. The coefficient of variation (CV) of the entire urban agglomeration continues to increase, with the IQR peaking in 2023, highlighting a significant differentiation in resilience between core cities and peripheral areas. The resilience levels of urban agglomerations have notably increased, with the disparity in resilience between median cities becoming more pronounced. Further evidence indicates that the variations in waterlogging resilience across urban agglomerations are closely linked to regional development disparities. Overall, the waterlogging resilience of the Chengdu-Chongqing Economic Circle urban agglomeration exhibits a trend of "core polarization and peripheral differentiation," necessitating the development of differentiated governance strategies through statistical indicator linkage analysis. By managing the disparities within high-value city clusters, preventing excessive concentration of resources, and identifying low-resilience cities within the primary city cluster, the overall capabilities of risk warning and waterlogging control systems can be enhanced.

4.2. Analysis of the Evolution of Urban Waterlogging Resilience Spatial Patterns

4.2.1. Characteristics of the Comprehensive Spatial Evolution of Urban Waterlogging Resilience

To reflect the spatial pattern evolution of waterlogging resilience in the Chengdu Chongqing urban agglomeration, ArcGIS spatial analysis function and natural breakpoint method were used to divide the waterlogging resilience index into five levels: low resilience, low resilience, medium resilience, high resilience, and high resilience. Based on the five time nodes of 2000, 2006, 2012, 2018, and 2023, a spatial visualization map of waterlogging resilience in the Chengdu Chongqing urban agglomeration was drawn (Figure 4) to reveal the spatial distribution characteristics and changing trends of regional waterlogging resilience.

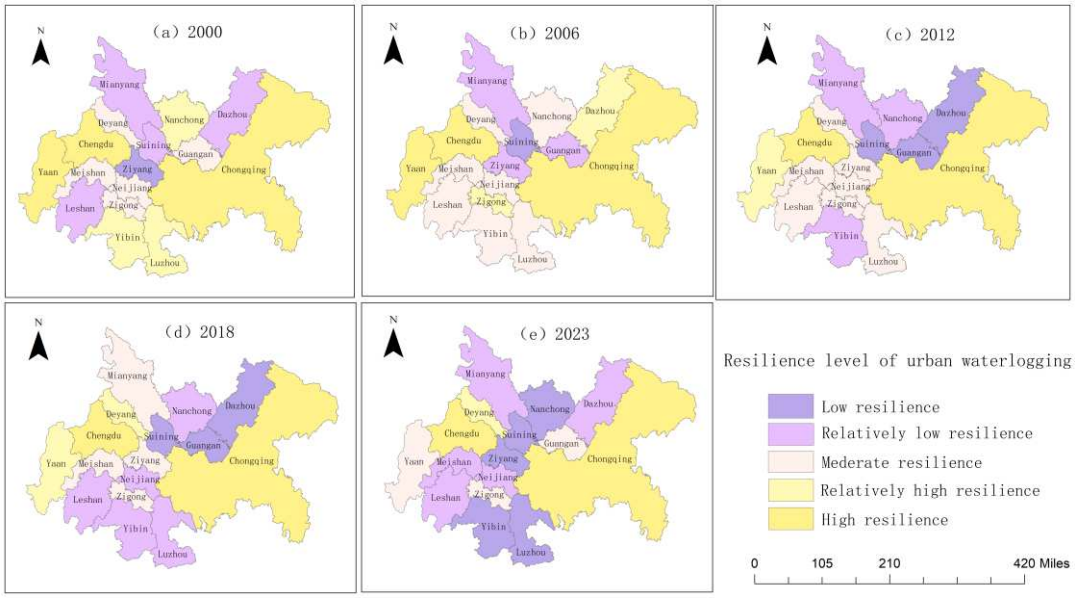


Fig.4 Spatial Patterns of Urban Waterlogging Resilience Levels by Year and Node

The results indicate that the spatial distribution of waterlogging resilience in the Chengdu-Chongqing urban agglomeration exhibits a pattern characterized by higher resilience on the eastern and western sides, and lower resilience in the central area. The extent of regions with low resilience is expanding annually, with the spatial coverage of these regions gradually increasing over time. This trend is consistent with the results of the temporal fluctuation analysis. The Chengdu-Chongqing twin cities have

consistently been situated in high-resilience areas, and Deyang City's resilience level has notably improved, which is closely linked to the rapid urbanization and infrastructure upgrades. In contrast, the waterlogging resilience of cities such as Ya'an, Nanchong, Yibin, and Luzhou has exhibited a significant decline, while other cities have experienced fluctuating development, primarily influenced by excessive ecological space occupation and substandard infrastructure construction. Therefore, changes in urban waterlogging resilience levels remained relatively balanced between 2000 and 2006. As urban construction progressed in later stages, social and economic resources gradually prioritized the development of core cities, significantly improving the overall capacity for infrastructure construction and waterlogging resilience in the short term. However, other cities, constrained by their size and stage of development, exhibit significant vulnerability to extreme weather, resulting in a gradual decline in the waterlogging resilience levels across the Chengdu-Chongqing urban agglomeration. This indicates that the spatial pattern of waterlogging resilience in the Chengdu-Chongqing urban agglomeration is gradually evolving into a dual-track pattern characterized by "core polarization and peripheral differentiation".

Although several cities in the study area have been incorporated into national or provincial pilot programs for sponge city construction, resulting in preliminary policy guidance and technological demonstration effects, in terms of actual construction outcomes, the Chengdu-Chongqing twin cities have significantly enhanced urban waterlogging resilience through infrastructure upgrades and resource aggregation, forming a high-resilience core area with radiating effects. While the waterlogging resilience level in other cities has steadily increased, the resilience index gap compared to core cities continues to widen, leading to a trend of negative growth. This highlights the structural imbalance in the regional collaborative governance system.

4.2.2. Spatial and Temporal Differentiation Characteristics of Urban Waterlogging Resilience Index

The global Moran's I index results presented in Table 3 confirm a significant increase in the spatial autocorrelation of waterlogging resilience in the Chengdu-

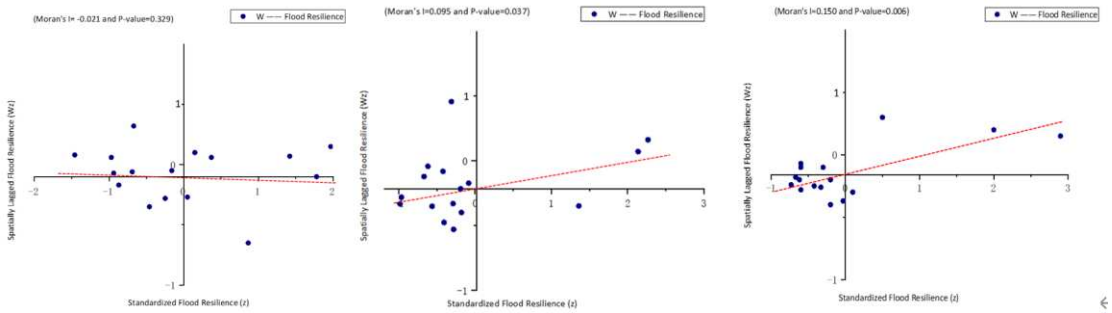
Chongqing urban agglomeration from 2000 to 2023. Excluding the year 2000, significant positive spatial autocorrelation was observed in all other years, with P values less than 0.05, indicating a strong spatial correlation of waterlogging resilience. Specifically, the global Moran's I fluctuated between -0.021 and 0.150, exhibiting an overall upward trend. This indicates that the spatial agglomeration effect in the study area has become more pronounced over time. High-value clustering areas reflect the continued development of regions with strong waterlogging resilience, while areas with random distribution may be influenced by local factors.

Table 3 Urban Waterlogging Resilience Moran's I Index

Year	Global Moran's I	z value	P value
2000	-0.021	0.443	0.329
2005	0.077	1.427	0.077
2010	0.125	2.024	0.021
2015	0.084	1.673	0.047
2020	0.159	2.586	0.005
2023	0.150	2.484	0.006

Spatial clustering analysis based on local Moran's I reveals significant aggregation patterns in urban waterlogging resilience within the Chengdu-Chongqing economic circle from 2000 to 2023, with a primary focus on 'low-high' (LH) and 'low-low' (LL) clusters. Figure 5 illustrates the dynamic evolution of spatial associations in key years (2000, 2011, 2023) based on the Moran scatter plot. In 2000, the spatial distribution was dispersed, with no significant clustering pattern. By 2011, the distribution was primarily concentrated in low-low clustering areas, forming regional cold spots. In 2023, Luzhou joined the LL cluster, expanding it to nine cities, while Deyang joined the 'high-high' (HH) cluster. Chengdu and Chongqing have remained in the HH cluster, reflecting the path dependence of advanced development, while the other cities have consistently been in the LH cluster, indicating the transitional nature of peripheral cities around the core. The spatial association pattern within the Chengdu-Chongqing

economic circle provides valuable insights for collaborative infrastructure planning and joint prevention and control of urban waterlogging.



（a）year 2000　　（b）year 2011　　（c）year 2023

Fig.5 Moran Scatter Plots of Urban Waterlogging Resilience Levels

4.3. Factors Influencing the Temporal and Spatial Evolution of Urban Waterlogging Resilience

4.3.1. Selected Influencing Factors and Variables

The evolution of the spatial pattern of urban waterlogging resilience in the Chengdu-Chongqing economic circle highlights a key contradiction in the ongoing resilience development of urban clusters: while high-intensity development of core cities leads to absolute capacity gains, it may simultaneously intensify developmental imbalances within the cluster. Using spatial econometric methods, this study proposes a new paradigm of resilience governance that balances efficiency with equity, ensuring the central role of development poles while addressing the relative decline of peripheral cities. The spatial disparities in urban waterlogging resilience within the Chengdu-Chongqing economic circle are shaped by various factors. Acknowledging the importance of enhancing urban waterlogging resilience, this study selects continuous, precise, operational, and well-targeted variables as key factors influencing urban waterlogging resilience[28,30]. This study selects the following factors from the perspectives of the natural environment, socio-economic conditions, and infrastructure development: the monthly average precipitation (x1), which serves as the primary climate driver, effectively smoothing out seasonal fluctuations while also reflecting the city's climatic characteristics; the urban green space ratio (x2), an important component

of the urban ecosystem, serves as a key indicator of urban greening status; economic development levels directly influence funding for urban waterlogging resilience and the sustainability of resilience initiatives[28,33]. Regional per capita GDP (x3) is chosen as an indicator of regional economic development levels; the density of the road network (x4) and the length of the drainage network (x5) are crucial indicators influencing the efficiency of urban traffic diversion and drainage capacity.

4.3.2. Results of the Spatial Measurement Model Regression

This study utilizes a spatial econometric model to examine the impact of various factors on urban waterlogging resilience in the Chengdu-Chongqing economic zone urban agglomeration. To explore the spatial dependence of the factors affecting urban waterlogging resilience, we estimated the Spatial Durbin Model (SDM) using Stata software, based on an economic geography nested matrix, and conducted LM and LR tests (Table 4). The results indicate that both the LM test and Robust-LM test returned p-values below the 1% significance level, confirming the presence of spatial lag effects and spatial error effects. The Hausman test statistic was 320.16, significant at the 1% level, indicating that fixed effects are more suitable than random effects. Furthermore, LR and Wald tests validated the appropriateness of the spatial Durbin model, which was significant under the economic geography nested matrix. A comparison of the spatial lag model and the spatial error model demonstrated that the spatial Durbin model outperformed the others in analyzing the factors influencing urban waterlogging resilience. To account for variations in time span and spatial division, we chose to apply the spatiotemporal double fixed effects Spatial Durbin Model (SDM).

Table 4 LM，LR，and Hausman test values under the spatial weight matrix

Testing Methods	Eigenvalue	P-value
LM test no spatial error	13.421***	0.000
Robust LM test no spatial error	6.803***	0.009
LM test no spatial lag	12.005***	0.001
Robust LM test no spatial lag	5.387**	0.020
Hausman	320.16***	0.000

LR lag	47.43	0.000
LR error	46.67	0.000

1): *, **, and *** respectively indicate significance levels of correlation at 0.1, 0.05, and 0.01, and the same applies hereafter.

A comprehensive analysis of the factors influencing urban waterlogging resilience within the Chengdu-Chongqing economic circle urban agglomeration (as shown in Table 5) indicates that all five key factors demonstrate a positive spatial effect within the geographic-economic nested framework, with a significance level of 1%. This finding highlights the critical importance of enhancing urban waterlogging resilience and its positive impact on spatial distribution. The analysis of the Main and Wx coefficients reveals both internal and spatial dependencies among the influencing variables. The Wx effect is lower than the Main effect, suggesting that spatial spillover exists, but is not dominant. This supports the strategy of optimizing local infrastructure to complement regional coordination initiatives. Overall, the control variables demonstrate that drainage networks and urban green spaces effectively mitigate urban waterlogging risks. An increase in per capita GDP and road network density stimulates urban investment in waterlogging control systems, thereby enhancing resilience to waterlogging. However, the Spatial Durbin Model (SDM) reveals a complex pattern of fixed effects: the individual fixed effect is $\rho=0.449$ ($p<0.01$), suggesting mimicry in waterlogging control capabilities across cities, while the spatio-temporal double fixed effect is $\rho=-0.427$ ($p<0.05$), underscoring the dominance of resource competition. This paradox underscores the tension between the Chengdu-Chongqing urban agglomeration's commitment to collaborative governance and the practical realities of resource competition.

Table 5 Results of the Space-Durbin Model Test

Variable	Individual fixed effects	Time fixed effects	Double fixed effects
X1	8.50e-05***	9.36e-05***	8.61e-05***
	(9.24e-06)	(9.89e-06)	(8.84e-06)

X2	0.000248	0.000654**	0.000284
	(0.000196)	(0.000280)	(0.000209)
X3	2.36e-06***	3.62e-06***	2.43e-06***
	(3.37e-07)	(2.94e-07)	(3.19e-07)
X4	0.0168***	0.0152***	0.0180***
	(0.00113)	(0.00128)	(0.00129)
X5	1.61e-05***	1.82e-05***	1.70e-05***
	(8.12e-07)	(8.40e-07)	(8.88e-07)
Spatial rho	0.449***	-1.161***	-0.427**
	(0.0788)	(0.215)	(0.190)
Σ^2	0.000704***	0.00136***	0.000616***
	(5.13e-05)	(0.000104)	(4.49e-05)
R^2	0.932	0.934	0.920

Note: The numbers in parentheses represent the t statistics, while the numbers outside the parentheses represent the coefficients of the test, and the same applies here.

4.3.3. Effect Decomposition

In the context of utilizing economic distance weight matrix and geographic spatial weight matrix, an analysis is conducted on the direct effects, indirect effects, total effects, and significance of various influencing factors on urban waterlogging resilience under the dual fixed effects model, as shown in Table 6.

Table 6 Effect decomposition of the spatial Durbin Mode

Variable	Geospatial Weight Matrix			Economic Distance Weight Matrix		
	Direct Effect	Indirect effects	Overall Effect	Direct Effect	Indirect effects	Overall Effect
X1	8.65e-05***	-5.36e-06	8.12e-05**	8.60e-05***	1.20e-06	8.72e-05***
	(9.76e-06)	(3.77e-05)	(3.39e-05)	(8.12e-06)	(2.25e-05)	(2.45e-05)
X2	0.000305	-0.000758	-0.000453	0.000447*	-0.00108*	-0.000633

				*		
	(0.000192)	(0.00120)	(0.00125)	(0.000178)	(0.000633)	(0.000677)
X3	2.39e-06***	1.89e-06	4.28e-06***	2.74e-06***	-4.34e-06***	-1.60e-06**
	(3.21e-07)	(1.65e-06)	(1.61e-06)	(4.91e-07)	(9.27e-07)	(7.26e-07)
X4	0.0176***	0.0104*	0.0280***	0.0156***	-0.00290	0.0127***
	(0.00119)	(0.00574)	(0.00620)	(0.00108)	(0.00311)	(0.00352)
X5	1.66e-05***	9.41e-06*	2.60e-05***	1.50e-05***	1.89e-05***	3.39e-05***
	(7.69e-07)	(5.35e-06)	(5.71e-06)	(6.62e-07)	(3.33e-06)	(3.48e-06)

（1） Direct Effects. Research has demonstrated that the ratio of urban green space significantly enhances urban resilience to waterlogging. In the economic distance weight matrix, a significance level of 5% is observed, suggesting that expanding green space area and urban green coverage can effectively mitigate waterlogging pressure, improve the city's capacity to manage waterlogging, and elevate the urban waterlogging resilience index. Furthermore, the average monthly rainfall significantly influences waterlogging resilience, and extreme rainfall events may encourage cities to invest in rainwater and waterlogging management infrastructure, thus improving their adaptive capacity. Per capita GDP demonstrates a positive and significant impact at the 1% level, suggesting that economic development, coupled with adequate capital investment and policy attention, can effectively address urban waterlogging issues. Furthermore, the region is increasingly prioritizing the coordinated advancement of urban development and waterlogging resilience. The density of road networks and drainage systems has a significantly positive impact, highlighting the importance of incorporating waterlogging considerations into infrastructure development.

（2） Indirect Effect. The monthly average rainfall did not exhibit significant differences across both the economic distance weight matrix and the geographic spatial weight matrix. This suggests that variations in rainfall in neighboring areas do not have

a substantial spatial spillover effect on the local waterlogging risk. Rainfall is highly localized and exerts a relatively limited impact on adjacent spatial regions. Within the economic distance weight matrix, the urban green space ratio negatively and significantly affects the waterlogging resilience of neighboring areas. This suggests that an increase in green space in economically proximate areas may considerably reduce local resilience to waterlogging, reflecting the competitive nature of regional resources. In the context of the economic distance weight matrix, per capita GDP exhibits a significant negative spatial spillover effect on neighboring regions. This finding is consistent with the 'siphon effect', suggesting that competition for economic resources among economically similar regions could be a potential mechanism inhibiting the development of urban waterlogging resilience in surrounding cities. The road network density exerts a significant positive influence on neighboring areas under the geographic spatial weight matrix, suggesting that higher road network density can improve the waterlogging resilience of neighboring regions. Drainage network density positively impacts the waterlogging resilience of neighboring areas and is statistically significant at the 1% level under the economic distance weight matrix. This indicates a strong interconnection effect between local and neighboring drainage systems. Specifically, improvements in drainage systems in economically proximate areas can enhance local waterlogging resilience through synergistic effects.

（3） Overall effect. By combining the dual-weight matrix of geographic space and economic distance, it was found that monthly average rainfall and the drainage network coefficient have significant positive effects. These factors constitute a dual driving mechanism of "natural pressure engineering response" and exhibit strong synergistic enhancement effects in terms of economic correlation. The impact of road network density and per capita GDP presents complex, multifaceted effects at the spatial scale. Road network density has a significant positive impact under the dual matrix, while the overall effect under the geographic matrix is approximately twice that under the economic matrix, revealing that its synergistic effect depends on geographic proximity. Per capita GDP also shows a significant impact under the dual matrix, with a positive impact under the geographic spatial matrix and a negative impact under the economic

distance matrix. This suggests the existence of a competitive effect between geographically adjacent areas for coordinated development and economically related regions, which is consistent with the current development trend of the Chengdu-Chongqing urban agglomeration. From the analysis of the overall effect, in the spatial structure of the Chengdu-Chongqing urban agglomeration, the Chengdu-Chongqing twin cities serve as growth poles and allocate resources based on their dominant economic position. Meanwhile, geographically adjacent cities achieve limited synergistic effects through infrastructure interconnection. This pattern of "collaboration and competition coexisting" aligns with the regional development strategy of "strengthening the core while considering the periphery", reflecting the complexity and challenges of collaborative governance across administrative regions for waterlogging resilience.

4.3.4. Robustness Test

This study employs four stability testing methods, as shown in Table 7: (1) Setting an additional spatial weight matrix and using the Spatial Durbin Model with both geographic and economic distance weight matrices for effect decomposition; (2) Excluding explanatory variables; (3) Excluding control variables while retaining only explanatory variables for regression; (4) Eliminating extreme values: the extreme values of monthly average precipitation were trimmed at both ends by 1%, minimizing the impact of extreme weather events. As shown in the results of Table 8, monthly average precipitation, per capita GDP, and road network density consistently exhibit highly significant positive effects, establishing them as core driving factors. Even when the spatial weight matrix is modified, the coefficients of these three variables fluctuate by less than 10%, indicating that the definition of spatial correlation does not affect the conclusions. However, the urban green space ratio is not significant in the geographic spatial matrix, but it is significantly enhanced in the economic distance matrix. Moreover, its effect increases substantially when control variables are excluded, suggesting that the urban green space ratio is influenced by economic connections and facility synergy. After trimming, the drainage network remains significant. However, in practical scenarios, extreme rainfall often leads to the failure of gray infrastructure,

underscoring the need for resilient urban water management through complementary green infrastructure. In conclusion, the robustness results demonstrate that most variables exert significantly positive effects, consistent with the conclusions derived from the economic geography embedding matrix, thus validating the stability of the research findings.

Table 7 Robustness testing of the spatial Durbin model

Variable	Geospatial Matrix	Economic Distance Matrix	Exclude explanatory variables.	Exclude control variables.	Eliminate extreme values.
X1	8.61e-05***	8.57e-05***	—	0.000122***	8.74e-05***
	(8.86e-06)	(7.91e-06)	—	(1.93e-05)	(8.94e-06)
X2	0.000285	0.000437**	—	0.00151***	0.000281
	(0.000209)	(0.000184)	—	(0.000444)	(0.000209)
X3	2.43e-06***	2.62e-06***	2.67e-06***	—	2.45e-06***
	(3.19e-07)	(4.95e-07)	(3.61e-07)	—	(3.18e-07)
X4	0.0180***	0.0156***	0.0181***	—	0.0180***
	(0.00129)	(0.00111)	(0.00145)	—	(0.00129)
X5	1.70e-05***	1.53e-05***	1.71e-05***	—	1.69e-05***
	(8.88e-07)	(6.55e-07)	(9.83e-07)	—	(8.88e-07)

5. Discussion

5.1. The spatiotemporal pattern and mechanism of waterlogging resilience in the Chengdu Chongqing urban agglomeration

This study systematically examines the spatiotemporal evolution patterns and impact mechanisms of waterlogging resilience in the Chengdu-Chongqing urban agglomeration from 2000 to 2023, utilizing an evaluation system integrating the PSR framework and SDM model. The research finds that the waterlogging resilience of the Chengdu-Chongqing urban agglomeration exhibits a spatial pattern of "dual core polarization and edge collapse"[34-35], which not only confirms the applicability of the "core-edge" theory in the context of disaster resilience[36], but also highlights its significant differences from the "multi-center networked" resilience model of coastal urban agglomerations, such as the Yangtze River Delta and the Pearl River Delta[37-38]. This difference likely arises because the Chengdu-Chongqing urban agglomeration is

still in a stage of strong core-driven development, where the dual-core "siphon effect" significantly outweighs the "diffusion effect", leading to an ineffective transformation of economic growth benefits into regional synergy, thereby exacerbating the imbalance in resilience development within the urban agglomeration. This finding aligns with the study's conclusion that "per capita GDP generates negative spatial spillovers in neighboring economic areas", offering new case studies for understanding the evolution of waterlogging resilience in urban agglomerations at different development stages. In contrast, the more mature regional collaborative governance mechanisms in the Yangtze River Delta have effectively mitigated this negative effect[39]. Thus, in the early stages of dual-core urban agglomeration development, the lack of effective regional coordination may result in economic growth exacerbating, rather than alleviating, the imbalance in internal resilience.

The decomposition of effects in the spatial Durbin model further uncovers the intricate spatial heterogeneity of the driving factors. The main finding is that economic driving factors exert both positive and negative spillover effects across social, economic, and geographical spaces. Per capita GDP significantly enhances local resilience, following the classic sequence: economic level → infrastructure investment → waterlogging control capacity improvement. However, significant negative spillover effects are observed in economically adjacent regions[40]. This confirms the occurrence of a resource "adsorption" phenomenon in peripheral cities during the expansion of the Chengdu-Chongqing dual core, which results in a "depression" cycle of waterlogging resilience in neighboring cities[41]. Natural and infrastructural factors also display complex synergies and trade-offs. As a long-term climate pressure indicator, "monthly average precipitation" demonstrates a robust positive effect on resilience improvement through the "pressure-driven" mechanism. However, its spatial spillover is insignificant, confirming the localized nature of rainfall events. Regarding infrastructure factors, the density of the road network shows a positive correlation with waterlogging resilience, which may stem from emergency evacuation capabilities. However, its association with the increase in impervious surfaces should be considered a potential risk for increased runoff. Therefore, in urban planning, the potential risk of runoff can be mitigated by increasing the provision of ground-level

green facilities. The drainage network exerts significant effects and positive spillover under normal conditions but reveals insufficient elasticity in extreme rainfall events, indicating the limitations of single grey infrastructure in addressing nonlinear climate risks[42]; However, the urban green space ratio is significant only in economically connected areas, suggesting that its benefits necessitate corresponding social, economic investments, and facility coordination[43].

The results suggest that, in the context of ongoing climate change, no single solution is sufficient for addressing the challenges of the Chengdu-Chongqing urban agglomeration. This study empirically highlights the necessity of transitioning to a systematic planning paradigm of "grey-green infrastructure collaborative integration", which aligns closely with Zheng et al.'s conclusion that grey-green integration can offer enhanced resilience[44]. By complementing the functions of engineering and ecological facilities[45], a more scientific management system can be constructed to address the increasingly evident non-linear climate risks.

5.2. Implications for Enhancing the Resilience of Inland Waterlogging and Regional Collaborative Governance

The research findings demonstrate a spatial spillover effect among the factors influencing urban waterlogging resilience. It is recommended to establish a regional collaborative governance system with a targeted mechanism. Based on assessments of waterlogging resilience and spatial spillover effects, this study proposes the following recommendations for enhancing waterlogging resilience in the Chengdu-Chongqing urban agglomeration:

First, It is necessary to establish a new concept of resilient governance based on "spatial coordination"[46]. The negative spatial spillover effect of per capita GDP revealed by the spatial Durbin model indicates that the respective governance models based on administrative districts have limitations. Policy-making should actively explore crossing administrative boundaries to establish compensation and coordination mechanisms for building regional urban waterlogging resilience. For instance, Draw on the experience of ecological compensation to establish a regional resilience

collaborative development fund[47], Guide the flow of resources from core cities to resilient “lowlands”, thereby transforming the negative “siphoning effect” into a positive “synergistic effect”.

Secondly, the engineering practice of "grey-green integration" should be comprehensively implemented[48]. This is not only a study on the positive synergistic effect between roads and drainage networks, but also a key measure to address the strong spatial dependence of urban green space ratio and the vulnerability of drainage networks to failure under extreme rainfall. In practice, a three-level regulation system of "retention-infiltration-drainage" can be constructed through the coupled design of "green space depression and network upgrading", so as to compensate for the functional shortcomings of grey infrastructure in extreme situations with the ecological resilience of green infrastructure, achieving a synergistic effect of 1+1>2[44]. This means that in planning and design standards, attention should not only be paid to the drainage capacity of grey infrastructure, but also mandatory provisions must be made for the regulation and storage capacity and spatial layout of green infrastructure, so that it can form functional cohesion and synergy with the grey pipe network system[49]. This strategy not only responds to the empirical conclusion in the model that "the green space ratio and drainage network coefficient need to work synergistically", but also scientifically implements the principle of "grey-green integration and systematic governance" in the "Pilot Work Plan for Climate-Resilient City Construction (2023)".

In summary, through the dual-driven approach of "spatial synergy" and "integration of grey and green", the Chengdu-Chongqing urban agglomeration can undergo a fundamental transformation from "local high resilience" to "systemic high resilience" in addressing climate change. This approach provides a regional paradigm for the coordinated and shared development of infrastructure construction and stormwater management in dual-core urban agglomerations[50].

5.3. Research Limitations and Future Prospects

The PSR-SDM coupling framework constructed by our research institute reveals spatiotemporal evolution law and driving mechanism of waterlogging resilience in the Chengdu Chongqing urban agglomeration from 2000 to 2023. It provides specific solutions for waterlogging control in the Chengdu Chongqing urban agglomeration, but there are still certain limitations. The data used in the study may have limitations

in accuracy, especially in the acquisition and processing of extreme precipitation data, and is limited in spatiotemporal span, which cannot fully reflect the characteristics of long-term maximum rainfall in urban agglomerations. This may affect the comprehensiveness of the research results. Future research, with available data, will introduce more refined short-term heavy rainfall indicators that can directly trigger urban waterlogging, which will help to more accurately characterize the impact of rainfall on urban waterlogging resilience.

The factors affecting urban waterlogging resilience are complex and diverse, and the future faces highly uncertain scenarios of climate change and socio-economic development. This study mainly focuses on historical and current assessments, without conducting scenario based predictive simulations. To better cope with future climate change, it is urgent to incorporate various climate change scenarios into the urban hydrology and resilience assessment framework, conduct dynamic simulations and predictions of the evolution trend of urban agglomeration waterlogging resilience under different development paths, and provide a more solid scientific basis for formulating forward-looking adaptation strategies.

6. Conclusion

This study focuses on the Chengdu-Chongqing urban agglomeration, developing an evaluation system integrating the PSR and SDM models. It systematically analyzes the spatiotemporal evolution and driving mechanisms, explores the spatial effects of various factors on waterlogging resilience, and proposes targeted strategies to enhance resilience. The main conclusions are as follows:

From 2000 to 2023, the waterlogging resilience in the Chengdu-Chongqing urban agglomeration exhibited an upward trend, with the average level of resilience increasing from 0.1579 to 0.5251 in each city. The growth rate in Chengdu and Chongqing, as the core areas of the twin cities, is significantly higher than that of peripheral cities, resulting in a “core-periphery polarization” pattern. This highlights the importance of avoiding resilience “depression” in the early stages of rapid regional development through collaborative governance. The spatial distribution of waterlogging resilience follows a “high on both sides, low in the center” pattern, with

Chengdu and Chongqing consistently maintaining a high level of resilience. The development of surrounding cities exhibits a clustering trend, reinforcing the “core-periphery” structure of regional resilience. The spatiotemporal evolution of the Chengdu-Chongqing Economic Circle urban agglomeration aligns with the national strategic development path, but it has gradually evolved towards a 'dual-core dominance' and “central collapse” trend.

The driving mechanism exhibits significant spatial heterogeneity, with variations across different regions. Monthly average precipitation demonstrates marked local variations. The urban green space ratio and per capita GDP significantly enhance local waterlogging resilience, yet they exhibit negative spatial spillover effects in economically neighboring areas, highlighting a competitive dynamic in resource allocation. The road and drainage networks primarily exhibit positive spatial spillover effects. This reveals a dual development model of “regional competition” and “local coordination” in the enhancement of waterlogging resilience within the Chengdu-Chongqing urban agglomeration. Building on this, we propose a dual-driven paradigm of spatial collaborative governance and grey-green integrated engineering. We further suggest transforming the negative “siphon effect” into a positive “collaborative effect” through various strategies, thereby enhancing the resilience of urban agglomerations to waterlogging.

One limitation of this study lies in the complexity and diversity of factors influencing urban waterlogging resilience, compounded by the highly uncertain scenarios of climate change and socio-economic development in the future. This study primarily focuses on historical and current assessments, without incorporating scenario-based predictive simulations. Future research should incorporate various climate change scenarios into the urban hydrology and resilience assessment framework to perform dynamic simulations and predict the evolutionary trends of waterlogging resilience in urban agglomerations under different development trajectories. This would provide a stronger scientific foundation for developing proactive adaptation strategies.

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Data availability statement

The datasets used and/or analyzed in this study can be reasonably requested from the corresponding author.