Spatiotemporal characteristics and influencing factors of urban resilience efficiency in the Yangtze River Economic Belt, China

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Abstract

Urban resilience efficiency is an important indicator to explore the relationship between resource consumption and urban resilience, shedding new light on the study of urban sustainable development. Based on the panel data of 2008, 2012, and 2017, this paper makes a spatiotemporal assessment on the urban resilience efficiency of 126 cities in the Yangtze River Economic Belt in China by applying an entropy weight-TOPSIS method and a slack-based measure (SBM) model. Combined with the analysis of a geographically weighted regression model (GWR), the influencing factors on resilience efficiency are also investigated. The results show that both the resource consumption index (RC, inputs) and the urban resilience index (UR, outputs) presented a steady upward trend, and their spatial distribution characteristics were similar, showing a gradual decrease from the eastern coastal cities to the central and western inland cities. Derived from inputs and outputs, the mean values of resilience efficiency index (RE) in three periods were 0.3149, 0.2906 and 0.1625, respectively, revealing that there had been a noticeable decline. Spatially, its spatial distribution has evolved from a relatively balanced pattern to an unbalanced one, showing a gradual decrease from west to east. The results of the GWR model analysis indicate that the total electricity consumption and area of construction land had a considerable correlation with the overall urban resilience of the YREB. Furthermore, total quantity of water supply and science and technology (S&T) expenditure continued to be the main driving factors on urban resilience of the upstream cities. The midstream regions mainly depended on the scale of construction land, and the influencing factors are relatively single. The influencing factors in the downstream areas have changed from dominance of resources and capital factors to the single dominance of resource factors, and total electricity consumption had a strong explanatory power. Based on these findings, we had put forward the overall and local regional policy implications.

Keywords

Urban resilience; Resilience efficiency; Evaluation; Influencing factors; Yangtze River Economic Belt; Entropy weight-TOPSIS method; SBM model; GWR model

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1. Introduction

The development of cities is accompanied by continuous external and internal shocks, which include chronic stress and sudden disturbances, such as sea level rise, hurricanes, accidents, public health emergencies, and social security events (Berkes, 2007; Meerow et al. 2019; Liu et al. 2020). Responding to the various threats and risks in urban areas, the term of urban resilience has attracted wide attention and gradually become a new paradigm for planning management and urban construction. It aims to improve the urban system diversity, functional redundancy, and autonomous adaptability through the optimization of social economy, infrastructure, ecological environment, or management strategy (Godschalk, 2003), so as to ensure that the city can maintain and enhance the primary characteristics and essential functions in the face of uncertain shocks (Alberti et al., 2003; Ribeiro & Pena Jardim Gonçalves, 2019).

As a result of reform and opening up policy, China has achieved rapid economic growth and urbanization over the past four decades (Qin and Zhang 2014; Yu 2021). According to the data from China Statistical Yearbook, between 1978 and 2019, China's urbanization rate increased from 17.92% to 60.60%. Undoubtedly, the rapid urbanization in China has given rise to the booming construction of the resilient city(Deng and Bai 2014; Zhu et al. 2019a). However, some cities have consumed large amount of energy and resources for rapid growth of resilience, which has ultimately resulted in insufficient resource utilization and sensitive urban environment, with extensive economic growth in the meantime (Wang et al. 2014). Furthermore, due to the concentration of various elements such as resources, labor, capital and industries in big cities, the level of resilience development in big cities is higher than that of small and medium-sized cities (Bai et al. 2019). But the fact that big cities consume more resources cannot be ignored (Kuang et al. 2018; Wang et al. 2020). Therefore, whether the resilience efficiency of big cities is higher or not remains a question, it is interesting to explore the performance of urban resilience efficiency and its disparity among big, medium and small cities. During the past decade, China has been committed to promoting changes in the quality, efficiency, and driving force of economic development, intensifying efforts in ecological and environmental protection, which is known colloquially as "green development" and "high-quality development" (Fang et al. 2017). These efforts have made urban resilience efficiency an issue worthy of further consideration. The basic concept of resilience efficiency refers to the ratio of urban resilience and resource consumption, with highlights on the importance of achieving optimal resilience based on limited resource consumption (Mickwitz et al. 2006). In other words, the assessment of resilience efficiency is an effective way to investigate the extent of coordination between resilience and resources, which would positively contribute to regional economic planning, industrial cooperation, and ecological conservation. Therefore, exploring the spatiotemporal evolution of resilience efficiency and its influencing factors have significant implications for the theory of urban resilience and practical actions.

Urban resilience assessment is an effective way to investigate the ability of cities to cope with disturbances, which is a necessary prelude for the evaluation of resilience efficiency. Resilience efficiency assessment is rooted in the exploration of urban resilience assessment. Some studies have focused on the quantitative assessment of the subsystems of urban resilience, such as social economy resilience (Bastaminia et al., 2017), natural disaster resilience (Zhang et al., 2019), infrastructure resilience (Ouyang & Dueñas-Osorio, 2012; Bruneau et al., 2003), spatial form resilience (Lu et al., 2020； Feng et al., 2020), and ecosystem resilience (Xiao et al., 2020), and thereby examined the driving factors or policy implications based on the assessment results. Moreover, due to the complexity and diversity of urban resilience (Folke et al., 2002；Berkes, 2007；Elmqvist et al., 2019), some other studies have developed a comprehensive assessment framework to quantify urban resilience. Different from the perspective of subsystems, the comprehensive assessment framework integrates multiple dimensions of city, including urban economy, society, ecology, infrastructure, and management (Khazai et al., 2018; Sharifi & Yamagata, 2016). Recently, urban resilience studies are turning from theoretical exploration to practice actions with paying enthusiastic attention to the local resilience policies. Since 2010, UN-Habitat, United Nations Development Progamme (UNDP), and United Nations International Strategy for Disaster Reduction (ISDR) have established strategic cooperation with many international organizations or institutions. They have successfully launched a range of campaigns on building resilient cities around the world to cope with risks and disasters. Besides, the Rockefeller Foundation has advocated the Urban Resilience Movement and proposed the "100 Resilient Cities" project, which aimed to promote the resilience of specific cities or regions through quantitative assessment and practical strategies (Trends in Urban Resilience 2017). The studies mentioned above provide sufficient theoretical evidence for our study in terms of conceptualization and indicator selection of urban resilience. As to the evaluation methods, technique for order preference by similarity to ideal solution (TOPSIS), fuzzy comprehensive evaluation method (FCEM), analytic hierarchy process (AHP), and principal component analysis (PCA) are commonly used in the previous scholarly works (Asadzadeh et al., 2015; Fu et al., 2020; Lamichhane et al., 2020; Orencio & Fujii, 2013; Xun & Yuan, 2020).

A growing number of studies have attempted to examine the relationship between urban resilience and resource consumption. However, there is few literature that directly measures the urban resilience efficiency. Related studies mainly focused on the following three aspects: urbanization efficiency, land use efficiency, and eco-efficiency. For example, Jin et al., (2018) selected urban built-up area, fiscal expenditure, non-agricultural employment, and capital stock as input indicators, and non-agricultural output value as output indicators to reveal the spatial characteristics of urbanization efficiency in the YREB. Yu et al., (2019) explored the land use efficiency (LUE) of 12 urban agglomerations in China. They found that the mean value of LUE is low. Furthermore, it presented a certain fluctuation during the research period. Using the data of 283 cities, Y. Zhang et al., (2019) made a comprehensive analysis of urban environmental efficiency from 2003 to 2016 in China. The study pointed out that the overall environmental efficiency was not very high, and the situations vary across cities. Although the above studies have different output indicators when discussing efficiency, capital, labor, energy, water resources, and land are mostly chosen as input indicators. Among the preceding studies on efficiency evaluation, Stochastic Frontier Approach (SFA), Data Envelopment Analysis (DEA), and Slack-based Measure (SBM) models are all popular methods.

Further analysis of driving factors on urban development efficiency is constructive for the proposal of effective resilience strategies. Recently, a considerable literature has grown up around the theme. For instance, Zhu et al., (2019) have investigated the main driving factors of eco-efficiency using a Tobit regression analysis, suggesting that the development scale and structure of economy, population, market and industry have a positive impact on eco-efficiency in the Western Taiwan Strait Economic Zone. C. Wu et al., (2017) utilized OLS GWR model to explore the major influencing factors of land use efficiency in the Yangtze River Delta during 2004-2012. The results revealed that foreign direct investment, labor flow, innovation, and land finance played key roles in improving LUE. Qian et al., (2021) adopted a geographical detector model to determine the driving factors of urbanization efficiency in China. They found that urbanization rate and GDP per capita were the leading cause of the increase in UE. In general, several methods, such as panel data model, logistics regression model, ordinary least squares method (OLS), geographical detector method (GDM), and Tobit model, have been used to identify the influencing factors on urban efficiency.

To date, much progress has been made in examining urban resilience, both theoretically and empirically. However, the more relevant studies have tended to focus on the resilience efficiency based on partial subsystem perspective, such as urbanization efficiency, eco-efficiency, and land use efficiency. Moreover, most studies have used cross-sectional rather than longitudinal data when identifying the spatial characteristics and driving forces of urban efficiency, which indeed ignored evolutionary trends. Responding to the deficiency, choosing the Yangtze River Economic Belt (YREB) as the study area, based on our previous research on quantitative framework of urban resilience efficiency (Peng et al., 2021), we first investigated the evolution of input and output indicators through the TOPSIS method. In particular, the framework of output indicators system highlighted a comprehensive understanding of urban resilience which reflected main aspects from four subsystems. Then, with the help of the SBM model and ESDA methods, we revealed the spatiotemporal patterns of urban resilience efficiency of 126 cities in 2008, 2012, and 2017. Finally, we applied the GWR model to study the trend of driving factors. The motive of doing so is not only to trace the spatial changes of YREB urban resilience efficiency from a dynamic perspective, but also to explore the changes of potential driving factors to provide some implications for the local sustainable development and policymaking of urban resilience.

The remaining part of this paper proceeds in the following way. Section Two describes the study area, methodology, data, and indicators. The third section provides the evaluation of resource consumption (inputs) and urban resilience(outputs). Then, we illustrate the results of the resilience efficiency of 126 cities from the perspective of temporal evolution, spatial distribution, and spatial correlation. Further, we analyze the influencing factors on resilience efficiency at two levels: a global level and a local level (upstream, midstream and downstream of the Yangtze River). The fourth section focus on detailed discussion and policy implications. The last section concludes the paper.

2. Methodology

2.1 Study area

The YREB spans the eastern, central, and western regions in China, covering 9 provinces and 2 municipalities (Fig.1). According to *the Guidelines for Development Along the Yangtze Economic Belt* (2016), Yunnan, Sichuan, Guizhou, and Chongqing are located in the upstream of the YREB; Hubei, Hunan, Jiangxi are located in the midstream regions ; Anhui, Jiangsu, Zhejiang, Shanghai are located in the downstream regions. YREB was chosen as the study area for the following reasons. Firstly, it covers about 21% of China’s territorial area and accounts for more than 40% in population and GDP. Thus, YREB is one of the regions with the strongest comprehensive strength and strategic support in China. Due to its unique natural conditions and urbanization potential, YREB is the primary pioneer region of pursuing urban resilience. Secondly, since *the Guidelines* was issued to promote the development of YREB in 2016, the region has accelerated its urbanization through more capital investment, energy utilization, and resource consumption. However, there is not yet a comprehensive framework for exploring urban resilience and its efficiency in the YREB. Thirdly, due to the faster urbanization rate in the YREB, the pressure on the balance between economic growth and environmental protection gradually increases.

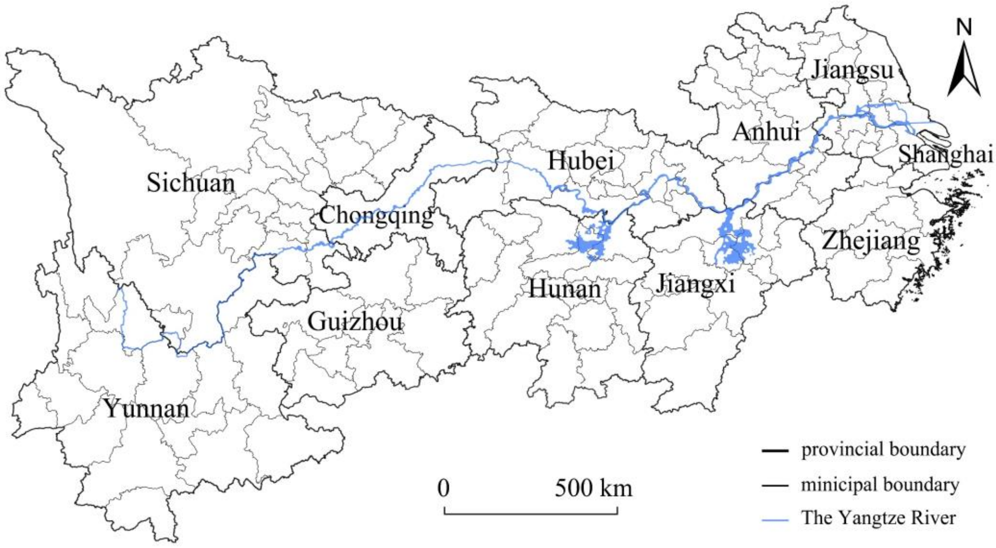


Fig. 1. General view of the YREB

2.2 Methods

2.2.1 Entropy Weight-TOPSIS model

Here, the entropy weight-TOPSIS model are used to assess the inputs (resource consumption index) and outputs (urban resilience index) of the cities in the YREB. Among all the methods mentioned in the literature review, the entropy weighted-TOPSIS model is a multi-objective decision-making method where weighting coefficients are improved by the entropy weight method to minimize the influence of subjective factors. Moreover, it is efficient to be calculated, with little restrictions on the sample size (Wang et al., 2019).

To establish the decision matrix:

$$X = (x_{ij})_{m\times n} \quad (1)$$

where x_{ij} is the value of city i on indicator j; m, n are the total number of assessed cities and indicators respectively.

To normalize the decision matrix with the deviation maximization method:

$$r_{ij}(x) = \frac{x_{ij} - min(x_j)}{max(x_j) - min(x_j)} \text{ (Positive indicators)} \quad (2)$$

$$r_{ij}(x) = \frac{max(x_j) - x_{ij}}{max(x_j) - min(x_j)} \text{ (Negative indicators)} \quad (3)$$

To calculate the entropy:

$$e_j = -k \sum_{i=1}^{m} p_{ij} \ln p_{ij} \tag{4}$$

where $p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}$, $k = \frac{1}{\ln m}$.

To calculate the weight of the index j:

$$w_j = \frac{1 - e_j}{\sum_{j=1}^{n}(1 - e_j)} \tag{5}$$

To establish the weighted normalized decision matrix:

$$Z = (z_{ij})_{m \times n}, z_{ij} = w_{ij} \times r_{ij} \tag{6}$$

To determine the ideal solution:

$$\begin{cases} z_i^+ = \max_j(z_{ij}) \text{ (Positive)} \\ z_i^- = \min_j(z_{ij}) \text{ (Negative)} \end{cases} \tag{7}$$

To calculate the comprehensive index:

$$Q_i^+ = \sqrt{\sum_{i=1}^{m}(z_i^+ - z_{ij})^2}, \quad Q_i^- = \sqrt{\sum_{i=1}^{m}(z_i^- - z_{ij})^2} \tag{8}$$

$$Y_i = \frac{Q_i^-}{Q_i^+ + Q_i^-} \tag{9}$$

where the higher Y_i is, the better the city is.

2.2.2 SBM model

We use SBM model to measure urban resilience efficiency (RE index). DEA is a sophisticated approach for estimating productive efficiency of a system (Charnes et al.,1978). The traditional DEA ignores the input excesses and output shortages (called slacks) in a Decision-Making Unit (DMU), and does not consider the significant influence of undesirable outputs on the efficiency of the DMU. As such, SBM model was proposed by (Tone, 2001) to avoid potential errors caused by slacks and undesirable outputs. In contrast to the traditional model, it can better reflect the real efficiency of the evaluation object.

$$\rho = \min \frac{1 - \frac{1}{N}\sum_{n=1}^{N} \frac{S_n^x}{x_{k'n}^{t'}}}{1 + \frac{1}{M+I}\left(\sum_{m=1}^{M} \frac{S_m^y}{y_{k'm}^{t'}} + \sum_{i=1}^{I} \frac{S_i^b}{b_{k'i}^{t'}}\right)} \tag{10}$$

$$s.t. \sum_{t=1}^{T} \sum_{k=1}^{K} z_k^t x_{kn}^t + S_m^y = x_{k'n}^{t'}$$

$$\sum_{t=1}^{T}\sum_{k=1}^{K} z_k^t y_{km}^t - S_m^y = y_{k'm}^{t'} \tag{11}$$

$$\sum_{t=1}^{T}\sum_{k=1}^{K} z_k^t b_{ki}^t + S_i^b = b_{k'i}^{t'}$$

$$z_k^t \geq 0, S_n^x \geq 0, S_m^y \geq 0, S_i^b \geq 0, (k = 1, \cdots, K)$$

where ρ refers to RE index, $N,\ M,\ I$ are the numbers of the input resource elements, desirable outputs, and undesirable outputs (since the negative indicator has been processed, as in Eq. (3), the undesired output is not set) respectively. S_n^x、S_m^y、S_i^b refer to slack vectors of input, desirable and undesirable outputs respectively. $x'_{k'n}$、$y_{k'm}^{t'}$、$b_{k'i}^{t'}$ refer to the outputs of DMUs k' at period t'. z_k^t stands for the weight of DMUs. The target function ρ is decreasing with respect to S_n^x、S_m^y、S_i^b monotonically, taking values in the range of (0,1]. If $\rho = 1$, the DMU is SBM-efficient. If $\rho < 1$, the DMU is inefficient.

2.2.3 GWR model

GWR is an improved spatial linear regression model based on spatial non-stationary data. It offers an effective and reliable way for analyzing non-stationary spatial characteristics. GWR model gives the fitting coefficients of a local model based on the function variable coefficient of each geographical location and perform a parameter estimation on studied factors. Therefore, GWR is widely adopted to address spatial heterogeneity issue across geography (Li et al., 2010; D. Wu, 2020).

$$y_i = \beta_0(u_i,\ v_i) + \sum_{i=1}^{k} \beta_k(u_i,\ v_i) x_{ik} + \theta_i \tag{12}$$

where y_i represents the observed value, $(u_i,\ v_i)$ represents the coordinates of sample i; $\beta_0(u_i,\ v_i)$ represents the regression constant of sample i; $\beta_k(u_i,\ v_i)$ is the regression coefficient of variable k at sample i, k refers to the number of independent variables; x_{ik} is the value of x_k at sample i; θ_i is a random error coefficient.

$\beta_k(u_i,\ v_i)$ is assessed by the weight matrix and Ordinary Least Squares Regression, and the formula is as follows:

$$\tilde{\beta}(u_i,\ v_i) = \left[X^T W(u_i,\ v_i) X\right]^{-1} X^T W(u_i,\ v_i) Y \tag{13}$$

where $\tilde{\beta}$ is the estimated value of β, W is spatial weights matrix. The selection of spatial weight function is crucial to the accurate estimation of model parameters. Gauss function is most commonly used among the weight functions and its function formula is:

$$W_{ij} = exp\left(-\frac{d_{ij}^2}{b^2}\right) \tag{14}$$

where d_{ij} refers to the Euclidean distance between i and j, b stands for the bandwidth.

2.3 Data and indicators

Firstly, using the entropy weight-TOPSIS method, input and output indicators were integrated into two indexes: a resource consumption index (RC) and an urban resilience index (UR). Secondly, selecting input indicators and UR index as output indicators, we undertook an evaluation of urban resilience efficiency (RE) using an SBM model and capture the spatiotemporal characteristics of 126 cities in YREB by applying exploratory spatial data analysis methods (Fig. 2). Thus, we explored the relationship between resource consumption and urban resilience through these three indexes: RC, UR, and RE. Finally, the GWR model was employed to investigate the influencing factors on RE with input indicators selected as independent variables and UR index as the dependent variable.

2.3.1 Input indicators

In the literature related to resilience efficiency, capital, labor force, energy resource, water resource, and land resource are the input elements that are widely adopted (Oh, 2010; Chiu et al., 2012; Ren et al., 2018). Further, as the investment in technology and education is crucial to the resilience of a city (Peng et al., 2021; Mou et al., 2021), we took technology input and education input into consideration. As for input indicators (Fig. 2), total electricity consumption, total quantity of water supply, area of construction land, fixed asset investment, number of employed persons in urban non-private units (NEPUNU), S&T expenditure, and education expenditure were selected to represent the above elements, respectively (Zhou et al., 2018; Huang et al., 2018).

2.3.2 Output indicators

We considered the urban resilience index (UR) as desirable outputs. The concept of urban resilience refers to the ability of a city to recover from disturbances. In a review of studies surrounding urban resilience assessment, we found that it is necessary to understand the properties and dimensions of urban resilience, which is closely related to the further selection of indicators. According to several systematic reviews of urban resilience (Sharifi & Yamagata, 2016; Meerow et al., 2016; X Sanchez et al., 2018; Peng et al., 2021), the most suggested dimensions are economic resilience, social resilience, infrastructure resilience, and ecological resilience. Specifically, (1) Economic resilience focuses on strong economic scale, diversified economic structure, and innovation-driven economic model, so as to enhance city's ability to deal with external economic turmoil (Simmie and Martin 2010; Spaans and Waterhout 2017). Therefore, indicators were selected considering three subdimensions: economic growth, economic structure, and economic vitality. Economic growth reflects the strength and stability of a city, which can provide basic support to resist or absorb the impacts resulting from economic crisis. Economic structure emphasizes multiple rather than single structure, which helps to maintain the functionally economic elements to adapt to different risks. Economic vitality provides power for economic innovation. (2) Social resilience aims to improve the ability of urban communities to reduce the uncertainty caused by demographic, political, and environmental changes (Allan and Bryant 2012; Adger 2016). Social equity and social service guarantee were taken into account when measuring social resilience with paying attention to the integration and exchange of social resources across the city. (3) The purpose of infrastructure resilience is to make urban infrastructure show characteristics of sufficient, redundant, and diversified through reasonable construction and planning, reducing the vulnerability of infrastructure to sudden disasters such as earthquakes, hurricanes, and floods (McDaniels et al. 2008; Heinimann et al. 2017). Thus, this dimension includes ICT infrastructure and disaster prevention to measure the robustness and redundancy of critical infrastructure. (4) Ecological resilience is related to the quality and capacity of urban ecosystems, together with the pressure from environmental pollution, resource scarcity, and climate change (Alberti and Marzluff 2004; Pickett et al. 2014).

Multifunctional blue and green spaces in the city promotes robustness and adaptation which are vital for attacks resisting and absorbing. Hence, indicators selection mainly emphasizes livable environment, environmental pollution, and ecological carrying capacity. As for the indicators, we selected indicators that can transform dimensions of urban resilience into a measurable property. Considering the data correlation as well as data availability, a final 29 indicators covered in the four dimensions were selected for UR index (Fig. 2).

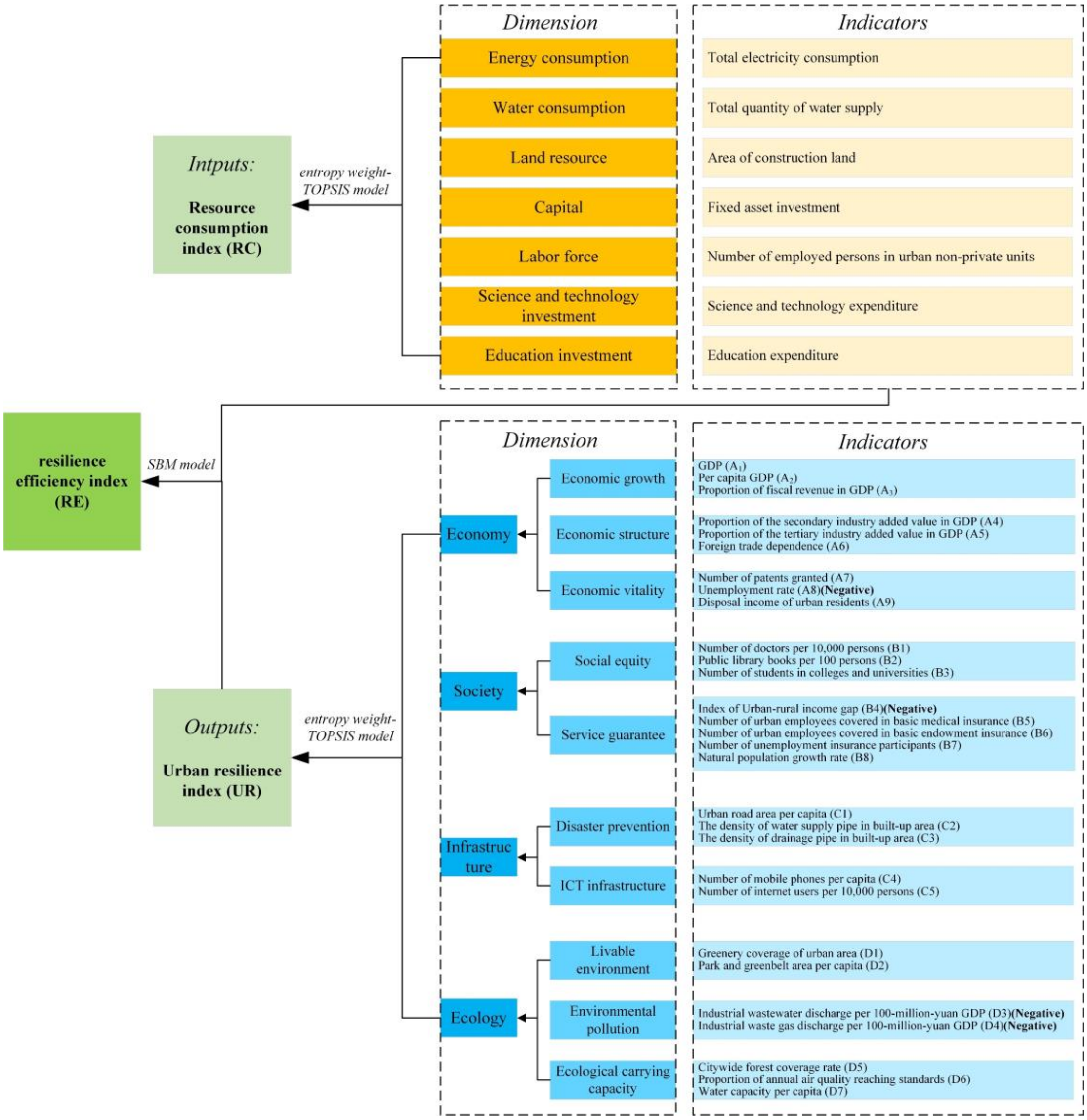


Fig. 2. Input and output indicators

2.3.3 Data sources

We collected data on the above indicators for 126 cities in the YREB of 2008, 2012, and 2017, among which, the data for input indicators were collected from the China City Statistical Yearbook and China Urban Construction Statistical Yearbook, and the data for output indicators were collected from China City Statistical Yearbook, China Urban Construction Statistical Yearbook, and the statistical bulletins of national economic and social development of each city. As Shennongjia, Tianmen, Xiantao, and Qianjiang cannot provide relevant data, they were not selected as sample cities.

3. Results

Based on the values of the RC, UR, and RE in 2017, the 126 assessed cities were classified into five groups using the natural breaks method (Jenks). In order to make the classification standards of the selected three years on urban resilience efficiency consistent, we processed the results of the other two years according to the classification of 2017, as illustrated in Fig. 3, Fig. 4, and Fig. 6. ARCGIS10.2 was used for all the visualization of the results in this paper.

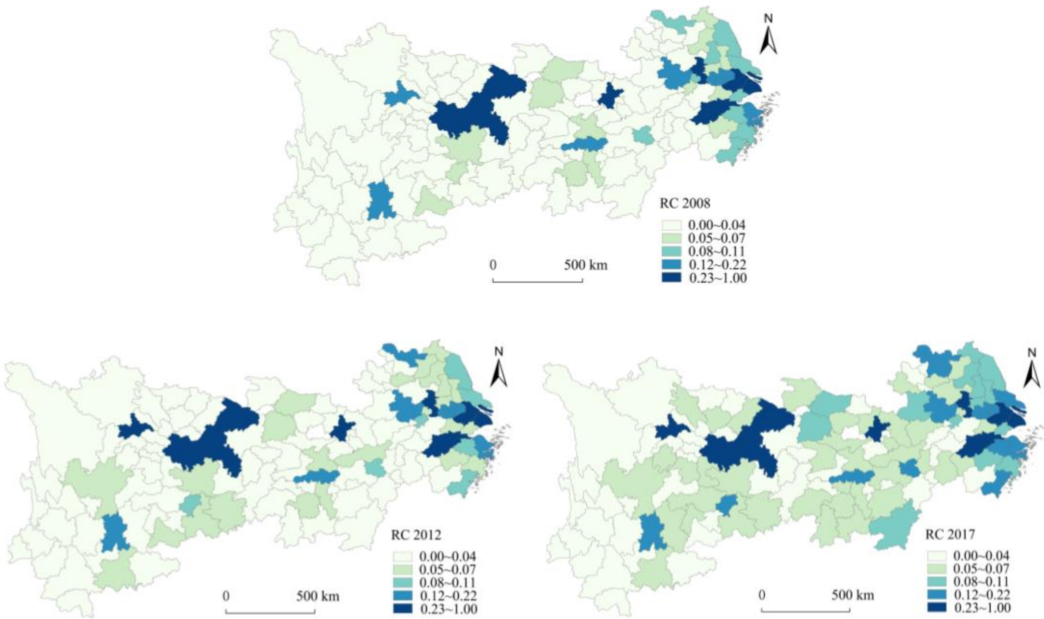


Fig. 3. Resource consumption distribution in the YREB

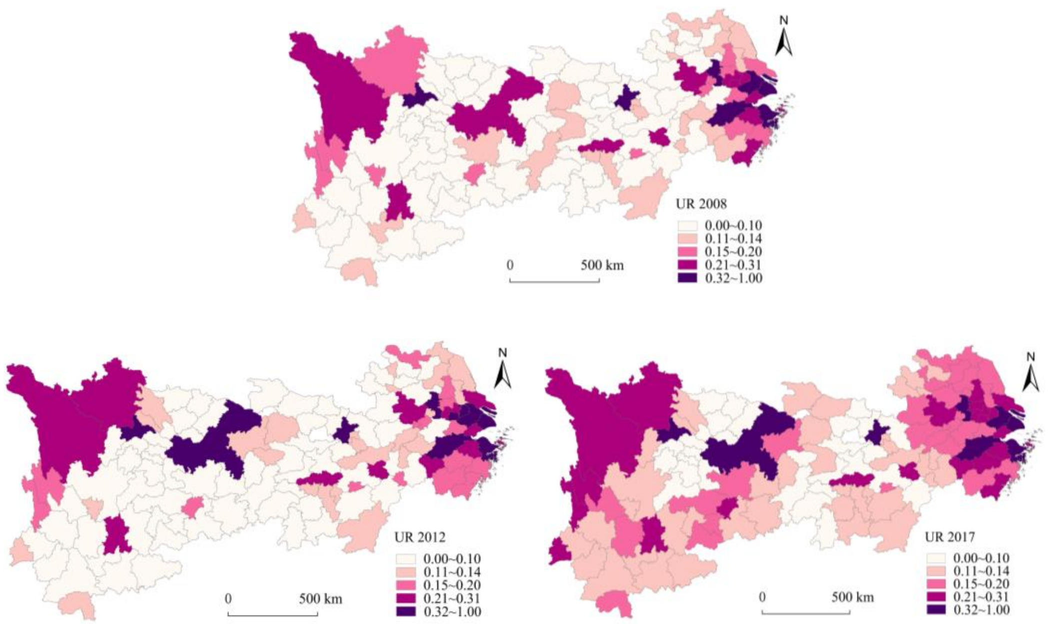


Fig. 4. Urban resilience distribution in the YREB

3.1 The spatiotemporal characteristics of resilience efficiency

3.1.1 The temporal evolution characteristics

In 2008, 2012, and 2017, the mean RE values were 0.3149, 0.2906, and 0.1625, presenting a steady decline trend. Furthermore, the mean values of the upper, middle and downstream regions decreased from 0.4050, 0.2931, and 0.2292 in 2008 to 0.2356, 0.1194, and 0.1158 in 2017, from which we can infer that the RE values dropped both at a global or local level. According to the classification of RE index in these three periods (Table 1), we can see that: (1) the numbers of cities in the range of 0.00~0.09 were 5, 4, and 57 respectively, and their proportion of the total sharply increased 4% in 2008 to 45% in 2017; (2) the numbers of cities in the range of 0.10~0.17 were 35, 42 and 43, accounting for 28%, 33% and 34% of the total, with a relatively small change range; (3) the numbers of cities in the range of 0.18~0.31 were 46, 45 and 17, accounting for 37%, 36% and 13% of the total, presenting a steeply decline; (4) the numbers of cities between 0.32 and 0.46 was 17, 16 and 3, accounting for 13%, 13% and 2% of the total, showing a sharply downward trend; (5) the numbers of cities in the range of 0.47~1.00 were 23, 19, and 6 respectively, accounting for 18%, 15%, and 5% of the total, also showing an obvious change range. It can be seen in Table 1 that there were few cities with RE values of 1, and the numbers of low-value cities with RE values below 0.17 increased rapidly, while the numbers of high-value cities showed a trend of rapid loss. Moreover, by calculating the rank-size distribution of RE index of 126 cities (Fig. 5), we found that the absolute value of the slope coefficient of the rank-size distribution increased from 0.6551 in 2008 to 0.7492 in 2017, indicating that the hierarchical gaps among high-value, medium-value, and low-value cities are further enlarged, together with a rising trend of unbalanced spatial distribution on resilience efficiency.

Table 1

Hierarchical division of urban resilience efficiency

Hierarchy		0.00~0.09	0.10~0.17	0.18~0.31	0.32~0.46	0.47~1.00
Number of cities	2008	5	35	46	17	23
	2012	4	42	45	16	19
	2017	57	43	17	3	6

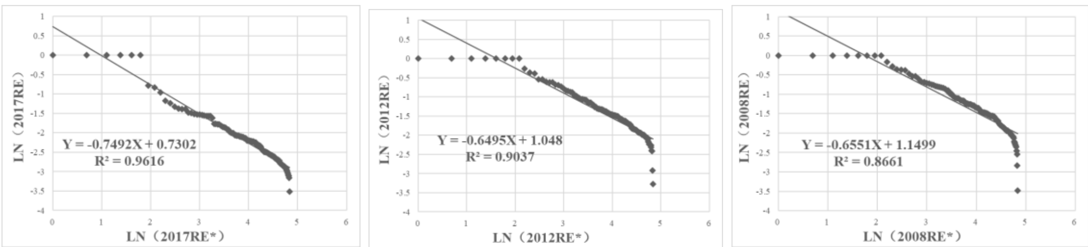


Fig. 5. Double logarithm fitting of rank-size distribution of resilience efficiency in the YREB

3.1.2 The spatial distribution characteristics

The spatial distribution pattern of RE index in the YREB changed from obvious urban agglomeration to single city isolation, and from relatively balanced spatial distribution to an unbalanced pattern. Further, the mean RE value in the upstream region ranked first, the midstream regions ranked second, and the downstream regions ranked last, decreasing from west to east. Fig.6 is quite revealing in several ways. Firstly, the cities with low RE values below 0.17 are mainly provincial capitals, municipalities, and their neighboring cities. These cities always have a high level of economy and urbanization, which is the agglomeration clusters of resource consumption. We can see that their resilience efficiency is relatively low due to the large gap between resource input level and urban resilience output. Secondly, the cities with median RE values ranging from 0.18 to 0.31 are mainly distributed in the west of the upstream regions, the periphery of the midstream regions, and the northwest of the downstream regions. These cities are comparatively far away from the regional core cities and have a low scale of economic development. As a result, they presented a certain level of resilience due to less resource consumption, thus, showing a low RE value. Thirdly, the cities with high RE index values above 0.31 are mainly distributed in the western part of the upstream, midstream, and downstream regions. Most of them are located around the region, with limited exposure to the radiation from regional core cites and a low level of industrialization. However, thanks to the excellent ecological environment, these cities had shown higher urban resilience with little resource input. Therefore, the coordinated relationship between resource consumption and urban resilience leads to a high RE value in these cities.

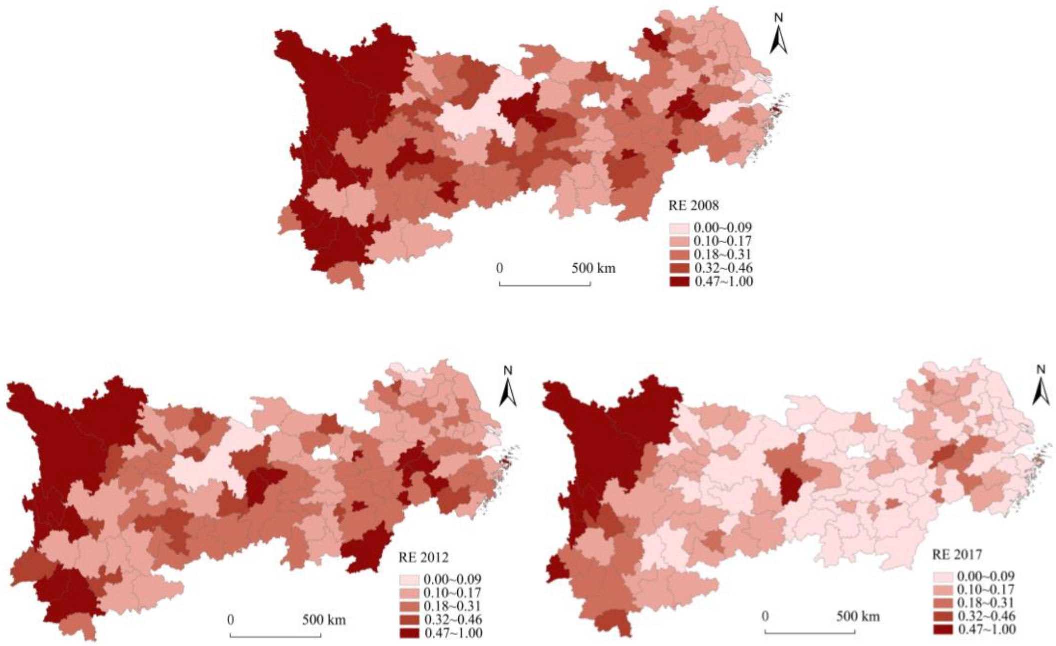


Fig. 6. Resilience efficiency distribution in the YREB

3.1.3 The spatial correlation characteristics

we applied Global and Local Moran's I to examine the spatial heterogeneity of resilience efficiency. The global Moran's I values of RE index in 2008, 2012, and 2017 were 0.256, 0.275, and 0.337 respectively with the significance level test of 5%(Fig. 8), indicating a relatively positive spatial autocorrelation, together with an upward trend of homogenous spatial agglomeration. Apparently, cities distributed in quadrants High- High and Low-Low were the majority, suggesting that a decreasing disparity in RE between one city and its neighbors. From the results of Local Moran's I (Fig. 7), we can see that the upstream, midstream, and downstream regions showed diversified types of spatial agglomeration. Spatially, the upstream regions were dominated by High-High and Low-High clusters, the High- High clusters generally appeared in Garze, Diqing, Nujiang, Lijiang, and Baoshan, and the Low-High clusters were located in Chengdu and Liangshan; The midstream regions mainly showed Low-Low clusters, and the areas of that presented an expanding trend. By 2017, the clusters were situated in the west and east of Hubei Province and the south and north of Hunan Province. The Low-Low clusters appeared in the downstream regions with most of the cities located in Jiangsu Province. Further, the numbers of Low-Low clusters gradually declined, from 14 cities in 2008 to 3 cities in 2017.

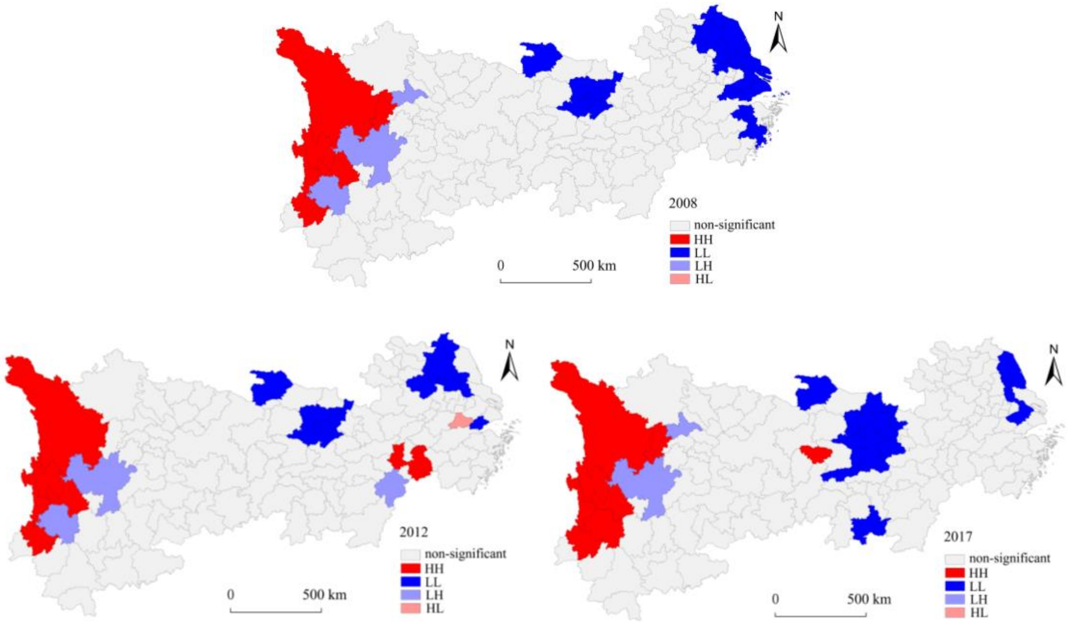


Fig. 7. Local Moran's I clusters of RE

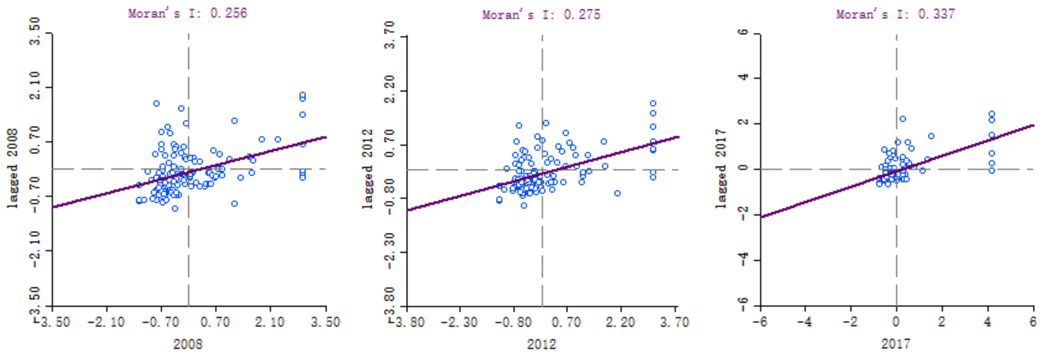


Fig. 8. Moran scatterplots of RE

3.2 Influencing factors on resilience efficiency

Based on GWR4.0.9 software for geographically weighted regression analysis, we took RC as independent variable and UR as dependent variable to reveal the relationship between resource consumption and urban resilience, which determines RE. The purpose of doing so is to provide mechanism analysis and optimization strategies for RE from the perspective of input and output according to the results. Thus, as mentioned above, the RC indicators, including total electricity consumption, total quantity of water supply, area of construction land, fixed asset investment, NEPUNU, S&T expenditure, and education expenditure were selected as independent variables and UR index as the dependent variable. From Table 2 to Table 4, we can see that the R sqaure values of GWR model in 2008, 2012, and 2017 were 0.9226, 0.9185, and 0.8968 respectively, which were higher than the OLS models. Moreover, the AICc value was significantly smaller in contrast to the OLS model with their difference more than 3, suggesting a statistically better fit.

Table 2

The regression coefficients of GWR model in 2008

Variables	Significance (%)	The coefficient of interval	Mean of coefficient

Intercept	100	0.0632~ 0.1045	0.0832
Total electricity consumption	35.71	-0.5526~ 1.0311	0.3733
Total quantity of water supply	53.17	-0.5433~ 3.0086	1.6855
Area of construction land	3.97	0.2238~ 0.2721	0.2506
Fixed asset investment	48.41	0.2545~ 0.5458	0.3648
NEPUNU	34.92	-0.5662~ 0.4847	0.3180
S&T expenditure	48.41	0.4743~ 3.0550	1.6212
Education expenditure	77.78	-1.2679~ -0.5218	-0.8599
Local R^2	0.8108~ 0.9482		
R2	0.9226		
Adjust R2	0.8890		
AICc	-464.2944		

Table 3

The regression coefficients of GWR model in 2012

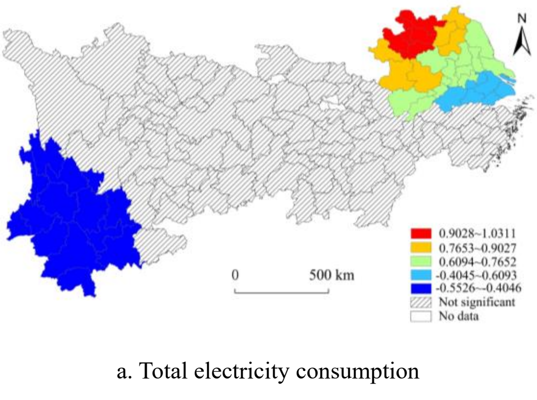
Variables	Significance（%）	The coefficient of interval	Mean of coefficient
Intercept	100	0.0662~ 0.1220	0.0880
Total electricity consumption	37.30	0.5796~ 0.9963	0.7807
Total quantity of water supply	37.30	0.6448~ 2.7584	1.8577
Area of construction land	13.49	-0.4158~ -0.3296	-0.3718
Fixed asset investment	48.41	-0.6000~ 0.6394	0.2958
NEPUNU	34.13	0.3365~ 0.5391	0.4371
S&T expenditure	28.57	1.0341~ 1.9655	1.4034
Education expenditure	51.59	-0.8446~ -0.4427	-0.7087
Local R^2	0.7974~0.9599		
R2	0.9185		
Adjust R2	0.8838		
AICc	-464.9874		

Table 4

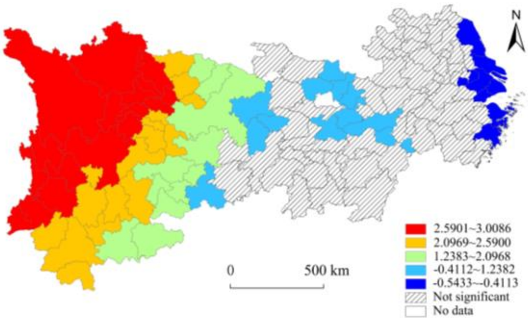
The regression coefficients of GWR model in 2017

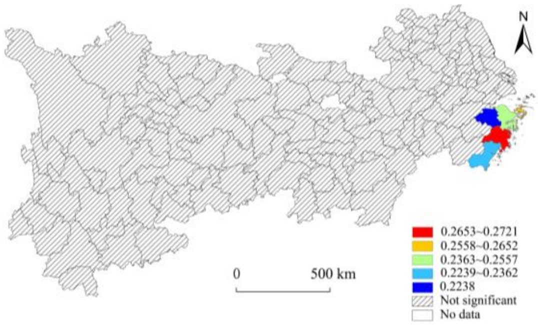
Variables	Significance（%）	The coefficient of interval	Mean of coefficient
Intercept	100	0.0817~ 0.1434	0.1132
Total electricity consumption	41.27	0.2797~ 0.4292	0.3087
Total quantity of water supply	30.16	1.6085~ 4.5834	3.1027
Area of construction land	50.00	-1.5467~ 1.0244	-0.1160
Fixed asset investment	12.70	-0.6922~ -0.3715	-0.5519
NEPUNU	31.75	-0.6654~ 0.1865	-0.4361
S&T expenditure	32.54	1.4098~ 2.9907	2.4998
Education expenditure	28.57	-0.4614~ 0.4484	-0.2860
Local R^2	0.7056~0.9515		
R2	0.8968		
Adjust R2	0.8617		
AICc	-457.1438		

Notes: The values of regression coefficients in the above Tables are those that pass the 5% significance level test.

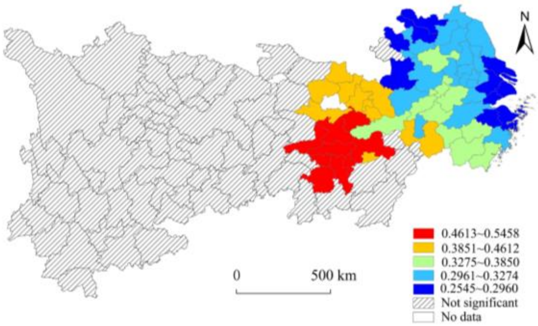


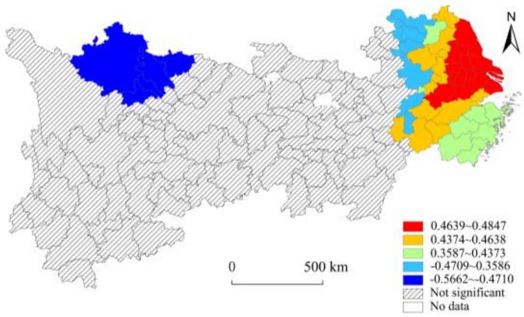
a. Total electricity consumption



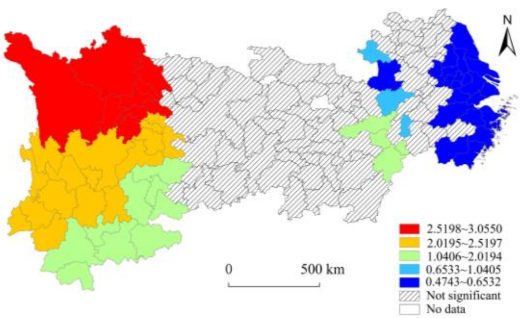


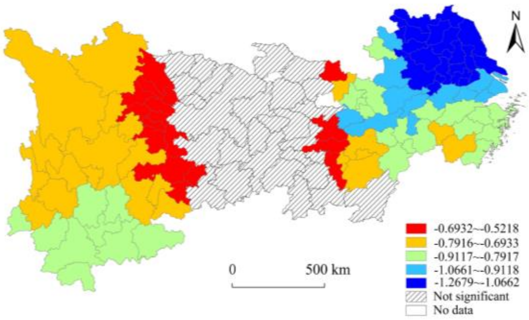
b. Total quantity of water supply c. Area of construction land





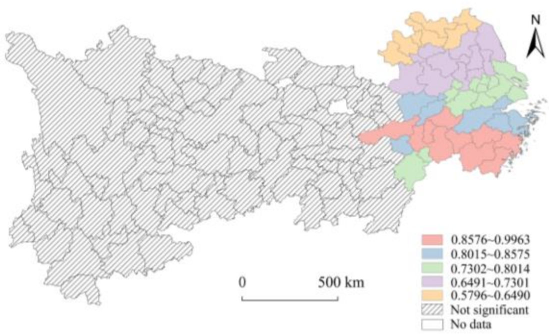
d. Fixed asset investment e. NEPUNU



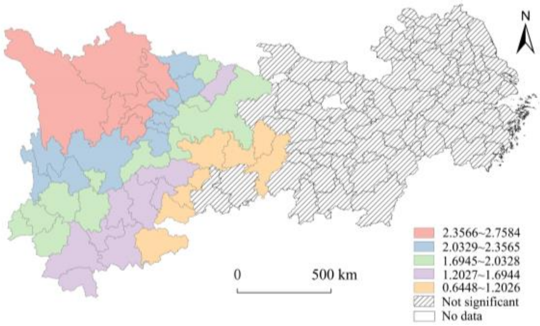


f. S&T expenditure g. Education expenditure

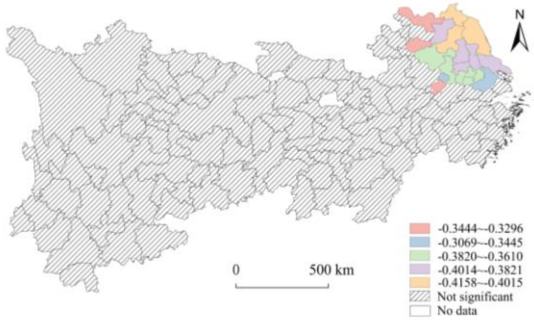
Fig. 9. Regression coefficients distribution of GWR model in 2008



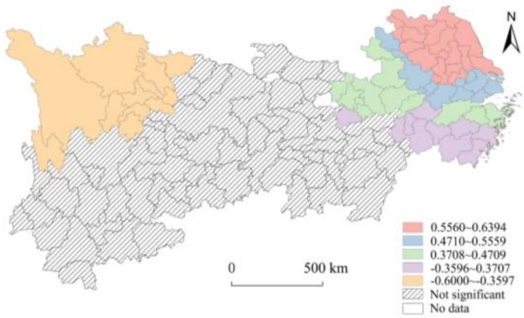
a. Total electricity consumption



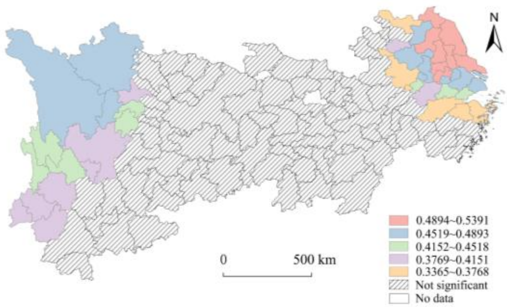
b. Total quantity of water supply



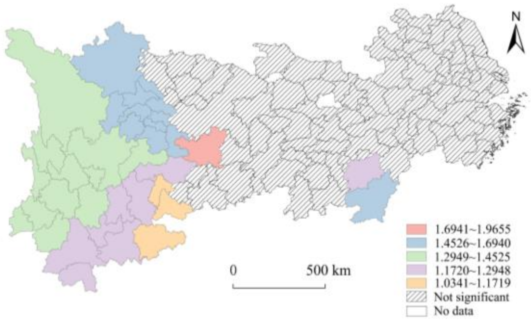
c. Area of construction land



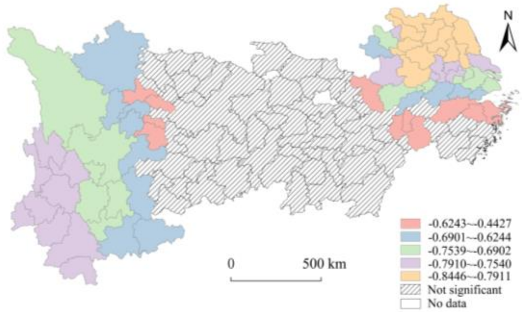
d. Fixed asset investment



e. NEPUNU

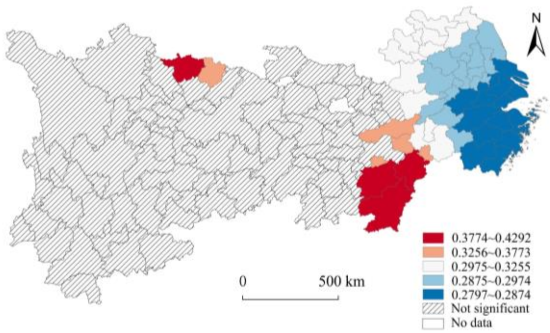


f. S&T expenditure

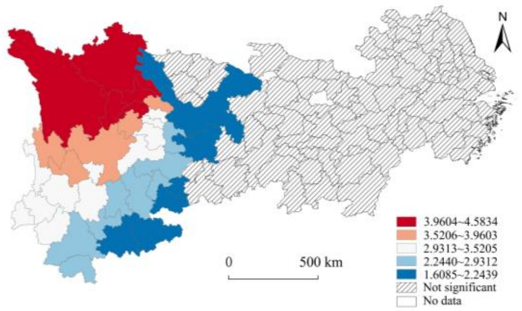


g. Education expenditure

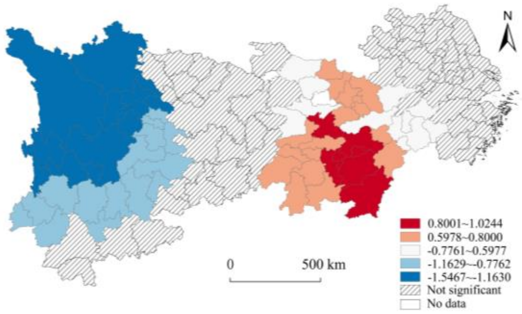
Fig. 10. Regression coefficients distribution of GWR model in 2012



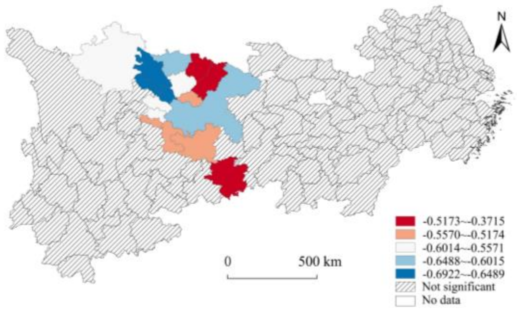
a. Total electricity consumption



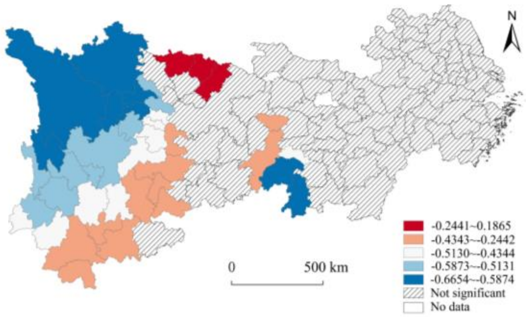
b. Total quantity of water supply



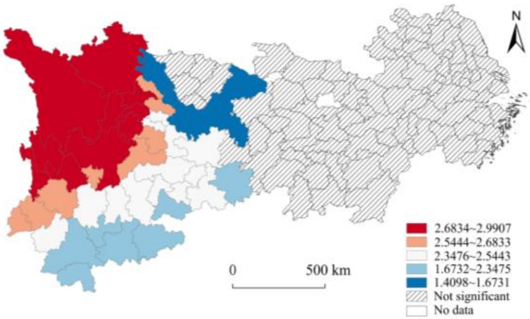
c. Area of construction land



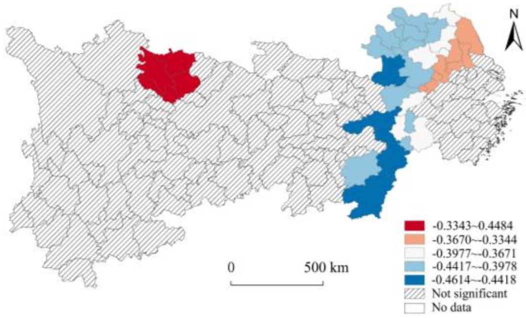
d. Fixed asset investment



e. NEPUNU



f. S&T expenditure



g. Education expenditure

Fig. 11. Regression coefficients distribution of GWR model in 2017

Notes: The values of regression coefficients in Fig.9 to Fig. 11 are those that pass the 5% significance level test.

3.2.1 Overall influencing factors of the YREB

We used t value to test the significance of the regression coefficients of each city, and regarded the indicators with significance proportion over 40% as influencing factors with certain explanatory power (Fig.8 to Fig.10). Among the significant unit, the tables above showed some main results. Firstly, in 2008, the average regression coefficients of total quantity of water supply, fixed asset investment, and S&T expenditure were 1.6855, 0.3648, and 1.6212 respectively, suggesting that these three variables were the main factors affecting urban resilience, and had a significant positive correlation with urban resilience. Among them, total quantity of water supply and S&T expenditure had the strongest effects, followed by fixed asset investment. Secondly, in 2012, the significant proportions of total quantity of water supply and S&T expenditure were 37.3% and 28.57%, falling below 40%, indicating insufficient explanatory power for urban resilience, while fixed asset investment was the main driving factor. Further, the mean regression coefficient of fixed asset investment decreased from 0.3648 in 2008 to 0.2958 in 2012, revealing that the positive promotion effect of fixed asset investment on urban resilience had shown a gradual downward trend. Thirdly, in 2017, total electricity consumption and area of construction land were considered as two main influencing factors on urban resilience. Among them, total electricity consumption had a positive effect on urban resilience, while the other one showed a negative correlation with that. Their average regression coefficients were 0.3087 and -0.1160 respectively.

In general, the overall influencing factors of urban resilience in the YREB had changed from total quantity of water supply, fixed asset investment, and S&T expenditure in 2008 to total electricity consumption and area of construction land in 2017, showing a trend from a multiple dominance of resources and capital factors to the single dominance of resource factors. Interestingly, we found that S&T expenditure does not show a strong positive promoting effect on urban resilience. As a result, it can be seen that the efficient use of resources as well as the intensive development of land significantly affect the improvement of resilience efficiency.

3.2.2 Local influencing factors of the YREB

We made statistical analysis on the significance proportion and regression coefficient of the upstream, middle and downstream cities, and the results presented remarkable regional differentiation characteristics. (1) Urban resilience was continuously affected by total quantity of water supply and S&T expenditure in the upstream regions with a high degree of positive correlation, and the mean value of their regression coefficient showed a gradually increasing trend (Table.5). While area of construction land and education expenditure presented a weak negative correlation with urban resilience index. (2) The influencing factors in the midstream regions were relatively single. In 2008, the main driving factor was fixed asset investment, and its average regression coefficient reached 0.4623; By 2017, as shown that the development of urban resilience is highly dependent on the scale of land use with its mean regression coefficient of 0.7244 among the significant units, which means that the improvement of resilience of most midstream cities was still closely related to the extensive use of land. (3) The influencing factors in downstream regions have changed from diversification to simplification. In 2008, total electricity consumption, S&T expenditure, NEPUNU, and fixed asset investment were the main influencing factors on urban resilience. According to their average regression coefficients, total electricity consumption and S&T expenditure had the strongest influence, followed by NEPUNU and fixed asset investment. In 2012, the influence of S&T expenditure became weaker, and the dominant factors were total electricity consumption, fixed asset investment, and NEPUNU. The average regression coefficients of these three factors showed an increasing trend. In 2017, the influencing factors of the downstream regions were gradually becoming single, and total electricity consumption became the main driving factor. For the cities in downstream regions, area of construction land and education expenditure had a strong inhibiting effect on urban resilience.

Table 5

Statistics on the mean values of regression coefficients of influencing factors

	2008			2012			2017		
	Upstream	Midstream	Downstream	Upstream	Midstream	Downstream	Upstream	Midstream	Downstream
Total electricity consumption	——	——	0.7533	——	——	0.7672	——	——	0.2919
Total quantity of water supply	2.3332	——	——	1.9107	——	——	3.1027	——	——

Area of construction land	——	——	——	——	——	-0.3718	-1.1311	0.7244	——
Fixed asset investment	——	0.4623	0.3137	——	——	0.5030	——	——	——
NEPUNU	——	——	0.4292	——	——	0.4418	-0.4344	——	——
S&T expenditure	2.3079	——	0.5761	1.4011	——	——	2.4998	——	——
Education expenditure	-0.7215	-0.7870	-1.0205	-0.6887	——	-0.7390	——	——	-0.3847

Notes: "--" indicates that the significance proportion of influencing factors in this kind of cities is less than 40%. The values of regression coefficients in the above Table are those that have passed the 5% significance level test; There are 48 cities in the upstream region, 37 cities in the midstream region, and 41 cities in the downstream region.

4. Discussion and policy implications

The results of this study indicated that, with the increase of RC and UR index in the YREB, the RE index was found to show a gradual decline in the past decade. This finding supports the work of other studies in this area linking resource consumption and urban development. Several previous studies have shown that the efficiency of land use and ecosystem was low or not very high, presenting significantly regional differences which is related to city size and economic development (Yu et al. 2019; Zhang et al. 2019b). A possible explanation for this result may be the extensive resource utilization mode and the pursuit of GDP growth (Zhou et al. 2018), which has overlooked the optimization of economic structure, the fairness of social welfare, and the protection of environment. Specifically, cities in the upstream regions are mostly located in mountainous areas, with generally a low level of economies and community service. Their industrial structure is generally dominated by agriculture, accompanying relatively weak secondary and tertiary industries. Since 2006, the Communist Party of China (CPC) Central Committee and the State Council had released a series of policies on boosting the rise of the central region, such as *Several Opinions on Promoting the Rising of the Central Region of China* (2006), *Several Opinions on Implementing the Plan for Promoting the Rise of the Central Region* (2012), and *Plan on the Rise of Central China 2016-2025* (2016). Under these policies, Hubei, Hunan, and Jiangxi province, as a connection linking the east and the west, has made efforts to reach the goal of modern equipment manufacturing and high-tech industrial base. Consequently, the middle reaches of the YREB became an industrial cluster area of equipment manufacturing, petrochemical industry, aviation, and metallurgy, of which required huge land utilization, resource consumption and resulted in damage to urban ecosystem. Due to the advantages of developed economy, convenient transportation, and strong industry, the downstream regions had formed Yangtze River Delta urban agglomeration with global influence and economic vitality. Rapid industrialization has driven the resources and labor to gather in the core cities such as Shanghai, Hangzhou, Suzhou, and Ningbo, which has brought about faster and lager economic growth as well as increasing resource demand and environmental damage. These factors may be the explanation for continuous decline of RE. Fortunately, since the release of *the Guidelines for Development Along the Yangtze Economic Belt* (2016), China has put forward the development goal of “to step up conservation of the Yangtze River and stop its overdevelopment”. The implementation of a series of measures, such as shutting down chemical enterprises along the river, restoring the ecology of the riverbank, and adding public recreational green space, had effectively alleviated the ecological problems in the cities along the Yangtze River.

We found that main influencing factors had changed from total quantity of water supply, fixed asset investment, and S&T expenditure to total electricity consumption and area of construction land during the past decade, which means that energy and land elements play a more sensitive and leading role on promoting urban resilience. This finding is partly in consistent with the results of other earlier studies (Wu et al. 2017). The trend of influencing factors showed a relationship with the policy guidance and development path of the YREB. After the outbreak of the global financial crisis in 2008, China adopted a series of measures such as industrial revitalization, economic restructuring, and increased investment to keep economic stability and boost domestic demand. Thus, financial investment and S&T innovation played an important role in economic recovery. It is probably the reason that fixed asset investment and S&T expenditure present more sensitive in promoting urban resilience at the beginning of the study period. In 2014, *National New-type Urbanization Plan (2014~2020)* was released to promote the quality and standard of urbanization, together with the YREB put forward as a region for national strategic development in China, resulting in rapid urbanization and industrialization of the cites along the Yangtze River. This may contribute to the dependence on energy and land elements for urban resilience.

These findings provide important implications for sustainable development. In terms of inputs, it is necessary to accelerate the structural optimization of both energy production and energy consumption by upgrading new technologies. Meanwhile, strict control and management on the scale of new urban construction land should be carried out to avoid the low utilization of land. It is clear that more attention should be paid to the relationship between the actual demand for construction land and population size, ecological protection, and industrial development. In terms of outputs, urban resilience is a complex concept which integrates urban economy, society, ecology, infrastructure, and management. Further, regarding the concept itself, urban resilience is not simply decided by single dimension. Thus, we have to consider a comprehensive strategy for improving urban resilience rather than partial optimization of its subsystems. For example, we should continue to promote the improvement of the economic structure, the optimization of the social security mechanism, and the efficient planning of urban infrastructures.

In addition, this paper explored the regional differences of the influencing factors in YREB, which is helpful for the dedicated practical action of resilience efficiency of the upstream, midstream, and downstream cities. (1) The results unravel that total quantity of water supply and S&T expenditure had a significant positive effect on urban resilience. Taking into account the fact that the upstream area is an important water source protection and ecological conservation land due to its unique natural resource endowment, more attention should be paid to the protection of aquatic ecology and water security in the river basin. On this basis, the government should actively develop industries such as mountain tourism, health preservation, and high-efficiency agriculture in order to tap the potential space for resource utilization. Also, some measures, such as improving the allocation of scientific and technological resources, completing the transformation mechanism of achievements, must be implemented to increase the efficiency of scientific and technological innovation. Externally, the upstream cities can further take advantage of the driving effect of the industrial chain in the midstream and downstream regions. Internally, it is essentially necessary to continue optimizing the allocation of capital, labor, technology, and other elements in the upstream regions. (2) According to our analysis of the influencing factors, we found that the area of construction land correlated positively with the urban resilience of the midstream cities. In other words, the development of urban resilience in the midstream regions still heavily depends on the booming expansion of construction land and the local fiscal revenue generated from land transfer.

Therefore, cities in the middle reaches of YREB could improve the efficiency of land use through measures such as reducing the cost of resources and environment, changing the way of land use, and promoting the reform of industrial technology on the basis of maintaining a steady increase in the urbanization rate. (3) In the downstream regions, the spillover effect of core cities and the industrial cooperation between general cities are constantly strengthened. According to the spatiotemporal distribution of the RC index (Fig. 3), not only the UR index but also the RC index presented a trend of agglomeration and spread. Total electricity consumption was found to significantly impact on urban resilience in the downstream regions at the end of the study period. Therefore, optimizing energy utilization efficiency through the adjustment of the industrial structure in urban agglomeration is the key to improve urban resilience efficiency in downstream regions.

To develop a full picture of comprehensive study on urban resilience, further research should be undertaken to investigate the coupling relationship among inner dimensions of urban resilience, which will help to explore the mutual promotion or inhibition of economic, social, engineering, and ecological efficiency. Besides, it is a pity that, in order to investigate the performance of urban resilience efficiency in the past decade after the global economic crisis in 2008, this paper takes the year of 2008 as a starting point of study period and selects three years instead of continuous longitudinal data of ten years to track the evolutionary trend due to the limitation of data collection, which limited our more refined analysis to a certain extent. Finally, further research needs to expand the size of the sample cities and provide an overall profile on the performance of urban resilience of the whole country at a city level.

5. Conclusion

The findings from this study mentioned previously make contribution to the current literature and put forward a series of targeted policy implications for the YREB. Main findings are as follows: (1) Both the RC index and the UR index presented an upward trend, and their spatial distribution characteristics were similar, showing a gradual decrease from the eastern coastal cities to the central and western inland cities. (2) we found that the RE index gradually decreased, and the hierarchy gap between cities continued to increase. Different from the RC and UR index, the RE index showed a spatial characteristic of gradually decreasing from west to east, and its spatial aggregation pattern changed from equilibrium to disequilibrium. Combined with spatial autocorrelation analysis, findings revealed that RE index presented a strong spatial positive correlation, and the agglomeration of the homogenous spatial unit showed a gradually increasing trend. (3) In terms of driving factors, the results of GWR showed that the influencing factors of urban resilience have changed from multiple dominance of resources and capital factors to the single dominance of resource factors. By the end of the study period, total electricity consumption and area of construction land had a significant impact on the development of urban resilience. Furthermore, we found that total quantity of water supply and S&T expenditure have always been the main driving factors for cities in the upstream regions. While the midstream regions mainly depended on the scale of construction land. As to the downstream regions, the influencing factors have changed from diversified to single one, and the total electricity consumption has a strong influence.

Declarations

Ethics approval and consent to participate Not applicable

Consent for publication Not applicable

Availability of data All data generated or analysed during this study are included in this published article.

Competing interests The authors declare that they have no competing interests.

Funding This work was supported by the National Natural Science Foundation of China (51778253).

Authors' contributions Yingzi Lin: conceptualization, formal analysis, methodology, writing – original draft, writing – review and editing. Chong Peng: conceptualization, funding acquisition, writing – review and editing. Jianfeng Shu: methodology. Wei Zhai: writing – review and editing. Chen Jianquan: writing – review and editing.

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