



# Regional differences in spatial determinants of land urbanization in China

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## Abstract

China has entered a critical stage of urbanization transition but still faces unbalanced regional development and uncoordinated urban–rural integration. Studying the regional differences in spatial determinants of land urbanization (LU) is crucial to achieving coordinated regional development of urbanization. However, the spatial determinants of LU remain unclear, especially in terms of their regional differences. Therefore, this study introduced dynamic distribution and spatial analysis to measure regional differences in spatial determinants of LU in China. During 1990–2020, the imbalance of LU in China was constantly decreasing, and the differences in LU among different regions were also decreasing. LU in China had significant spatial dependence and spatial spillover effects, and the trend of group development was gradually becoming obvious. LU in eastern region was more affected by natural factors than in central and western regions, while central and western regions were more affected by socioeconomic factors than in eastern region. This study can provide a scientific reference for understanding the spatial disequilibrium of LU and promoting the regional implementation of LU coordinated development.

**Keywords** Land urbanization · Regional differences · Distribution dynamics · Spatial analysis · Spatial determinants · China

## Introduction

China's urbanization has grown rapidly under market-oriented development and has become a powerful engine of world economic growth in the twenty-first century (Gu et al. 2012; Jiang et al. 2022; Zhang et al. 2022a). Land is the central support element of the urbanization process and carries the initial accumulation of material capital (Gao et al. 2018; Yang et al. 2023b). In China, large regional differences and unbalanced regional development are still the basic national

conditions, and narrowing regional differences and promoting balanced regional development is an important path to realizing high-quality development (Deng et al. 2021). China is in the critical stage of achieving high-quality urbanization and coordinated regional development. How to balance regional differences in land urbanization (LU) is an important issue to be solved urgently. However, existing literature lacks research on regional differences in driving factors of LU, while ignoring the spatial effects of LU (Zhang and Wang 2018). This may limit the specific implementation of shared prosperity in spatial dimensions. Studying the regional differences in spatial determinants of LU can provide a theoretical tool for decision-makers to build a spatial support system for high-quality urbanization development.

LU refers to a dynamic process of changing land use attributes from rural land to urban land due to various natural and socioeconomic factors (Gao et al. 2018). LU can profoundly change the original land use pattern and structure and affect regional sustainable development (Chen et al. 2021c; Lin et al. 2015). On the one hand, the rapid advancement of LU has significantly improved the living standards of residents and the level of economic development (Wang et al. 2016; Xu et al. 2020). On the other hand, it is also an

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important reason for the widening gap between urban and rural areas, uncoordinated regional development, threats to food security, and deterioration of regional ecosystems (Chen et al. 2021a; Chen and Chi 2022; Ju et al. 2018; Yao and Jiang 2021). Different studies have different definitions, focuses, and research directions of LU, which lead to great differences in the measurement methods of LUR. The measurement of LUR includes the following: using the ratio of urban construction land area to urban and rural construction land area (Gao et al. 2018), dividing the built-up area by the total administrative area (Lv et al. 2019), constructing a LUR evaluation index system (Zhang and Wang 2018), and directly using the urban built-up area (Lin et al. 2015). Using the ratio of urban construction land area to urban and rural construction land area can not only reflect the LU level but also the difference between urban and rural land use structures (Gao et al. 2018). On this basis, scholars have used spatial statistics, variation coefficient method, land use dynamics, kernel density estimation, function fitting, and other methods to focus on the spatiotemporal characteristics, internal structure, quality evaluation, and result prediction of LU (Cui et al. 2019; Lei et al. 2022; Lin et al. 2015; Zhang and Wang 2018; Gao et al. 2018; Jiang et al. 2022; Tang et al. 2020; Yao and Jiang 2021). In addition, the panel regression model, multiple linear regression model, mediation effect model, geographically weighted regression model, and quantile regression model are used to analyze the driving forces of LU (Jiang et al. 2022; Tang et al. 2020; Yao and Jiang 2021; Xu et al. 2020; Gao et al. 2018).

Realizing coordinated regional development has become the theme of China's urbanization development (Deng et al. 2021). Although previous studies have made some explorations in the monitoring and driver analysis of LU, there are still some limitations (Lin et al. 2015; Zhang and Wang 2018; Gao et al. 2018). Differences in land use development patterns, development strategies, and natural background conditions in Eastern Region (ER), Central Region (CR), and Western Region (WR) of China have led to significant regional differences in LU (Zhang and Xu 2017; Deng et al. 2021). Previous studies lack quantitative disclosure of differences in LU among different sub-regions, which could not well support the formulation of regional coordinated development policies for LU (Lin et al. 2015; Gao et al. 2018). Therefore, it is necessary to quantitatively reveal the differences in spatiotemporal patterns of LU among different sub-regions in China to support the formulation of coordinated LU development policies. Moreover, cities will form radiation centers in the process of their development, drive the development of surrounding areas through diffusion effects, or transfer the economy and population of surrounding areas through siphoning effects. Therefore, LU has spatial effects (Jiang et al. 2022; Zhang and Wang 2018; Gao et al. 2018). Understanding the spatial aspect of LU is crucial for

realizing high-quality spatial coordinated development of urbanization. However, previous studies often ignore the spatial effects of LU and lack exploration of regional differences in LU's drivers, which cannot effectively support the formulation of urbanization development strategies.

To fill the gap of previous studies, this study constructed an evaluation index of LU based on land use data (30 m resolution) and comprehensively adopted a series of dynamic distribution, spatial statistics, and spatial regression methods to measure the regional differences and dynamic evolution of China's LU at the county level. Then, the differences in spatial determinants of LU in different regions were explored. This study set the following three research objectives: (1) to measure the spatiotemporal patterns of land urbanization rate (LUR) in China, (2) to reveal the regional differences of LUR, and (3) to explore the regional differences in driving forces of LUR.

## Materials

### Study area

China is one of the countries with the most drastic changes and the most prominent conflicts in LU in the world (Zhang and Li 2020). The rapid LU has caused a series of social problems (e.g., LU faster than population urbanization, uncoordinated regional development, further widening income gap between urban and rural areas), resulting in continuous distortion of economic structure, seriously affecting China's high-quality development process (Ji et al. 2020; Zhu et al. 2014; Jin et al. 2017). Furthermore, due to the vast territory of China, the differences in development strategies, natural background conditions, and land use patterns in ER, CR, and WR have led to great regional differences in the development patterns of LU (Chen et al. 2016; Zhang and Xu 2017). Therefore, it is crucial to analyze regional differences in the spatial determinants of LU in China (Fig. 1).

### Data sources

The land use remote sensing monitoring data with a resolution of 30 m in China from 1990 to 2020 were obtained from the Data Center for Resources and Environment, Chinese Academy of Sciences (<http://www.resdc.cn>). It is currently the most advanced land use remote sensing monitoring data in China (Liu et al. 2014; Ning et al. 2018). Shpfile data for the eastern, central, and western region were also obtained from the Data Center for Resources and Environment, Chinese Academy of Sciences. Because administrative divisions change over many years, this study uniformly uses the 2021 county administrative divisions as the study area. Basic geographic information data were derived from the National

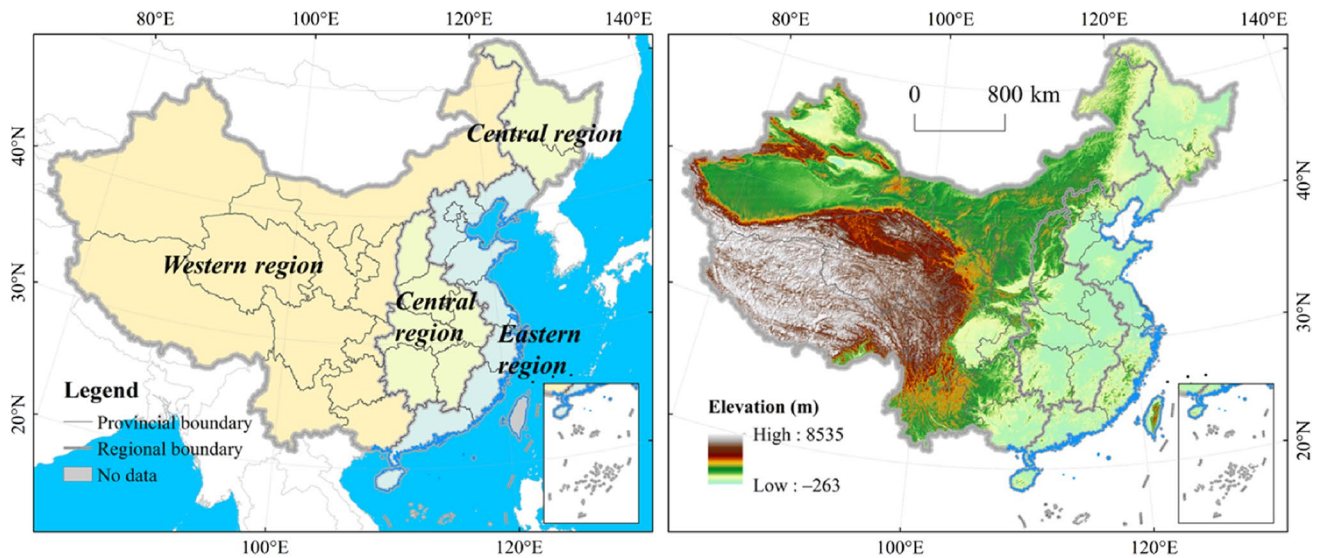


Fig. 1 Maps of the study area

Geomatics Center of China (<http://www.ngcc.cn>). The data sources and calculation methods of potential factors selected in this study are shown in Table 1.

## Methods

### Land urbanization level measurement

This study used LUR to measure the level of LU in China (Zhang et al. 2022a; Gao et al. 2018). The LUR was defined as the ratio of urban land and transportation construction land to urban and rural construction land. The equation is as follows:

$$LUR_{it} = (ula_{it} + ila_{it} + tla_{it}) / (ula_{it} + ila_{it} + tla_{it} + rla_{it}) \tag{1}$$

where  $LUR_{it}$  represents LUR in county  $i$  at time  $t$ ;  $ula_{it}$  represents urban land area in county  $i$  at time  $t$ ;  $ila_{it}$  represents industrial and mining land in county  $i$  at time  $t$ ;  $tla_{it}$  represents transportation land area in county  $i$  at time  $t$ ; and  $rla_{it}$  represents rural settlements area in county  $i$  at time  $t$ .

### Gravity center analysis

The method of gravity center analysis has been widely used to monitor the spatiotemporal evolution trajectories of various geographic elements (Chen et al. 2019a; Wang et al. 2018). Referring to previous studies, the concept of “gravity center” in physics was introduced, and the gravity center analysis was used to measure the spatial migration direction and migration size of LUR in China. The equations are as follows:

$$X_t = \sum_{i=1}^n LUR_i X_{i,t} / \sum_{i=1}^n LUR_i \tag{2}$$

$$Y_t = \sum_{i=1}^n LUR_i Y_{i,t} / \sum_{i=1}^n LUR_i \tag{3}$$

where  $X_t$  and  $Y_t$  represent the  $x$ -coordinate and  $y$ -coordinate of LUR center at time  $t$ , respectively.  $X_{i,t}$  and  $Y_{i,t}$  represent the coordinates of the geographic center of county  $i$  at time  $t$ .  $LUR_i$  represents LUR of county  $i$ .

Table 1 Data sources for each factor

Variables	Data sources	Variables	Data sources
Average elevation (X1)	( <a href="http://www.resdc.cn">http://www.resdc.cn</a> )	River density (X6)	( <a href="https://www.webmap.cn">https://www.webmap.cn</a> )
Average slope (X2)	( <a href="http://www.resdc.cn">http://www.resdc.cn</a> )	Cultivation index (X7)	( <a href="http://www.resdc.cn">http://www.resdc.cn</a> )
Annual average temperature (X3)	( <a href="http://www.geodata.cn">http://www.geodata.cn</a> )	Economic density (X8)	( <a href="http://www.resdc.cn">http://www.resdc.cn</a> )
Annual average precipitation (X4)	( <a href="http://www.geodata.cn">http://www.geodata.cn</a> )	Population density (X9)	( <a href="https://www.worldpop.org">https://www.worldpop.org</a> )
Vegetation coverage (X5)	( <a href="http://www.resdc.cn">http://www.resdc.cn</a> )	Road density (X10)	( <a href="http://www.resdc.cn">http://www.resdc.cn</a> )

## Dagum Gini coefficient decomposition method

The Gini coefficient is often used to measure the imbalance of regional development (Yang et al. 2023c). In view of the shortcomings of the traditional Gini coefficient, Dagum (1997) proposed a decomposition method of the Gini coefficient; at present, it has been widely used to measure the size and source of differences in development level of various regions (Zhang et al. 2022b). The equation is as follows:

$$G = \sum_{j=1}^k \sum_{h=1}^k \sum_{i=1}^{n_j} \sum_{r=1}^{n_h} |LUR_{ji} - LUR_{hr}| / 2n^2 \overline{LUR} \quad (4)$$

where  $j$  and  $h$  represent different regions in ER CR and WR;  $k$  is the number of sub-regions;  $n$  is number of counties;  $n_j$  and  $n_h$  represent the number of counties in region  $j$  and region  $h$ , respectively;  $LUR_{ji}$  and  $LUR_{hr}$  represent the LUR of county  $i$  in region  $j$  and county  $r$  in region  $h$ ;  $\overline{LUR}$  represents the mean value of LUR in China.

According to Dagum Gini coefficient decomposition method, the Gini coefficient can be decomposed into intra-regional contribution  $G_w$ , inter-regional contribution  $G_{nb}$  and intensity of transariation contribution  $G_t$ , and  $G = G_w + G_{nb} + G_t$  holds. Dagum (1997) has shown the specific equations.

## Kernel density estimation

Kernel density estimation is a non-parametric estimation method that describes the probability distribution of random variables through continuous density curves (Quah 1997). It has the advantages of robustness and low model dependence and is often used to analyze the differences and dynamic evolution between different regions (Wu et al. 2021a, 2021b). In this study, kernel density estimation was introduced to analyze the regional differences in dynamic evolution of LUR. The equations are as follows:

$$f(x) = \frac{1}{Nh} \sum_{i=1}^N K\left(\frac{X_i - x}{h}\right) \quad (5)$$

$$K(x) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right) \quad (6)$$

where  $K(x)$  is the Gaussian kernel function;  $N$  is the number of observations;  $X_i$  represents the value of observation object  $i$ ;  $x$  represents the mean of all observations; and  $h$  is the bandwidth; the larger the bandwidth, the smoother the curve and the lower the estimation accuracy, and vice versa.

## Spatial Markov chain model

The Markov chain model is used to explore the transition trend of research objects in various regions over time by constructing a Markov transition probability matrix (Yang et al. 2023b, 2023c). Compared with the traditional Markov chain, the spatial Markov chain adds a space lag term, which can explore the probability of the type transition of the research object in a region under a certain space lag condition (Yang et al. 2020). It can not only explore the transfer trend of the research object but also measure the strength of spatial dependence (Agovino et al. 2019). This study introduced the spatial Markov chain model to explore the dynamic evolution and transition trend of LUR in China.

## Spatial regression model

According to Tobler's First Law, the physical, economic, social, and other aspects of adjacent units will be more closely connected than distant units (Chen et al. 2020; Chi 2010; Tobler 1970). The development of urban land will form a central area and affect the development of surrounding areas. Therefore, LU and its driving factors always show significant spatial agglomeration in space (Jiang et al. 2022). When analyzing the driving forces of LU, previous studies ignore the spatial dependence and spatial spillover effects of independent variables and dependent variables, leading to biased estimation results. Therefore, we introduce a series of spatial regression models to address the above issues.

To explore whether China's LU has spatial agglomeration, we introduced Global Moran's  $I$  to measure the intensity of its spatial agglomeration (Chen and Chi 2022), and Local Moran's  $I$  was applied to demonstrate the spatial aggregation pattern of LU (Wu et al. 2022).

This study uses a cross-sectional model to analyze the drivers of LU in different subregions for two main reasons. One is that the cross-sectional model can analyze the changes in the regression coefficients of the drivers over time, and the other is because the panel model may not have the same optimal shape in different subregions. Therefore, this study introduced three spatial regression models to explore the driving forces of regional differences in China's LU, including spatial lag model (SLM), spatial error model (SEM), and spatial error model with spatial lag term (SEMLD) (Chen et al. 2022; Liu et al. 2020). SLM assumes that there is spatial autocorrelation between dependent variables and considers the influence of the dependent variable itself and the influence of this variable in other units. That is, the spatial spillover effects between adjacent units are considered. SEM assumes a spatial dependence in the error term and considers the influence of the error term of adjacent units' dependent variable on the dependent variable in local units. SEMLD enhances the original SEM by adding a

spatially lagged dependent variable. The purpose is to deal with the situation where the dependent variable and the error term have spatial dependence at the same time. Liu et al. (2020) have provided specific equations for these models.

### Selection of variables

Natural factors, including terrain, climate, vegetation, and hydrology, constitute the site conditions of urban land and are the endogenous driving force in LU (Li et al. 2018). Terrain affects the advancement of LU by controlling a series of natural factors such as soil, hydrology, climate, and land supply quality that affect human activities and urban landscape patterns (Müller et al. 2010). The early urban expansion was mostly carried out in a way of spreading pie in plain, which was less constrained by the terrain. However, with the rapid growth of population, the original land resources were in short supply, the three-dimensional pattern of urban began to change, and the terrain became an important factor (Zhou et al. 2021a). In addition, there is an observable interaction between LU and climate. LU will lead to heat island effect, changing the interaction of earth-atmosphere system and triggering a series of extreme weather (Bassett et al. 2020; Chen and Frauenfeld 2016). Climate change, in turn, will react to urbanization, specifically affecting human welfare and changing surface landscape (Chen et al. 2021b). Numerous studies have explored the impact of LU on vegetation coverage (Luo et al. 2021; Ren et al. 2018; Yao et al. 2019). Urban expansion will encroach on ecological land, resulting in continuous ecosystem deterioration. With the constant deepening of ecological civilization construction concept, ecological restoration in urban areas is gaining attention, especially weighing the relationship between ecological and urban land (Fu et al. 2018). Previous studies have shown a significant relationship between rivers and urban settlements. Rivers will directly affect the process of LU by providing water sources and climate regulation. Therefore, river density may become another important factor affecting LU (Chen et al. 2020; Duran et al. 2012).

Socioeconomic factors constituted by policies, economy, society, and transportation are the external driving forces in the process of LU, which directly or indirectly affect the expansion of urban land and the conversion of land types, thereby affecting LU (Yirsaw et al. 2017). The rapid spread of urban land will continue to erode the original cropland around the city (Chen et al. 2021a; Liu et al. 2017), which will cause tremendous hidden risks to food security. In recent years, the introduction of various cropland protection policies and the delineation of urban development boundaries have guaranteed cropland areas to a certain extent (Zhou et al. 2021b). Therefore, the cultivation index has become an important factor affecting LU. In the context of land finance, economic growth is the main driving force behind

LU. Economic growth will not only bring about the rapid expansion of urban land but also greatly improve the quality of LU (Du 2017; Turok and McGranahan 2013). Besides, LU will, in turn, act on economic growth, forming a positive feedback effect (Liang et al. 2022). Meanwhile, the increasing population will stimulate the demand for urban land such as housing land and public facilities land (Xu et al. 2020), affecting land cost of LU. This effect is either positive or negative, showing different modes of action in different regions (Xu et al. 2019). Furthermore, transportation plays an important role in the process of LU, which promotes urban metabolism by accelerating the population flow, material flow, and information flow and is an important driving force for the rapid growth of urban land (Liu and Su 2021; Müller et al. 2010; Ju et al. 2022).

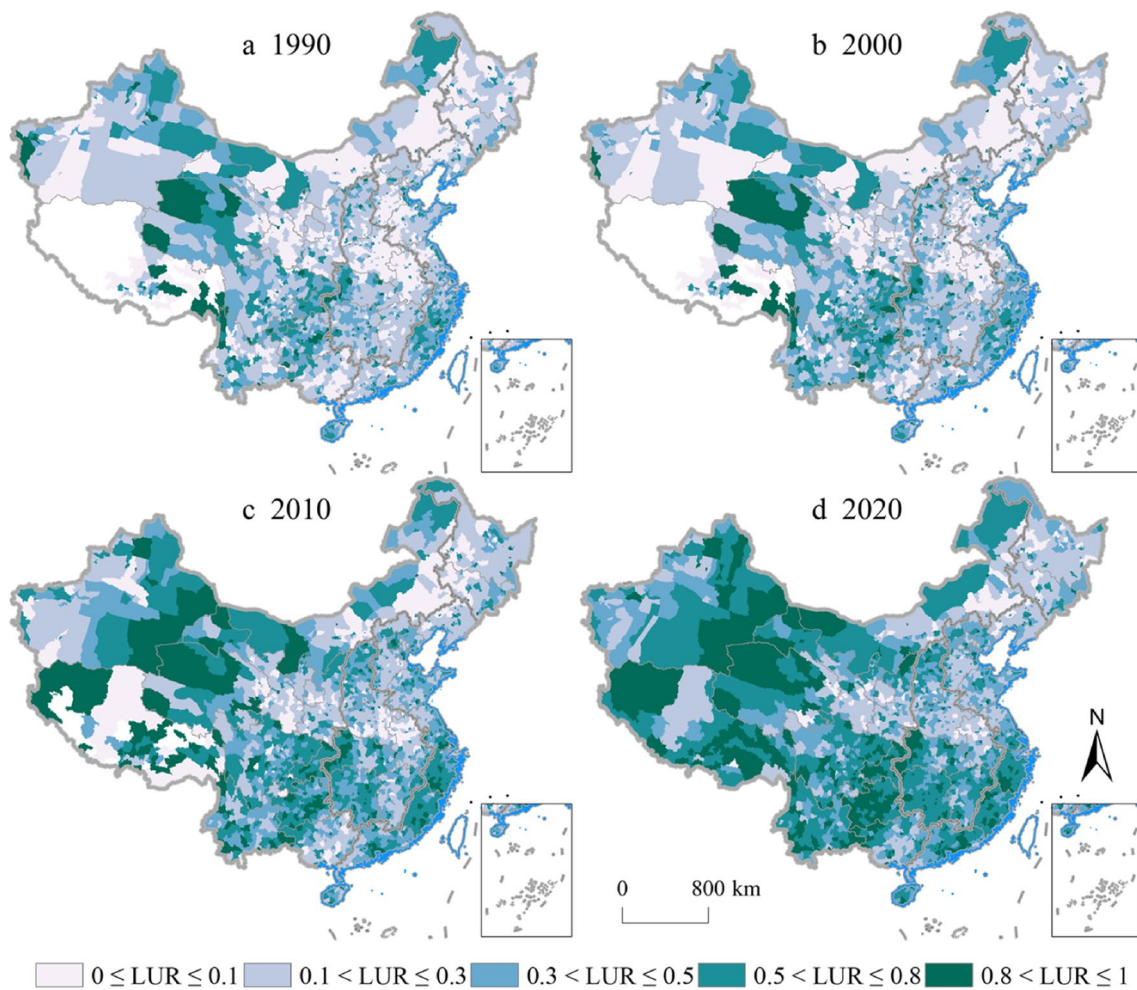
Through a review of previous literature, we selected 6 natural factors and 4 socioeconomic factors totaling 10 impact factors as potential drivers of LU. In terms of natural aspect, average elevation (X1), average slope (X2), annual average temperature (X3), annual average precipitation (X4), vegetation coverage (X5) (Chen et al. 2020), and river density (X6) were chosen as variables. In terms of socioeconomic factors, we selected 4 variables of cultivated index (X7), economic density (X8), population density (X9), and road density (X10). The selected factors in each region have all passed the collinearity diagnostics, and their variance inflation factor values are all less than 9, indicating that there is no obvious collinearity in these factors.

## Results

### Spatiotemporal patterns of land urbanization in China

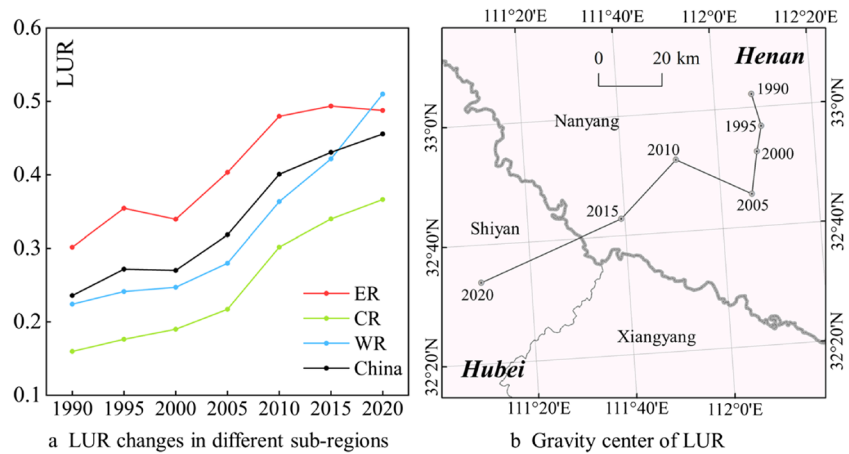
Figure 2 shows the spatiotemporal patterns of LUR in China from 1990 to 2020. In 1990, 2000, 2010, and 2020, China's LUR was 0.236, 0.270, 0.401, and 0.456, respectively. During the study period, China's LUR changed significantly and maintained an upward trend. From the spatial perspective, traditional agricultural areas such as the North China Plain, the Northeast China Plain, the Qilian Mountains, and the Guangxi Basin had relatively low levels of LUR. The south-eastern coastal regions, the middle and upper reaches of the Yangtze River, and parts of Xinjiang and Tibet were regions with high LUR.

This study also measured the spatiotemporal evolution trajectories of LUR in China (Fig. 3). Figure 3a shows the variation of LUR in different regions during 1990–2020. It can be concluded that the LUR of different regions showed an upward trend. The average LUR of China, ER, CR, and WR had increased by 0.220, 0.186, 0.206, and 0.286, respectively. ER had the smallest increase in LUR, but was higher



**Fig. 2** Spatial pattern of LUR in China during 1990–2020

**Fig. 3** Spatiotemporal evolution characteristics of LUR in China during 1990–2020



than the average LUR in China, while WR had the largest increase and surpassed ER to become the region with the highest LUR in 2020. Figure 3b shows the direction of the gravity center of China’s LUR during the study period. The gravity center of China’s LUR had moved 103.974 km to

the southwest, echoing the conclusion drawn above that the LUR in WR was growing faster than that in ER. Specifically, from 1990–2005, the gravity center of China’s LUR was located in Nanyang, Henan Province, while in 2020 was located in Shiyan, Hubei Province. From 1990–2005, the

gravity center of China's LUR basically moved to the south, and the migration distance was 31.459 km. From 2005 to 2020, the gravity center of China's LUR remarkably shifted to the west, with a migration distance of 89.865 km.

### Regional differences of land urbanization in China

The results of Dagum Gini coefficient are shown in Fig. 4. During 1990–2020, the Gini coefficient of each region continued to decline, indicating that the development level gap of LU within each region was narrowing. Specifically, the Gini coefficients of ER, CR, WR, and China decreased by 0.166, 0.160, 0.177, and 0.169, respectively, with a decrease rate of 36.889%, 33.195%, 38.147%, and 36.188%, respectively. In terms of regional differences in Dagum Gini coefficients, the gaps between sub-regions were generally similar, with the largest gap between CR and WR and the smallest gap between ER and WR. Meanwhile, the LU gaps between regions showed a continuous downward trend, indicating that the LU gaps between different regions continued to narrow. The gaps between ER-WR, ER-CR, and CR-WR decreased by 0.172, 0.166, and 0.169, respectively, with a decrease rate of 37.555%, 35.244%, and 35.654%, respectively. In terms of regional differences contribution rate of LUR in China, the contribution rate of intensity of transvariation was the highest (57.442% in 2020), followed by the contribution rate of intra-regional differences (33.283% in 2020), while the contribution rate of inter-regional differences was the smallest (9.275% in 2020). The intensity of transvariation and inter-regional differences are both indicators of inter-regional disparity. The results showed that the disparity between different regions was the main reason for regional differences of LU in China. Moreover, the contribution rate of intensity of transvariation and intra-regional differences showed a trend of first decreasing and then increasing, reaching the minimum value in 2005, while

the changing trend of inter-regional differences showed the opposite.

In this study, kernel density estimation was introduced to characterize the regional differences in the dynamic evolution of LUR in China during the study period (Fig. 4). If the kernel density contour distribution is near the 45° diagonal line, it indicates that the LUR did not change significantly during the study period. Overall, the LUR in various regions of China had obvious upward shifts, and the trend of changes in CR and WR was more obvious. In the contour maps, the kernel density peaks were located from high to high and from low to low, indicating that these two change types were the main types of LUR changes in China. Specifically, the LUR in ER, CR, WR, and China all moved to higher levels. Among them, WR had the largest change range, and the trend of evolution from low-value units to high-value units was more obvious. The change in ER was minimal, generally with a slight shift towards higher values, indicating that the development speed of LU in WR was much higher than that in ER.

### Spatial dependence of land urbanization

We also introduced a spatial autocorrelation model to detect whether China's LU had spatial effects. The global Moran's  $I$  calculated by Queen's contiguity matrix is shown in Fig. 5, and the results are all significant at 0.0001 level. The results showed that China's LUR had a strong spatial agglomeration effect, with the global Moran's  $I$  exceeding 0.4 and a continuous increase of 0.123 from 1990 to 2020, indicating that its spatial agglomeration strength became more and more obvious. The LISA cluster map provides the spatial cluster patterns of LUR, and the results are shown in Fig. 6. The dominant spatial cluster patterns in China were the high-high types and low-low types. Specifically, low-low types were mainly distributed in traditional agricultural

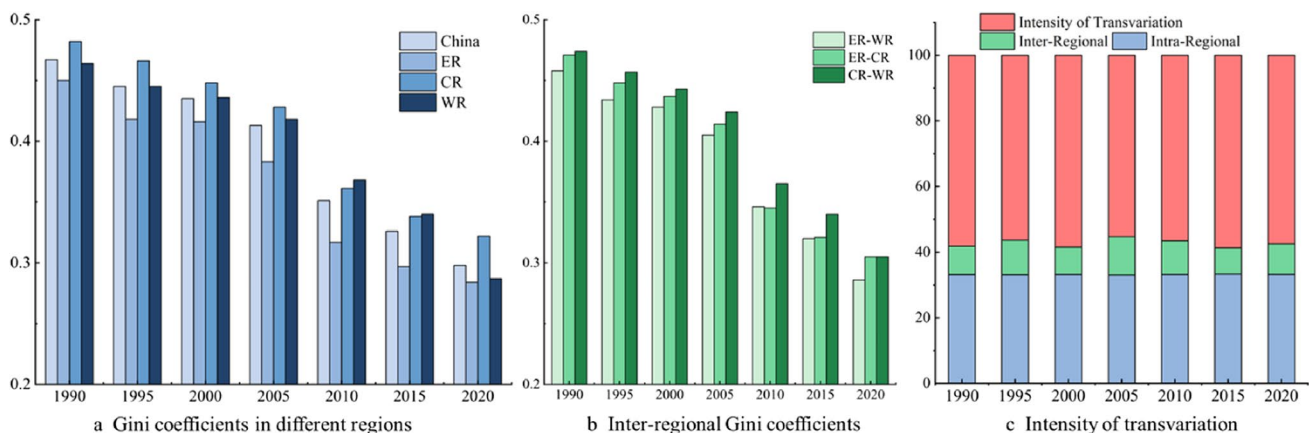
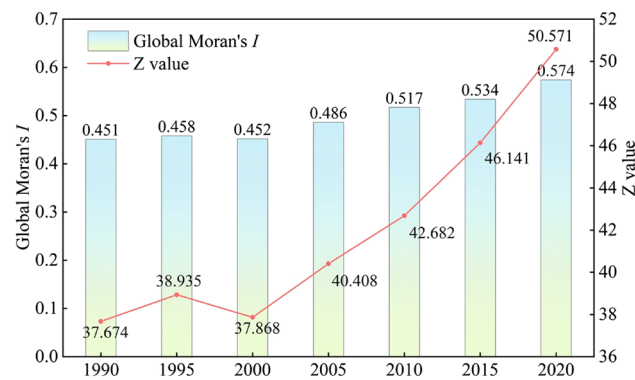
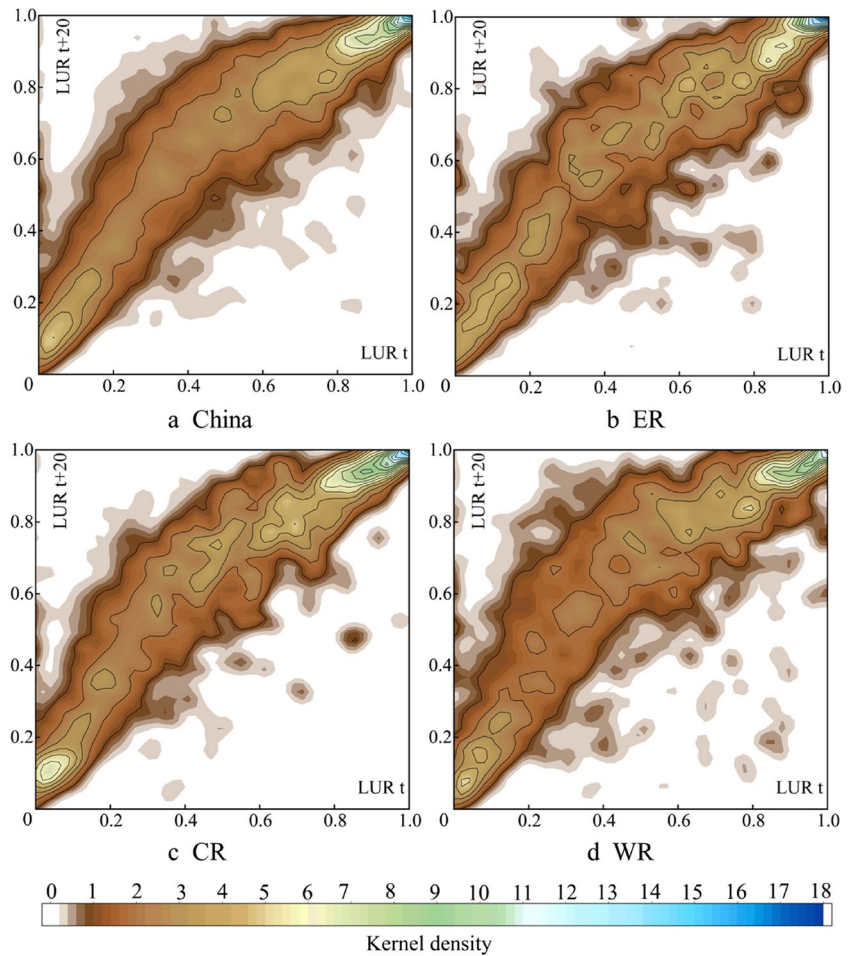


Fig. 4 Gini coefficient and its decomposition result

**Fig. 5** Contour maps of kernel density in different regions



**Fig. 6** Global Moran's *I* of LUR in China during 1990–2020

areas including the North China Plain, the Northeast Plain, the Qinling Mountains, and the Xinjiang River Valley. The high-high types had been increasing over time, and they were mainly distributed in the upper and middle reaches of the Yangtze River, the southeastern coastal areas, the Pearl River Delta, and the Qaidam Basin. The low–high types and high-low types were not obvious spatially, but they were

mostly distributed around cities. During the study period, the spatial group development trend of LU became more and more obvious.

We also introduced a spatial Markov chain to explore the future change trend of LUR in China (Figs. 7, 8, and 9). Referring to previous studies, this study ranked the LUR of all units in all years during the study period. Regions below the lower quartile are defined as low-level regions (L types), regions between the lower and the median quartile are defined as middle-low-level regions (ML types), regions between the median and upper quartile are defined as middle-high-level regions (MH types), and regions above the upper quartile are high-level regions (H types). Generally, the greater the transition probability of elements on the diagonal line, the worse the spatial mobility of the research elements, showing a trend of convergence. The results obtained in this study still conformed to this law and showed a trend that the larger the time slice, the smaller the transition probability of the diagonal line, while the longer the time slice, the higher the transformation mobility between types of LUR. Meanwhile, the regions with high-level spatial lag terms had higher transition probability from low-level to



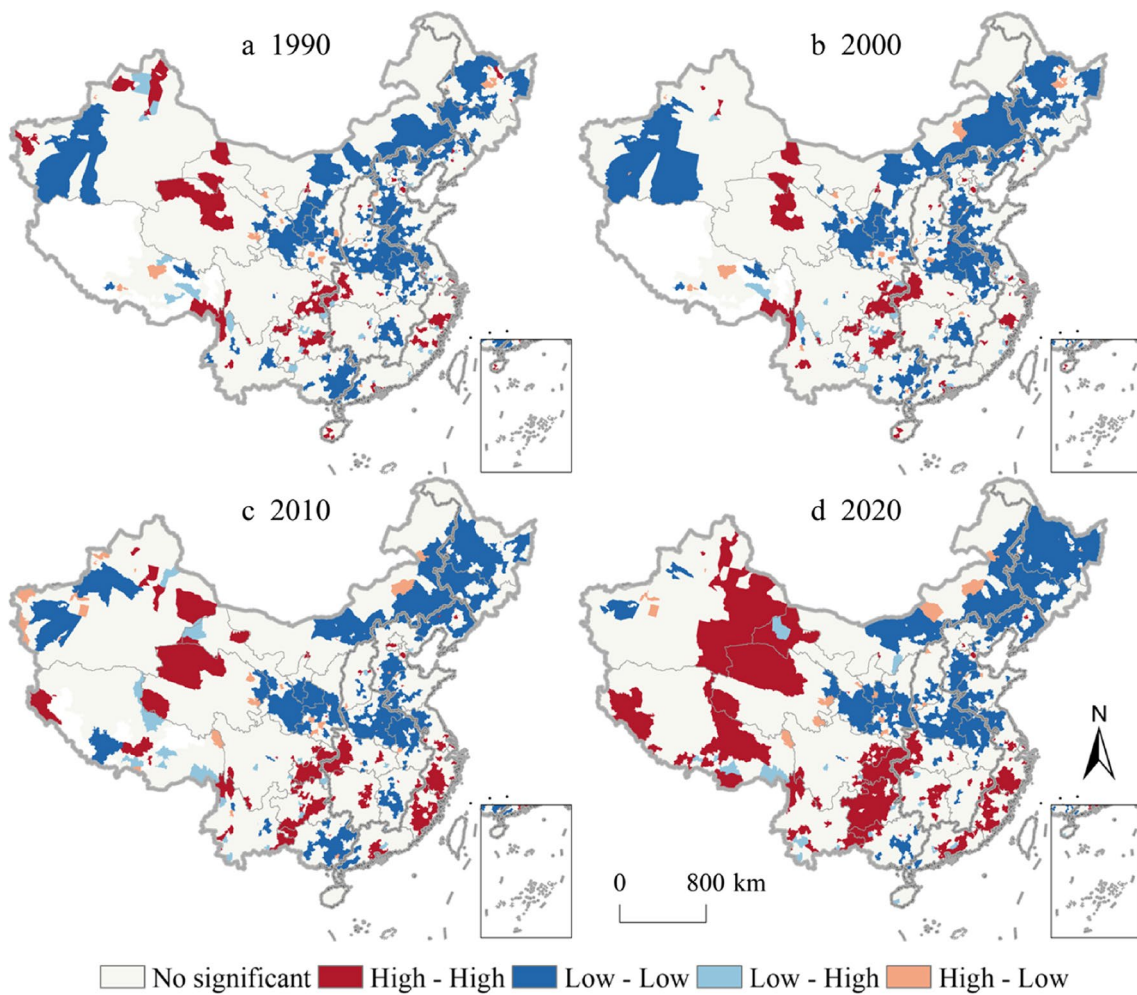


Fig. 7 LISA cluster maps of LUR in China during 1990–2020

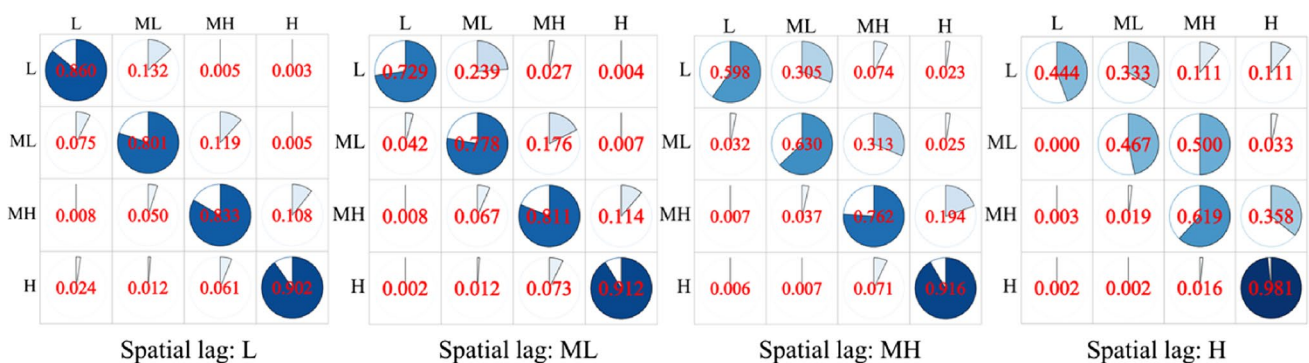


Fig. 8 Spatial Markov transition probability matrix of LUR with a time span of 5 in China. Notes: L denotes low-level type; ML denotes middle-low-level type; MH denotes middle-high-level type; H denotes high-level type

high-level, and this phenomenon became more obvious with the increase in time slice, showing that the development of LU had significant spatial spillover effects. The transition probability from high-level to low-level was much smaller

than that from low-level to high-level. The transition probability hopping phenomenon rarely occurs, but the longer the time slice, the more likely it will occur, indicating that the LUR in China was developing steadily to a higher level.

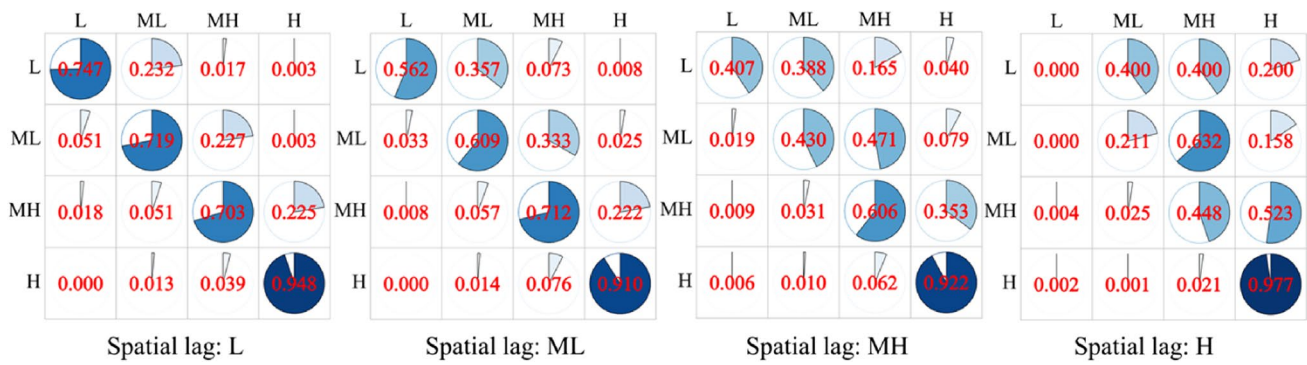


Fig. 9 Spatial Markov transition probability matrix of LUR with a time span of 10 in China

### Regional differences in driving forces of land urbanization

According to the residual test results of OLS model (Table S1), there is an obvious spatial autocorrelation in the residuals. Therefore, compared with traditional linear regression, the spatial regression model should be given priority. Accordingly, this study introduced a series of spatial regression models, including SLM, SEM, and SEMLD, to explore the effects of potential impact factors on LU in different regions of China (Table S2–S4). A series of criteria including Log-likelihood (LogL), Akaike information criterion (AIC), Schwartz’s Bayesian information criterion (SC), and  $R^2$  were used to find the best model to explain. The larger the values of LogL and  $R^2$  and the smaller the values of AIC and SC, the better the performance of the model. In this study, all diagnostic indicators showed that SEMLD is the optimal model. In addition, all models selected in this study passed the robust LM test, indicating that these models were available. Meanwhile, the statistical values of Breusch-Pagan test and Koenker-Bassett test of all models passed the significance test, showing that there was no heteroscedasticity in the independent variables.

Table 2 shows the regression results of each factor in ER, CR, and WR by using the SEMLD model. The regression coefficients of average elevation in three regions were all negative, meaning that LUR was gradually decreasing with the increase in average elevation. The influence of average slope on LUR was not strong in all regions. The influence of annual average temperature on LUR in ER and the influence of annual average precipitation on LUR in CR were higher than those in other regions. Vegetation coverage exerted a negative influence on LUR in all regions, among which ER had the greatest influence, and the absolute values of regression coefficients of vegetation coverage in ER and WR continued to decrease with time, while that in CR continues to increase. An increase in river density leads to an increase in LUR of ER and CR, while in WR, the influence of river

density on LUR is lower than that in ER and CR. The impact of cultivation index on LUR was negative, with the largest influence in ER, followed by CR, while WR was the last in line. Rapid economic development is a strong driving force for LU, and this phenomenon was more obvious in CR and WR. However, in 2020, the driving force of economic growth on LUR had turned from positive to negative, which may be due to the proposal of new urbanization. The further intensive use of urban land has been promoted, and economic growth is no longer the main reason driving the increase in LUR. The influence of population density on LUR was positive and negative, with a negative influence in ER and CR, while a positive influence in WR. In ER and CR, road density showed a strong positive influence on LUR, but in 2020, this effect decreased rapidly, while in WR, road density also showed a positive influence on LUR. The spatial lag terms of all regions were positive and significant, indicating that the increase of LUR in adjacent regions tended to bring about the increase of LUR in local region. Besides, the coefficient value of the spatial lag term is the largest in WR and the smallest in ER, indicating that the spatial spillover effects of LU in WR were stronger than that in other regions. The spatial error term was significant in all regions and negative in both ER and CR, while WR had positive values in 2020 but negative values in other years, indicating that the error terms in adjacent regions often had a negative impact on the error terms in the local region.

## Discussion

### Interpretation of findings

Differences in the growth rates of LUR in different regions of China during the study period led to a continuous shift in the gravity center of China’s LUR to the west. One of the main reasons is that WR is supported by central and local policies (Zhang and Wang 2018). Against the

**Table 2** Regression results of SEMLD

Explanatory variables	2000			2010			2020		
	ER	CR	WR	ER	CR	WR	ER	CR	WR
X1	-0.164*** (0.036)	-0.044 (0.028)	-0.079** (0.029)	-0.135*** (0.036)	-0.023 (0.031)	-0.044*** (0.011)	-0.130*** (0.031)	-0.074* (0.031)	-0.020*** (0.005)
X2	0.085 (0.048)	0.011 (0.042)	0.022 (0.026)	0.121* (0.052)	-0.002 (0.043)	0.013 (0.010)	0.017 (0.044)	-0.058 (0.043)	0.002 (0.004)
X3	-0.053 (0.050)	0.017 (0.031)	-0.031 (0.032)	-0.042 (0.034)	-0.001 (0.028)	-0.007 (0.011)	0.006 (0.034)	0.054 (0.031)	-0.005 (0.005)
X4	0.025 (0.047)	-0.077* (0.038)	0.030 (0.037)	0.043 (0.038)	-0.033 (0.030)	-0.005 (0.017)	-0.008 (0.042)	-0.079* (0.038)	0.002 (0.007)
X5	-0.204*** (0.039)	-0.000 (0.031)	-0.047* (0.026)	-0.179*** (0.040)	-0.039 (0.031)	-0.016 (0.010)	-0.174*** (0.032)	-0.082** (0.29)	-0.013** (0.004)
X6	0.284*** (0.064)	0.091 (0.088)	0.123 (0.117)	0.174** (0.063)	0.218* (0.089)	-0.060 (0.048)	0.128* (0.061)	0.188* (0.092)	0.009 (0.019)
X7	-0.355*** (0.037)	-0.140*** (0.034)	-0.089*** (0.019)	-0.331*** (0.038)	-0.151*** (0.035)	-0.042*** (0.008)	-0.430*** (0.031)	-0.277*** (0.033)	-0.021*** (0.004)
X8	-0.757 (2.077)	12.155 (2.206)	7.194 (5.193)	8.876** (2.918)	10.004*** (1.081)	1.432* (0.770)	-0.127 (0.094)	-0.261 (0.167)	-0.014 (0.020)
X9	0.011 (0.102)	0.244* (0.125)	-0.267 (0.157)	-0.214** (0.072)	-0.051 (0.100)	0.074 (0.042)	-0.135* (0.064)	0.173 (0.126)	0.066*** (0.015)
X10	3.645*** (0.544)	3.723*** (0.822)	1.916*** (0.043)	4.007*** (0.589)	4.735*** (0.959)	0.400** (0.143)	0.149* (0.059)	0.242* (0.112)	-0.003 (0.010)
Constant	0.326*** (0.038)	0.090** (0.030)	0.027 (0.019)	0.318*** (0.038)	0.097** (0.031)	-0.003 (0.007)	0.381*** (0.031)	0.202*** (0.030)	-0.003 (0.003)
Spatial lag term	0.737*** (0.032)	0.911*** (0.028)	1.088*** (0.019)	0.678*** (0.034)	0.848*** (0.028)	1.069*** (0.007)	0.762*** (0.030)	0.954*** (0.028)	1.037*** (0.003)
Spatial error term	-0.312*** (0.049)	-0.566*** (0.049)	-0.908*** (0.043)	-0.141** (0.049)	-0.430*** (0.050)	-0.758*** (0.046)	-0.200*** (0.049)	-0.465*** (0.050)	0.998*** (0.001)
Log-likelihood	446.295	370.674	294.027	522.996	429.787	1428.715	600.158	425.690	2836.332
AIC	-868.589	-717.348	-564.055	-1021.990	-835.573	-2833.430	-1176.32	-827.380	-5648.660
SC	-809.841	-657.996	-503.663	-963.243	-776.221	-2733.04	-1117.57	-768.027	-5588.270
R <sup>2</sup>	0.715	0.623	0.586	0.745	0.669	0.898	0.759	0.668	0.988

\*\*\* $p \leq 0.001$ , \*\* $p \leq 0.01$ , \* $p \leq 0.05$ . Numbers in the parentheses denotes standard deviation. X1 denotes average elevation of each county; X2 denotes average slope; X3 denotes annual average temperature; X4 denotes annual average precipitation; X5 denotes vegetation coverage; X6 denotes river density; X7 denotes cultivation index; X8 denotes economic density; X9 denotes population density; X10 denotes road density

background of unbalanced regional development in the 1990s, China began to put the urbanization development in WR on a daily basis and constructively implemented a series of strategic measures for the development of WR, which had greatly promoted the infrastructure construction and industrial system optimization in WR, and thus promoting the continuous narrowing gap of LU between western and eastern China (Deng et al. 2021). In addition, due to the irreversibility of LU, LUR basically shows an increasing trend in all regions (Deng 2021). Simultaneously, the unbalanced development of LU in each sub-region of China is decreasing, with the largest decrease in WR and the smallest decrease in CR. The probability distribution of LUR moving to a high level shows the largest in WR and the smallest in ER, resulting in a continuous decline in the differences between different regions. However, the huge differences in natural background and

socioeconomic development have led to a wide disparity in land use patterns and economic development between the eastern and western of China, but policy interventions have helped to alleviate the imbalance in land use patterns (Chen et al. 2016; Zhang and Wang 2018; Zhang et al. 2022a). Besides, China's LU has obvious spatial dependence and spatial spillover effects. During the study period, the tendency of land urbanization to develop in groups became more and more obvious. Regions neighboring high-level LUR, the transition probability to high-level LUR was higher, and the larger the time slice, the more obvious the transition trend. This is because with the continuous development of information, technology, transportation, and logistics, the virtual distance between urban agglomerations is constantly shrinking (Liu et al. 2015). Furthermore, cities will form radiation centers in the process of their development and will greatly affect

the development of surrounding areas (Jiang et al. 2022). Therefore, LU has a strong spatial dependence and spatial spillover effects (Gao et al. 2018).

### Driving forces of land urbanization

The regression results show that the LU of ER is more influenced by natural factors, while the LU of CR and WR is more influenced by socioeconomic factors. The economic development-oriented land development model makes urban land closely linked to the local economy, which in turn has resulted in irrational urban land use (Turok and McGranahan 2013; Zhang and Wang 2018). However, the driving force of economic factors on LU has declined in all regions in recent years, indicating the exhaustion of the “land for economic development” model (Du 2017; Yang et al. 2023b). The land issue has always been a major issue involving national development and people’s well-being (Yang and Li 2000). Since the reform and opening up, China’s economic system has undergone a great transition, and land finance has made the local government overly dependent on the sale of land resources to directly obtain realizable financial revenue. Developers will choose high-yield real estate after obtaining land use rights, and local governments will mostly develop urban public service facilities after obtaining the fiscal revenue from land transfer. Both of these will lead to the disorder expansion of construction land, which is often irreversible (Deng 2021; Yang et al. 2023b). Excessive urban land expansion will lead to encroachment of cropland around the city, and rural settlements will be left behind due to the high cost of demolition, gradually evolving into urban villages (Chen et al. 2021a; Lang et al. 2016). Furthermore, the central government is committed to narrowing the gap between different regions and realizing balanced regional development. As induced by top-down policies, the speed of LU in WR is higher than that in CR and ER, which also leads to the greater impact of socioeconomic factors in WR. Meanwhile, with the continuous deepening of new development concepts, LU in traditionally developed regions has gradually slowed down, and the role of economic development in promoting LU has been further weakened.

### Policy implications

This study analyzes the regional differences and spatial determinants of LU in China, which can support the understanding of the current status of LU in China and the related driving forces and provide a reference for the formulation of related policies. Based on the results of this study and summarizing the relevant findings of previous studies, we propose the following policy implications.

Urbanization is an important engine of socioeconomic development, but too fast LU will also bring a series of

socioeconomic problems and environmental problems. LU is faster than population urbanization, resulting in the continuous increase of urban villages and urban fringe villages, and it is difficult for primitive villagers to integrate into urban society (Lang et al. 2016). Due to the irreversibility of LU, a large number of “empty cities” and “ghost towns” seriously endanger local sustainable development and intensive use of land resources (Deng 2021; Jin et al. 2017). Moreover, the rapid progress of LU can bring about the deterioration of regional ecosystems (Yang et al. 2023a). Thus, LU is a double-edged sword on the road to high-quality development. Based on the great variation of LU among different sub-regions, urban development patterns should be transformed in areas with redundant urban land according to the local conditions, focusing on revitalizing existing urban land resources, supplemented by controlling the increment of urban land, and accelerating the transformation of urban development by focusing on people. And in some mountainous areas where urban land is scarce, urban development boundaries should be rationally planned to achieve orderly expansion.

By analyzing regional differences in drivers of LU, we find that LU in ER is more influenced by natural factors than in CR and WR, while LU in CR and WR is more influenced by socioeconomic factors than in ER. It also represents the fact that socioeconomic development in the Midwest is still strongly linked to LU, while in ER, natural factors dominate. This also helps policymakers to regulate the growth rate of LU and realize balanced regional development by providing ideas and regulatory means to control the size of the influencing factors and thus the speed of LU in different regions and realize the high-quality development of LU. Meanwhile, LU was also detected to have a strong spatial spillover effect. Policymakers should consider the spatial dependence of land use and spatial spillover effects in the framework of urban agglomerations development policies to realize the goal of high-quality development of urban agglomerations (Zhang and Wang 2018).

### Limitations and future directions

This study measured the spatiotemporal evolution characteristics of China’s LU and its regional differences and explored the differences in the driving forces of LU among different regions. However, this study still has some limitations. When analyzing the driving forces of LU, policy factors were not taken into account. Moreover, with the rapid development of society, science, and technology, different parts of the world are becoming increasingly interconnected, but this study fails to consider the theoretical framework of telecoupling (Chen et al. 2019b; Liu et al. 2015). In the follow-up work, we will continue to explore the impact of policy factors on the regional differences and dynamic

evolution of LU and try to quantify its impact. Meanwhile, we will also try to introduce the theoretical framework of telecoupling to analyze the impact of other regions or other countries on LU in China.

## Conclusion

This study systematically analyzed the regional differences and dynamic evolution of LU and analyzed the regional differences in their drivers. We find that LU grew fastest in the WR and slowest in the ER, resulting in a shift of the gravity center of LUR to move westward by 103.974 km. In addition, the imbalance pattern of China's LU continues to improve, and the differences among different regions were constantly shrinking. Results also showed that China's LU had strong spatial dependence and spatial spillover effects, and the spatial group development was more and more obvious. In terms of regional differences in driving factors of LU, the LUR in ER was more affected by natural factors, while the influence of socioeconomic factors in CR and WR was greater. This study can provide a scientific reference for the formulation of effective LU regional coordinated development policies and provide examples for other countries and regions in the world to study the regional differences in LU.

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**Data availability** All data used in this study are publicly available.

## Declarations

**Ethics approval and consent to participate** All our research complies with ethical guidelines, including compliance with the legal requirements of the research country. The authors of this paper have participated in the entire process of this article, including conceptualization, paper ideas, methods, writing, and review.

**Consent for publication** As a result of the research, we unanimously agree that this paper can be published in your journal.

**Conflict of interest** The authors declare no competing interests.

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