

Spatial-temporal Dynamics and Driving Forces of Land Development Intensity in the Western China from 2000 to 2015

HUANG Xin^{1,2}, HUANG Xiaojun^{3,4}, LIU Mengmeng³, WANG Bo³, ZHAO Yonghua^{1,2}

(1. School of Earth Science and Resources, Chang'an University, Xi'an 710054, China; 2. Shaanxi Key Laboratory of Land Consolidation, Xi'an 710054, China; 3. College of Urban and Environmental Science, Northwest University, Xi'an 710127, China; 4. Shaanxi Key Laboratory of Earth Surface System and Environmental Carrying Capacity, Xi'an 710127, China)

Abstract: The change in land development intensity is an important perspective to reflect the variation in regional social and economic development and spatial differentiation. In this paper, spatial statistical analysis, Ordinary Least Squares (OLS), and Geographically weighted regression (GWR) methods are used to systematically analyse the spatial-temporal characteristics and driving forces of land development intensity for 131 spatial units in the western China from 2000 to 2015. The findings of the study are as follows: 1) The land development intensity in the western China has been increasing rapidly. From 2000 to 2015, land development intensity increased by 3.4 times on average. 2) The hotspot areas have shifted from central Inner Mongolia, northern Shaanxi and the Beibu Gulf of Guangxi to the Guanzhong Plain and the Chengdu-Chongqing urban agglomeration. The areas of cold spots were mainly concentrated in the Qinghai-Tibet Plateau, Yunnan, and Xinjiang. 3) Investment intensity and the natural environment have always been the main drivers of land development intensity in the western China. Investment played a powerful role in promoting land development intensity, while the natural and ecological environment distinctly constrained such development. The effect of the economic factors on land development intensity in the western China has changed, which is reflected in the driving factor of construction land development shifting from economic growth in 2000 to economic structure, especially industrial structure, in 2015.

Keywords: construction land; land development intensity; spatial-temporal dynamic; driving force; the western China

Citation: HUANG Xin, HUANG Xiaojun, LIU Mengmeng, WANG Bo, ZHAO Yonghua, 2020. Spatial-temporal Dynamics and Driving Forces of Land Development Intensity in the Western China from 2000 to 2015. *Chinese Geographical Science*, 30(1): 16–29. <https://doi.org/10.1007/s11769-020-1095-2>

1 Introduction

Land use change is an important topic that has gained interest in recent years because of its role as a driver of environmental change (Foley et al., 2005). Land use change encompasses two aspects: changes in land cover and land development intensity (Erb et al., 2014). Current research on land use change mainly focuses on land cover change, such as its spatial-temporal characteris-

tics, driving mechanisms, patterns and processes, and ecological and environmental effects (García and García-Romero, 2007; Kroll and Haase, 2010; Zia, 2012; Zachary, 2013; Houghton and Nassikas, 2017; Arowolo et al., 2018). In comparison, research on land development intensity has not received much attention over the past few years. Land development intensity is defined as the extent of land being used, which is also an indication of the amount and degree of land development in an

Received date: 2019-05-14; accepted date: 2019-09-17

Foundation item: Under the auspices of Fundamental Research Funds for the Central University (No. 310827171012); National Natural Science Foundation of China (No. 41971178; 31670549; 31170664); National Key Research & Development Program of China (2017YFC0504705); Open Fund of Shaanxi Key Laboratory of Earth Surface System and Environmental Carrying Capacity (No. SKLESS201807); Key Research & Development Program of Shaanxi Province (No. 2019SF-245)

Corresponding author: HUANG Xiaojun. E-mail: huangxj@nwu.edu.cn

© Science Press, Northeast Institute of Geography and Agroecology, CAS and Springer-Verlag GmbH Germany, part of Springer Nature 2020

area and a reflection of the comprehensive effects that the natural environment and human activities have on land (Quintas-Soriano et al., 2016; Cegielska et al., 2018; Wellmann et al., 2018; Yang et al., 2019).

At present, many developing countries in the world are experiencing rapid industrialization and urbanization, which greatly stimulates the growing demand for land, especially construction land. The remarkable land use change that occurred in China over past decades has been primarily characterized by the astonishing expansion of construction land (Long et al., 2007; Liu et al., 2015a; Huang et al., 2017b). According to the statistical yearbook, the area of China's construction land has increased from 362 600 km² in 2000 to 385 930 km² in 2015 (National Bureau of Statistics of China, 2016). This demand is driven by multidimensional factors, such as population growth, industrial development, urbanization, investment, and national policies (Gao et al., 2018). However, the growth of construction land is limited by the scarcity of land resources. The eventual consequence must be a high concentration of various elements in the limited land space, which leads to enhancement of land development intensity. Therefore, research on land development intensity can reflect changes in social and economic development, this research also provides an important perspective to explore the spatial pattern heterogeneity of socio-economic development.

The concept of land development intensity has traditionally been used in and has developed from agriculture (Erb et al., 2013). The commonly accepted concept of land development intensity in agriculture can be denoted as the degree of yield amplification caused by human activities or socioeconomic inputs, including: labour, resources, water, energy, and capital (Liiri et al., 2012). A large number of studies have been carried out focusing on agricultural land development intensity, including dynamic change (van der Sluis et al., 2016), measurement analysis (Dietrich et al., 2012), spatial pattern (Yin et al., 2019), driving forces (Teixeira et al., 2014), and impacts on ecology and the environment (Margritter et al., 2014). A variety of different data were used in the research, such as agricultural census, land use/cover maps, satellite images, field surveys, and statistics data (Persson et al., 2010). Multiple approaches were applied in related studies, including spatially explicit maps (Yan et al., 2017), comparative analysis (Lu et al., 2012), measuring models (Ferdous and Bhat, 2013), and re-

mote sensing technology (Howison et al., 2018). Compared with agricultural land development intensity, the research on other types of land (e.g., construction land, urban land, and industrial land) is relatively scarce.

Land development intensity is an important topic in the field of land studies in China. During China's rapid economic development and urbanization in the past decades, the change in construction land has become not only the most significant aspect of land use change but also the focus of land use research. A broad array of studies have been carried out in recent years, mainly focusing on the spatiotemporal changes (Jiang et al., 2016), spatial pattern (Xie et al., 2017) and driving forces (Liu et al., 2015b) of construction land, construction land expansion and cultivated land protection (Liu et al., 2015a), assessment of construction land potential (Xu et al., 2011; Dang et al., 2015), and economic efficiency of construction land (Ye et al., 2018). The intensity of urban construction land use has been widely addressed by an increasing number of scholars (Gong et al., 2014; Liang et al., 2018). Compared with construction land, the research on land development intensity is still relatively scarce. Relevant researches mainly focus on the spatial-temporal characteristics of the land development intensity in a province or city (Tan et al., 2011; Shen et al., 2019), while systematic research on driving mechanisms of land development intensity at regional or national scales has been pursued relatively less often. In addition, there are few studies on the measurement, spatial-temporal dynamics, and spatial heterogeneity of construction land, and there are even fewer studies on land development intensity as a reflection of the pattern of socio-economic development. It is worth noting that Liu provides a systematic regional case research on the evolution of the pattern and spatial differentiation mechanism of construction land development intensity in Northeast China (Liu et al., 2018).

Since the Reform and Opening Up of China in 1978, the eastern coastal areas of China have rapidly developed. Meanwhile, the gap between the eastern coastal and central and the western inland areas have also begun to widen. To promote balanced development, the central government of China began to implement the Grand Western Development Program in 2000. Since then, the western China has rapidly developed, with the level of urbanization rising from 28.7% in 2000 to 48.7% in 2015, and the gross domestic product (GDP) per capita rising

from 4624 to 39 210 yuan (RMB) (National Bureau of Statistics of China, 2011; 2016). The rapid development caused a high rate and massive scale of construction land expansion. The largest area of increase was observed in the western China from 2010 to 2015, which showed an expansion of $10.6 \times 10^3 \text{ km}^2$, or 43.0% of the total increase of construction land area in China (Ning et al., 2018). The increase in area and intensity for construction land may not only alter socio-economic development patterns in the western China but also create a potential threat to the vulnerable ecological environment. Therefore, a clear and systemic understanding of land development intensity in the western China is a crucial task to optimize development pattern here and achieve sustainable development in the new period. The main research objective of this paper is to analyse the dynamic characteristics and spatial patterns of land development intensity and reveal spatial heterogeneity and its driving forces in the western China since the implementation of the Grand Western Development Program. It is hoped that this paper provides decision support for exploring socio-economic development patterns, optimizing land use and promoting sustainable development in the western China.

2 Materials and Methods

2.1 Study area

The Grand Western Development Program in China covers 12 provinces, autonomous regions, and municipalities, including Sichuan, Shaanxi, Gansu, Qinghai, Yunnan, Guizhou, Chongqing, Guangxi, Inner Mongolia, Ningxia, Xinjiang, and Tibet. The study area is composed of 131 administrative units with a total area of 6.87 million km^2 , accounting for 72% of the whole country (Fig. 1). In 2015, the total population of the western China was 371 million, and the gross domestic product (GDP) was 14.5 trillion yuan (RMB), accounting for 27.1% and 20.1% of the country totals, respectively (National Bureau of Statistics of China, 2016).

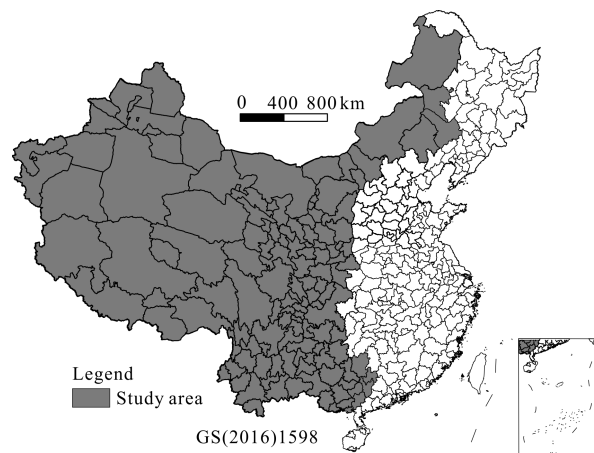


Fig. 1 Location of the western China

2.2 Data source and processing

The land use data of the western China were downloaded from Data Center for Resources and Environmental Sciences of Chinese Academy of Sciences (RESDC) (<http://www.resdc.cn>). The land use data were acquired by a user-computer interactive interpreting method based on Landsat TM/ETM at different stages. We mainly extracted construction land of the western China, including urban built-up lands, rural settlements, and other construction lands (e.g., industrial parks, transportation facilities, mining areas, etc.) in 2000 and 2015. The construction land area of each administrative unit in the western China was calculated using the tabulate area tool in ArcGIS 10.2. The socio-economic data were obtained from the statistical yearbooks of the western provinces of China in 2001 and 2016. Topographic and ecological data were also obtained from the Data Center for Resources and Environmental Sciences of Chinese Academy of Sciences. The slope was calculated using a 250 m digital elevation model. The forest ecosystem area of each administrative unit was obtained from spatial distribution data of China's terrestrial ecosystem types in 2000 and 2015. Details of the above data are shown in Table 1.

Table 1 Detailed information of the data

Data	Year	Component	Source	Resolution
Construction land	2000/2015	Urban built-up land, rural settlement land, other construction land	Landsat TM/ETM	1000 m
Forest ecosystem	2000/2015	Woodland, shrubbery, sparse Woodlot, other forest land	Landsat TM/ETM	100 m
DEM	2000		Shuttle Radar Topography Mission (SRTM)	250 m

2.3 Methodology

2.3.1 Land development intensity

The concept of land development intensity was proposed in Major Function-Oriented Zone Planning (MFOZ Planning) of China in 2010 and used in the evaluation of construction land development and MFOZ Planning at different scales (Fan et al., 2010). Land development intensity (LDI) is a comprehensive reflection of human construction activities, which is measured by the ratio of the area of regional construction land to the total area of the region. The calculation formula is as follows:

$$LDI = CLA/TA \quad (1)$$

where LDI is land development intensity, CLA is the area of regional construction land, and TA is the total area of the region.

2.3.2 Spatial statistical analysis

Spatial autocorrelation and Hot Spot Analysis are used to reveal spatial patterns and agglomeration characteristics of LDI . Moran's I statistic is used to detect whether nearby areas have similar or dissimilar attributes overall, which represent positive or negative spatial autocorrelation, respectively (Wang, 2015). Moran's I is calculated as:

$$I = \frac{N \sum_i \sum_j w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{(\sum_i \sum_j w_{ij}) \sum_i (x_i - \bar{x})^2} \quad (2)$$

where N is the total number of areas, w_{ij} is the spatial weight linking area i and j , x_i and x_j are the LDI values for area i and j , respectively, and \bar{x} is the mean of the LDI values.

The Getis-Ord G_i^* statistic in the Hot Spot Analysis tool of ArcGIS was used to indicate the clustering of high or low LDI values. A large G_i^* value (a positive Z score) indicates clustering of high values. A small G_i^* value (a negative Z score) indicates clustering of low values. G_i^* is calculated as:

$$G_i^*(d) = \frac{\sum_i \sum_{j \neq i} w_{ij}(d) x_i x_j}{\sum_i \sum_{j \neq i} x_i x_j} \quad (3)$$

where d is critical distance from each other, w_{ij} is the spatial weight linking area i and j , x_i and x_j are the LDI values for areas i and j , respectively.

2.3.3 Driving forces analysis

Against the background of accelerated urbanization and

industrialization, construction land use changes are tightly interrelated with human production activities (Liu et al., 2015a; Dadashpoor et al., 2019). The growth of urban population is one of the driving forces for the expansion of urban built-up land (Oueslati et al., 2015; Mustafa et al., 2018). Regions with more urbanization level have a greater demand for construction land, which will lead to higher land development intensity. Regional economic growth promotes the growth of various factors, which will also generate demand for construction land such as industrial land, residential land, and transportation facilities (Seto et al., 2011). The development of the manufacturing industry will produce a certain demand for construction land and promote land development intensity. The service industry is usually concentrated in the urban built-up area. Therefore, centralized development of the service industry may have a negative effect on the increase of construction land (Chen et al., 2016). Government investment is one of the main drivers of regional development and urbanization. In particular, investment could play an important role in the development of transport and infrastructure in the western China (Liu et al., 2009). Transportation and infrastructures can directly drive the expansion of regional construction land, which has a positive effect on land development intensity. The western China is characterized by great topographic fluctuations and vulnerability in the ecological environment. Adverse topographic conditions and strict ecological protection will limit the land development intensity to a certain extent. Therefore, in view of the actual characteristic and development status of the western China, this paper uses land development intensity (LDI) as the dependent variable and selects independent variables from above-mentioned natural and socio-economic factors (Fig. 2, Table 2).

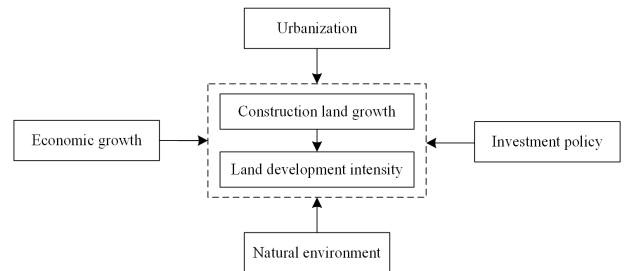


Fig. 2 Analytical framework of driving forces to land development intensity in the western China

Table 2 Independent variables to analyse the driving forces of land development intensity

Factors	Independent variables	Calculation methods
Population	Urbanization level	Urban population/total population
Economy	Per capita GDP	GDP/total population
	Per capita fiscal revenue	Regional fiscal revenue/total population
Investment	Per unit area fixed assets investment	Total fixed asset investment/total area
	Per unit area fiscal expenditure	Local fiscal expenditure/total area
Industry	Industrialization level	Added value of the secondary industry/GDP
	Development of service industry	Added value of the tertiary industry/GDP
Environment	Topographic conditions	Average slope value according to DEM
	Ecological constraints	Forest ecosystem area/total area

2.3.4 Geographically weighted regression

In the absence of spatial autocorrelation or spatial dependence, the ordinary least squares (OLS) regression model can be used. When spatial dependence is present, the residuals are not independent from each other, and the OLS regression is no longer applicable. Geographically weighted regression (GWR) is a partial regression model that introduces a spatial nonstationary location and spatial regression coefficients. The spatial position is embedded into the regression coefficients, which not only describe the relationship between explained and explanatory variables but also reflect the spatial variation of their relationship. It is an effective modelling technique used to treat spatial nonstationarity (Su et al., 2012). The model can be expressed as:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^n \beta_k(u_i, v_i)x_{ik} + \varepsilon_i \quad (4)$$

where y_i is the dependent variable, that is, LDI value, x_{ik} is the independent variable, ε_i is the random error or residual, (u_i, v_i) is the location of i , and $\beta_k(u_i, v_i)$ is the regression coefficient of explanatory variables.

GWR uses a locally weighted least squares method to estimate the parameters, and the resulting regression coefficients are usually not constant but vary with respect to changes in spatial position, which reflects the nonstationarity of the spatial relationship (Gao and Li, 2011). The regression parameters of any point can be estimated by the following formula (Su et al., 2012):

$$\beta(u_i, v_i) = (X^T W(u_i, v_i) X)^{-1} X^T W(u_i, v_i) Y \quad (5)$$

where W is a diagonal matrix with diagonal elements being the weight of observations for location i . Usually, a monotone decreasing function of the distance is used to assign weights to observations (Wang, 2015).

3 Results

3.1 Spatiotemporal variation of LDI

We calculated LDI for each administrative unit in 2000 and 2015. Fig. 3 shows the distribution of LDI values in the western China for 2000 and 2015. The maximum, minimum, and average values of LDI were 0.1196 (Wuhai, Inner Mongolia), 0.0001 (Ali, Tibet), and 0.0140, respectively, in 2000. In 2015, the maximum, minimum, and average values of LDI were 0.2307 (Chengdu, Sichuan), 0.0001 (Ali, Tibet), and 0.0476, respectively. Compared to 2000, the average value of LDI in 2015 increased by 3.4 times.

In 2000, high LDI values only appeared in a few cities such as Wuhai, Xi'an, Chengdu, and Beihai. The LDI values in most administrative units were generally low. In 2015, the high-value areas of LDI increased significantly, mainly concentrated in the eastern cities of the western China, such as Shaanxi, Sichuan, Chongqing, and Guangxi. Overall, the values of LDI in the western areas of the western China such as Tibet, Qinghai, and Xinjiang have not changed much. The LDI values of the above areas were always low from 2000 to 2015. In addition, the variation coefficient of LDI values decreased from 1.4170 to 0.9112 from 2000 to 2015, indicating that the gap in land development intensity among the different regions has narrowed.

3.2 Hotspot analysis of LDI

The global Moran's I was calculated for LDI in the western China in 2000 and 2015. The Moran's I was 0.134 and 0.353, respectively, with a Z score of 5.012 and 12.359. The result shows that LDI is not spatially independent but displays a stronger clustering of similar LDI . This result also provides a basis and support for validity of the GWR model.

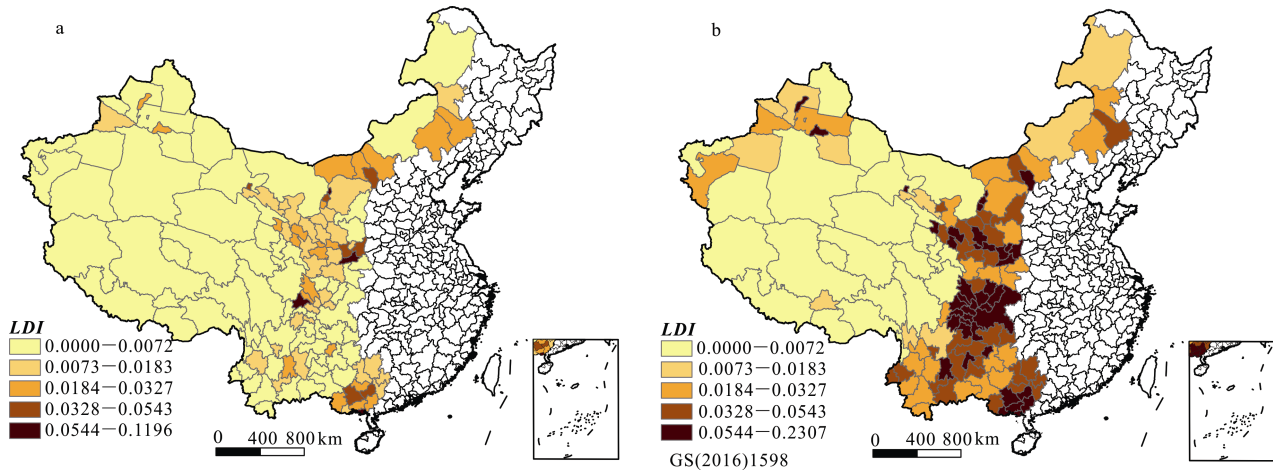


Fig. 3 Spatial patterns of land development intensity in western China in 2000 (a) and 2015 (b)

To reveal the distribution of hot spots and cold spots for *LDI*, we calculate the Getis-Ord G_i^* of *LDI* in the western China in 2000 and 2015. The natural breaks method in ArcGIS 10.2 was used to divide Getis-Ord G_i^* statistics into five categories from high to low. Fig. 4 shows the spatial distribution of hot spots and cold spots areas for *LDI* in 2000 and 2015. Overall, the Getis-Ord G_i^* of *LDI* show a relatively high value in the eastern area and a low value in the west. In 2000, *LDI* hot spots were mainly concentrated in central Inner Mongolia, northern Shaanxi, and south-eastern Guangxi, whereas cold spots were located in south-eastern Qinghai-Tibet Plateau and Yunnan Province. In 2015, *LDI* hot spots were more concentrated and were mainly distributed in the central and southern Shaanxi Province and the Chengdu-Chongqing Urban Agglomeration. The area of

cold spots spread to the whole Qinghai-Tibet Plateau and southern Xinjiang.

3.3 Driving forces of *LDI*

The original nine variables in Table 2 were standardized using the Z score method in SPSS. Meanwhile, multicollinearity for some variables was found through the variance inflation factor (VIF) test. We then used principal components analysis (PCA) to create independent factors and limit the number of variables. A varimax rotation was applied to minimize the number of original variables that load highly on any one factor and increase the variation among factors, thus making these new factors more statistically independent than the original variables. We extracted three and four factors based on a combination of standard criteria: eigenvalues > 1 in

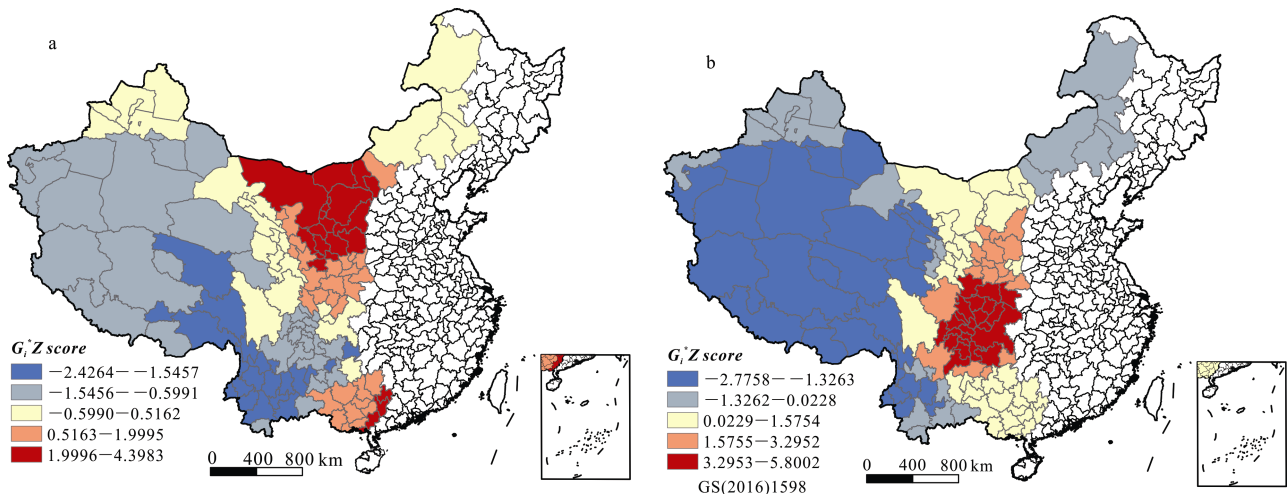


Fig. 4 Spatial patterns of G_i^* Z score for *LDI* in the western China in 2000 (a) and 2015 (b)

2000 and 2015, respectively. Three factors explained 75.38% of the total variance in the original nine variables in 2000, and four factors explained 89.34% of the total variance in the original nine variables in 2015. In 2000, PCA yielded three factors with primary loadings: economic development, investment intensity, and natural environment. In 2015, PCA yielded four factors with primary loadings: economic development, investment intensity, industrial structure, and natural environment, as shown in Table 3.

In this paper, *LDI* was taken as the dependent variable, and the principal factors-based PCA was taken as the independent variable. OLS analysis was conducted on the influencing factors of land development intensity in the western China in 2000 and 2015. Table 4 shows that both models pass the significance test ($P < 0.01$). The adjusted R^2 values are 0.4482 and 0.8316 in 2000 and 2015, respectively, which indicates that both OLS regression models fit well.

In the OLS regression model of 2000, all factors pass the significance test of 99%. Three factors have a significant impact on land development intensity, and the positive and negative effects are basically consistent with the theoretical hypothesis. It can be found that economic development has a positive driving effect on land development intensity in the western China. However, compared with investment intensity, the regression coefficient of factor 1 is relatively small, indicating that land development intensity in the western China is mainly driven by

investment. A large amount of fixed asset investment and fiscal expenditure has been invested in infrastructure construction in the western China, which has greatly promoted land development intensity in the region. The regression coefficient of the natural environment factor is negative, indicating that the natural environment in the western China has played a certain role in constraining and limiting land development intensity.

In the OLS regression model of 2015, the economic development factor fails the test, and the other three factors pass the significance test of 99%. By comparing the regression coefficients of various factors, it can be found that the regression coefficient of investment intensity is as high as 0.8846. This indicates that land development intensity in the western China in 2015 is still mainly dependent on capital investment. Industrial structure factors also have a positive effect on land development intensity. The constraints of the natural environment are hard to change, and still restrict construction land development in this region. Overall, compared with 2000, the regression model in 2015 shows that investment intensity is still the primary driving force of land development intensity in the western China, and the effect is further enhanced. Industrial structure is a new driving factor in 2015, but its regression coefficient is relatively small, indicating that its role is limited. In the regression models for 2000 and 2015, the natural environment has always been the key limiting factor on land development in the western China.

Table 3 The principal drivers of land development intensity

Year	Factors	Indicators and correlation coefficient
2000	Factor 1: economic development	Per capita revenue (0.908), per capita GDP (0.907), industrialization level (0.815), urbanization level (0.718)
	Factor 2: investment intensity	Per unit area fixed assets investment (0.838), per unit area fiscal expenditure (0.811)
	Factor 3: natural environment	Ecological constraints (0.885), topographic condition (0.827)
2015	Factor 1: economic development	Per capita GDP (0.942), per capita fiscal revenue (0.935), urbanization level (0.787)
	Factor 2: investment intensity	Per unit area fixed assets investment (0.969), per unit area fiscal expenditure (0.969)
	Factor 3: industrial structure	Industrialization level (0.864), development of service industry (−0.969)
	Factor 4: natural environment	Ecological constraints (0.891), topographic condition (0.809)

Table 4 Results of the OLS model for land development intensity

Year	Independent variables	Coefficients	Probability	R^2	Adjusted R^2
2000	Factor 1: economic development	0.2548	0.0001	0.4608	0.4482
	Factor 2: investment intensity	0.5798	0.0000		
	Factor 3: natural environment	−0.2443	0.0002		
2015	Factor 1: economic development	0.0633	0.0786	0.8367	0.8316
	Factor 2: investment intensity	0.8846	0.0000		
	Factor 3: industrial structure	0.1691	0.0000		
	Factor 4: natural environment	−0.1468	0.0000		

3.4 Spatial heterogeneity of driving forces

The GWR model of land development intensity in the western China in 2000 and 2015 was carried out in ArcGIS 10.2. Since the economic development factor in 2015 did not pass the significance test, it was excluded from the GWR model. The results of the GWR model are provided in Table 5. The adjusted R^2 values of the GWR model for 2000 and 2015 are 0.686 and 0.884, respectively, which are better than those obtained with the OLS model. To compare the influencing characteristics of various variables on land development intensity, detailed statistics parameters of the GWR model are given in Table 6. The statistical results for 2000 show that the positive coefficient proportion of the economic development factor and the investment intensity factor are more than 90%, while the negative coefficient proportion of natural environment factor is more than 80%, which indicates that the spatial heterogeneity of these variables on land development intensity is not very significant. The statistical results for 2015 show that the positive effect of investment intensity is further strengthened. Land development intensity for all spatial units is significantly affected by the investment intensity factor. The positive coefficient proportion of the industrial structure factor is also more than 90%. Compared with 2000, the impact of the natural environment on land development intensity decreased slightly.

To express the spatial heterogeneity of the various driving factors, their coefficients are estimated and mapped from the GWR model for 131 administrative units in the western China in 2000 and 2015. The natural breaks method in ArcGIS 10.2 is used to classify the

coefficients in Fig. 5 and reveals the spatial pattern of the impacts on land development intensity of various driving forces including economic development, investment intensity, industrial structure, and natural environment.

Economic development. In 2000, the regression coefficient of the economic development factor showed a gradual decrease from northeast to southwest and from southeast to northwest. Two positive high-value clusters were formed in Inner Mongolia and the Beibu Gulf region of Guangxi, while the regression coefficients of other regions were relatively lower. By comparison, the spatial distribution of the high-value areas for the regression coefficient of economic development is consistent with the hot spot areas of land development intensity, while the distribution of the low-value areas is roughly the same as the cold spot areas, indicating that the local economic development factor has a significant impact on land development intensity.

Industrial structure. In 2015, the economic development factors did not pass the significance test, and the industrial structure which was embodied in the industrialization level and development of the service industry, became the significant influencing factor, indicating that the driving forces of land development intensity have changed from economic level to economic structure. The high value of the regression coefficient for the industrial structure factor is concentrated in the Chengdu-Chongqing urban agglomeration and northern Xinjiang, indicating that land development intensity in the above areas is highly sensitive to the change in industrial structure.

Table 5 Results of the GWR model for land development intensity

Parameter	Bandwidth	Residual squares	Sigma	AICc	R^2	Adjusted R^2
2000	496609.2693	28.9849	0.5603	261.1381	0.7804	0.6860
2015	605887.5066	11.7888	0.3406	116.4943	0.9107	0.8840

Table 6 Statistical parameters of the GWR model for land development intensity

Year	Independent variables	Minimum	Upper quartile	Median	Lower quartile	Maximum	Percentage of positive (%)	Percentage of negative(%)
2000	Factor 1	-1.1780	0.2036	0.2632	0.3784	0.6722	96.99	3.01
	Factor 2	-0.1668	0.2572	0.4870	0.6427	1.7397	99.25	0.75
	Factor 3	-0.7624	-0.4116	-0.2173	-0.1280	0.3932	12.78	87.22
2015	Factor 2	0.4851	0.7645	0.7891	0.8640	1.2307	100.00	0.00
	Factor 3	-0.1688	0.1302	0.1696	0.2274	0.4398	93.98	6.02
	Factor 4	-0.5168	-0.3296	-0.2695	-0.1878	1.4713	15.79	84.21

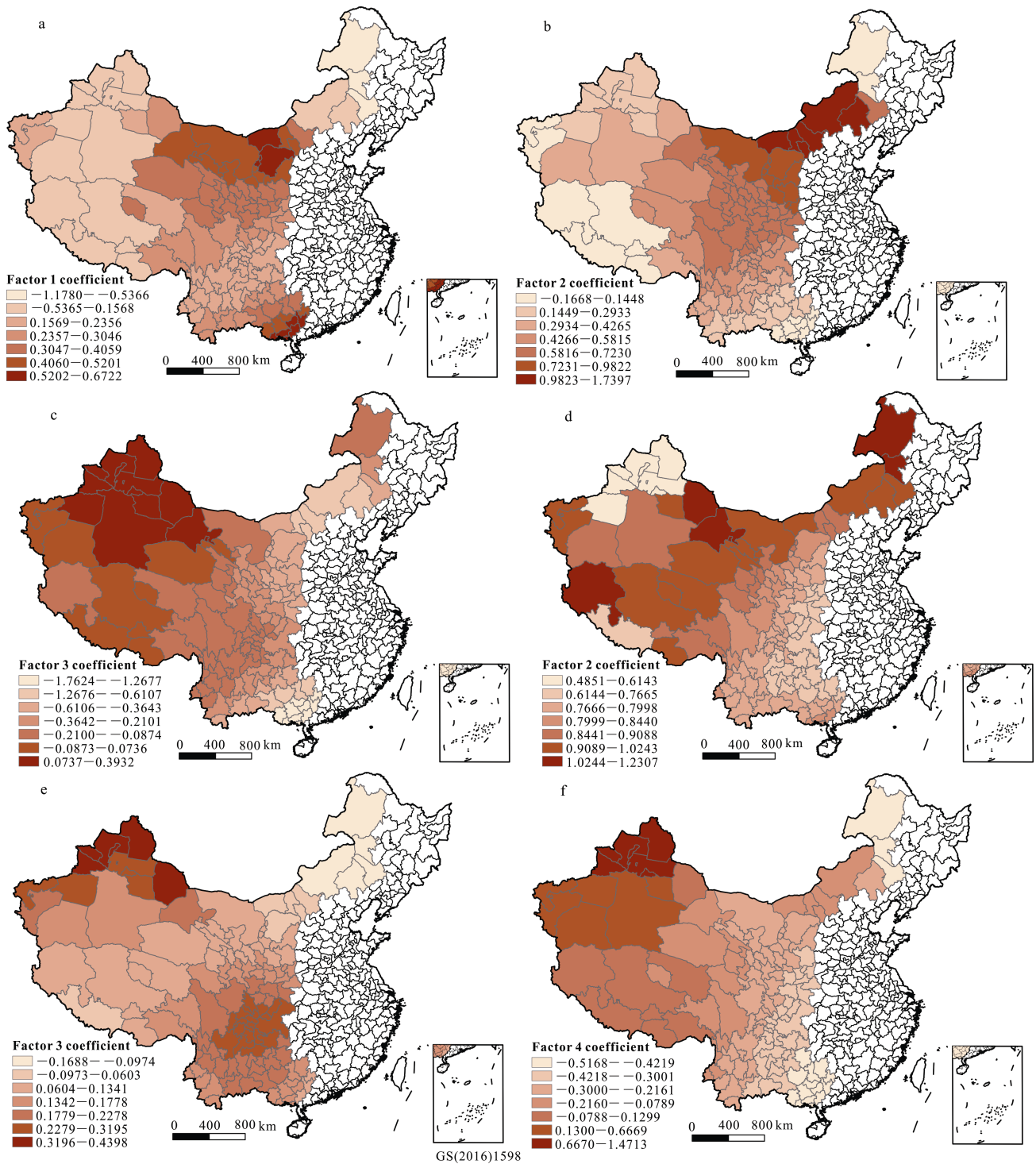


Fig. 5 Spatial distributions of the coefficients of GWR models in the western China in 2000 and 2015. a. Factor 1: economic development in 2000; b. Factor 2: investment intensity in 2000; c. Factor 3: natural environment in 2000; d. Factor 2: investment intensity in 2015; e. Factor 3: industrial structure in 2015; f. Factor 4: natural environment in 2015

Investment intensity. In 2000, the regression coefficient of the investment intensity factor showed a gradual decrease from northeast to southwest. Two positive high-value clusters were formed in central and eastern

Inner Mongolia and the north of Shaanxi, and a low-value cluster was formed in Tibet. Compared with 2000, the spatial distribution of the regression coefficient for the investment intensity factor changed greatly

in 2015. The regression coefficient of this factor showed a gradual increase from east to west. Multiple clusters with high regression coefficients appeared in the west. This result shows that the land development intensity in the western China is highly sensitive to investment intensity. The development of construction land driven by investment is weakening in the eastern China, while it is obviously enhancing in the western China.

Natural environment. In 2000 and 2015, the spatial distribution pattern of the regression coefficients for the natural environment factor tended to be similar and showed a gradual decrease from west to east. This result fully shows the impact and constraints of the natural and ecological environment on land development intensity in the western China. Compared with 2000, the regression coefficient of the natural environmental factor increased slightly in 2015, indicating that the constraint of the natural and ecological environment on land development intensity decreased to some extent. Meanwhile, the hierarchical characteristic of the regression coefficient distribution for the natural environmental factor was more obvious in 2015, indicating that the impacts of the local natural environment on land development intensity tended to be similar.

4 Discussion

Since the Grand Western Development Program in 2000, the western China has witnessed rapid socioeconomic development. From 2000 to 2015, the total GDP of the western China grew from 1 666 billion yuan to 14 502 billion yuan. Correspondingly, the proportion of the total GDP contributed by the western China increased from 17.13% to 20.10%. The Grand Western Development Program has improved inequality between China's coastal and inland areas. In the context of rapid social and economic development, the amount of construction land in the western China has grown rapidly. From 2000 to 2015, the area of construction land in the western China increased from 34 600 km² to 112 700 km². Correspondingly, the proportion of construction land in the western China in the total amount of construction land increased from 9.56% to 29.21%. In the past 15 years, the growth of construction land in China has mainly been concentrated in the western China.

According to the analysis of driving forces from OLS and GWR, although the economic factor is one of the

driving forces of land development intensity the way it works has changed. From 2000 to 2015, the driving factor of land development intensity in the western China changed from economic development to industrial structure. This change is consistent with the current transformation trend of China's economic development from being driven by economic growth to being driven by modification of the economic structure.

Investment intensity and the natural environment have always been the drivers of land development intensity in the western China in 2000 and 2015. Due to superior location conditions, China's coastal areas have attracted many foreign investments and achieved rapid development after the reform and opening. By contrast, the western China has been unable to attract much foreign investment. After the Grand Western Development Program, the western China gained huge policy advantages, and the central government began to invest a great deal of capital in here. In particular, a large amount of investment has been poured into transportation and other infrastructures, which has promoted the land development intensity in the western China. Since 2000, many major projects have been built, such as the Qinghai-Tibet railway, the West-East power transmission lines, and the West-East natural gas transmission line. Furthermore, the transportation infrastructure has developed rapidly. From 2000 to 2015, the length of railway in operation in the western China increased from 22 109 km to 48 005 km, the length of highway from 553 874 km to 1847 479 km, and the length of expressway from 3 677 km to 44 412 km. (National Bureau of Statistics of China, 2016) In conclusion, the growth of construction land in the western China is mainly driven by investment in national infrastructure.

Although the amount of construction land in the western China has grown rapidly, it is still greatly constrained by terrain and other natural conditions. The western China covers 6.87 million km², accounting for 71.5% of the country's total area. However, nearly half of the land in the western China is desert, Gobi, or mountainous areas. In fact, the area of construction land in the western China accounts for only 1.64% of the total western area. In addition, the ecological environment in the western China is very sensitive and the ecological function is very important. In 2015, the comprehensive vegetation coverage of grassland and forest coverage rates were 50.6% and 18.5%, respectively. In

the thirteenth Five-year Plan for China's western development and new spatial planning, ecological conservation and national ecological security are the main goals. It is foreseeable that the development of construction land in the western China will still be restricted to some extent.

China's Grand Western Development Program has been implemented for many years, and the growth of construction land and regional land development intensity in the western China has also undergone great changes. Existing relevant studies mainly focus on the overall land use change in the western China or typical areas (Zheng et al., 2004; He et al., 2006; Ma et al., 2012). However, research on the construction land change and land development intensity in the western China is still rare. This paper explores the spatial-temporal dynamics and driving forces of the land development intensity in the western China from 2000 to 2015. The research results reveal the spatial and temporal evolution rules of the land development intensity in the western China since the implementation of the Grand Western Development Program, which provides systematic research for understanding the change of the land development intensity in the western China.

Most scholars have realized that land development intensity is synthetically influenced by various factors. However, many studies still analyse the effect of each individual indicator (e.g. population density, GDP, fiscal revenue, urbanization level, *etc.*) on land development intensity (Huang et al., 2017a; Li et al., 2018). In this paper, the principal component analysis method is used to extract the comprehensive factors affecting land development intensity, which can better reflect the comprehensive driving force of land development intensity. Multiple linear regression is a commonly used method to explore the driving forces of land development intensity (Di et al., 2015; Wang et al., 2018). The multiple regression model can only identify the positive and negative effects of the influencing factors on the overall land development intensity. However, it cannot analyse the degree of the influencing factor on each research unit. In this paper, OLS and GWR models are used to not only identify the driving forces of land development intensity, but also explain the spatial differences of the driving forces to further reveal the differentiation mechanism of influencing factors in different spatial units.

China's Grand Western Development Program is an important regional policy, which plays a crucial role in promoting the development of the western China, reducing inequality between the eastern coastal and the western areas, and improving poverty in the western China. Meanwhile, the western China is an important ecological function area. The increase of land development intensity is bound to enhance the pressure on resources and ecological environment. Land development intensity has become a very important obligatory target in the National Land Planning (2016–2030). Controlling the land development intensity, strengthening the ecological civilization construction, and implementing land spatial planning are also significant contents of China's land management system in the future. This article has important practical significance and decision-making support for the governance of land development intensity, supply of construction land, optimization of land development patterns, and formulation of land management policies in the western China.

5 Conclusions

Since the implementation of the Grand Western Development Program, the land development intensity in the western China has been increasing rapidly. From 2000 to 2015, land development intensity increased by 3.4 times on average. The pattern of land development intensity has changed significantly. The hot spot areas have shifted from central Inner Mongolia, northern Shaanxi, and the Beibu Gulf of Guangxi to the two main urban agglomerations, the Guanzhong Plain and the Chengdu-Chongqing urban agglomeration. The areas of cold spots were mainly concentrated in the Qinghai-Tibet Plateau, Yunnan, and Xinjiang, which have not changed significantly.

The main driving factors of land development intensity in the western China include economic development, investment intensity, and natural environment in 2000, while the main driving factors are investment intensity, industrial structure, and natural environment in 2015. Investment intensity and the natural environment have always been the main driving factors affecting the land development intensity in the western China. Investment played a powerful role in promoting land development intensity in the western China, while the natural and ecological environment distinctly con-

strained land development intensity. Although economic factors are the driving factors of land development intensity in western China in 2000 and 2015, its critical factors have changed significantly, which is reflected in the driving factor of land development intensity shifting from economic growth in 2000 to economic structure, especially industrial structure, in 2015.

References

- Arowolo A O, Deng X Z, Olatunji O A et al., 2018. Assessing changes in the value of ecosystem services in response to land-use/land-cover dynamics in Nigeria. *Science of the Total Environment*, 636: 597-609. doi: 10.1016/j.scitotenv.2018.04.277
- Cegielska K, Noszczyk T, Kukulska A et al., 2018. Land use and land cover changes in post-socialist countries: Some observations from Hungary and Poland. *Land Use Policy*, 78: 1-8. doi: 10.1016/j.landusepol.2018.06.017
- Chen J L, Gao J L, Chen W, 2016. Urban land expansion and the transitional mechanisms in Nanjing, China. *Habitat International*, 53: 274-283. doi: 10.1016/j.habitatint.2015.11.040
- Dadashpoor H, Azizi P, Moghadasi M, 2019. Land use change, urbanization, and change in landscape pattern in a metropolitan area. *Science of the Total Environment*, 655: 707-719. doi: 10.1016/j.scitotenv.2018.11.267
- Dang L J, Xu Y, Tang Q, 2015. The pattern of available construction land along the Xijiang river in Guangxi, China. *Land Use Policy*, 42: 102-112. doi: 10.1016/j.landusepol.2014.07.010
- Di Xianghong, Hou Xiyong, Wang Yuandong et al., 2015. Spatial-temporal characteristics of land use intensity of coastal zone in China during 2000-2010. *Chinese Geographical Science*, 25(1): 51-61. doi: 10.1007/s11769-014-0707-0
- Dietrich J P, Schmitz C, Müller C et al., 2012. Measuring agricultural land-use intensity-a global analysis using a model-assisted approach. *Ecological Modelling*, 232: 109-118. doi: 10.1016/j.ecolmodel.2012.03.002
- Erb K, Niedertscheider M, Dietrich J P et al., 2014. Conceptual and empirical approaches to mapping and quantifying land-use intensity. In: Fischer-Kowalski M, Reenberg A, Schaffartzik A et al (eds). *Ester Boserup's Legacy on Sustainability*. Dordrecht: Springer, 61-86. doi: 10.1007/978-94-017-8678-2_5
- Erb K H, Haberl H, Jepsen M R et al., 2013. A conceptual framework for analysing and measuring land-use intensity. *Current Opinion in Environmental Sustainability*, 5(5): 464-470. doi: 10.1016/j.cosust.2013.07.010
- Fan Jie, Tao Anjun, Ren Qing, 2010. On the historical background, scientific intentions, goal orientation, and policy framework of major function-oriented zone planning in China. *Journal of Resources and Ecology*, 1(4): 289-299. doi: 10.3969/j.issn.1674-764x.2010.04.001
- Ferdous N, Bhat C R, 2013. A spatial panel ordered-response model with application to the analysis of urban land-use development intensity patterns. *Journal of Geographical Systems*, 15(1): 1-29. doi: 10.1007/s10109-012-0165-0
- Foley J A, DeFries R, Asner G P et al., 2005. Global consequences of land use. *Science*, 309(5734): 570-574. doi: 10.1126/science.1111772
- Galicia L, García-Romero A, 2007. Land use and land cover change in highland temperate forests in the Izta-Popo National Park, Central Mexico. *Mountain Research and Development*, 27(1): 48-57. doi: 10.1659/0276-4741(2007)27[48:LUALCC] 2.0.CO;2
- Gao J B, Li S C, 2011. Detecting spatially non-stationary and scale-dependent relationships between urban landscape fragmentation and related factors using geographically weighted regression. *Applied Geography*, 31(1): 292-302. doi: 10.1016/j.apgeog.2010.06.003
- Gao Jinlong, Bao Jingwei, Liu Yansui et al., 2018. Regional disparity and the influencing factors of land urbanization in China at the county level, 2000-2015. *Acta Geographica Sinica*, 73(12): 2329-2344. (in Chinese)
- Gong J Z, Chen W L, Liu Y S et al., 2014. The intensity change of urban development land: implications for the city master plan of Guangzhou, China. *Land Use Policy*, 40: 91-100. doi: 10.1016/j.landusepol.2013.05.001
- He Shujin, Wang Xiuhong, Deng Xiangzheng et al., 2006. Analysis on influencing factors of land use change in three typical areas of western China. *Geographical Research*, 25(1): 79-86. (in Chinese)
- Houghton R A, Nassikas A A, 2017. Global and regional fluxes of carbon from land use and land cover change 1850-2015. *Global Biogeochemical Cycles*, 31(3): 456-472. doi: 10.1002/2016GB005546
- Howison R A, Piersma T, Kentie R et al., 2018. Quantifying landscape-level land-use intensity patterns through radar-based remote sensing. *Journal of Applied Ecology*, 55(3): 1276-1287. doi: 10.1111/1365-2664.13077
- Huang Baorong, Zhang Huizhi, Song Dunjiang et al., 2017a. Driving forces of built-up land expansion in China from 2000 to 2010. *Acta Ecologica Sinica*, 37(12): 4149-4158. (in Chinese)
- Huang X J, Huang X, He Y B et al., 2017b. Assessment of livelihood vulnerability of land-lost farmers in urban fringes: a case study of Xi'an, China. *Habitat International*, 59(1): 1-9. doi: 10.1016/j.habitatint.2016.11.001
- Jiang M, Xin L J, Li X B et al., 2016. Spatiotemporal variation of China's state-owned construction land supply from 2003 to 2014. *Sustainability*, 8(11): 1137. doi: 10.3390/su8111137
- Kroll F, Haase D, 2010. Does demographic change affect land use patterns?: a case study from Germany. *Land Use Policy*, 27(3): 726-737. doi: 10.1016/j.landusepol.2009.10.001
- Li Jintao, Liu Yansui, Yang Yuanyuan et al., 2018. Spatial-temporal characteristics and driving factors of urban construction land in Beijing-Tianjin-Hebei region during 1985-2015. *Geographical Research*, 37(1): 37-52. (in Chinese)

- Liang X, Liu X P, Li X et al., 2018. Delineating multi-scenario urban growth boundaries with a CA-based FLUS model and morphological method. *Landscape and Urban Planning*, 177: 47–63. doi: 10.1016/j.landurbplan.2018.04.016
- Liiri M, Häsä M, Haimi J et al., 2012. History of land-use intensity can modify the relationship between functional complexity of the soil fauna and soil ecosystem services—a microcosm study. *Applied Soil Ecology*, 55: 53–61. doi: 10.1016/j.apsoil.2011.12.009
- Liu T, Liu H, Qi Y J, 2015a. Construction land expansion and cultivated land protection in urbanizing china: insights from national land surveys, 1996–2006. *Habitat International*, 46: 13–22. doi: 10.1016/j.habitatint.2014.10.019
- Liu Xuehua, Zhang Xueliang, Peng Mingming, 2009. Traffic infrastructure investment and regional economic growth—an empirical analysis on the case of west China development. *Areal Research and Development*, 28(4): 57–61. (in Chinese)
- Liu Yanjun, Yu Huisheng, Liu Degang et al., 2018. Spatial differentiation mechanisms of the pattern evolution of construction land development intensity in Northeast China. *Acta Geographica Sinica*, 73(5): 818–831. (in Chinese)
- Liu Y L, Luo T, Liu Z Q et al., 2015b. A comparative analysis of urban and rural construction land use change and driving forces: implications for urban–rural coordination development in Wuhan, Central China. *Habitat International*, 47: 113–125. doi: 10.1016/j.habitatint.2015.01.012
- Long H L, Tang G P, Li X B et al., 2007. Socio-economic driving forces of land-use change in Kunshan, the Yangtze River Delta Economic Area of China. *Journal of Environmental Management*, 83(3): 351–364. doi: 10.1016/j.jenvman.2006.04.003
- Lu Xiao, Huang Xianjin, Zhong Taiyang et al., 2012. Comparative analysis of influence factors on arable land use intensity at farm household level: a case study comparing Suyu district of Suqian city and Taixing city, Jiangsu Province, China. *Chinese Geographical Science*, 22(5): 556–567. doi: 10.1007/s11769-012-0563-8
- Ma Jian, Ji Changlong, Zhang Yike et al., 2012. Cluster analysis of land-use change of China's Western region. *China Population, Resources and Environment*, 22(5): 149–152. (in Chinese)
- Margrter S C, Bruland G L, Kudray G M et al., 2014. Using indicators of land-use development intensity to assess the condition of coastal wetlands in Hawaii. *Landscape Ecology*, 29(3): 517–528. doi: 10.1007/s10980-013-9985-7
- Mustafa A, van Rompaey A, Cools M et al., 2018. Addressing the determinants of built-up expansion and densification processes at the regional scale. *Urban Studies*, 55(15): 3279–3298. doi: 10.1177/0042098017749176
- National Bureau of Statistics of China, 2011; 2016. China Statistical Yearbook 2016. China Statistics Press.
- Ning Jia, Liu Jiyuan, Kuang Wenhui et al., 2018. Spatiotemporal patterns and characteristics of land-use change in China during 2010–2015. *Journal of Geographical Sciences*, 28(5): 547–562. doi: 10.1007/s11442-018-1490-0
- Oueslati W, Alvanides S, Garrod G, 2015. Determinants of urban sprawl in European cities. *Urban Studies*, 52(9): 1594–1614. doi: 10.1177/0042098015577773
- Persson A S, Olsson O, Rundlöf M et al., 2010. Land use intensity and landscape complexity—analysis of landscape characteristics in an agricultural region in Southern Sweden. *Agriculture, Ecosystems & Environment*, 136(1–2): 169–176. doi: 10.1016/j.agee.2009.12.018
- Quintas-Soriano C, Castro A J, Castro H. 2016. Impacts of land use change on ecosystem services and implications for human well-being in Spanish drylands. *Land Use Policy*, 54: 534–548. doi: 10.1016/j.landusepol.2016.03.011
- Seto K C, Fragkias M, Güneralp B et al., 2011. A meta-analysis of global urban land expansion. *PLoS One*, 6(8): e23777. doi: 10.1371/journal.pone.0023777
- Shen Chunzhu, Tan Qichuan, Wang Danyang et al., 2019. Research on land development intensity based on carrying capacity of resources and environment and suitability of development and construction: a case study of Jiangsu. *Resources and Environment in the Yangtze Basin*, 28(6): 1276–1286. (in Chinese)
- Su S L, Xiao R, Zhang Y, 2012. Multi-scale analysis of spatially varying relationships between agricultural landscape patterns and urbanization using geographically weighted regression. *Applied Geography*, 32(2): 360–375. doi: 10.1016/j.apgeog.2011.06.005
- Tan Xuejing, Jiang Guanghui, Fu Jing et al., 2011. Analysis on land development intensity under the framework of Major Functional Land Zoning: taking Beijing as an example. *China Land Science*, 25(1): 70–77. (in Chinese)
- Teixeira Z, Teixeira H, Marques J C, 2014. Systematic processes of land use/land cover change to identify relevant driving forces: Implications on water quality. *Science of the Total Environment*, 470–471: 1320–1335. doi: 10.1016/j.scitotenv.2013.10.098
- van der Sluis T, Pedroli B, Kristensen S B P et al., 2016. Changing land use intensity in Europe—recent processes in selected case studies. *Land Use Policy*, 57: 777–785. doi: 10.1016/j.landusepol.2014.12.005
- Wang F H, 2015. *Quantitative Methods and Socio-Economic Applications in GIS*. 2nd ed. Boca Raton, FL: CRC Press, 176–180.
- Wang X F, Xiao F Y, Zhang Y et al., 2018. Thirty-year expansion of construction land in Xi'an: spatial pattern and potential driving factors. *Geological Journal*, 53(S1): 309–321. doi: 10.1002/gj.2987
- Wellmann T, Haase D, Knapp S et al., 2018. Urban land use intensity assessment: the potential of spatio-temporal spectral traits with remote sensing. *Ecological Indicators*, 85: 190–203. doi: 10.1016/j.ecolind.2017.10.029
- Xie Jinyuan, Jin Xiaobin, Lin Yinan et al., 2017. Quantitative estimation and spatial reconstruction of urban and rural construction land in Jiangsu Province, 1820–1985. *Journal of Geographical Sciences*, 27(10): 1185–1208. doi: 10.1007/s11442-017-1430-4
- Xu Y, Tang Q, Fan J et al., 2011. Assessing construction land potential and its spatial pattern in China. *Landscape and Ur-*

- ban Planning*, 103(2): 207–216. doi: 10.1016/j.landurbplan.2011.07.013
- Yan Huimin, Liu Fang, Liu Jiyan et al., 2017. Status of land use intensity in china and its impacts on land carrying capacity. *Journal of Geographical Sciences*, 27(4): 387–402. doi: 10.1007/s11442-017-1383-7
- Yang J, Guo A D, Li Y H et al., 2019. Simulation of landscape spatial layout evolution in rural-urban fringe areas: a case study of Ganjingzi District. *GIScience & Remote Sensing*, 56(3): 388–405. doi: 10.1080/15481603.2018.1533680
- Ye Y Y, Li S F, Zhang H O et al., 2018. Spatial-temporal dynamics of the economic efficiency of construction land in the pearl river delta megalopolis from 1998 to 2012. *Sustainability*, 10(1): 63. doi: 10.3390/su10010063
- Yin G Y, Lin Z L, Jiang X L et al., 2019. Spatiotemporal differentiations of arable land use intensity-a comparative study of two typical grain producing regions in northern and southern China. *Journal of Cleaner Production*, 208: 1159–1170. doi: 10.1016/j.jclepro.2018.10.143
- Zachary D S, 2013. Land cover change using an energy transition paradigm in a statistical mechanics approach. *Physica A: Statistical Mechanics and Its Applications*, 392(20): 5065–5073. doi: 10.1016/j.physa.2013.04.016
- Zheng Binghui, Tian Ziqiang, Wang Wenjie et al., 2004. Analysis of recent land usage and survey in Western China. *Acta Ecologica Sinica*, 24(5): 1078–1085. (in Chinese)
- Zia A, 2012. Land use adaptation to climate change: economic damages from land-falling hurricanes in the Atlantic and Gulf States of the USA, 1900–2005. *Sustainability*, 4(5): 917–932. doi: 10.3390/su4050917