STUDY ON THE SPATIAL PATTERNS, EVOLUTION CHARACTERISTICS AND DRIVING MECHANISM OF GREEN SPACES IN A TYPICAL RESOURCE-EXHAUSTED CITY IN CHINA

LI, H. D.[1] – XU, X. J.[1] – SHEN, H. Q.[1] – LI, Z. G.[1] – ZHAI, F. F.[1] – LI, C.[2] – ZHANG, Y. X.[1*]

[1]School of Architecture and Artistic Design, Henan Polytechnic University,
Jiaozuo 454000, China
(phone: +86-157-3856-8196, +86-137-8849-6122, +86-176-5599-7179, +86-196-0391-5643, +86-150-9372-8689)

[2]He Nan Xiao Shang Construct Co. LTD., Jiaozuo, Henan 454003, China
(phone: +86-136-7391-1195)

**Corresponding author*
e-mail: yxzh17@hpu.edu.cn; phone: +86-159-9379-0101

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Abstract. Urban transformation is an inevitable choice for resource-exhausted cities to achieve sustainable development in the world today. Green space is one of the basic elements of cities and plays an irreplaceable role in promoting sustainable urban development. Taking Jiaozuo City, a typical resource-exhausted city in China, as the research object, this study analyzed the spatial-temporal evolution and driving mechanism of green space in Jiaozuo by using land use transfer matrix, landscape pattern index, and Partial Least Squares Regression (PLSR) model. The research found that: First, from 2000 to 2020, the green space area in Jiaozuo decreased by 220.21 km^2. Second, from 2000 to 2020, the ecological level of each landscape type in Jiaozuo showed a downward trend, and the patch connectivity decreased. Third, the PLSR model analysis showed that the urbanization rate, per capita GDP, urban disposable income per capita and population density were important driving forces for the evolution of green space in Jiaozuo (the VIP values were greater than 1). The findings of this study can provide scientific reference and theoretical support for formulating reasonable and scientific policies on green space development and protection in Jiaozuo and other resource-exhausted cities in the world.
Keywords: *Jiaozuo, spatial and temporal evolution, transfer matrix, PLSR model, land use*

Introduction

Urbanization is an inevitable process for social development. Since its reform and opening-up, China has experienced rapid urbanization (Xu et al., 2019; Sui et al., 2022). With the accelerated urbanization process, land for construction has been expanding, and more green space has been occupied. The urbanization process often uses land as a spatial carrier, and drastic land use changes can lead to a series of problems, such as atmospheric pollution, urban heat islands, local habitat quality degradation and deterioration of the quality of the human living environment, thus putting enormous pressure on environmental protection (Deng et al., 2022; Ma et al., 2022; Aneseyee et al., 2020). At present, there is no clear definition of urban green space in academic circles. First, green space in a narrow sense is more often used in urban planning systems, referring to green space located within construction land for citizens' leisure and recreation or production protection, which is the term used in urban planning or special planning for green space systems (Tao et al., 2013). The second is green space in the broad sense, which can be understood as green space, i.e., ecological space that permeates both inside and outside urban construction sites and plays an important role in the urban and regional ecological

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environment (Du and Chen, 2022). The broad concept, according to relevant scholars, is more in line with the needs of contemporary Chinese territorial spatial planning and urban-rural synergistic development (Yang et al., 2015). This paper draws on the definition of green space as defined by relevant scholars, so green space includes arable land, woodland, grassland and water (Weng et al., 2021; Cai et al., 2019; Liu et al., 2022; Sathyakumar et al., 2020). It not only improves the living environment and enriches the spiritual and cultural life of residents but also ensures the sustainable development of the environment (Salman et al., 2022; Bussi et al., 2016; Kabisch et al., 2013).

In recent years, many scholars have conducted studies on green space. For example, some scholars have analyzed the dynamic change process of the size, quantity and spatial distribution of urban green space patches in different periods based on land use changes (Najihah et al., 2021). Some experts have carried out a great deal of research on the functions of urban green space, such as its prominent role in improving urban microclimate (Milena et al., 2021), absorbing pollutants (Bagheri et al., 2017), and maintaining biodiversity (Bastiaensen et al., 2023). Some researchers have analyzed urban green space mainly from the perspective of spatial layout planning and design, using a variety of quantitative and qualitative research methods and tools, the equity of green space (Cheng et al., 2021), accessibility (Vuokko et al., 2023), and for the added value of social health (Huang and Lin, 2023), in-depth revelation of the role of urban green space in the modern society in the depth of the expansion. The current research on green spaces mainly focuses on its changes and functions, and the method of driving the spatial and temporal evolution of green space is mainly qualitative or quantitative research based on simple regression. In this type of research, traditional linear regression is not applicable to the amount of data with less sample capacity (Han et al., 2017), and ordinary principal component analysis will directly exclude multiple covariates affecting the accuracy of the results. Therefore, this study used partial least squares regression (PLSR) model to analyze the natural and socio-economic factors affecting the green space in Jiaozuo City, and selected the green space in Jiaozuo City from 2000-2020, when the city's urbanization was developing rapidly, as the research object, and combined ArcGis10.5 and Frsgstat4.2.1 software to analyze the evolution characteristics of green space area, conversion position and landscape pattern index in Jiaozuo City. It provides theoretical basis and scientific reference for Jiaozuo City to formulate a reasonable green space development plan, build a national garden city, and promote the high-quality transformation of resource-exhausted cities.

Jiaozuo was in the first batch of resource-exhausted cities in China. With the rapid socioeconomic development and urbanization processes that have occurred since the transformation of Jiaozuo city at the end of the last century, the way and structure of land use have continuously reshaped the city, and this has profoundly affected the green spatial pattern of Jiaozuo city. At present, studies on the green space of Jiaozuo have focused mainly on the ecological impact of mine rehabilitation (Lu et al., 2018), and the overall change in its green space is still unclear. Monitoring and evaluating the changes in green space is a necessary prerequisite for rational development and effective protection, which is of great practical significance for optimizing the spatial layout of national land, promoting the green development of cities and promoting a sustainable ecological environment (Tang et al., 2020). This study focuses on the green spaces in Jiaozuo City, employing PCA to examine the correlation between the spatiotemporal evolution of these green spaces and natural and social factors, thereby exploring the driving factors' impact on the green spaces.

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Materials and methods

Study area

This study was conducted in Jiaozuo city (34°49′N-35°29′N, 112°43′E-113° 38′E), in northwest Henan Province, China. It is located north of the Taihang Mountains, south of the Yellow River and has a total area of approximately 4071 km^2. The total population of Jiaozuo City in 2000, 2005, 2010, 2015, and 2020 were 3.3067 million, 3.5203 million, 3.498 million, 3.7063 million, and 3.7789 million, respectively. Due to the rapid economic development during the transformation period in Jiaozuo City, the total population also showed an upward trend during the research period. Jiaozuo has a temperate monsoon climate with an average annual temperature of 15.8°C, a total annual precipitation of 562.7 mm and a rich supply of mineral and forestry resources, such as 2.42 billion tons of coal reserve, 59.79 million tons of sulfur iron ore and 1.08 billion tons of limestone in Jiaozuo in 2019, and 5.92 million m^3 of forest wood reserves (Cai et al., 2019). Jiaozuo has jurisdiction over 6 counties (cities) and 4 districts (including urban and rural integration demonstration areas) (*Fig. 1*). As one of the five major coal bases, Jiaozuo has made great contributions to the national and local economic construction of China. However, the excessive exploitation of coal has had a great impact on the local ecological environment. In 2008, Jiaozuo was listed among the first group of resource-exhausted cities in China. In the late 1990s, Jiaozuo began to adjust its economic structure and introduced a series of environmental improvement measures to transform it into an eco-friendly tourist city. Its transformation process is the epitome of the development of many resource-exhausted cities.

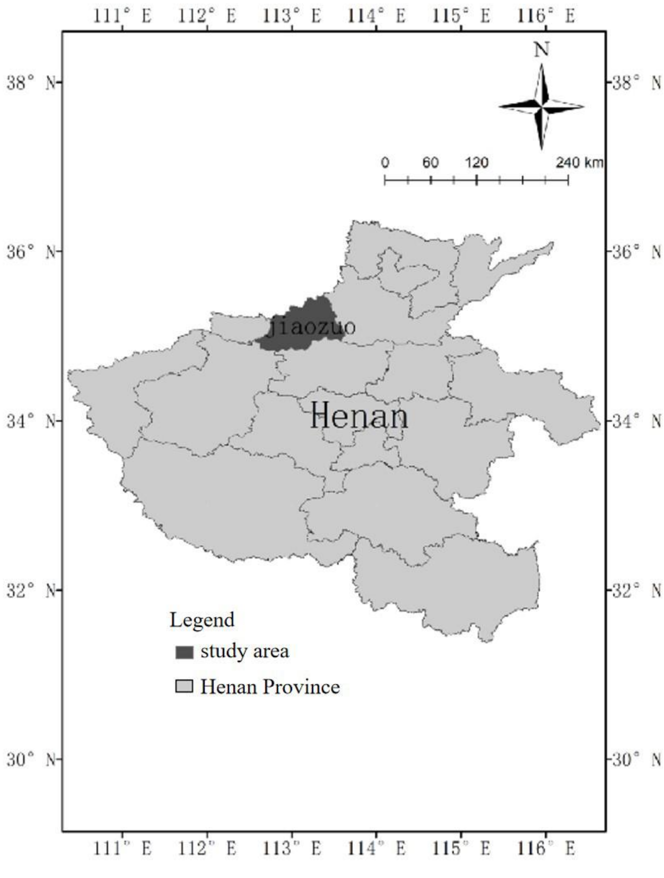

Figure 1. *Location of the study area*

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Data sources

Remote sensing data and basic geographic information data were used in this study. The former mainly included remote sensing image geospatial data clouds of 2000, 2005, 2010, 2015 and 2020 (https://www.gscloud.cn) with a resolution of 30 m × 30 m, The remote sensing images from 2000 and 2005 were obtained from Landsat 5 satellite, while the images from 2010, 2015, and 2020 were obtained from Landsat 7 satellite. In this study, the maximum likelihood supervised classification method was used to classify 5 phases of remote sensing image data, and then the classification results were visually interpreted and modified to improve accuracy. Finally, the accuracy of the classified results was verified, the accuracy of the 5 phases was greater than 88%, and the kappa coefficients were all greater than 0.85, which met the accuracy requirements needed for this study. The latter were mainly administrative vector data from the Chinese Academy of Sciences’ Data Center for Resources and Environmental Sciences (http://www. resdc.cn). The map of China was obtained from the Map Standard Service (http://bzdt.ch.mnr.gov.cn/), review number GS(2022)4316. Jiaozuo city is located at the junction of the Taihang Mountains and the northern Henan Plain. The terrain of Jiaozuo city changes from the northern mountains to the southern plain in a stepped manner, and landforms include mountains, hilly areas, plains and other landforms. On the basis of referring to the national standard for land use status classification (GB/T 21010-2017) and combining this information with the actual land use situation in Jiaozuo city, ENVI5.3 supervision classification (maximum likelihood method) and visual interpretation were adopted. The land use types in the study area were divided into woodland, grassland, cultivated land, water area, construction land and unused land.

This study mainly discussed the driving factors of green space evolution in Jiaozuo city from the perspective of the social economy and nature. Jiaozuo City has successfully transformed from a coal-exhausted city to a tourist city, in order to explore the impacts of energy consumption, population, economic and natural factors, etc. on the green space during its transformation process, and in conjunction with the fact that the selection of the driving factors should follow the three principles of representativeness of the factors, availability of data, and independence of the factors from each other, the socioeconomic data (including tourism industry income, energy consumption per 10,000 Yuan GDP, urbanization rate, GDP per capita, coal mining and washing industry, GDP growth rate, industrial sulfur dioxide emissions urban per capita disposable income, rural per capita disposable income, population density, and industrial soot emissions) and natural factor data (total annual precipitation, average annual temperature, and coal) were used and came from the 2001 statistical yearbook of Jiaozuo city, the 2006 statistical yearbook of Jiaozuo city, the 2011 statistical yearbook of Jiaozuo city, the 2016 statistical yearbook of Jiaozuo city and the 2020 statistical yearbook of Jiaozuo city (due to the lack of data in the 2021 statistical yearbook of Jiaozuo city, the 2020 statistical yearbook was used instead).

Research methods

Land use transfer matrix

In this study, land use cover types were obtained through remote sensing images, and land use classification data in 2000, 2005, 2010, 2015 and 2020 were obtained using ENVI5.3 and ArcGis10.5. The green space changes were mainly analyzed through a

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transfer matrix (Shi et al., 2018), which is a powerful tool currently used to quantitatively describe the characteristics, direction and structure of land use/cover. The transfer matrix can reflect not only the structure of land use types at the beginning and end of the study period but also the origin and composition of each land type during the study period (Wu et al., 2022b). Therefore, in this study, the conversion of green space areas in Jiaozuo in 2000, 2005, 2010, 2015 and 2020 was calculated with the help of ArcGIS, and a utilization transfer matrix from 2000 to 2020 was obtained. Finally, the direction and amount of green space transfer in each period were analyzed.

Landscape pattern indexes

The landscape pattern index is a quantitative indicator that reflects the structural composition of a landscape and certain aspects of the spatial configuration of the land and can reflect the intensity and trend of changes in landscape types over a certain period of time (Zhou et al., 2021; Wang et al., 2022a). In this study, based on the landscape indices and their structural and spatial characteristics reflecting different patterns at different levels, the patch density (PD), Largest patch index (LPI), landscape shape index (LSI), aggregation index (AI), sprawl index (CONTAG), Shannon diversity index (SHDI) and Shannon evenness index (SHEI) were selected at the landscape level (*Table 1*). ENVI5.3 and ArcGis10.5 were used to derive the raster data of land use types for five periods, and with the help of Fragstats4.2.1 software, the landscape pattern indices were calculated for different periods as a means to analyze the structure and change characteristics of the landscape pattern in Jiaozuo (Fu and Sieng, 2022).

Table 1. *The meaning and calculation of the selected landscape pattern index*

Name	Description	Significance
Patch density (PD)	PD = N/A (Eq.1) The number of patches per square kilometer (i.e. 100 ha), taking the value of PD＞0, no upper limit	PD represents the density of a certain patch in the landscape, which can reflect the overall heterogeneity and fragmentation of the landscape and the degree of fragmentation of a certain type, reflecting the heterogeneity of the landscape per unit area
Largest patch Index (LPI)	$LPI = \frac{max（a_1...,...,...a_n）}{A} 100$ (Eq.2) The total landscape area is divided into the area of the largest patch in the landscape, and then converted into a percentage, the value range is 0< LPI ≤ 100	Help to determine the pattern or dominant type of landscape. Its value determines the ecological characteristics such as the abundance of dominant species and internal species in the landscape: the change of its value can change the intensity and frequency of disturbance, reflecting the direction and strength of human activities
Largest shape index (LSI)	$LSI = \frac{0.25E}{\sqrt{A}}$ (Eq.3) The total length of boundaries for all patches in the landscape is denoted as E, while A represents the total area of the landscape. LSI ≥ 1	LSl is the total landscape boundary and all edge within the boundary divided by the square root of the total landscape area (m^2) and adjusted by a constant (circular standard for vector layers, square standard for rasters). The LSl will increase with increasing landscape shape irregularity or increasing amounts of edge within the landscape

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Aggregation index (AI)	$AI = \left[\frac{g_{ii}}{max \to g_{ii}} \right] (100)$ (Eq.4) g_{ii} represents the number of similar adjacent patches for a corresponding landscape type	The AI examined the connectivity between patches of each landscape type. The smaller the value, the more discrete the landscape
CONTAG	$CONTAG = \left[1 + \frac{\sum_{i=1}^{m}\sum_{k=1}^{m}[(P_i)]\left\{\frac{g_{ik}}{\sum_{i=1}^{m} g_{ik}}\right\}}{2In(m)} \left[In(P_i)\left\{\frac{g_{ik}}{\sum_{k=1}^{m} g_{ik}}\right\}\right] \right] (100)$ (Eq.5)	CONTAG describe the degree of aggregation or the trend of extension of different patch types in a landscape. Because it contains spatial information, it is one of the most important indexes to describe landscape pattern. The high spread value indicates that some dominant patch types form good connectivity in the landscape. On the contrary, it indicates that the landscape is a dense pattern with multiple elements, and the fragmentation degree of the landscape is high
Shannon diversity index (SHDI)	$SHDI = -\sum_{i=1}^{m} \left[P_i In(P_i) \right]$ (Eq.6)	SHDI can reflect landscape heterogeneity, and is especially sensitive to the unbalanced distribution of different landscape block types. SHDI is also a sensitive index when comparing and analyzing the diversity and heterogeneity of different landscapes or the same landscape in different periods
Shannon evenness index (SHEI)	$SHEI = \frac{-\sum_{i=1}^{m} (P_i \times InP_i)}{In\, m}$ (Eq.7) m refers to the total number of patch types in the landscape, while P_i represents the proportion of patch type i to the entire landscape area	The SHEl, like the SHDI, is also a powerful means of comparing changes in the diversity of different landscapes or the same landscape over time. SHEl and Dominance index can be transformed into each other (evenness = 1-dominance), that is, the dominance is generally higher when the SHEI value is small, reflecting that a landscape is dominated by one or a few dominant block types. When SHEl approaches 1, the dominance degree is low, indicating that there is no obvious dominant type in the landscape and all block types are evenly distributed in the landscape

Partial least squares regression (PLSR) model

The PLSR model was used to analyze the relationship between the green space area and natural and socioeconomic factors in different years and to identify key predictors of green space change (Majid and Ali, 2022). PLSR analysis was conducted in SIMCA 14.1 software, with Q^2 (the fraction of one component predicting the total variation in the dependent variable) representing the cross-validation of the components, and the model is expected to have good predictive power when Q^2 was greater than 0.5 (Samadi et al., 2022). To avoid overfitting problems, the PLSR model was optimized by iteratively removing nonsignificant variables to minimize the difference between the explained variance (R^2) and the predictive power of the model (Q^2) in the response

(Sahbeni, 2021). The contribution of each explanatory variable to the model fit was determined by the variable importance in projection (VIP). It is generally accepted that explanatory variables with a VIP value greater than one are significant for the response variable (Ward et al., 2020). The regression coefficient (RC) was used to indicate the direction and strength of the influence of each explanatory variable on the response variable in the PLSR model (Wang et al., 2021). The formulae are as follows (Li et al., 2019):

First the data were standardized before regression analysis to obtain the matrices of the dependent and independent variables, noted as $S_0 = Y$ and $F_0 = X$. After that the extraction of the firstly principal component was carried out. Subsequently the equation for the firstly principal component t_1 and the matrices F_0 and S_0 for the 1st principal component t_1 were calculated.

$$F_0 = t_1 n_1^T + F_1 \quad \text{(Eq.8)}$$

$$S_0 = t_1 r_1 + S_1 \quad \text{(Eq.9)}$$

$$r_1 = \frac{S_0^T t_1}{\|t_1\|^2} \quad \text{(Eq.10)}$$

$$n_1 = \frac{F_0^T t_1}{\|t_1\|^2} \quad \text{(Eq.11)}$$

where: r_1 and n_1 are vectors; S_1 and F_1 are residual matrices of partial least squares regression. The 1, 2 3,4...n principal components t_2, t_3, t_4...t_n are computed and extracted as above.

In this study, the area of each type of green space from 2000 to 2020 was used as the dependent variable, and twelve factors, namely, tourism industry income, energy consumption of 10,000 yuan GDP, urbanization rate, per capita GDP, coal mining and washing industry, GDP growth rate, industrial sulfur dioxide emissions urban per capita disposable income, rural per capita disposable income, population density, industrial soot emissions, total annual precipitation, average annual temperature and coal reserves, were used as independent variables to construct the PLSR model to analyze the driving forces of green space in Jiaozuo city.

Results and discussion

Analysis of green space changes in Jiaozuo in different periods

Analysis of land use changes in Jiaozuo

As shown in *Figure 2*, the land cover types in Jiaozuo generally showed a pattern of mainly arable land and forestland supplemented by grassland and water areas. Forestland and grassland in Jiaozuo were mainly distributed in the north, arable land

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and construction land were mainly distributed in the middle, and water areas and unused land were mainly concentrated in the south. In terms of spatial distribution (*Fig. 3*), land use changes were mainly concentrated in the urban areas of the counties and their surrounding areas, mainly reflecting the mutual transformation of arable land and construction land. From 2000-2020, the land use change was mainly from 279.91 km^2 of cropland to construction land and from 82.42 km^2 of construction land to cropland (*Schedule 1* in the *Appendix*). In general, the land use change in Jiaozuo city during the study period was mainly characterized by the interconversion of arable land and construction land, while the rest of the land use types did not change much.

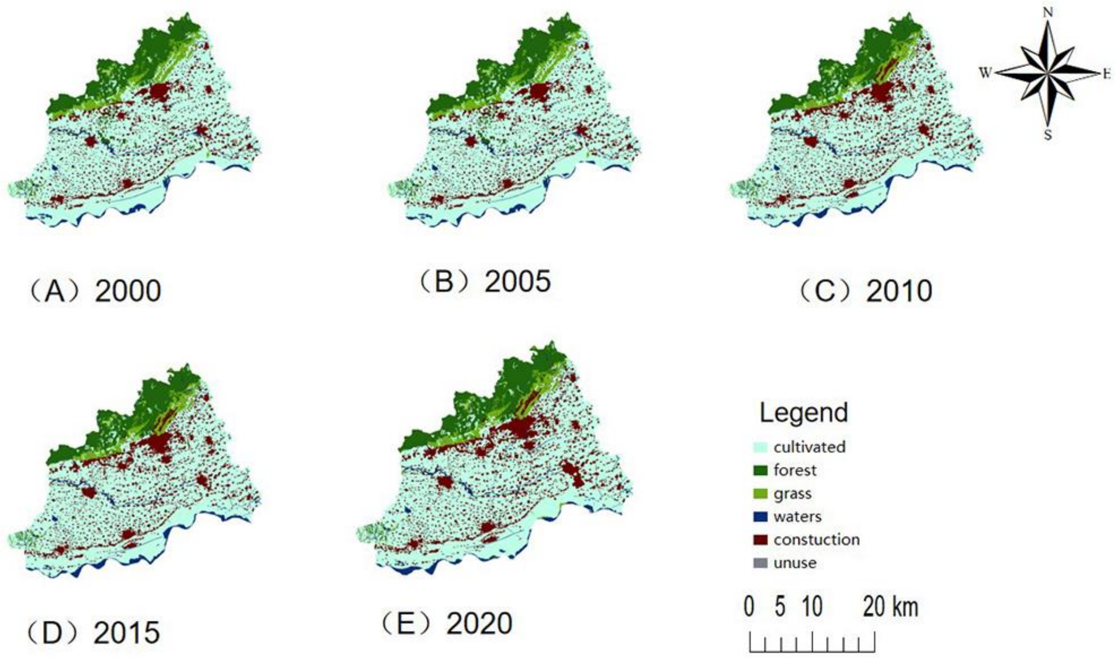

Figure 2. *Land use distribution and changes in the Jiaozuo region*

Analysis of temporal and spatial changes of green space

From 2000 to 2020, the total area of green space and the area of a single type in Jiaozuo both showed a decreasing trend (*Table 2*). The total area of green space in Jiaozuo city, China, in 2000, 2005, 2010, 2015 and 2020 was 3538.2, 3510.82, 3385.26, 3365.75 and 3317.99 $km^{2,}$ respectively. The area of green space in Jiaozuo decreased by 220.21 km^2, while the area of nongreen space increased by 41.27% during the study period. During the study period, arable land decreased by only 6.51%, although it decreased by 176.16 km^2; and forestland and grassland decreased by 8.96% and 10.96%, respectively; water surface showed a trend of increase followed by decrease but increased by 25.52 km^2 during the study period (*Table 2*).

However, the change in green space in Jiaozuo city varied within different periods. From 2005 to 2010, which was the period with the most intense change in green space, the green space decreased by 125.56 km^2 (*Table 2*), the green space transferred to nongreen space was 232.68 km^2 and the nongreen space transferred to green space was 107.51 km^2 (*Schedule 2* in the *Appendix*). The main change was that the change in green space was most intense, the type of land use with the greatest conversion from green space to nongreen space was the conversion of arable land to construction land, with an

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area of 213.05 km^2, while the type of land use with the most conversion from nongreen space to green space was the conversion of construction land to arable land, with an area of 103.52 km^2. For the rest of the period, the change in green space in Jiaozuo was relatively smooth. During the period 2000-2020, the conversion of green space to nongreen space in Jiaozuo city was 302.37 km^2, and the conversion of nongreen space to green space was 88.04 km^2 (*Schedule 2*).

Table 2. *Land use distribution and changes in Jiaozuo region/km^2*

Type \ Year	Green space				Non green space	
	Cultivated	**Forest**	**Grass**	**Water**	**Construction**	**Unuse**
2000	2704.54	533.76	198.26	101.64	516.37	3.07
2005	2660.77	535.10	198.25	116.70	544.54	2.71
2010	2587.00	491.38	173.45	133.43	669.15	3.28
2015	2561.16	492.38	172.57	139.64	688.67	3.27
2020	2528.38	485.92	176.53	127.16	729.14	4.65

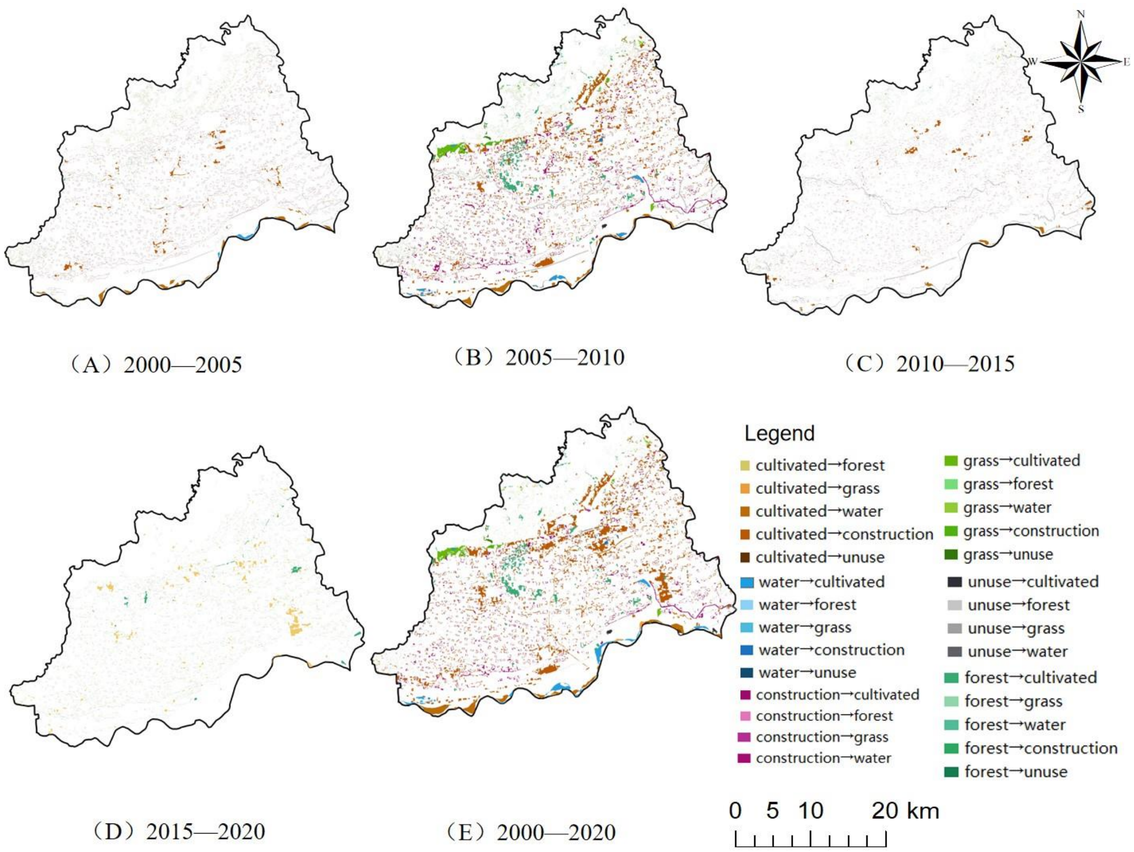

Figure 3. *Spatial changes in major land-use types during 2000–2020*

Analysis of changes in the landscape pattern indexes

As shown in *Table 3,* the patch density (PD) increased from 0.4293 per 100 hm^2 in 2000 to 0.5000 per 100 hm^2 in 2020, indicating an increasing trend in the fragmentation

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of landscape types in the city during the study period. The landscape shape index (LSI) for Jiaozuo increased from 27.0527 in 2000 to 32.0992 in 2020, indicating the gradual fragmentation and increasing dispersion of each landscape type. The spread (CONTAG) continued to decrease from 67.3370% in 2000 to 64.9616% in 2020, and the aggregation index (AI) decreased from 97.6264% in 2000 to 97.1515% in 2020, both decreasing each year over the study period, indicating an increase in landscape fragmentation in Jiaozuo, with an intermittent distribution of the landscape types and gradual differentiation. The growth rates of the Shannon evenness index (SHEI) and Shannon diversity index (SHDI) were 6.28% and 6.29%, respectively, during the study period, indicating that the landscape diversity of Jiaozuo has been increasing. The patch types tended to be evenly distributed over the past 20 years, and the dominant landscape type gradually decreased its dominance in the overall landscape, making the area share of each landscape type more even. The differences between landscape types have been reduced. In general, the fragmentation of the overall landscape in Jiaozuo increased, the average patch size of each landscape type decreased, and the fragmentation of several small patches led to a reduction in landscape connectivity, indicating that the expansion of land for construction led to the fragmentation of each landscape type and the irregularity of the patches.

Table 3. *Landscape index at the landscape level in Jiaozuo*

Year	PD/100 hm^2	LSI	CONTAG/%	SHDI	SHEI	AI/%
2000	0.4293	27.0527	67.3370	1.0445	0.583	97.6264
2005	0.4360	27.9434	66.5752	1.0680	0.596	97.5426
2010	0.4591	29.9708	65.7266	1.0922	0.6096	97.3522
2015	0.4678	30.1164	65.3909	1.1034	0.6158	97.3387
2020	0.5000	32.0992	64.9616	1.1102	0.6196	97.1515

Analysis of the driving factors of green space evolution in Jiaozuo city

Analysis of the driving role of socioeconomic factors in the evolution of green space area

In this study, nine socioeconomic indicators and two natural indicators related to the development of resource-depleted cities were selected as independent variables and each green space type was selected as the dependent variable, and the main components driving the evolution of green space types were extracted based on the results of the partial least squares regression analysis model. With $Q^2 > 0.097$ and $R^2Y > 0.5$ as the termination conditions for the extraction of the model principal components, the areas of arable land, forestland, grassland and water all met the termination conditions of the model in the first principal component. The analysis of the model results for cropland, forestland, grassland and water with each influencing factor showed that the R^2Y values were 0.9545, 0.8478, 0.7582 and 0.6685, respectively, all of which were greater than 0.5; the values of Q^2 were 0.9048, 0.7784, 0.6134 and 0.3500, respectively, all of which were greater than 0.097 (*Table 4*). Thus, these results indicate that the regression model had good robustness and predictive ability.

The results of the partial least squares regression analysis of arable land and the influencing factors (*Table 5*) showed that the important factors (VIP values greater than 1) affecting the evolution of the area of arable land patch types were the tourism industry income, energy consumption per 10,000 yuan of GDP, urbanization rate, per

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capita GDP, urban disposable income per capita, rural disposable income per capita, population density and industrial fume emissions; the industrial sulfur dioxide emissions played a role in the evolution of the area index of arable land patches (0.5 < VIP < 1). The regression coefficients (RC) of the variables showed that the factors that were positively correlated with the area of cultivated land included the energy consumption per 10,000 yuan of GDP and the industrial fume emissions; the factors that were negatively correlated with the area of cultivated land included the tourism industry income, the urbanization rate, per capita GDP, urban disposable income per capita, urban disposable income per capita, rural disposable income per capita and industrial sulfur dioxide emissions.

Table 4. *PLSR model results between green space area and socioeconomic indices*

PLSR	Cultivated	Forest	Grass	Water
Major component	1	1	1	1
Model interpretability (R^2Y)	0.9545	0.8478	0.7582	0.6685
Cross validity (Q^2)	0.9048	0.7784	0.6134	0.3500

Table 5. *Variable importance of projection (VIP) and regression coefficients (RC) of the PLSR model of green space area*

Socioeconomic	Cultivated		Forest		Grass		Water	
	VIP	RC	VIP	RC	VIP	RC	VIP	RC
Tourism industry income	1.0971	-0.1028	1.0534	-0.0936	0.9917	-0.0841	0.9290	0.0756
Energy consumption per 10,000 yuan of GDP (tons of coal per 10,000 yuan)	1.0511	0.0985	1.0529	0.0935	1.0326	0.0876	0.9445	-0.0768
Urbanization rate	1.1602	-0.1088	1.1243	-0.0999	1.1159	-0.0947	1.1548	0.0939
Per capita GDP	1.1389	-0.1068	1.1086	-0.0985	1.0711	-0.0909	1.0441	0.0849
Industrial sulfur dioxide emissions	0.7323	0.0686	0.8313	0.0738	0.7545	0.0640	0.4404	-0.0326
Urban disposable income per capita	1.1319	-0.1061	1.1026	-0.0979	1.0672	-0.0905	1.0356	0.0842
Rural disposable income per capita	1.0977	-0.1029	1.0675	-0.0948	1.0672	-0.0863	0.9485	0.0771
Population density	1.1771	-0.1103	1.2080	-0.1073	1.2400	-0.1052	1.2748	0.1037
Industrial fume emissions	1.1026	0.1033	1.1572	0.1028	1.1187	0.0949	0.9636	-0.0784

The results of the partial least squares regression analysis of forestland and each of the influencing factors (*Table 5*) showed that the variables that influenced forestland area included the tourism industry income, energy consumption per 10,000 yuan of GDP, urbanization rate, per capita GDP, urban disposable income per capita, rural disposable income per capita, population density and industrial fume emissions; industrial sulfur dioxide emissions played a role in the evolution of forestland area (0.5 < VIP < 1). The regression coefficients (RC) of each variable showed that the only

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factors positively correlated with forestland area included the energy consumption per 10,000 yuan of GDP, industrial sulfur dioxide emissions, and industrial fume emissions; the factors negatively correlated with forestland area included the tourism industry income, urbanization rate, per capita GDP, urban disposable income per capita, rural disposable income per capita and population density.

The results of the partial least squares regression analysis of grassland with each of the influencing factors (*Table 5*) showed that the variables that had a projected influence (VIP > 1) on grassland area included the energy consumption per 10,000 yuan of GDP, urbanization rate, per capita GDP, urban disposable income per capita, rural disposable income, per capita population density and industrial fume emissions; the tourism industry income and industrial sulfur dioxide emissions had a certain influence on the evolution of grassland area (0.5 < VIP < 1). The regression coefficients (RC) of the variables showed that the only factors positively correlated with grassland area included the energy consumption per 10,000 yuan of GDP, industrial sulfur dioxide emissions and industrial fume emissions; the factors negatively correlated with grassland area included the tourism industry income, urbanization rate, per capita GDP, urban disposable income per capita, rural disposable income per capita and population density.

The results of the partial least squares regression analysis of the water area and the influencing factors (*Table 5*) showed that the variables that influenced the water area in terms of projection importance (VIP > 1) included the urbanization rate, per capita GDP, urban disposable income per capita and population density. The proportion of tourism industry income, energy consumption per 10,000 yuan of GDP, industrial sulfur dioxide emissions, rural disposable income per capita and industrial fume emissions had a certain influence on the evolution of grassland area (0.5 < VIP < 1). From the regression coefficients (RC) of the variables, it can be seen that the factors that were positively correlated with the area of water included the tourism industry income, urbanization rate, per capita GDP, urban disposable income per capita, rural disposable income per capita and population density; the factors that were negatively correlated with the area of water included the energy consumption per 10,000 yuan of GDP, the industrial sulfur dioxide emissions and the industrial fume emissions.

Analysis of the driving role of natural factors on the evolution of green space area

The results of the partial least squares regression analysis of green space and each influencing factor (*Table 6*) showed that annual precipitation had a significant influence on grassland and water surface (VIP > 1) and a moderate influence on arable land and woodland (0.5 < VIP < 1). The average annual temperature had only a moderate effect on all types of green space (0.5 < VIP < 1), except for waters (VIP > 1). Coal reserves had a moderate effect on only arable land and water (0.5 < VIP < 1). The regression coefficients (RC) for each variable showed that annual precipitation was only negatively correlated with water surface and positively correlated with the other three types of green space; the mean annual temperature and coal reserves were only positively correlated with water surface and negatively correlated with the other three types of green space.

Discussion

Impact of urban transformation on green space

Natural driving factors are the basis of land use transformation, and natural conditions determine the regional land use cover (Teng et al., 2022). Jiaozuo city is

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located at the junction of the Taihang Mountains and the North Henan Plain, and the land cover is mainly arable land, so most of the land use transformation in Jiaozuo city involved the mutual transformation of arable land and construction land. With the continuous transformation and development of Jiaozuo (Zhao et al., 2022a), the area of green space in Jiaozuo continued to decline between 2000 and 2020, while the area of nongreen space showed a significant upwards trend. Jiaozuo city was in the early stage of transformation and development from 2000 to 2010, the situation of relying on coal energy development had not yet changed greatly (Tao and Deng, 2009), and the area of construction land had been expanding, encroaching on a large area of green space, severely decreasing the area of green space. With the promotion of urban development transformation, the policy of industrial upgrading and transformation led to a change in economic structure, and economic development reduced the dependence on coal energy mining and changed the demand for land use; furthermore, the policies of industrial parks, green mine construction, ecological environmental protection of mining areas and tourism resource development directly changed the type of land use (Yang et al., 2021), maintaining the green space area at a stable level from 2010 to 2020. Therefore, the transformation of the city can alleviate the imbalance of land use at the present stage to a certain extent, representing an important way to promote urban development (Xia et al., 2020).

Table 6. *Variable importance of projection (VIP) and regression coefficients (RC) of the PLSR model of green space area*

Natural factors	Cultivated		Forest		Grass		Water	
	VIP	**RC**	**VIP**	**RC**	**VIP**	**RC**	**VIP**	**RC**
Annual precipitation	0.8533	0.0800	0.9741	0.0865	1.1240	0.0954	1.3117	-0.1067
Annual average temperature	0.6220	-0.0583	0.6642	-0.0590	0.8580	-0.0728	1.0560	0.0859
Coal reserves	0.5565	-0.0522	0.2330	-0.0207	0.1635	-0.0139	0.5473	0.0445

The changes in green space occurred mainly in the central and southern regions, and these changes were determined not only by the transformation process of Jiaozuo city but also possibly by the topography. The changes in green space occurred mainly in the central and southern regions, and these changes may have been determined by the topography (Thabo Michael et al., 2022). In the study area, the mountains are located in the north and the plains are in the center and south; as a result, the urban center is mostly in the plain area. As rapid urbanization occurred mainly around urban centers, anthropogenic-induced green space changes were concentrated in the plains. In the northern part, the areas of woodland and grassland, which were mainly distributed in the northern part, remained at a relatively stable level due to the large difference in altitude from the plains (Jiaozuo has an altitude difference of approximately 1200 m) and the lower human activity. This result was consistent with the results of studies in Wuhan (Zhang et al., 2022), the Dianchi basin (Wu et al., 2022a) and Xi'an (Zhao et al., 2022b), where there have been dramatic reductions in the area of arable land and rapid expansions of built-up land. The proportion of forestland area decreased from 13.11% in 2000 to 12.04% in 2020 (*Table 1*), which was not a major reduction, and the area of forestland transfer remained at a low level. Water areas were the only type of green

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space that increased during the study period. This was mainly due to Jiaozuo's insistence on the ecological management and restoration of mountain, water, forest, field, lake and grass systems, the preparation of plans such as the Jiaozuo Water Ecological System Plan and the construction of the Bai Lu Lake Wetland Park and the Dasha River Ecological Park, all of which contributed to the increase in the area of water.

Impact of green space on the landscape pattern indexes

During the period of 2000-2020, the land use and landscape pattern of Jiaozuo underwent significant changes (especially in the plain areas) due to natural and socioeconomic factors. The yearly expansion of construction land during the study period further encroached on other surrounding land, leading to increased landscape fragmentation, increased heterogeneity and an irrational land use structure. This result was consistent with the dynamic evolution of the landscape patterns in Anshan (Fu and Zhang, 2022), Inner Mongolia (Li et al., 2022) and the Yangtze River Delta (Zhou and Wang, 2022), where landscape fragmentation is increasing and landscape connectivity and aggregation are decreasing to varying degrees. Because in the transition process of Jiaozuo City, the rapid growth of population and economy as well as the adjustment of industrial structure has burdened the urban landscape ecology, making all kinds of landscapes in Jiaozuo City show an obvious trend of fragmentation (Bindajam et al., 2023). In terms of policies, the government's macroscale-control of ecological construction and timely adjustment of land use planning have played certain roles in alleviating this trend (Liu et al., 2023). For example, in the future, Jiaozuo should continue to implement protection policies in the northern mountainous areas to reduce soil erosion in the mountains; in the plains, to speed up the urbanization process, the area of construction land should be strictly controlled, and abandoned land should be reclaimed to expand the area of arable land and forestland. By coordinating population growth and economic development and optimizing the land use structure, sustainable land use can be achieved, and ecological security can be guaranteed (Wang et al., 2022b).

Drivers of the spatial evolution of the green space

This study analyzed the driving mechanism of green space evolution in Jiaozuo from two perspectives: socioeconomic and natural factors. In the results of the PLSR model, the socioeconomic influence on various types of green space was greater. In particular, the urbanization rate, GDP per capita and population density played an important role in the evolution of green space, indicating that the socioeconomic and population growth of Jiaozuo city occupied part of the green space in the process of transformation and development to meet the needs of urban construction (Kar and Tuong, 2017). This is consistent with the impact of population growth on green space following urban expansion in Tehran (Sharifi and Hosseingholizadeh, 2019) and the trend in green space change in Shanghai from 1980 to 2015 (Wu et al., 2019). While arable land, forestland and grassland were the main types of green space in Jiaozuo City, the energy consumption of 10,000 Yuan GDP and industrial soot emissions played an important role and were positively correlated in terms of the variable correlation coefficient (RC), suggesting that the Jiaozuo government was expanding the area of green space to absorb industrial emissions while developing industry during the transition period, further safeguarding the healthy lives of the people. The urban disposable income per capita

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and rural disposable income per capita were both important for all types of green space, indicating that as people's incomes increase, they pursue a higher quality of life, and the demand for green space further increases. This is in line with the findings of previous studies. China's GDP per capita in 2014 in 289 cities had a positive effect on the urban green space rate and public green space area per capita (Zhou et al., 2022), and the interaction effect of economic growth and green space growth in 31 provinces from 2001 to 2020 had a two-way positive spatial spill-over effect (Li et al., 2018), which could be optimized using an SD-CA model for Beijing's economic growth rate (Li et al., 2021).

Jiaozuo has a temperate monsoon climate, with four distinct seasons and abundant sunshine, and these conditions are conducive to the growth of vegetation. In terms of natural factors, the average annual precipitation and average annual temperature were more obvious drivers of the evolution of green space in Jiaozuo. This was consistent with the findings of a significant positive correlation between the spectral vegetation index and the growing season precipitation in a study of the city of Belgrade (Milena et al., 2021) and a study of green spaces during urbanization and the vegetation of the Tibetan Plateau (Michael et al., 2022), which showed that climatic variables contributed significantly to changes in green spaces. Compared with the previous two natural factors, coal reserves had less of an impact on the green space of Jiaozuo city. This was mainly because before the transformation, Jiaozuo took coal mining as the pillar industry, and after the coal resources were exhausted, Jiaozuo transformed into a tourist city and gradually eliminated its dependence on coal resources. Therefore, the driving factors of coal reserves on green space are relatively unclear (Wang et al., 2016). This study analyzed the trends of green space in Jiaozuo at different time periods and explored the relationship with socioeconomic and natural factors. As the spatiotemporal evolution of green space and its driving factors are extremely complex, both remote sensing images and some objective factors need to be analyzed (Ren et al., 2022). However, due to the limited access to objective data, this study analyzed only the data that were available. In future studies, we will conduct in-depth research in conjunction with the changes in green space in different regions of Jiaozuo.

Conclusions

This paper used ArcGIS to analyze land use/cover changes in Jiaozuo city from satellite remote sensing image data in 2000, 2005, 2010, 2015 and 2020, analyzed the overall changes in green space in each period by building a transfer matrix and other methods, and analyzed the changes in the landscape pattern of Jiaozuo city in each period using Fragstats. A partial least squares regression model was developed using SIMCA to quantify the driving forces. Key findings of the study include the following:

(1) The area of green space in Jiaozuo city has been gradually decreasing over the 20-year period, but the reduction in green space in Jiaozuo city from 2010 to 2020 had a greater decline than that from 2000 to 2010, especially in the last five years, remaining at a more stable level.

(2) During 2000-2020, the accelerated urbanization of Jiaozuo city led to a decline in dominant landscape dominance, the further intensification of landscape fragmentation, and the weakening of connectivity among patches.

(3) Among the 12 driving factors, the influence of socioeconomic factors on green space in Jiaozuo was significantly higher than that of natural factors, especially the

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urbanization rate, population density and GDP per capita of the city, which contributed more to the change in green space.

(4) This study focuses on multiple socio-economic and natural factors affecting the evolution of green space, and explores the strength of the influence of each influencing factor in avoiding the problem of multicollinearity, which provides scientific reference for Jiaozuo and related depleted cities to formulate a reasonable green space development plan in the process of transformation. However, this article has not yet analyzed the mutual influence between different driving factors and the intrinsic driving mechanism of green space. In the future research, we will comprehensively consider the green space changes caused by urban changes and strengthen local parameterization based on the field survey data in order to analyze the spatial and temporal changes of green space more accurately.

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APPENDIX

Schedule 1. *Land use type transfer matrix/km^2*

Year	Land use type	Cultivated	Forest	Grass	Water	Construction	Unuse
2000-2005	Cultivated	2607.74	5.76	3.59	10.36	31.90	0.18
	Forest	5.96	521.64	5.51	0.28	0.70	0.11
	Grass	4.54	4.20	188.49	0.11	0.86	0.03
	Water	24.81	0.42	0.22	90.19	0.53	0.23
	Construction	60.63	1.06	0.35	0.34	482.14	0
	Unuse	0.06	0.05	0.08	0	0	2.52
2005-2010	Cultivated	2407.93	38.91	19.01	15.79	103.52	1.14
	Forest	4.46	480.97	4.59	0.37	0.38	0.02
	Grass	3.71	5.41	163.06	0.09	1.11	0.04
	Water	30.35	1.71	1.05	98.51	1.28	0.03
	Construction	213.05	7.30	8.90	1.62	438.23	0
	Unuse	0.03	0.12	1.65	0	0	1.48

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2010-2015	Cultivated	2528.63	2.07	1.88	4.22	23.81	0.03
	Forest	2.36	485.88	2.98	0.21	0.32	0.06
	Grass	1.91	2.24	167.31	0.12	0.86	0.12
	Water	9.94	0.26	0.47	128.13	0.21	0.001
	Construction	43.57	0.34	0.67	0.14	643.93	0
	Unuse	0.05	0.02	0.12	0.02	0	3.07
2015-2020	Cultivated	2452.79	2.95	3.76	32.04	36.95	0.70
	Forest	2.65	479.06	2.92	0.33	0.43	0.03
	Grass	3.28	3.93	165.41	3.15	0.68	0.17
	Water	24.85	0.35	0.17	99.91	1.80	0.004
	Construction	77.10	0.78	1.48	0.96	648.80	0
	Unuse	0.25	0.09	0.15	1.79	0	2.38
2000-2020	Cultivated	2364.87	37.15	16.51	24.80	82.42	2.01
	Forest	2.99	479.13	2.74	0.14	0.30	0.02
	Grass	5.15	2.57	166.79	1.04	0.94	0.02
	Water	49.82	1.23	1.39	72.31	2.26	0.07
	Construction	279.91	7.66	9.52	0.75	430.45	0
	Unuse	1.27	0.05	1.63	0.76	0	0.95

Schedule 2. *Green space transfer matrix/km^2*

Year	Green space to nongreen space	Non green space to green space
2000-2005	62.57	34.75
2005-2010	232.68	107.51
2010-2015	44.93	25.41
2015-2020	82.60	40.76
2000-2020	302.37	88.04

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