Analysis of Spatiotemporal Evolution of Landscape Patterns and Its Driving Factors Based on Land-Use Changes: A Case Study of Zhuzhou, China's Industrial Capital

Kai Huo[1*], Jianqiang Yang[2] and Qingxiu Cai[3]

[1]PhD student, Southeast University 210000

School of Architecture, Southeast University, Xuanwu District, Nanjing, Jiangsu Province, China, 210000. Hanlinyi37@gmail.com

[2]PhD, Southeast University 210000

School of Architecture, Southeast University, Xuanwu District, Nanjing, Jiangsu Province, China

[3]Undergraduate, Guangzhou development district communications investment group Co.LTD, 510000.

Abstract: This study investigates the evolution of landscape patterns and the driving forces behind these changes in Zhuzhou City from 2000 to 2020, utilizing Landsat 5TM/8OLI remote sensing imagery and GIS tools. The main objective is to analyze the spatial and temporal dynamics of landscape types and identify the key factors influencing these changes. Five periods of Landsat images (2000, 2005, 2010, 2015, and 2020) were processed to generate distribution maps of landscape types. The Fragstats tool was used to calculate landscape pattern indices, and Principal Component Analysis (PCA) in SPSS was employed to identify the main driving factors.The results indicate significant changes in landscape patterns, particularly the rapid expansion of construction land and the decline of arable land. Construction land area grew at an annual rate of over 100%, contributing to a loss of arable land, which affected other landscape types such as woodland, grassland, and unused land. At the patch class level, landscape fragmentation increased, while connectivity deteriorated. Despite an overall increase in landscape richness, the degree of external disturbance has intensified.The principal driving forces behind these landscape changes include urban economic development, industrial structure shifts, and environmental climate factors. Population growth and the expansion of tertiary industries have significantly impacted the landscape, especially in the western urban areas. Infrastructure development has encroached on arable land, leading to further fragmentation. The study concludes that these findings provide valuable insights for urban and ecological planning in Zhuzhou City, highlighting the need for integrated land use strategies to mitigate fragmentation and support sustainable development.

Keywords: Landscape Patterns; GIS; driving factors; Principal component analysis

1. Introduction

Nowadays, the rapid expansion and development of urbanization, while providing people with a better life, has also led to the erosion of large-scale ecological patches [Dupras. J.2016], intensified landscape fragmentation, and gradually weakened the connection between ecological patches, which, to a certain extent, has resulted in the reduction of biodiversity and the extinction of species [Li.C. 2013, Alberti. M. 2010]. Against this backdrop, the impact of changes in landscape patterns on the ecological environment has emerged as a research hotspot. Simultaneously, the interpretation of land use types through remote sensing imagery [Chan, K.M. 2017], the spatial and temporal dynamic evolution of landscape patterns [Liu.S.2019, Wu. S.2023], analysis of driving force causes [Luo. Y. 2022], construction of ecological networks [Cui. L. 2020, Hamid. A.R.2017], and assessment of habitat quality have become the mainstream focus of current research [Li.Y. 2021, Zhang.X. 2010]. Land use/land cover (LULC) serves as a crucial indicator for interpreting the ecological environment of the land surface [Li. P. 2021]. The overall landscape pattern is influenced by changes in the spatial configuration and pattern characteristics of landscape patches resulting from the contraction or expansion of land use/land cover (LULC) types [Huang.F. 2022], impacting the aggregation and dispersion of these patches. Analyzing the evolution of landscape patterns based on changes in land use is a crucial aspect of landscape ecology research [Perring. M.P. 2016]. Therefore, investigating dynamic changes in landscape patterns and analyzing the driving factors influencing them contribute to understanding the impacts of human activities on ecological changes in the region [Zhao.W.2014], this provides a scientific foundation for regional eco-protection and planning [Li.M.2015]. Current quantitative analysis methods employed to evaluate the drivers of landscape patterns encompass multiple regression analysis, correlation analysis, principal component analysis, and Geode tector [Zhang. S.2017, Zhu. Z.2021, Yushanjiang. A. 2018, Baus, P.2014]. By combining multi-temporal Landsat images with Principal Component Analysis (PCA), our study closes the gap in pattern index analysis and landscape classification by identifying the main forces influencing landscape changes. Our method provides a more comprehensive, city-wide view, in contrast to many studies that only concentrate on small-scale or regional assessments. Furthermore, we integrate environmental and socioeconomic factors to investigate the intricate forces behind landscape change, providing a more comprehensive view of ecological and urban dynamics. One of the major innovations in the subject is this methodological integration.

Zhuzhou, Hunan Province, is rich in natural resources, as one of the eight industrial bases in China, the ecological problems accumulated in history are still under treatment [Xie. J.2022]. With the introduction of Hunan Province's "Five-Year Action Plan for the Integrated Development of ChangZhuTan (2021-2025)", which promotes the construction of the ChangZhuTan National Ecological Civilization Pilot Zone, Zhuzhou's development opportunities coexist with ecological problems[Zhan. W.2020, Li, J.2021]. Most of the current studies on urban landscape patterns tend to focus on general cities or more macroscopic city clusters (e.g., ChangZhuTan City Cluster), and there is a lack of quantitative studies of traditional industrial cities and municipal scales [Quan. B.2013, Zeng.Y.2012]. Hence, this paper focuses on Zhuzhou City, a traditional industrial city, to study and analyze land use changes, spatiotemporal evolution of landscape patterns, and driving factors from 2000 to 2020. The aim is to establish a scientific foundation for sustainable development, eco-environmental protection, and effective land management in industrial cities [Huang. L. 2020].

2. Research Materials and Methods

2.1.Study Area

Nestled in the eastern region of Hunan Province and downstream of Xiangjiang River, Zhuzhou stands out as one of China's first eight priority industrial cities and a pivotal old industrial base. The study area covers the municipal district of Zhuzhou City (112°93′-113°37′E, 27°19′-28°04′N), which is now under the jurisdiction of Hetang, Lusong, Shifeng, Tianyuan, and Lukou districts, with a total area of about 1916.73 km2. The study area is a typical hilly area with high terrain on the periphery and open intermountain basins and alluvial terraces in the center. The region falls under the subtropical monsoon humid climate, characterized by four distinct seasons, ample rainfall, abundant sunlight, and warmth, more northwest winds in winter and more due south winds in summer, an annual mean temperature of 20 degrees Celsius and receives an average precipitation of 1,280 millimeters; soil types are mainly red loam, paddy soil, tidal soil, loam, purple soil, and calcareous soil, which are rich in biological resources [Ren.J.2024].

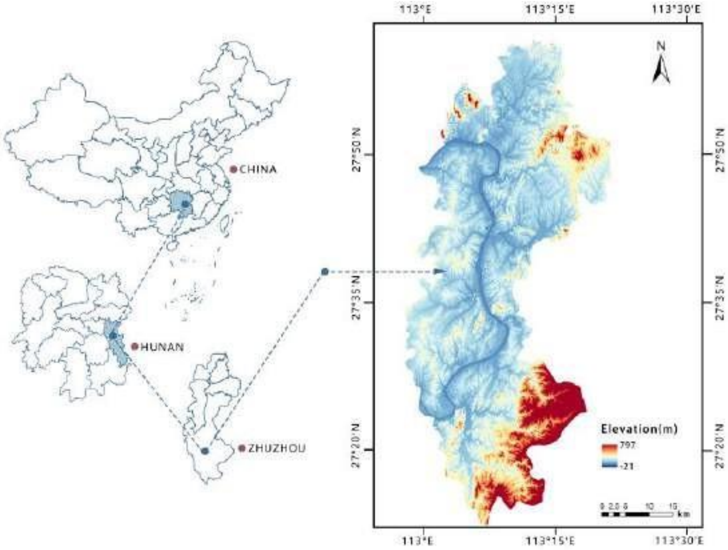


Figure 1. The Location of the study area.

2.2.Data Sources

The essential data originated from the Chinese Academy of Sciences Resource and Environmental Science Data Center (https://www.resdc.cn/) with a spatial resolution (30m×30m). The study chose five periods of surface cover data in 2000, 2005, 2010, 2015, and 2020. Following the study's scope, image data underwent processing through cropping and reclassification using the GIS platform is shown in table 1. The processed images were then sequentially imported into the Fragstats platform for landscape index analysis. Digital Elevation Model (DEM) obtained from the Geospatial Data Cloud Platform (http://www.gscloud.cn/). The socio-economic and environmental data include population figures, industrial output, GDP percentages by sector, sulfur dioxide emissions, and climate data (precipitation and temperature). These variables are sourced from the Chinese Academy of Sciences, the China City Statistical Yearbook, the Zhuzhou City National Economic and Social Development Statistical Communique, and the Hunan Province Environmental Condition Communique. The ten categories analyzed using the SPSS tool encompass demographic, economic, and environmental factors, which are standardized for further factor analysis to determine the driving forces behind landscape changes.

Table 1. Description of data metrics

Metric	**Description**
Landscape Types	Arable land, Woodland, Grassland, Water, Construction land, Unused land.

Time Periods	2000, 2005, 2010, 2015, 2020 (five periods of analysis).
Spatial Resolution	30m × 30m resolution for remote sensing imagery.
Data Sources	Landsat imagery, socio-economic data (China City Statistical Yearbook), environmental data (Hunan Province Environmental Condition Communique).
Analysis Tools	GIS platform for data processing, Fragstats for landscape indices, SPSS for PCA and factor analysis.
PCA Indicators	10 indicators: Population, industrial output, GDP components, environmental factors like temperature and precipitation.

2.3.Research Methods

2.3.1. Classification of landscape types

Based on Zhuzhou City's land use status and characteristics of remote sensing images, and following the classification standard of Current Land Use Classification (GB/T21010-2017), the study, considering the specific conditions of the area, classified land resources into six landscape types: arable land, grass land, construction land, woodland, water, and unused land.

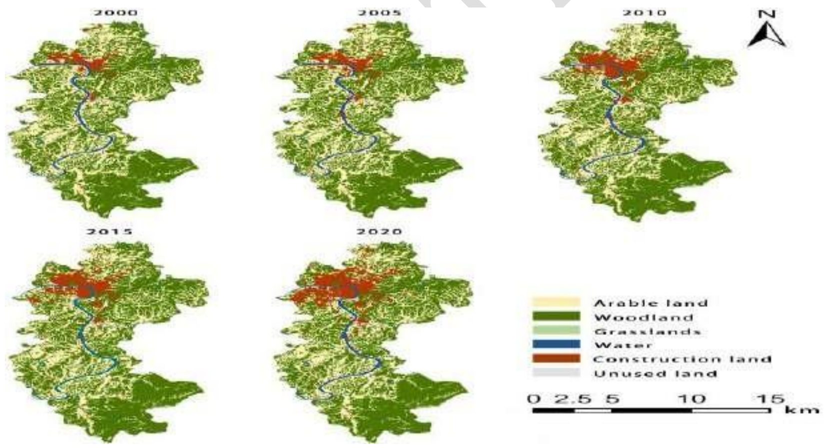


Figure 2. Distribution of land use types in the study area from 2000 to 2020.

2.3.2. Landscape pattern index analysis

The landscape index is a quantitative measure that condenses information on landscape patterns, offering insights into the characteristics of landscape structure and spatial pattern changes [Wu.

J.G. 2000]. In this study, FRAGSTATS software calculated relevant landscape pattern indices to analyze fragmentation [Lamine.S.2018], complexity, and diversity in the study area. Six landscape indices at two levels—class level and landscape level—were selected for examination [Xi. Y.2018]. In this set, the class level indices comprised the largest patch index (LPI), patch density (PD), and landscape shape index (LSI), while the landscape level indices encompassed the contagion index (CONTAG), Shannon diversity index (SHDI), and Shannon evenness index (SHEI). The meanings calculations of the landscape pattern indices relevant to this study are outlined as follows:

Largest patch index (LPI); Indicates the ratio of the largest patches of a given type to the total area of the landscape, and the magnitude of its value determines the dominant type and species richness within the landscape.

$$LPI=\frac{Max(a_1,...,a_n)}{} \times 100 \tag{1}$$

Where: Max(a1,...,an) is the area of the largest patch in the landscape and A represents the total area of the landscape or patch. Value range: $0 < LPI \leq 100$.

Patch Density (PD); It indicates a degree of fragmentation and spatial heterogeneity. A higher value leads to increased fragmentation and enhanced spatial heterogeneity.

$$PD = \frac{N}{A} \times 1000000 \tag{2}$$

Where: In the context of patch density (PD), N represents the number of patches of the corresponding patch type; A denotes the total area of the landscape or patch. The constraint is PD>0. Landscape shape index (LSI); It reflects the boundary patterns of different landscape types, and the larger its value, the more irregular in pattern.

$$LSI = \frac{P}{2\sqrt{\pi^* A}} \tag{3}$$

Where: P indicates the perimeter of the patch type in the study area; A indicates the total area of th regional landscape. LSI≥1, no limit. The value increases as the shape of the landscape patch becomes more irregular or the edge length becomes longer.

Contagion index (CONTAG); Reflecting the degree of aggregation or spreading trend among different landscape types, the larger the value, the stronger the connectivity among dominant landscape types.

$$CONTAG = 1 + \frac{2\sum_{i=1}^{m}\sum_{k=1}^{m} g_{ik} g_{lk} . \ln(p_i)}{\sum_{i=1}^{m} g_{ik} \sum_{k=1}^{m} g_{lk}} \tag{4}$$

Where: pi is the percentage of area occupied by type patches; gik indicates the number of type i and k patches adjacent to each other; and m is the total number. Shannon diversity index (SHDI); Reflecting the richness of land use types and changes in landscape heterogeneity, SHDI≥0. As the value tends to 0, it indicates that only one landscape type is included in the composition.

$$SHDI = -\sum_{i=1}^{m}(p_i ln p_i) \quad (5)$$

Where: (pi represents the percentage of landscape patches to the overall area of the landscape. Shannon evenness index (SHEI); It indicates the uniformity and dominance of landscape types, with 0≤SHEI≤1. A higher value suggests a more uniform distribution of each patch type and greater landscape diversity.

$$SHEI = \frac{-\sum_{i=1}^{m}(p_i ln p_i)}{ln m} \quad (6)$$

Where: m is the sum of patch types present in the landscape, and pi is the percentage of the area of patch type i in the overall landscape.

2.3.3. Principal Component Analysis (PCA) and Factor Analysis Methodologies

A multivariate statistical method known as principal component analysis (PCA) utilised for investigating and evaluating the correlations among the variables. To convert the high-dimensional datasets into a lower-dimensional dataset is mostly utilised for dimensionality reduction. The complex datasets made simpler by the transformation process, that extracts the comprehensive variables which encapsulate the key patterns of the original data. To minimise the dimensions counts, the PCA kept the data's variability while enhancing clarity of the correlations among the variables. This method is efficient for locating the data's underlying structures, that helps to pinpoints the primary forces over the dynamic landscape. Reducing observed variables to reduces the unseen variables, or factors, is another statistical model employed for finding the links among them. Correlated variables are modelled of shared factors in attempt to the explain in their variance. This method groups correlated indications into a common elements, which is significant for comprehending the structure of complex systems.

Both PCA and factor analysis are employed to explore the driving forces behind landscape pattern changes. In this study, they are used to quantitatively analyze the factors influencing landscape changes in Zhuzhou City.

The following ten indicators were selected and combined with the current situation in the study area, both socio-economic and natural: Total population at the year-end (X1), non-agricultural population (X2), gross regional product (X3), total industrial output value above the large-scale industry (X4), percentage of primary industry in GDP (X5), percentage of secondary industry in

GDP (X6), percentage of tertiary industry in GDP (X7), sulfur dioxide emissions from industry (X8), annual average precipitation (X9), and annual mean temperature (X10).

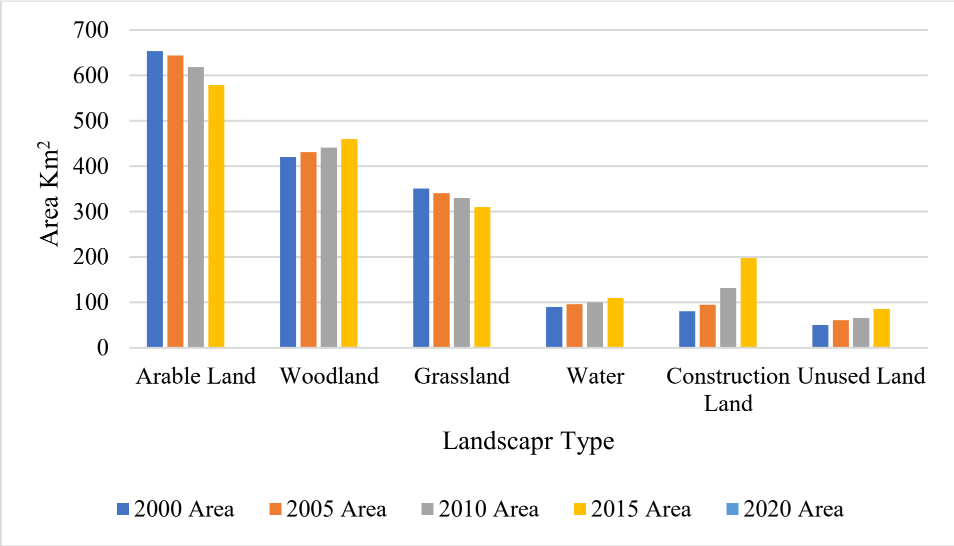
The SPSS software platform employed for performing the analysis, that allows an extraction of various factors and principal components to detect the major causes of the variations in landscape patterns. Understanding the relationships between those parameters and finding the main causes of landscape can modify the objectives. The approach enables detailed comprehensive analysis of the intricate connections among environmental and socioeconomic factors leads an landscape change.

This study is based on the SPSS platform, using principal component analysis and factor analysis to analyze quantitatively the factors affecting landscape changes in Zhuzhou City, and then find the main driving factors [Pan.J.H.2015, Wen.B.2020], which strengthen the analytical framework and enhance the robustness of the conclusions drawn from the study.

3. Results

3.1.Landscape type transfer analysis

During 2000-2020, the area changes of landscape types in Zhuzhou City exhibited a trend of "three increases and three decreases": The areas of construction land, water, and unused land increase, while the areas of arable land, woodland, and grassland decrease (Figure 3). From 2000 to 2020, the construction land has shown a leaping expansion trend, increasing from 79.952 km2 to 197.304 km^2, with an annual growth rate of 146%. The water exhibited an increasing trend, rising from 61.378 km2 to 63.809 km^2, with a growth rate of 3.96%. The woodland decreased from 1108.552 km^2 to 1065.647 km^2, with an annual reduction rate of 3.87%. The grassland is small and decreasing gradually, from 10.794 km^2 to 10.554 km^2, with a year-on-year reduction rate of 2.22%. The arable land witnessed a sharp decrease from 653.575 km^2 to 578.683 km^2, with an annual reduction rate of 11.46%. There was no unused land in 2000, and the area grew to 0.117 km^2 in 2020. Overall, the arable land in the study area is decreasing every year, and the protection of arable land is urgent [MURALI.B. 2024, Poornima. P.U. 2025, Sharma. K. 2024].



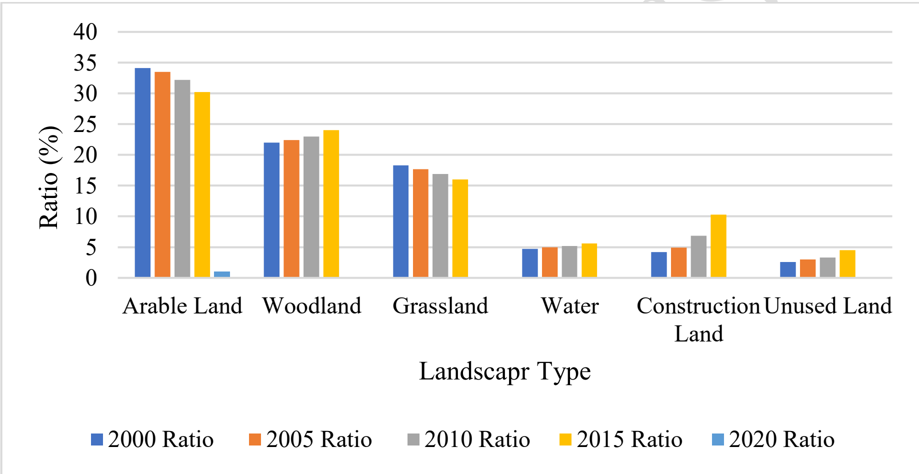


Figure3. The changes in area of each landscape type in study area from 2000 to 2020.

Based on ArcGIS 10.5 software, land use dynamic transfer analysis was conducted to generate the land use transfer matrix for the study area from 2000 to 2020 (Table 2). As shown in Table 2 (2000-2020), arable land was converted into woodland, grassland, water bodies, construction land, and unused land. The area converted to construction land had the largest contribution, with converted areas of 38.945 km², 0.120 km², 5.904 km², 69.226 km², and 0.002 km², respectively.The type of construction land showed a sharp expansion trend, with the main contributors being 69.226 km2 of arable land and 53.016 km2 of woodland, the sum of which accounted for 97.70% of the area transferred to construction land, more than doubling the area. The change in grassland type isminimal, with the main contributors being 0.535 km2 of woodland, 0.185 km2 of water, and 0.120 km2 of arable land. The primary contributors to the water area are also arable land, with an area of 5.904 km2,1.542 km2 of woodland, 0.215 km2 of construction land, while contribution from other type are minimal,with negligible change in the amount of unused land. Overall, the predominant transfer pattern in the region occurred in the mutual conversion of arable land, woodland, and construction land [Rajagopal. R, Gupta. S 2023, Karthik A. 2025]. There was a net outflow of 75.102 km2 of arable land, a net outflow of 44.363 km2 of woodland, and a net inflow of 117.314

km2 of construction land. The primary features of the changing landscape pattern during this period were the reduction of large amounts of arable land resources and the dramatic expansion of construction land.

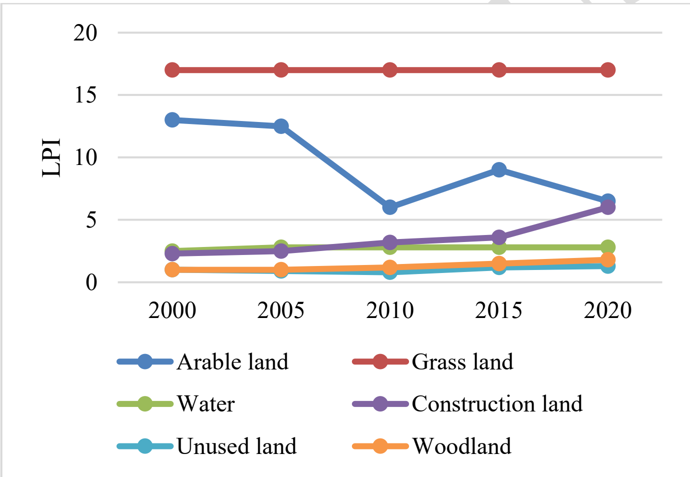
Table 2. Land use transfer matrix in study area from 2000 to 2020 (km2).

Landscape type	**2020**							
	Arable land	**Woodland**	**Grass land**	**Water**	**Construction land**	**Unused land**	**Total**	**Transfer out Area**
Arable land	539.378	38.945	0.120	5.904	69.226	0.002	653.575	114.19
Woodland	32.275	1021.069	0.535	1.542	53.016	0.115	1108.552	87.484
Grass land	0.133	0.822	9.671	0.086	0.082		10.794	1.123
Water	1.496	0.969	0.185	55.941	2.788		61.378	5.437
Construction land	5.191	2.385	0.006	0.215	72.154		79.952	7.798
Unused land						0.000		
Total	578.473	1064.190	10.518	63.687	197.267	0.117	1914.252	216.038
Transfer in Area	39.095	43.121	0.847	7.746	125.112	0.117	216.038	

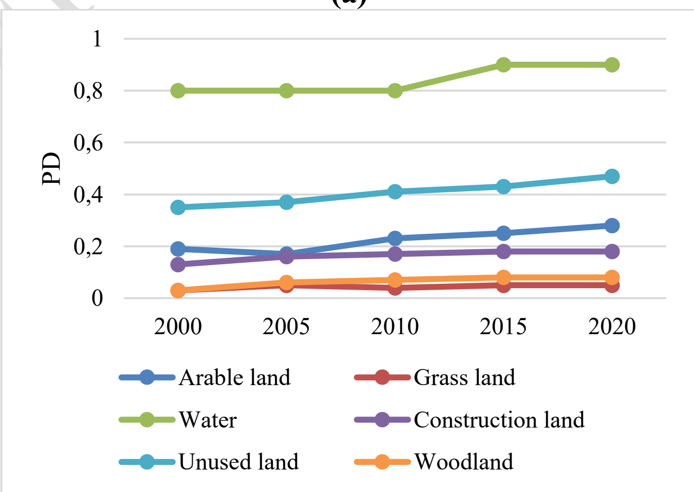
3.2.Analysis of changes in landscape pattern indices

3.2.1. Evolution of class level indices

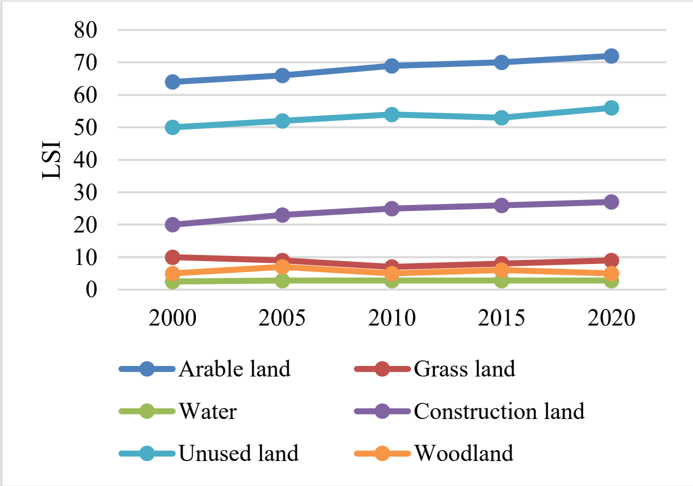
Figure 4 illustrates the changing characteristics and dynamics of the various landscape types in the study area. According to Figure 4a, the maximum patch index (LPI) of woodland has always been the highest in the five periods, indicating that woodland has always been the predominant landscape in the area. The maximum patch index (LPI) for woodland, water, and construction land generally exhibits an upward trend from 2000 to 2020, and the LPI value for construction land increases significantly, while arable land shows a downward trend and grassland shows no significant change. It was judged that during this period, due to the development and expansion of the city, it threatened the dominance of arable land area to make its LPI index decrease rapidly, which led to the continuous degradation of arable land, the increasing of construction land area, degree of dominance of construction land is increasing. Figure 4b illustrates that the patch density (PD) of woodland and arable land is generally on an escalating trend, indicating an increasing degree of patch fragmentation. The PD of construction land rose from 2000 to 2015, then declined from 2015 to 2020, reflecting a gradual decrease in the risk of fragmentation in these five years. Meanwhile, grassland and water PD changes have been relatively flat overall, with PD slightly decreasing from 2015 to 2020 [REDDY. A.R 2023]. As shown in Figure 4c, the landscape shape index (LSI) of arable land, construction land, and woodland generally exhibited an upward trend, while the LSI of water and grassland was stable. It means that, with the economic and social development and population increase, the landscape spatial shape of construction land is gradually complex and Varied. It results in the continuous fragmentation of arable land patches, increased fragmentation intensity, and more complex landscape structure and heightened landscape heterogeneity.



(a)



(b)



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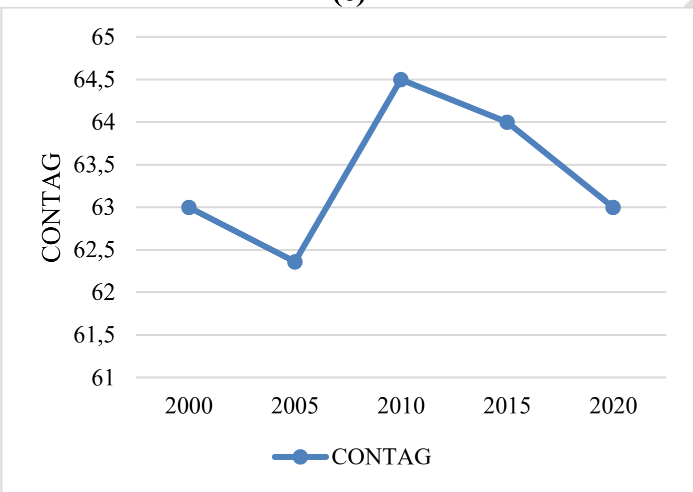

(d)

Figure 3. The changing trend of landscape indices in the study area from 2000 to 2020.

3.2.2. Evolution of landscape level indices

By analyzing the landscape-level index, the evolution of the landscape pattern in ZhuZhou City was assessed. As shown in Figure 4d, the Contagion Index (CONTAG) sharply decreased from 2000 to 2005, increased rapidly from 2005 to 2010, and then steadily declined from 2010 to 2020. It is indicated that the connectivity of the different patches is currently poor. However, through manual intervention and plan- ning in the intermediate years, the connectivity tends to be optimized, but the degree of human interfer- ence has shown a gradual decrease in recent years. According to Figure 4e, the Shannon diversity index (SHDI) increased sharply from 2000 to 2020, showing that the landscape heterogeneity among patches increased in this period, the connectivity among patches declined, but the overall landscape richness in- creased. According to Figure 4f, Shannon's evenness index (SHEI) decreased significantly and rapidly from 2005 to 2010, then upturn from 2010 to 2020, indicating that the distribution of various patch types gradually became more even [Veeraiah.D.].

Analysis of driving factors of landscape patterns Use the principal component analysis method. From the analysis results, the KMO is 0.675, more than 0.6, and the data passes Bartlett's sphericity test ($p<0.05$), meeting the prerequisite requirements for principal component analysis. The principal component analysis of the ten selected indicator factors using SPSS26.0 resulted in a total of 3 principal components with eigenvalues greater than 1. The initial eigenvalue of the 1st principal component is 4.330 (Table 3), which explains 48.115% of the total variance contribution, while the 2nd and 3rd principal components explain 23.885% and 15.624%. The first three principal components explained more than 87.623% of the total indicator information, so use the first three indicators as principal component factors [Sharma.K. 2024, Poloju.N.2024].

Table 3. Characteristic values and variance contribution rates of indicators.

Composition	Initial Eigenvalue	Percentage of Variance (%)	Cumulative Percentage (%)
1	4.330	48.115	48.115
2	2.150	23.885	72.000
3	1.406	15.624	87.623

3.2.3. Economic development factors

The three principal components were rotated orthogonally by the maximum variance method to obtain the factor loading matrix (Table 3). According to Table 3, there are four drivers on the 1st principal component with loadings over 0.8, including X2 (non-agricultural population) and X1 (total population at the year-end) with loadings over 0.9, X4 (total industrial output value above the scale) with the loading of 0.851, and X3 (Gross Regional Product) with the loading of 0.810, mainly reflecting the level of economic development of the city, it shows that urban construction, economic development, industrialization de- velopment level, and regional population scale are important factors influencing the change of landscape pattern in Zhuzhou City, occupying a dominant position.

From 2000 to 2020, the non-agricultural population will grow from 555,400 to 1.51 million, the total population at the year-end will grow from 748,500 to 1.73 million, the total industrial output value above the large-scale industry will increase from 16.85 billion yuan to 202.7 billion yuan, and the Gross Regional Product (GDP) will increase from 15.46 billion yuan to 163.5 billion yuan. From this, it can be inference that along with the progress of social economy and industrialization, the non-agricultural population and total population in the Zhuzhou City area gradually grew, leading to the continuous increase of urbanization rate, and the city expanded outward dramatically, further threatening the ecological resources of the surrounding areas. Therefore, urban economic development is an essential factor influencing the change of landscape patterns in Zhuzhou City.

4. Discussion

From the above results, the factors affecting landscape pattern changes in Zhuzhou City are complex and diverse. In general, slope, slope direction, hydrology, climate, and soil are the natural driving factors of landscape pattern evolution [Liu.C.2021], and climate change factors can often affect landscape pattern change in a short time, playing a role that cannot underestimated [Xu. D.2021]. Factors such as population, urban expansion, policy, and industry are increasingly close to landscape pattern changes, occupy a dominant role, and show an increasing trend [Fan.Q.2022]. The degree of fragmentation of the landscape pattern in Zhuzhou City has been climbing along with the rapid development of the city and the degree of urbanization rate. With the concentration of population and the growth of construction land, the urban area, in general, is expanding significantly to the northeast and southwest, and the space for ecological lands such as arable land and woodland is constantly being eroded, with increased density of patches and accelerated fragmentation. At the same time, the increased fragmentation of the overall patches is also one of the reasons for the reduction of the overall habitat quality, which is not conducive to the maintenance and protection of biodiversity.

4.1.Dynamic changes in land use and landscape patterns

The 2005-2010 and 2015-2020 periods are the two periods in which the landscape pattern of Zhuzhou City has changed the most. The construction of the Zhuzhou Aviation and Power Hub project officially began in August 2002 and was completed in December 2006. With the continuous storage of water in the dam, the level of the Xiangjiang River rose, the floodplain, as well as arable land on both sides of the Zhuzhou segment of the Xiangjiang River, was inundated by the water, and the area of water and wetland increased by 3.31 km2. From 2005 to 2010, the arable land decreased sharply by 25.53 km2, the woodland decreased by 15.18 km2, and the construction land increased to 36.98 km2. At the same time, the old industrial area of Qingshuitang is in the most severe pollution period, "Three wastes" emissions accounted for two-thirds of the city, including thermal power generation, non-ferrous smelting, chemical industry, three industries accounted for 89.5% of the city's total emissions of sulfur dioxide emissions, the frequency of acid rain in the urban area of Zhuzhou amounted to 79%, it was rated as the "Top Ten AirPollution Cities in China" in 2003-2004[Ren.J.2024]. " During this period, the coarse industrial production pattern led to soil acidification and vegetation damage; land quality degradation, and increased risk of erosion, which seriously affected the stability of the ecosystem and, to a certain extent, influenced the change of the landscape pattern of Zhuzhou City. Landscape index analysis revealed that the degree of landscape superiority of arable land declined rapidly as habitat fragmentation increased; habitat connectivity and aggregation of woodland patches deteriorated and fragmentation increased, and the landscape superiority of construction land patches gradually improved.

In this period of 2015-2020, the area of arable land decreased rapidly by 27.45km2, the city's total grain output dropped sharply by 16.2% compared with the same period last year; the woodland reduced by 20.58km2, and the construction land increased rapidly by 48.69km2. In March 2013, the pollution problem in the old industrial area of Qingshui Tong aroused great attention from the Central Government. In June 2014, the old industrial zone of Qingshuitang was established as a pilot for the relocation and reconstruction of old industrial zones in 21 urban areas in China by the National Development and Reform Commission (NDRC). In 2018, all enterprises within the industrial zone were closed down, marking the commencement of long-term ecological restoration efforts. According to the landscape index analysis the fragmentation of arable land and woodland patches continues to increase, while construction land patches show the opposite trend, with a significant rise in landscape dominance, a reduction in fragmentation, and a more clustered and contiguous distribution. From 2000 to 2020, in addition to construction land and water, arable land, woodland, and grassland all declined to varying degrees. In June 2018, approved by the State Council, Zhuzhou Lukou districts were officially established from the original four districts, and adjusted to five districts. Zhuzhou urbanization expansion and infrastructure construction greatly crowded Xiangjiang part of the arable land space, a vast expanse of arable land and woodland have been into numerous patches of various sizes. The data on the growth of construction land area over the past 20 years, as well as the results from the principal component analysis, strongly support this point, as illustrated in Figure 5.

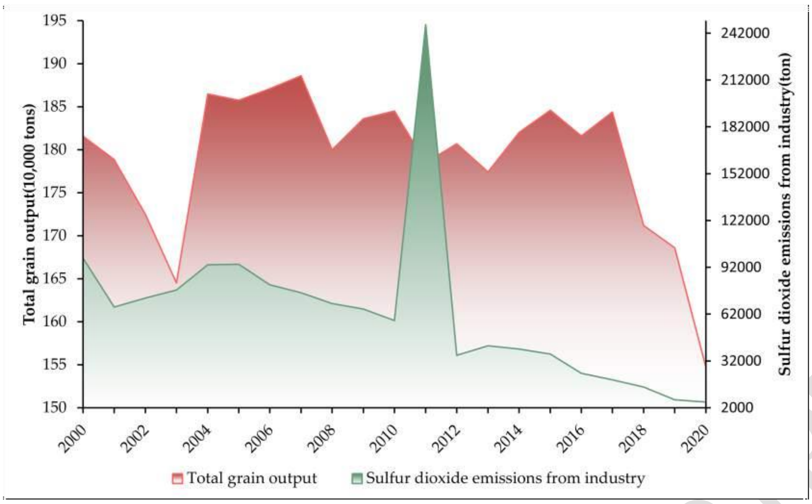

Figure 5. Total Grain Production and Industrial Sulfur Dioxide Emissions from 2000 to 2020.

4.2.Landscape pattern optimization suggestions

At present, in the territory spatial planning in Zhuzhou City, there is the phenomenon of basic farmland red line, ecological protection red line, urban development boundaries crossing each other, arable land occupation balance, in and out of the balance of the implementation of the policy is not in place, the arable land area has been declining. Therefore, it is urgent to protect the red line of arable land [Fan. X.2022]. Landscape index analysis shows that in Zhuzhou City, in general, the landscape heterogeneity is increasing, patch fragmentation tends to be serious, the degree of human interference is deepening, and the superposition of various influencing factors causes the current situation of arable land with ecological land protection in Zhuzhou City to come to the fore. Based on the above analysis, we make relevant recommendations for arable land and eco-land protection:

(1) Establishing an ecological evaluation index system and clarifying the location and function of eco-land land protection and supplementary arable land resources. Areas with a high proportion of ecological land patches that are concentrated and contiguous are divided into core protection zones and buffer zones. The region should resolutely implement the policy of returning farmland to forests and grasslands, and large-scale exploitation is strictly prohibited to maintain the stability and integrity of the regional ecosystem.

(2) Enhance the protection of arable land throughout the entire process. First, implement the arable land protection policy, delineate permanent basic farmland in quality and quantity, and establish and perfect the system of permanent basic farmland reserve areas; strictly control the occupancy of arable land by construction land [Jiang.P.2018], improve the balance of arable land occupancy and replenishment and the balance between incoming

and outgoing land. In the second place, scientific planning the red line for ecological protection. The demarcation of the red line should try to make eco-land patches centralized and connected, improve patch connectivity, and provide a survival base for the maintenance of biodiversity. Accelerating the construction of forest corridors, enhancing the connectivity of forest landscapes, relying on natural mountain ranges and water systems, and constructing backbone ecological corridors with regional connectivity through restoration and widening, and afforestation to fill in the gaps, to build a landscape pattern combining centralization and decentralization [Poloju.N.2022].

(3) Accelerate the ecological restoration area project in the northern towns and improve the restoration and management of the old industrial area in Qingshuitang. Through the protection and development of industrial sites, create an ecological circle of northern towns with industrial culture and leisure tourism as its core and eco-protection as its focus. Strictly supervise and control the transfer out of eco-land to prevent ecological land from becoming a victim of urbanization and expansion.

(4) Further balancing the relationship between economic development and land use. The conflict between production activities and ecological land, arable land, is essentially a complex human activity and eco-boundary problem. The present distribution of eco-land and arable land in Zhuzhou City should be evaluated in a variety of disciplinary fields, such as environmental benefits, economic benefits, and ecological values, to weigh the value of output after the conversion of land functions, and to propose a new spatial planning program for the land.

5. Conclusions

In recent years, there have been fewer studies on ecological planning in Zhuzhou City, and the scope of research focused on small plots and small areas; the research direction is often in the green space system, ecological network construction, ecological restoration [Huang.B.2021, Zhang. H.2022], and other aspects, which has certain limitations in targeting ecological planning aspects. This study is based on a large amount of data analysis, with a wide range of research scope and more precise boundaries, and has practical significance. It analyzes the landscape structure and evolution characteristics of Zhuzhou City from the macro perspective, combining the PCA method with the data changes of driving factors to deeply explore the changing driving factors of the landscape pattern in Zhuzhou City. However, the study only analyzes the current situation from the perspective of the landscape pattern index, which has some limitations. Its exclusive focus on landscape pattern indices may overshadow other important ecological factors, such as ecological sensitivity and connectivity. Furthermore, the effects of human activity and climate change on landscape evolution are not evaluated. More thorough insights for Zhuzhou City's land use and ecological planning should come from future research on ecological sensitivity, eco-networks, and corridors. Additionally, incorporating climate change estimates and spatial-temporal dynamics might strengthen the findings' resilience. Further exploration is warranted to assess ecological sensitivity, eco network [Lu.J.2023], and ecological corridors to provide more data support and planning reference for land use and ecology planning in Zhuzhou City.

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