Analysis of Changes in Land Use Landscape Patterns and Their Driving Forces in Jingzhou City Over the Past 30 Years

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Abstract This study analyzed four periods of land use raster data in 1992, 2002, 2012, and 2022, utilizing software tools such as ArcGIS 10.7, Fragstats 4.2, and the PLUS model. The objective was to identify the characteristics of land use changes in the major urban areas of Jingzhou City, specifically in Jingzhou District and Shashi District, over the past 30 years. Additionally, the analysis incorporated 14 influencing factors to determine the primary influencing factors of various land use changes. The findings indicated that: (i) the area designated for construction within the study region had consistently expanded in a distinct north-easterly direction from 1992 to 2022. The primary increase in construction land was attributable to the decrease in cultivated land. Despite a decrease in its proportion, cultivated land remained the predominant landscape throughout this period. (ii) The expansion of construction land led to a reduction in the spatial aggregation of various land types, an increase in fragmentation, a decrease in heterogeneity, and a rise in the complexity of land shapes. (iii) Socio-economic factors, including distances to primary and secondary roads, highways, and natural elements such as precipitation, DEM, and distance to water systems, were the primary driving factors influencing various land use changes. Overall, socio-economic factors serve as the principal driving force of changes in land use landscape patterns in the study area.

Keywords Land use change, Landscape pattern, Influencing factor
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In recent years, the rapid pace of urbanization has resulted in a range of ecological and environmental challenges, including the degradation of urban ecosystems, significant environmental deterioration, shortage of soil and water resources, and traffic congestion. These issues have profoundly impacted the sustainable development of urban economies and societies in China. Land use changes can comprehensively illustrate the environmental changes induced by human activities[1]. In this research domain, scholars both domestically and internationally have conducted studies and analyses to varying extents across different spatial scales[2], employing diverse research methods[3]. Nevertheless, there is a paucity of research concerning the changes in land use landscape patterns across various small urban lands in China. In this study, ArcGIS 10.7, Fragstats 4.2, and PLUS model software were employed to analyze land use data from the study area spanning the years 1992 to 2022, to identify the change trends of land use landscape patterns over the past 30 years. Furthermore, the study examined the primary factors influencing the changes in each type of landscape, thereby providing support for the subsequent utilization and conservation of land resources within the study area.

1 Overview of the study area

Jingzhou City is situated in the south-central region of Hubei Province. It exhibits a maximum horizontal extent of 274.8 km from east to west and a maximum vertical extent of 130.2 km from north to south, demonstrating a zonal distribution along the Yangtze River. The Yangtze River traverses the city from west to east, with a total length of 483 km. The terrain of the city is characterized by a gradual elevation from the east to the west, transitioning from low hills to downlands and plains.

The study focused on two primary urban areas within Jingzhou City, Hubei Province: Jingzhou District and Shashi District. Jingzhou District is situated at the western extremity of Jingzhou City, within the central region of the Jianghan Plain. Jingzhou is recognized as one of the first 24 historical and cultural cities designated in China. It encompasses the core area of the Jingzhou Large Site Protection Zone in Southern China, which includes the Chuji South City, as well as the well-preserved Jingzhou Ancient City Wall. Jingzhou District encompasses a total area of 104,580 hm^2, which constitutes 7.4% of the overall area of Jingzhou City. As of the conclusion of 2022, the resident population of Jingzhou District was recorded at 579,200 individuals. Shashi District, another central district within Jingzhou City, is situated in the eastern region of the city, along the northern bank of the Jingjiang section of the Yangtze River. This district covers an area of 52,275.38 hm^2, representing approximately 3.7% of the total area of Jingzhou City. As of the end of 2022, the resident population of Shashi District was recorded at 681,100 individuals. Both Shashi and Jingzhou districts are situated within the same subtropical humid monsoon climate zone, characterized by four distinct seasons, ample heat, and significant rainfall. The annual precipitation in Shashi District typically ranges from 958 to 1,325 mm, whereas Jingzhou District experiences annual rainfall between 1,100 and 1,300 mm. Furthermore, the average annual temperature in both districts is approximately 16°C. The geographical location of the study area is illustrated in Fig.1.

2 Data and methods

2.1 Data sources

The study primarily utilized land use data captured in the years 1992, 2002, 2012, and 2022, all at a resolution of 30 m. The land use types were categorized into six distinct classifications: cultivated land, forest land, grassland, water bodies, construction land, and unused land, in accordance with the objectives of the study. The results of this classification are presented in Fig.2. Data pertaining to population, gross domestic product (GDP), and other relevant metrics were sourced from various online platforms, including the Geospatial Data Cloud, the Resource and Environmental Science Data Centre, and the National Earth System Science Data Centre.

2.2 Study methods

The research examined the changes in landscape patterns over the past 30 years within the study area by analyzing the land use transfer matrix and landscape pattern index from 1992

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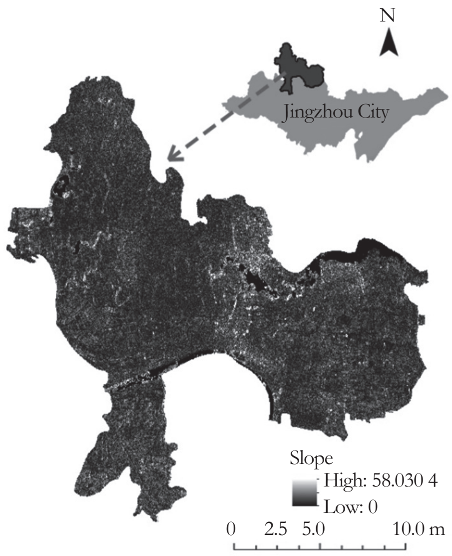

Fig.1 Study area

to 2022. The land use transfer matrix serves as a tool to characterize the transitions among various land use types, thereby illustrating both the magnitude and direction of these transitions over a specified study period[4]. The analysis of landscape index within the field of landscape ecology serves to characterize the composition, shape, spatial configuration, and spatial patterns of landscape units[5]. This study analyzed the characteristics of landscape pattern changes from 1992 to 2022, taking into account various factors, including patch characteristics. Seven types of landscape indices were selected for this analysis: percentage of landscape (PLAND), patch density (PD), splitting index (SPLIT), inters-persion and juxtaposition index (IJI), lands-cape shape index (LSI), patch aggregation index (AI), and patch cohesion index (COHESION)[6]. The calculations were performed using Fragstats 4.2 software. Additionally, 14 influencing factors were identified using the PLUS model to examine the primary determinants of landscape pattern changes.

3 Results and analysis

3.1 Analysis of land use change

By analyzing and sorting the land use data across four distinct periods, Fig.2 and Table 1 were generated. Fig.2 illustrates the transfer of land use types within the study area over different time intervals, which were delineated into three periods, each spanning 10 years. By compiling and examining the transfer area exceeding 100 hm^2, as presented in Table 1, the predominant trends in land type transfer across various locations was inferred. The alterations in unused land and grassland were negligible and therefore not significant enough to warrant consideration.

Between 1992 and 2002, a total of 2,348.01 hm² of cultivated land was converted to construction land, 118.62 hm² to forest land, and 5,263.29 hm² to water bodies. Additionally, 1,151.82 hm² of water bodies was converted back to cultivated land, 190.35 hm² to construction land, while 344.79 hm² of forest land was converted to cultivated land. The area of sporadic conversions between various land types was minimal, measuring less than 100 hm^2. Overall, the predominant trend involved the conversion of cultivated land into water bodies, construction land, and forest land. This was followed by the conversion of water bodies into construction land and cultivated land, as well as the conversion of forest land into cultivated land.

From 2002 to 2012, a total of 2,372.76 hm^2 of cultivated land was converted to construction land, 467.1 hm^2 to forest land, and 904.05 hm^2 to water bodies. In contrast, the area of construction land converted back to cultivated land was negligible, while the area of forest land converted to cultivated land amounted to 94.68 hm^2. In the context of water bodies, an area of 5,301.45 hm^2 was converted to cultivated land, while 382.59 hm^2 were transformed into construction land. When compared to the preceding decade, there was a greater conversion of cultivated land to other land types. Additionally, between 2002 and 2012, a significant amount of water bodies was converted into cultivated land.

The trend observed from 2012 to 2022 closely resembled the combined trends of the periods from 1992 to 2002 and from 2002 to 2012. This trend was characterized by the conversion of cultivated land into construction land, forest land, and water bodies. Additionally, there were notable transitions from water bodies to cultivated land and construction land, as well as from forest land to cultivated land and from construction land to water bodies. A total of 4,439.07 hm² of cultivated land was converted to construction land, 594.27 hm^2 to forest land, and 1,047.96 hm^2 to water bodies. Conversely, water bodies were converted to cultivated land in an area of 3,123.36 hm^2, and to construction land in an area of 329.04 hm^2. Additionally, forest land was converted to cultivated land in an area of 250.56 hm^2, and construction land was converted to water bodies in an area of 107.37 hm^2.

The analysis presented above indicated that the predominant spatial change patterns of land use types within the study area included the conversion of cultivated land to construction land, forest land, and water bodies, the transfer of water bodies to cultivated land and construction land, alongside a minor exchange between forest land and cultivated land. The most significant increase in land use change was characterized by the transition of cultivated land and water bodies to construction land, whereas the alterations involving grassland and unused land were relatively insignificant. In conjunction with the data presented in Table 1, it can be inferred that throughout the study period, the area designated for construction within the study region showed a consistent annual increase. Conversely, the trends associated with cultivated land, water bodies, and forest land were more complex. The final results indicated an increase in forest land area, while both cultivated land

Table 1 Transfer matrix of land use types in the study area from 1992 to 2022 hm^2

Time interval		Cultivated land	Construction land	Forest land	Water bodies
1992–2002	Cultivated land	127,669.68	2,348.01	118.62	5,263.29
	Construction land	2.61	5,265.09	0.00	47.16
	Forest land	344.79	5.31	370.80	8.10
	Water bodies	1,151.82	190.35	9.00	15,493.05
2002–2012	Cultivated land	125,416.17	2,372.76	467.10	904.05
	Construction land	6.57	7,777.89	0.00	25.83
	Forest land	94.68	2.70	394.56	6.48
	Water bodies	5,301.45	382.59	0.90	15,122.97
2012–2022	Cultivated land	124,737.57	4,439.07	594.27	1,047.96
	Construction land	5.49	10,423.17	0.00	107.37
	Forest land	250.56	1.62	610.11	0.27
	Water bodies	3,123.36	329.04	0.18	12,606.12

and water bodies experienced a decline. This phenomenon is closely linked to the processes of development and construction, as well as the impacts of human activities in Jingzhou District and Shashi District over the past 30 years.

3.2 Analysis of changes in landscape patterns

The landscape pattern indices for grassland and unused land were not analyzed, as these areas were relatively small and can not be accurately calculated using Fragstats 4.2.

The analysis of PLAND, which denotes the proportion of various land types relative to the total area, reveals that the highest PLAND values are associated with the predominant landscapes within the study area. The data presented in Table 2 indicated that, despite a 4.6% decrease in the PLAND values of cultivated land from 1992 to 2022, these values consistently remained significantly higher than those of other landscape types throughout the 30 years. Cultivated land had consistently been the predominant landscape in the region, affirming that the landscape characteristics of the study area were influenced by cultivated land. The second most prevalent landscape type, on average, was water bodies, which constituted between 8.69% and 13.14% of the total landscape area across the entire region. The trend in the PLAND values from 1992 to 2012 exhibited an inverse trend with that of cultivated land, which initially increased before subsequently declined. However, both landscape types demonstrated a consistent decrease in PLAND values in 2022. Overall, both types experienced a reduction in PLAND values over the past 30 years. The other two land types, namely construction land and forest land, generally exhibited an upward trend; however, the increase in construction land was significantly more pronounced than that of forest land. Specifically, the PLAND value for construction land ultimately rose by 6.25%. The results of the analyses indicated that construction land experienced the most significant changes over the past 30 years. This finding suggests that cultivated land has predominantly characterized the landscape pattern of the study area during the past 30 years, while the alterations in construction land have played a central role in the overall transformation of the landscape pattern within the study area.

From the perspective of PD, as illustrated in Table 2, the PD values over the past 30 years can be ranked from highest to lowest as follows: construction land, water bodies, cultivated land, and forest land. Notably, the PD value for construction land exhibited a consistent increase, rising from 2.41 in 1992 to 2.86 in 2022. The PD value of water areas experienced a significant increase from 1.82 in 1992 to 2.77 in 2002, followed by a gradual decline over subsequent years, ultimately reaching a value of 1.88, which is comparable to the level recorded in 1992. In contrast, the PD value of forest land initially decreased from 0.67 in 1992 to 0.42 in 2002, subsequently stabilizing around an average value of 0.40, indicating minimal overall change in this type. The trend observed in cultivated land exhibited a more complex pattern, characterized by an initial increase, followed by a decrease, and then a resurgence, culminating in an increase of 0.24 by 2022. In conjunction with the SPLIT data, the mean values of SPLIT over the past 30 years, in descending order, was as follows: forest land, construction land, water bodies, and cultivated land. Notably, the SPLIT of forest landscape patches was the highest among the four landscape types, despite forest land comprising the smallest proportion of PLAND and PD. Conversely, cultivated land had the largest PLAND, but exhibited the least SPLIT among the four landscape types. Over the 30 years, the SPLIT of cultivated land exhibited a partial increase, but this growth was not statistically significant. In contrast, the PLAND and PD of construction land experienced an increase, accompanied by a significant and continuous reduction in SPLIT. This trend suggested a gradual expansion of construction land, characterized by a tendency towards aggregation. Furthermore, the SPLIT associated with water bodies and forest land did not demonstrate a consistent pattern of increase or decrease. Instead, these landscapes exhibited two distinct trends: one that initially increased and subsequently decreased, and another that first decreased and then increased. These observations indicate that the dynamics of landscape SPLIT in the study area have become increasingly complex over the past 30 years.

The data analyzed in conjunction with

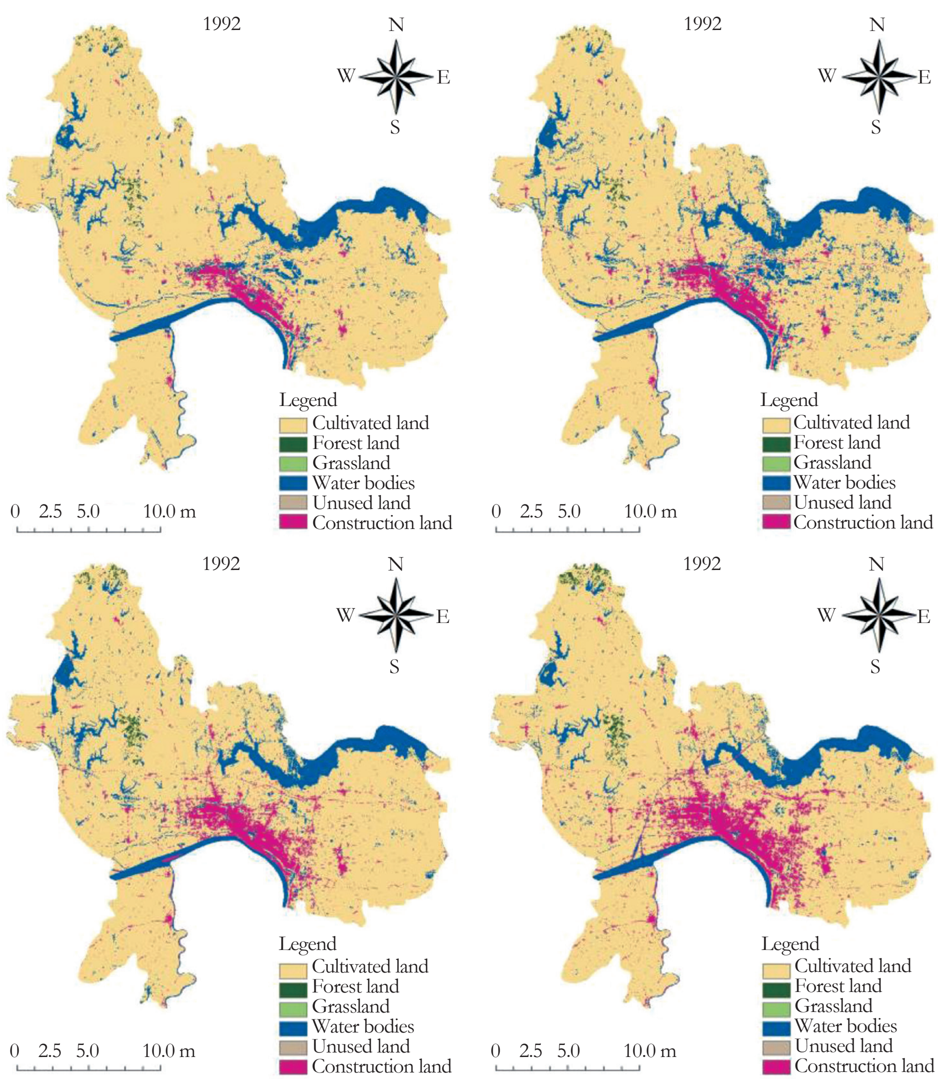

Fig.2 Land use status in the study area from 1992 to 2022

AI and COHESION revealed the extent of aggregation and disaggregation within the landscape. The mean values of landscape AI in the study area, ranked from highest to lowest, were as follows: cultivated land, water bodies, construction land, and forest land. The AI values for cultivated land across all four periods exceeded 95, signifying a very high level of landscape spatial connectivity. Similarly, the AI values for water bodies consistently surpassed 88, indicating a strong landscape spatial connectivity as well. The mean AI value of forest land just reached 69.66, suggesting a more dispersed spatial distribution of forest land. Furthermore, both the AI and COHESION values for forest land and construction land exhibited an upward trend from 1992 to 2022. This trend indicated an increase in the spatial connectivity between forest land and construction land, as well as an improvement in the degree of aggregation. The AI values associated with water bodies exhibited a trend characterized by an initial decrease followed by an increase. Additionally, the landscape aggregation of water bodies demonstrated an upward trend based on the results. In contrast, the AI and COHESION values for cultivated land displayed minimal fluctuation and indicated a decreasing trend, while the landscape aggregation of cultivated land experienced a slight decline according to the findings.

The alterations in IJI over the past 30 years indicated significant changes in landscape heterogeneity across four distinct landscape types. Notably, a significant reduction in cultivated land was observed between 1992 and 2002, while the other three types remained relatively stable, maintaining an IJI value around 53%. The final analysis indicated an overall reduction of 2.32%, with the IJI value for cultivated land being markedly higher than that of the other three types. The data trends for construction land exhibited an initial increase followed by a subsequent decrease, culminating in a final reduction of 3.33%. In contrast, the data for water bodies demonstrated a decrease followed by an increase, resulting in a final increase of 7.15%. Similarly, the changes in forest land mirrored the trend observed in construction land, characterized by an increase followed by a decrease. However, the fluctuations in forest land were more pronounced, leading to a final decrease of 12.64%. Overall, cultivated land patches exhibited the highest degree of landscape heterogeneity, followed by forest land, water bodies, and construction land.

LSI serves as an indicator of both the irregularity and complexity of patch shape characteristics. As indicated in Table 2, the complexity of patch shapes associated with construction land exhibited a gradual increase, rising from an initial value of 53.12 to 68.50. Furthermore, based on the mean value, the current complexity of patch shapes in construction land was found to be the highest among the four landscape types analyzed. The trends and magnitudes of change in the three remaining types of landscapes exhibited variability. Specifically, the trend for water bodies initially increased and subsequently decreased, while forest land experienced a decrease followed by an increase. Cultivated land demonstrated a pattern of first increasing, then decreasing, and finally increasing again. In terms of the magnitude of change, the order was as follows: water bodies exhibited the greatest change, followed by cultivated land, and finally forest land. In conclusion, the complexity of patch shapes among the four types of landscape patches was ranked in descending order as follows: construction land, water bodies, cultivated land, and forest land.

3.3 Analysis of influencing factors

The factors influencing changes in landscape patterns primarily encompass both natural and socio-economic elements. The natural factors include, but are not limited to, climate, hydrology, geology, geomorphology, atmospheric conditions, and vegetation, and other environmental components[7]. Socio-economic factors encompass a range of elements, including the level of urbanization, land use policies, population change, economic growth, technological advancements, and political and economic policies[8]. In this study, the change in area of each land type from 1992 to 2022 was designated as the dependent variable. The LEAS model, which is

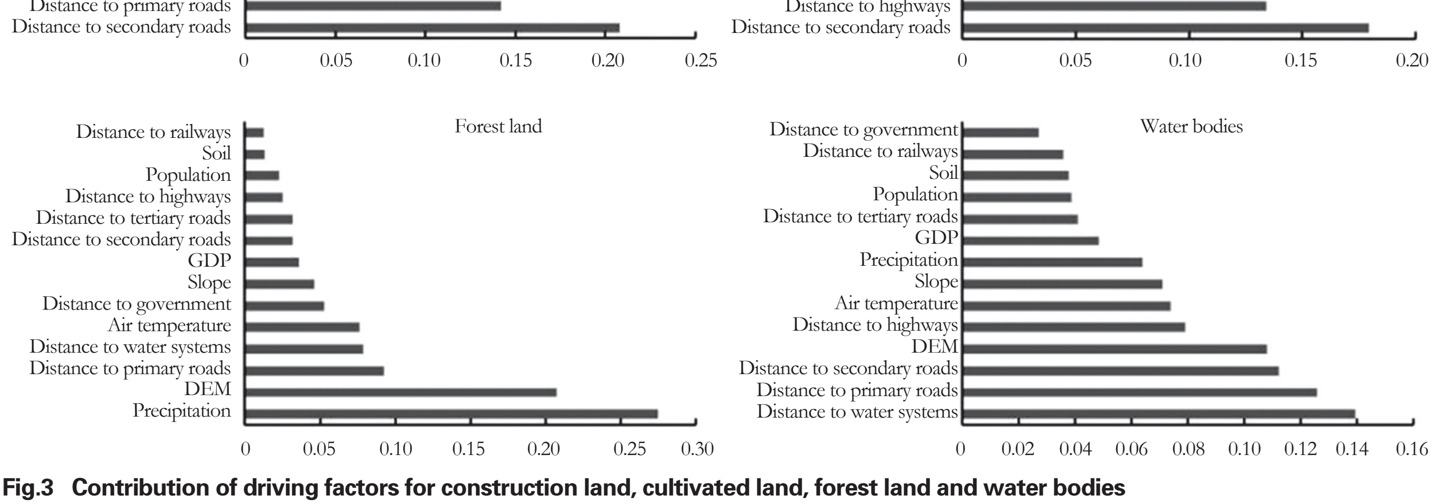

Fig.3 Contribution of driving factors for construction land, cultivated land, forest land and water bodies

part of the PLUS model, was employed to assess the contribution of 14 influencing factors to the changes observed in each land type. A higher contribution value indicates a greater impact on the expansion of land use[9-11]. The 14 influencing factors selected for this analysis included: GDP, population, DEM, slope, air temperature, precipitation, soil type, and distances to primary roads, secondary roads, tertiary roads, railways, highways, government, and water systems. The grassland and unused land were not addressed at this time, as their size was insufficient for meaningful data analysis.

As illustrated in Fig.3, the primary factors influencing changes in construction land included distances to secondary roads, primary roads, and highways. The analysis of the study area over a specified time interval revealed that the expansion of construction land was significant and concentrated in areas located near secondary and primary roads. Furthermore, an examination of the ratios of these influencing factors indicated that social and economic factors were the predominant determinants of changes in construction land. The primary factor influencing cultivated land was the distance to secondary roads and highways, followed by DEM and precipitation. The findings indicated that the distance to secondary roads within the study area significantly influenced the extent of cultivated land that was converted to construction land. Specifically, areas of cultivated land that were located closer to secondary roads exhibited a greater degree of conversion into construction land. Furthermore, an analysis of the influencing factors revealed that socio-economic factors were the primary determinants of changes in cultivated land. The primary factors influencing forest land were precipitation and DEM. In the study area, regions characterized by higher annual average precipitation exhibited a significant increase in forest land area. As illustrated in Fig.3, the most substantial changes were observed in the forest regions of Balingshan Township and Chuandian Township, where natural factors constituted a predominant portion of the influencing factors, accounting for 69%. The primary factors influencing water bodies included distances to water systems, primary and secondary roads, and DEM. In the study area, which encompasses parts of Long Lake and the Yangtze River Basin, there has been an increase in the area of water bodies. Conversely, the water bodies located near the urban area of Jingzhou City have experienced a significant reduction in size. This observation indicates that as the distance from water systems decreases, the area of water bodies tends to increase. In contrast, areas closer to primary and secondary roads are associated with a decrease in the size of water bodies. Furthermore, the ratio of natural factors to human factors in their impacts on water bodies is approximately one to one.

Table 2 Changes in landscape patterns in the study area from 1992 to 2022

Landscape index	Land type	1992	2002	2012	2022
PLAND	Cultivated land	85.538 9	81.602 7	82.645 0	80.938 2
	Forest land	0.460 5	0.314 9	0.544 9	0.761 0
	Construction land	3.357 7	4.934 2	6.656 2	9.606 3
	Water bodies	10.641 4	13.148 0	10.145 6	8.694 0
PD	Cultivated land	0.697 5	0.942 6	0.754 9	0.935 6
	Forest land	0.674 7	0.429 6	0.391 1	0.407 5
	Construction land	2.410 1	2.540 3	2.675 5	2.863 1
	Water bodies	1.825 8	2.775 9	2.003 9	1.888 9
SPLIT	Cultivated land	1.729 1	1.935 1	1.880 9	1.985 0
	Forest land	3,874,698.523 0	4,022,595.550 0	405,571.819 9	319,705.305 8
	Construction land	3,004.588 3	1,414.959 8	858.745 9	362.645 5
	Water bodies	475.165 2	431.869 3	464.397 9	665.973 8
AI	Cultivated land	97.679 9	96.686 4	97.189 4	96.918 8
	Forest land	63.695 4	65.178 0	73.313 3	76.492 3
	Construction land	78.419 7	80.954 7	82.239 8	83.519 2
	Water bodies	88.640 2	86.071 0	88.749 9	90.044 7
COHESION	Cultivated land	99.975 0	99.972 6	99.972 0	99.967 0
	Forest land	80.832 2	83.542 7	92.437 2	92.426 5
	Construction land	97.683 5	98.045 7	98.329 2	98.960 3
	Water bodies	98.241 0	97.867 6	98.261 5	97.604 9
IJI	Cultivated land	54.470 8	46.637 3	53.993 5	52.149 3
	Forest land	33.013 7	43.509 1	31.173 4	20.369 6
	Construction land	15.530 6	16.760 0	14.821 5	12.193 5
	Water bodies	17.641 8	16.279 1	20.911 1	24.798 8
LSI	Cultivated land	29.423 8	40.647 5	34.847 0	37.720 2
	Forest land	33.311 1	26.536 9	26.831 6	27.887 9
	Construction land	53.121 1	56.835 6	61.527 0	68.501 8
	Water bodies	49.987 3	67.825 4	48.401 2	39.782 9

4 Conclusions

This study focuses on the primary urban areas of Jingzhou City, specifically Jingzhou District and Shashi District. An analysis of remote sensing images from 1992 to 2022 was conducted utilizing GIS, Fragstats, and PLUS software. The objective was to derive insights regarding land use and landscape patterns within the study area. The following conclusions were drawn from the analysis.

(1) Between 1992 and 2022, the predominant land use type in the study area was cultivated land, succeeded by water bodies, construction land, and forest land. Notably, both construction land and forest land experienced an increase in area. However, only construction land exhibited a consistent upward trend, while both water bodies and cultivated land showed a reduction in area. The primary transformation processes observed in the study area included the conversion of cultivated land to construction land, water bodies, and grassland, as well as the transition of water bodies to cultivated land and construction land.

(2) The analysis of landscape pattern indices in the study area revealed that cultivated land had been the predominant landscape from 1992 to 2022. During this period, the expansion of construction land had increasingly contributed to the fragmentation of other landscape types within the study area. Consequently, the shapes of landscape patches became more complex, while the heterogeneity of other landscape types, with the exception of water bodies, had gradually diminished. Overall, the findings indicate a trend of fragmentation in the landscape of the study area.

(3) The analysis of driving forces showed that the primary influencing factor on the conversion of construction land and cultivated land was the distance to secondary roads. Predominantly, socio-economic factors played a significant role in this dynamic. The development of various types of artificially planned roads had resulted in a gradual transformation of cultivated land adjacent to secondary roads into construction land, leading to a consistent annual

(To be continued in P68)

within the context of study tour activities by designing specific case studies. The findings not only offer innovative insights and directions for the organization and design of study tour activities but also contribute to the development of essential competencies in students, including place identity, global perspective, and critical thinking. A regional exploration was conducted utilizing Dongyi Town as a case study. While this case is representative and typical, it is relatively limited in scope. Future research should consider expanding to additional regions and areas to validate and enhance the conclusions and findings of this study.

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decrease in the area of cultivated land. The most significant influence on forest land was precipitation, with human factors contributing approximately 30% to this impact. In contrast, the effects of both human and natural factors on water bodies were more uniformly distributed. The findings indicate that all forms of landscape alterations within the study area are collectively influenced by both human and natural factors. However, urban expansion and human interventions exert a more significant impact on the various landscape types in the region. Consequently, the direction and rate of changes in land use landscape are still affected by a range of socio-economic factors.

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