SPATIOTEMPORAL EVOLUTION AND DRIVING FORCES OF LAND USE PATTERNS IN CHANGDE CITY, CHINA (1995–2020)

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Abstract. This study aims to reveal the spatiotemporal evolution characteristics and driving mechanisms of land use patterns in Changde City, China, from 1995 to 2020, providing scientific support for the sustainable utilization of regional land resources and territorial spatial planning. By comprehensively applying various methods, including the land use dynamic degree model, transfer matrix, kernel density analysis, land use intensity composite index, and geographical detectors, the study analyzed the quantitative changes, spatial pattern evolution, and driving factors of land use types in Changde City. The results indicate that significant changes in land use types occurred during the study period, characterized by a gradual decrease in cropland and grassland areas, significant expansion of impervious surfaces, and relatively stable forest and water areas. Cropland was primarily converted into impervious surfaces, reflecting the profound impact of rapid urbanization and industrialization on land use patterns. Kernel density analysis revealed that the spatial distribution of cropland gradually expanded, while impervious surfaces expanded rapidly along transportation corridors and industrial parks, highlighting urban land expansion. Driving factor analysis demonstrated that socioeconomic factors were the dominant forces behind land use changes in Changde City, with population density, secondary industry output, and gross domestic product (GDP) having the most significant impact. Natural factors influenced land use patterns indirectly through interactions with socio-economic factors. The study highlights the dynamic balance between urbanization and ecological protection in Changde City and provides scientific recommendations for future land use planning and regional sustainable development.
Keywords: *land use, spatiotemporal evolution, driving force, geographical detector, Changde City*

Introduction

Land is the foundation for human survival and socio-economic development. Changes in land use not only involve economic growth but are also closely linked to ecological environments and societal development. Land use change is a significant driver of global climate and environmental change, reflecting how human activities interact with the natural environment across temporal and spatial dimensions. Moreover, it directly reflects human impacts on the Earth's surface (Zhou et al., 2019). In 1995, the "International Geosphere-Biosphere Programme" (IGBP) and the "International Human Dimensions Programme on Global Environmental Change" (IHDP) jointly launched the "Land Use/Land Cover Change" (LUCC) research project (Zhang et al., 2010). This initiative aimed to explore the impacts of land use and land cover changes on global environmental change and the driving mechanisms behind these changes. Subsequently, in 2005, the "Global Land Project" (GLP) identified this research area as a core component of global environmental change and sustainable development studies. This research focus has garnered significant global attention and has been incorporated in national development plans by numerous countries, providing a critical scientific basis

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for the sustainable management of land resources and policymaking (Kotoky et al., 2012).

Currently, scholars have conducted extensive research on various aspects of land use, including the spatial pattern characteristics of land use (Schulz et al., 2021; Wang et al., 2021; Fu et al., 2022), land use transformation (Long et al., 2021; Long, 2022; Nguyen et al., 2023; Zou et al., 2024), land use change processes (Liang et al., 2021; Winkler et al., 2021; Zhu et al., 2021), changes in the ecosystem service values of land use (Cao et al., 2021; Peng et al., 2021; Wang et al., 2022), driving forces and mechanisms of land use change (Wu et al., 2021; Li et al., 2022; Wang et al., 2022), the simulation of land use patterns (Chaturvedi and de Vries, 2021; Wang et al., 2022), and scenario-based simulations and future predictions of land use changes (Chang et al., 2021; Gao et al., 2022; Ghalehteimouri et al., 2022). With technological advancements, research methods for land use change have continually evolved, particularly in terms of data acquisition and processing, model application, and analytical techniques. Remote sensing imagery and GIS technology have become core tools for monitoring and analyzing land use, supporting accurate land cover classification and spatiotemporal dynamic analysis across multiple scales and time periods (Vivekananda et al., 2021; Li et al., 2022). In addition to remote sensing data, many studies have integrated various data sources, such as socio-economic statistics, meteorological data, and survey data, thereby enhancing the comprehensiveness and precision of land use change research (Luo et al., 2022; Touseef et al., 2023). Innovations in models and methodologies have enabled the analysis of the driving forces, spatial evolution processes, and patterns of land use, such as geographic detectors (Wu et al., 2021; Cui et al., 2022), regression analysis (Xie et al., 2022), the CA-Markov model (Fu et al., 2022), the CLUE-S model (Song et al., 2024), and deep learning algorithms (Yao et al., 2023). Research on land use change has also expanded from a single scale to multiple scales (Li et al., 2024) and from a single dimension to multiple dimensions (Wang et al., 2024), enabling the integrated analysis of spatiotemporal dynamics and comprehensive effects.

Land use change remains a prominent topic in regional studies, with existing research primarily focused on large-scale regions such as nations or river basins, while small-scale case studies are relatively scarce. Therefore, this study, based on the natural and socio-economic development characteristics of Changde City, employs multiple research methods to characterize the spatiotemporal patterns of land use over the past 30 years across different developmental stages. The study aims to reveal the evolutionary laws of various land use types, analyze the driving factors of these changes using geographic detectors, and compare the driving factors across different developmental stages. The results are expected to provide theoretical references for the sustainable development and utilization of Changde City's land resources, as well as its socio-economic development, and to offer scientific support for territorial spatial planning.

Material and methods

Study area

Changde, located in the northwest of Hunan Province, is an important hub city along the Yangtze River Economic Belt and a key component of the Dongting Lake Eco-economic Zone. The city is geographically characterized by its connection to the Yangtze River, surrounded by two rivers (the Yuan River and the Li River), bordered by Dongting Lake to the east and Zhangjiajie to the west. It falls within the subtropical

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humid monsoon climate zone, with an average annual temperature of 16.7°C and an annual precipitation ranging from 1,200 to 1,900 mm. Changde administers 2 districts, 6 counties, and 1 county-level city: Wuling District, Dingcheng District, Hanshou County, Taoyuan County, Linli County, Shimen County, Lixian County, Anxiang County, and Jinshi City (*Figure 1*). The total area of the city is 18,200 km². By the end of 2023, Changde's permanent population reached 5.187 million, including 3.007 million urban residents and 2.179 million rural residents. In 2023, Changde's GDP totaled 438.57 billion yuan, representing a 3.6% increase compared to the previous year.

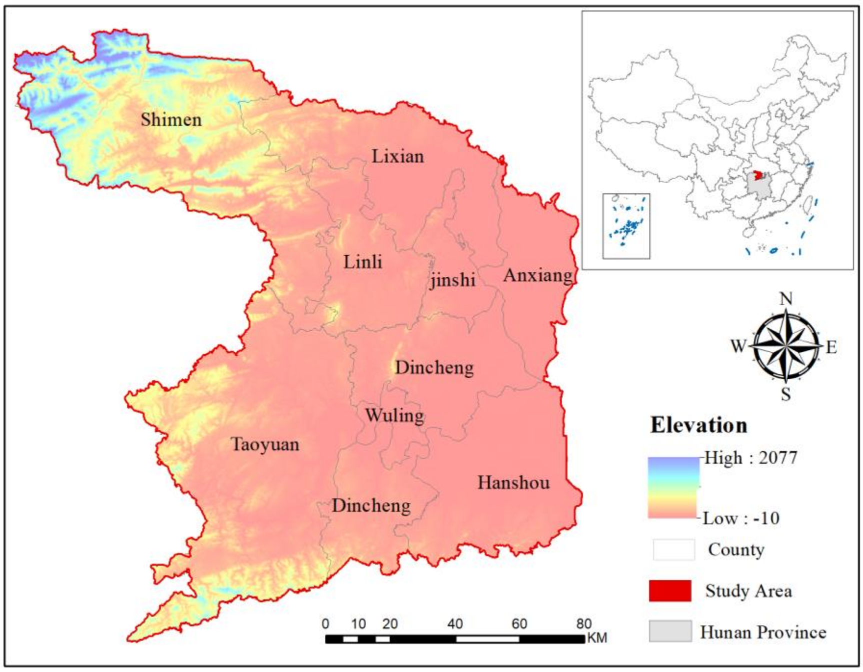

Figure 1. *Map of Changde City's location and topography distribution*

Data sources

The data utilized in this study include satellite imagery obtained from the Geospatial Data Cloud of the Computer Network Information Center, Chinese Academy of Sciences. Land use data for Changde City (1995–2020), with a spatial resolution of 30 meters, was sourced from the Resource and Environmental Science Data Center, Chinese Academy of Sciences (http://www.resdc.cn). Following national and international land use classification systems, the study area's land use types were categorized into six classes (*Table 1*). Soil data were acquired from the Soil Science Data Center of the Nanjing Institute of Soil Science, Chinese Academy of Sciences (http://data.issas.ac.cn/), while DEM data with a spatial resolution of 30 meters was obtained from the Geospatial Data Cloud. Meteorological information, including climate-related parameters, was gathered from the China Meteorological Data Service Center (http://data.cma.gov.cn/site/index.html). Social and public data necessary for analysis were collected from the official website of the Changde Municipal People's Government (https://www.changde.gov.cn/), the Changde Statistics Bureau (https://tjj.changde.gov.cn/), and the Hunan Statistical Yearbook.

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Table 1. *Land use classification system in Changde City*

Primary Category	Secondary Category
Arable Land	Plain paddy fields, plain dry land, hilly paddy fields, hilly dry land, mountainous paddy fields, mountainous dry land
Forest Land	Forest land, shrubland, sparse woodland, other forest land
Grassland	High-coverage grassland, medium-coverage grassland, low-coverage grassland
Water Bodies	Rivers and canals, lakes, reservoirs and ponds, tidal flats
Impervious Surfaces	Urban residential land, rural residential land, industrial and mining construction land
Unused Land	Sandy land, saline-alkali land, bare land, bare rocky land

Methods

This study employs a variety of spatial analysis methods and geographic detection tools, with data processing conducted through ArcGIS 10.8, to comprehensively uncover the patterns and driving factors of land use changes. First, using the land use dynamic degree model and transfer matrix, the study analyzes the quantitative changes, type conversions, and change rates of various land use types in Changde City from 1995 to 2020, revealing the evolutionary characteristics of the quantitative structure of different land use types. Second, kernel density analysis is applied to examine the aggregation changes in land types during the same period, providing a clearer representation of the spatial aggregation features of land use. Third, to gain a more comprehensive understanding of the changes in land use intensity in Changde City, the study employs the comprehensive index of land use intensity and its change rate, combined with hotspot analysis, to evaluate the spatial distribution patterns of land use and reveal the impacts of human activities on land use. Finally, based on the analysis of the spatiotemporal evolution of land use, the study applies geographic detectors to analyze the driving factors of land use changes in different periods and regions, identifying the influence of various factors and the magnitude of interactions among driving factors.

The comprehensive dynamic degree of land use types refers to the overall rate and direction of change for all land use types within the study area during a research period. The calculation method is as follows:

$$LC = \frac{\sum_{i=1}^{n} \Delta S_{i-j}}{2\sum_{i=1}^{n} \Delta S_i} \times \frac{1}{T} \times 100\% \qquad \text{(Eq.1)}$$

In *Equation 1*, *LC* represents the comprehensive dynamic degree of land use change during a research period; *n* is the number of land use types; S_i refers to the area of the *i*th land use type at the beginning of the research period; $\Delta S_{i\text{-}j}$ denotes the absolute value of the area converted from the *i*th land use type to other land use types during the period; and *T* represents the duration of the research period.

The dynamic degree of a single land use type represents the rate and direction of change for a specific land use type during a research period. The absolute value indicates the rate of change, while the sign reflects the direction of change. The calculation formula is as follows:

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$$K = \frac{S_{t_1} - S_{t_0}}{S_{t_0}} \times \frac{1}{T} \times 100\% \qquad \text{(Eq.2)}$$

In *Equation 2*, K represents the dynamic degree of a specific land use type during a research period; S_{t0} and S_{t1} are the areas of that land use type at the beginning and end of the research period, respectively; $T=t_1 - t_0$ is the duration of the research period.

The land use transfer matrix represents the changes in land use types at the beginning and end of the research period in the form of a contingency table. Its calculation method is as follows:

$$S = \begin{bmatrix} S_{11} & S_{12} & \cdots & S_{1n} \\ S_{21} & S_{22} & \cdots & S_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ S_{n1} & S_{n2} & \cdots & S_{nn} \end{bmatrix} \qquad \text{(Eq.3)}$$

In *Equation 3*, n represents the number of land use types; S_{ij} represents the area of land use type i at the beginning of the research period that has been converted to land use type j by the end of the research period.

Results and analysis

Spatiotemporal evolution of land use

The land use types in Changde City exhibited significant dynamic changes between 1995 and 2020 (*Figure 2*). According to the data (*Table 2*), cropland and forestland consistently occupied the largest proportions of land use across six time points, making them the dominant land use types in the city, followed by water bodies and grasslands. Impervious surfaces and unused land accounted for relatively smaller areas; however, the area of impervious surfaces (mainly urban, rural residential, and industrial land) showed a significant upward trend during the study period.

The findings indicate that the proportion of cropland decreased from 42.12% in 1995 to 39.86% in 2020 (*Table 2*), demonstrating an overall declining trend. This suggests that, with the advancement of urbanization and industrialization, parts of the cropland were gradually converted into urban land or ecological spaces. The transformation of agricultural land into urban space particularly influenced the structure of regional land use. Forestland, which accounted for the largest proportion of land use, decreased slightly from 45.82% in 1995 to 45.40% in 2020, reflecting minimal overall changes. This stability suggests that forestland development was relatively restricted under ecological protection policies, maintaining a stable spatial distribution pattern. Grasslands accounted for a small proportion and showed a slow declining trend during the study period, decreasing from 2.79% in 1995 to 2.59% in 2020.

The proportion of water bodies increased over the study period, rising from 6.02% in 1995 to 7.56% in 2020. Conversely, the proportion of impervious surfaces steadily increased from 1.96% in 1995 to 3.22% in 2020. This change reflects the rapid urbanization of Changde City, with an expansion of urban and industrial land driving the increase in impervious surfaces. Unused land remained relatively stable, decreasing slightly from 1.30% in 1995 to 1.38% in 2020. Due to its small proportion and

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distribution in remote areas, changes in unused land had a minimal impact on the overall land use structure.

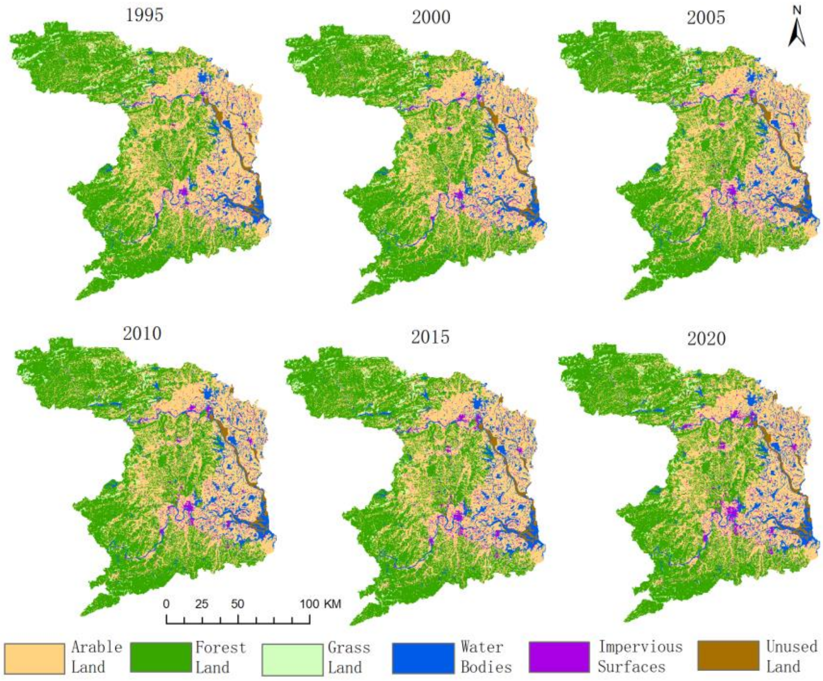

Figure 2. *Spatiotemporal patterns of different land use types in Changde City from 1995 to 2020*

Table 2. *Percentage of Land Use Types in Changde City from 1995 to 2020 (%)*

Land use type	**Proportion of Each Land Use Type (%)**					
	1995	**2000**	**2005**	**2010**	**2015**	**2020**
Arable Land	42.12	41.67	41.14	40.40	40.16	39.86
Forest Land	45.82	45.64	45.61	45.55	45.48	45.40
Grassland	2.79	2.77	2.73	2.62	2.61	2.59
Water Bodies	6.02	6.53	6.94	7.52	7.56	7.56
Impervious Surface	1.96	2.11	2.30	2.52	2.81	3.22
Unused Land	1.30	1.28	1.28	1.38	1.38	1.38

Overall, between 1995 and 2020, the changes in land use types in Changde City were primarily characterized by the conversion of cropland into impervious surfaces (urban, industrial, and mining land). Forestland and water bodies remained relatively stable, while grassland gradually decreased. The increase in impervious surfaces reflects the expansion of land use driven by urbanization and industrialization, while the decline in cropland and grassland indicates that agricultural land was increasingly replaced by urban land. The stability of forestland demonstrates the effectiveness of Changde City's ecological protection efforts. With economic development and intensified human activities, the trend of land use changes reveals the dual demands of urban expansion and ecological conservation in Changde City.

Analysis of land use pattern evolution

Evolution of quantity structure

Based on the dynamic degree data of different land use types in Changde City from 1995 to 2020, significant trends in the quantitative structural changes of various land use types can be clearly observed (*Figure 3*). The single dynamic degree and comprehensive dynamic degree for each time period reflect the overall characteristics of land use changes in Changde City as well as the detailed transformation processes.

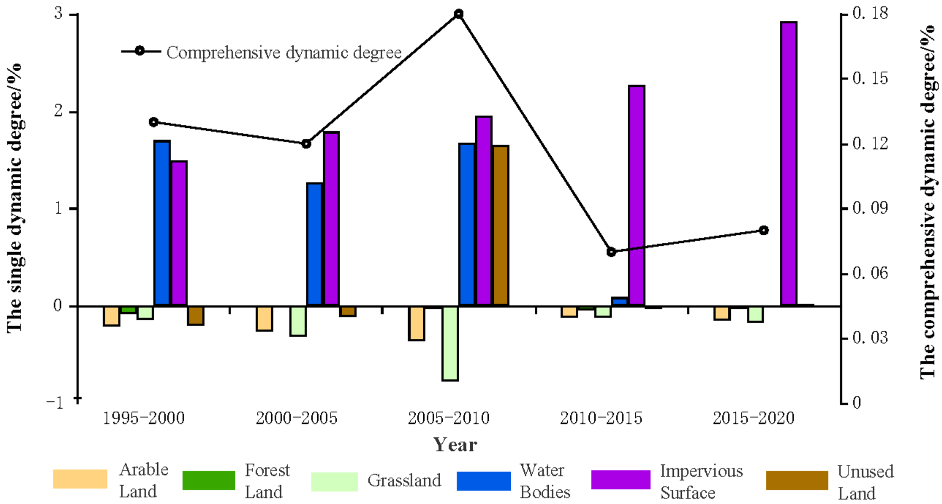

Figure 3. *Dynamic changes of different land use types in Changde City from 1995 to 2020*

The single dynamic degree of cropland remained negative throughout the study period, indicating a continuous decrease in cropland area. Notably, during 2005-2010, the dynamic degree of cropland dropped to -0.36%, the fastest rate of reduction observed. This phenomenon is primarily attributed to the conversion of large areas of cropland into construction land due to urbanization. While the decline slowed during 2010-2015 and 2015-2020, the overall trend remained downward. The single dynamic degree of forestland exhibited minor fluctuations and showed a stable, slight decreasing trend, with values ranging from -0.01% to -0.08%. This suggests that Changde City has made some progress in ecological protection. Although forestland area decreased slightly, its stability indicates that the ecological space remained relatively intact.

Grassland was the most significantly reduced land use type. During 2005-2010, its dynamic degree reached -0.77%, reflecting a sharp decline in grassland area during this period. This reduction may be linked to the conversion of grassland into cropland or construction land. Although the rate of decline slowed during 2010-2020, the negative dynamic degree suggests that grassland area remained in a shrinking state overall. The area of water bodies increased between 1995 and 2010, with dynamic degrees reaching 1.70% and 1.67% during 1995-2000 and 2005-2010, respectively. This growth may be attributed to the implementation of water resource management and ecological conservation policies in Changde City. However, from 2010 to 2020, the area of water bodies stabilized, with a slight decline recorded during 2015-2020 (dynamic degree of -0.01%). The dynamic degree of impervious surfaces was positive throughout all time periods, showing a gradual upward trend. It increased from 1.49% during 1995-2000 to

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2.92% during 2015-2020. The continuous expansion of impervious surfaces reflects Changde City's rapid urbanization and industrialization processes, which were mainly achieved by occupying cropland and grassland. The trends in unused land showed greater variability, with the most significant increase occurring during 2005-2010, with a dynamic degree of 1.65%. This increase may result from preserving or reallocating areas unsuitable for agriculture or construction. However, during other periods, changes in unused land were less pronounced, indicating a relatively stable pattern.

The comprehensive dynamic degree for each time period reflects the overall degree of land use changes in Changde City. Higher values during 1995-2000 and 2005-2010, at 0.13% and 0.18%, respectively, indicate more significant land use changes during these periods, which likely correspond to peaks in urbanization and land development in Changde. From 2010 to 2020, the comprehensive dynamic degree gradually declined, suggesting that land use changes in Changde City were becoming more stable.

In summary, the changes in the quantitative structure of land use types in Changde City from 1995 to 2020 reflect the dual influences of urbanization and ecological protection. The reduction in cropland and grassland primarily served to meet the expanding demand for construction land, while the stability of forestland and water bodies indicates the effectiveness of ecological conservation efforts. The significant expansion of construction land further highlights the profound impact of Changde City's socioeconomic development on its land use structure.

Land type transition

The land use transfer matrix illustrates the structure of various land use types in Changde City from 1995 to 2020 and their mutual conversion relationships. A chord diagram was used to visualize the land use transition dynamics (*Figure 4*).

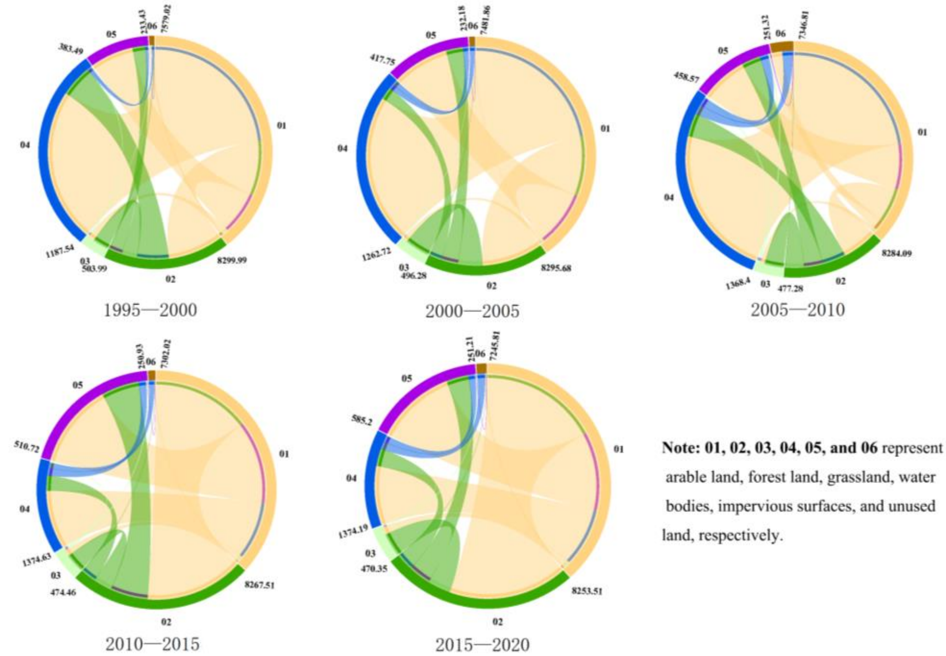

Figure 4. *Chord diagram of changes in different land use types in Changde City from 1995 to 2020*

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Between 1995 and 2000, the total area of land use transitions was relatively small, accounting for only 2% of the total area. This indicates that during this study period, human activities had a limited impact on land use, and changes in the land use pattern were relatively minor. During this time, forestland experienced an outward transfer area of 84.64 km², with the majority being converted to cropland, approximately 46.06 km². This forest-to-cropland conversion was primarily driven by population growth and increased demand for food, which raised the need for additional cropland and prompted the reclamation of some forested areas. Cropland, on the other hand, experienced an outward transfer area of 168.64 km², with the primary transitions being to forestland and water bodies, accounting for 40.00 km² and 99.90 km², respectively. This was due to the conversion of some cropland into forestland as part of reforestation efforts or its transformation into water bodies due to declining soil fertility and unsuitable terrain for farming. Grassland saw an outward transfer area of 11.47 km², mainly transitioning to forestland and cropland, with 6.53 km² and 3.94 km², respectively.

Between 2000 and 2005, the total area of land use transitions decreased compared to the 1995–2000 period. The primary transitions during this phase were concentrated in cropland and grassland. Cropland experienced an outward transfer area of 146.86 km², mainly transitioning to forestland and water bodies, accounting for 35.86 km² and 80.07 km², respectively. This shift was influenced by agricultural policy adjustments or natural environmental changes, such as the restoration of cropland to forestland or its conversion into water bodies due to flooding. Forestland saw an outward transfer area of 53.81 km², primarily transitioning to impervious surfaces and cropland, with 9.48 km² and 36.00 km², respectively. This reflects how, with social development, parts of forestland were developed for construction or reclaimed as cropland.

During the 2005–2010 period, the total area of land use transitions increased to some extent. The major transitions in this phase were concentrated in forestland and cropland. Forestland experienced an outward transfer area of 110.21 km², mainly transitioning to cropland and impervious surfaces, with 54.15 km² and 25.96 km², respectively. The acceleration of urbanization led to increased demand for impervious surfaces, while some forestland was converted to cropland to meet agricultural production needs. Cropland experienced a significant outward transfer area of 289.00 km², primarily transitioning to forestland and water bodies, accounting for 60.05 km² and 162.59 km², respectively. This was due to the implementation of reforestation policies and the conversion of cropland to water bodies for water management projects.

From 2010 to 2015, the total area of land use transitions continued to increase, with cropland and forestland remaining the primary transition types. Cropland experienced an outward transfer area of 131.86 km², mainly transitioning to forestland and impervious surfaces, accounting for 66.26 km² and 40.91 km², respectively. This was due to heightened government emphasis on ecological protection, leading to the reforestation of cropland, while urban expansion also resulted in some cropland being used for construction. Forestland experienced an outward transfer area of 92.31 km², primarily transitioning to cropland and impervious surfaces, accounting for 60.99 km² and 21.26 km², respectively. This reflects the dual influence of urban development, where some forestland was developed into impervious surfaces while other areas were reclaimed for agricultural use.

Finally, during the 2015–2020 period, the total area of land use transitions was relatively large, with cropland and water bodies being the primary transition types. Cropland experienced an outward transfer area of 339.84 km², primarily transitioning to

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forestland and impervious surfaces, accounting for 191.21 km² and 92.02 km², respectively. This highlights the increasing emphasis on ecological protection and the advancement of urban development, which led to the conversion of large amounts of cropland into forestland and impervious surfaces. Water bodies experienced an outward transfer area of 74.01 km², primarily transitioning to cropland, accounting for 46.66 km². This was influenced by water management adjustments or natural factors such as drought, which led to the reduction of water areas and their conversion into cropland.

Spatial pattern evolution

Changes in spatial patterns of land use

Based on the kernel density distributions of cropland, forestland, grassland, water bodies, impervious surfaces, and unused land in Changde City in 1995 and 2020 (*Figure 5 and Figure 6*), the spatial distribution characteristics and changing trends of various land use types can be observed.

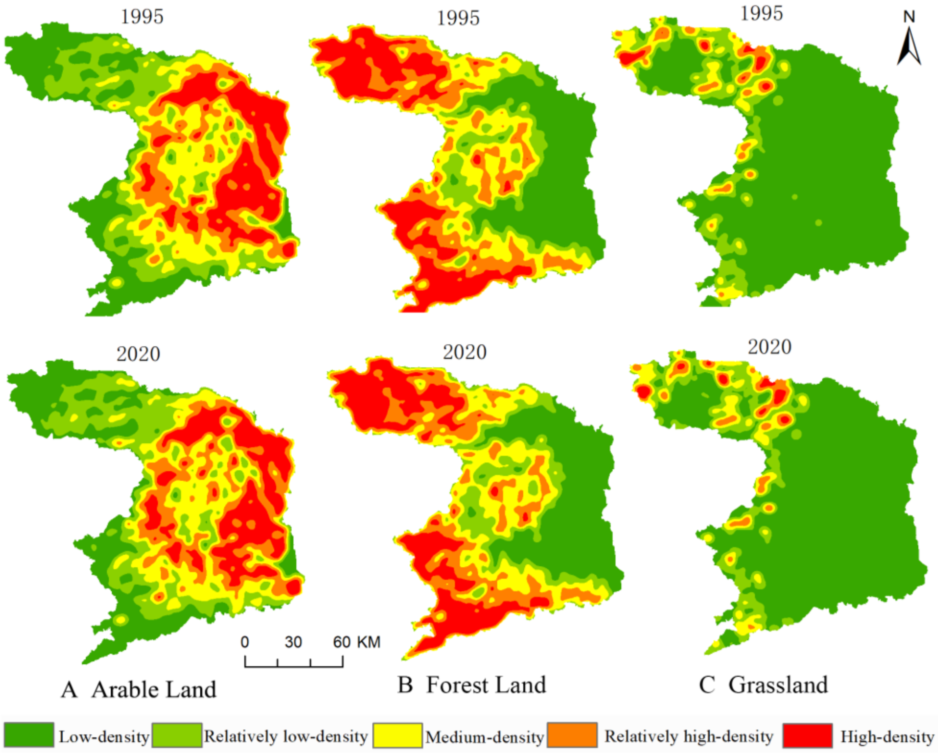

Figure 5. *Kernel density distribution of arable land, forests, and grassland in Changde City from 1995 to 2020*

In 1995, high-density cropland areas were mainly concentrated in the northeastern and central regions of Changde City, exhibiting a relatively clustered distribution pattern, while low-density areas were located in the southern regions. By 2020, the high-density cropland regions further expanded towards the central and western areas, indicating that, along with the development of agricultural production, the spatial distribution of cropland gradually spread westward. However, the overall density of cropland showed a decline.

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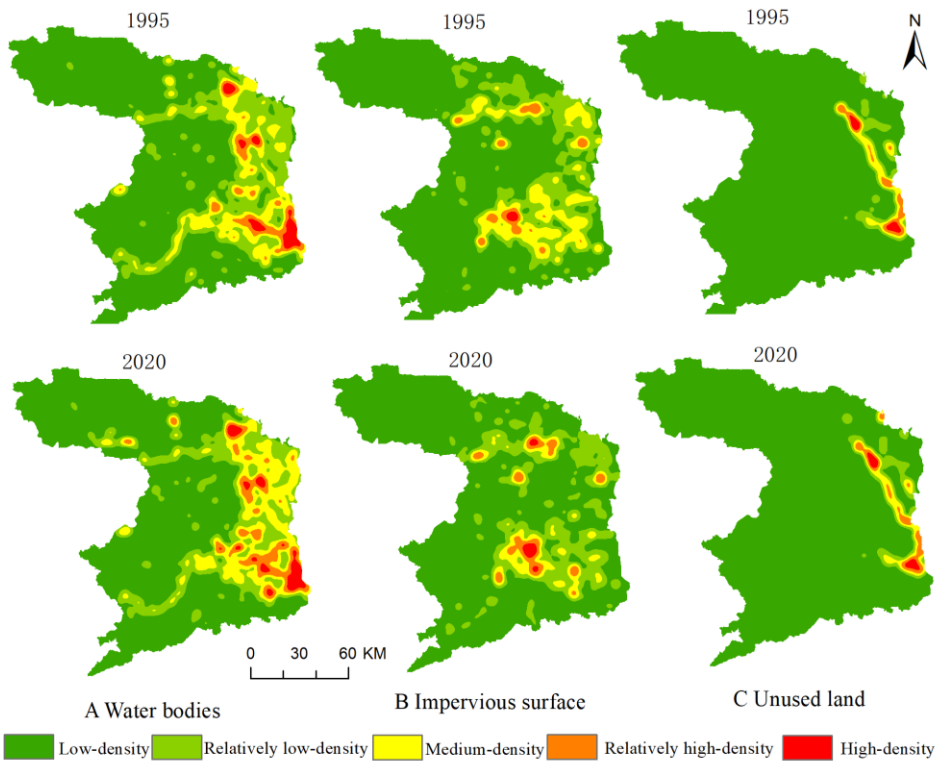

Figure 6. *Kernel density distribution of water bodies, impervious surface, and unused land in Changde City from 1995 to 2020*

In 1995, high-density forestland areas were predominantly distributed in the southwestern and northern mountainous regions of Changde City, particularly in areas near Shimen County and Linli County. By 2020, the high-density forestland areas remained relatively stable, reflecting the stability of forestland in these regions. With the implementation of ecological conservation measures, forestland areas have remained largely unchanged, though forestland in low-density areas has shifted towards ecological conservation zones.

High-density water bodies in 1995 were concentrated along the Yuan River and surrounding river areas, including Dingcheng District and Taoyuan County. As water resource management and protection improved, the high-density water body areas expanded further by 2020, exhibiting stable kernel density characteristics, especially along major river basins such as the Yuan and Li Rivers. While the spatial distribution of water bodies remained relatively stable, some local expansion was observed.

The distribution of impervious surfaces (including urban and industrial construction land) experienced significant expansion in Changde City. In 1995, high-density impervious surface areas were primarily concentrated in core urban areas such as Dingcheng District and Wuling District. By 2020, these high-density areas had expanded further towards surrounding regions, particularly along major transportation corridors and emerging industrial parks. This expansion reflects the significant increase in impervious surfaces driven by Changde City’s urbanization and industrialization processes.

Through the kernel density analysis of various land use types in Changde City from 1995 to 2020, it was found that cropland and impervious surfaces (mainly urban

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construction land) expanded spatially, while forestland and water bodies remained relatively stable. Grassland and unused land showed a declining trend. This pattern of change reflects the combined impacts of urbanization, ecological conservation, and land resource optimization in Changde City. Additionally, it highlights the adjustments to Changde's "three-zone spatial" structure, indicating a shift towards balancing urban development and ecological protection.

Evolution of land use intensity

An analysis of the comprehensive land use intensity index across the districts and counties of Changde City from 1995 to 2020 reveals a general upward trend over time (*Figure 7*). During the study period, the land use intensity index in Changde City reflected changes in land use density brought about by urbanization, particularly in urban areas such as Wuling District and Dingcheng District, where the growth in land use intensity was especially pronounced.

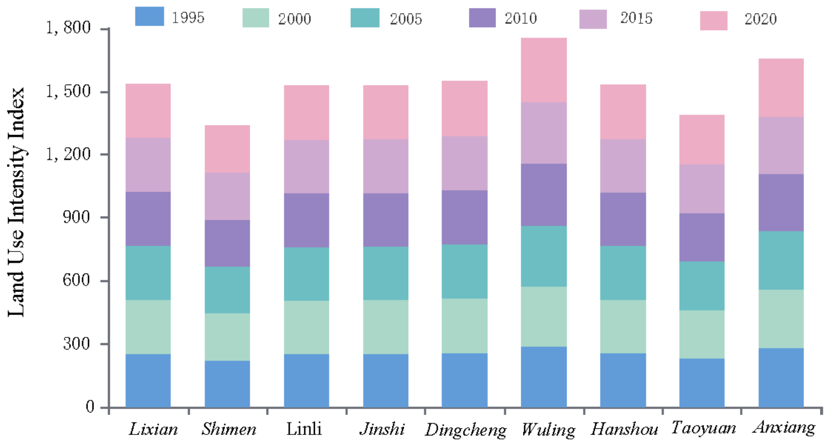

Figure 7. *Changes in land use intensity in Changde City from 1995 to 2020*

From 1995 to 2020, the comprehensive land use intensity index of Changde's districts and counties increased year by year. For instance, Wuling District's index grew steadily from 287.56 in 1995 to 301.15 in 2020, highlighting the characteristics of urban expansion and intensive land development in the region. Similarly, Dingcheng District, Lixian County, and Anxiang County also showed stable growth trends in their land use intensity indexes. In contrast, counties like Shimen and Taoyuan exhibited relatively stable indexes with smaller growth margins, reflecting lower development intensity and a greater emphasis on preserving agricultural and ecological land use.

According to the hotspot distribution map of land use intensity (*Figure 8*), the hotspots of land use in Changde City were primarily concentrated in regions such as Wuling District and Dingcheng District. From 1995 to 2020, the distribution of hotspots remained largely stable, indicating a high demand for land resources in urban core areas. In contrast, cold spots were mainly located in areas such as Shimen County, Taoyuan County, and Anxiang County, where land use intensity was low, dominated by agricultural and ecological land, with relatively limited development activities. This spatial pattern of distribution reflects the imbalance in land use density between urban and rural areas in Changde City, as well as the varying roles and functions of different districts and counties in the urbanization process.

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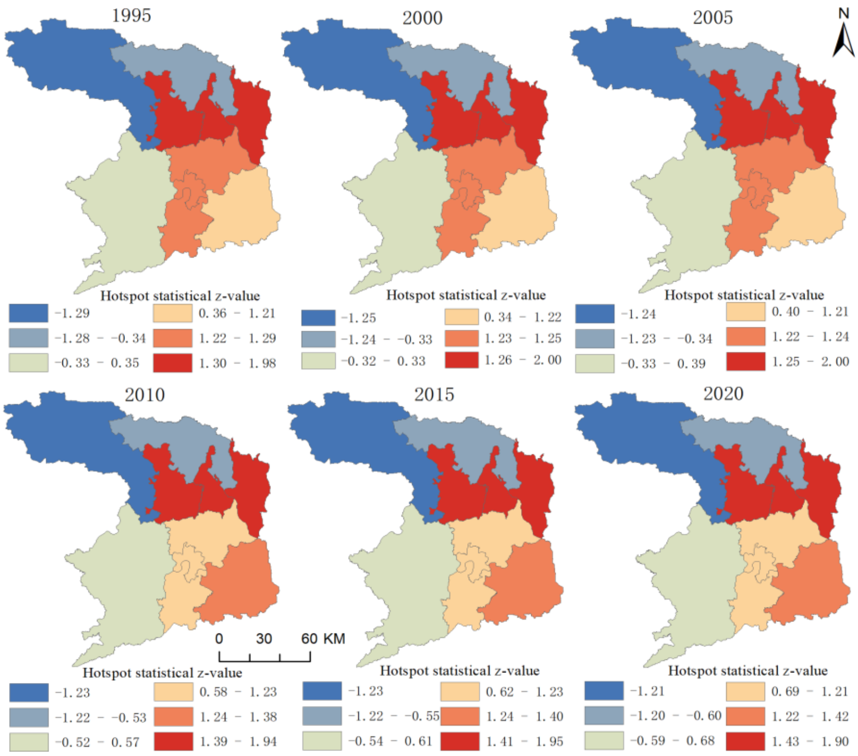

Figure 8. *Hotspot (z) distribution of land use degree in each district and county of Changde City from 1995 to 2020*

As shown in *Figure 9*, the rate of change in land use intensity varied significantly across Changde’s districts and counties from 1995 to 2020. Between 1995 and 2000, Wuling District and Anxiang County experienced notable changes in land use intensity. Wuling District exhibited a higher rate of change, while Anxiang County showed a negative rate, indicating the initial impacts of early urbanization on the land use structure. From 2005 to 2010, the rate of change in Dingcheng District, Wuling District, and Linli County increased significantly, reaching 0.031996 and 0.010260, respectively, driven by urban expansion and the corresponding increase in urban land use. During the period from 2015 to 2020, Wuling District recorded the highest rate of change at 0.060621, reflecting heightened development activities in recent years.

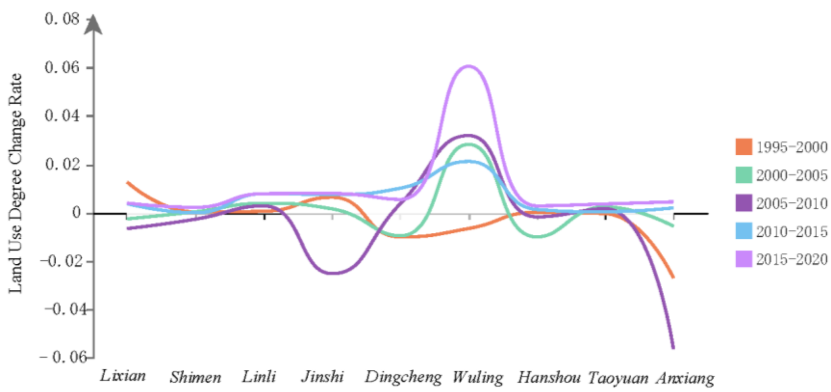

Figure 9. *Land use degree change rate in each district and county of Changde City from 1995 to 2020*

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Overall, from 1995 to 2020, land use intensity in Changde City demonstrated a significant upward trend, particularly in areas such as Wuling District and Dingcheng District. The hotspots of land use were concentrated mainly in central urban areas, and the rates of change exhibited stage-specific characteristics across different periods. These trends indicate that land use intensity in Changde City has increased with the process of urbanization, leading to the gradual formation of a spatial pattern of urban and rural land use. The growing demand for land resources driven by urban expansion continues to shape the land use structure of the region.

Driving force analysis

Factor detection

From both socio-economic and natural perspectives, eight driving factors were selected, including population density (X1), GDP (X2), year-end total population (X3), primary industry output (X4), secondary industry output (X5), elevation (X6), slope (X7), and aspect (X8), to analyze their influence on land use changes in 2000, 2005, 2010, 2015, and 2020. The results are shown in *Table 3*.

Table 3. *Geographical detection results of land use change impact factors in Changde City from 1995 to 2020*

Detection Factors	Impact Factors	2000		2005		2010		2015		2020	
		q	Rank	q	Rank	q	Rank	q	Rank	q	Rank
X1	Population Density	0.82	1	0.81	1	0.67	1	0.71	1	0.99	1
X2	Gross Domestic Product	0.43	2	0.58	5	0.63	2	0.25	3	0.15	5
X3	Year-End Total Population	0.19	4	0.59	3	0.40	4	0.18	6	0.39	4
X4	Primary Industry Output	0.06	5	0.58	4	0.21	6	0.58	2	0.50	2
X5	Secondary Industry Output	0.04	6	0.80	2	0.35	5	0.71	1	0.99	6
X6	Elevation	0.02	7	0.00	7	0.02	7	0.24	5	0.06	7
X7	Slope	0.02	7	0.00	7	0.02	7	0.24	5	0.06	7
X8	Aspect	0.19	3	0.27	6	0.43	3	0.25	4	0.40	3

The analysis reveals the following key findings:

1. Dominant role of population density. From 2000 to 2020, population density (X1) consistently ranked first in influence, with all *q*-values exceeding 0.8. In 2020, it reached the highest value of 0.9883, indicating that population density is the most critical socio-economic factor driving land use changes in Changde City.

2. Significant impact of secondary industry output. The *q*-values for secondary industry output (X5) were notable throughout the time series, particularly in 2005 (q=0.8038, ranked second) and 2020 (q=0.9883, ranked first). This highlights the significant role industrialization plays in driving land use transformations.

3. Long-term effect of GDP. The *q*-value for GDP (X2) was 0.4263 in 2000 (ranked second). Although it decreased to 0.1489 in 2020 (ranked fifth), its long-term influence remains significant.

4. Restrictive role of natural factors. The *q*-values for natural factors such as elevation (X6) and slope (X7) were consistently low throughout the time series. Although the *q*-value for aspect (X8) was relatively high in certain years, its overall impact was not significant. This indicates that the direct influence of natural factors on land use changes is limited.

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Interaction detection

Interaction detection of the driving factors influencing land use changes in Changde City from 1995 to 2020 revealed the following patterns (*Table 4*).

Table 4. *Interactive detection results of land use change impact factors in Changde City (1995-2020)*

A	B	min(A,B)	max(A,B)	q(A+B)	q(A∩B)	Interaction	Criterion
X6	X7	0.01	0.01	0.02	0.1185	Non-linear Enhancement	q(A+B)<q(A∩B)
X6	X8	0.01	0.38	0.39	0.4622	Non-linear Enhancement	q(A+B)<q(A∩B)
X6	X1	0.01	0.82	0.83	0.8486	Non-linear Enhancement	q(A+B)<q(A∩B)
X6	X2	0.01	0.25	0.26	0.3800	Non-linear Enhancement	q(A+B)<q(A∩B)
X6	X3	0.01	0.40	0.41	0.8611	Non-linear Enhancement	q(A+B)<q(A∩B)
X6	X4	0.01	0.34	0.35	0.4289	Non-linear Enhancement	q(A+B)<q(A∩B)
X6	X5	0.01	0.82	0.83	0.8486	Non-linear Enhancement	q(A+B)<q(A∩B)
X7	X8	0.01	0.38	0.39	0.4622	Non-linear Enhancement	q(A+B)<q(A∩B)
X7	X1	0.01	0.82	0.83	0.8486	Non-linear Enhancement	q(A+B)<q(A∩B)
X7	X2	0.01	0.25	0.26	0.3800	Non-linear Enhancement	q(A+B)<q(A∩B)
X7	X3	0.01	0.40	0.41	0.8611	Non-linear Enhancement	q(A+B)<q(A∩B)
X7	X4	0.01	0.34	0.35	0.4289	Non-linear Enhancement	q(A+B)<q(A∩B)
X7	X5	0.01	0.82	0.83	0.8486	Non-linear Enhancement	q(A+B)<q(A∩B)
X8	X1	0.38	0.82	1.20	0.8859	Bivariate Enhancement	max(A,B)<q(A∩B)
X8	X2	0.25	0.38	0.63	0.9970	Non-linear Enhancement	q(A+B)<q(A∩B)
X8	X3	0.38	0.40	0.78	0.9970	Non-linear Enhancement	q(A+B)<q(A∩B)
X8	X4	0.34	0.38	0.72	0.9877	Non-linear Enhancement	q(A+B)<q(A∩B)
X8	X5	0.38	0.82	1.20	0.8859	Bivariate Enhancement	max(A,B)<q(A∩B)
X1	X2	0.25	0.82	1.07	0.8621	Bivariate Enhancement	max(A,B)<q(A∩B)
X1	X3	0.40	0.82	1.22	0.8583	Bivariate Enhancement	max(A,B)<q(A∩B)
X1	X4	0.34	0.82	1.16	0.8553	Bivariate Enhancement	max(A,B)<q(A∩B)
X1	X5	0.82	0.82	1.64	0.8386	Bivariate Enhancement	max(A,B)<q(A∩B)
X2	X3	0.25	0.40	0.65	0.8648	Non-linear Enhancement	q(A+B)<q(A∩B)
X2	X4	0.25	0.34	0.59	0.8685	Non-linear Enhancement	q(A+B)<q(A∩B)
X2	X5	0.25	0.82	1.07	0.8621	Bivariate Enhancement	max(A,B)<q(A∩B)
X3	X4	0.34	0.40	0.75	0.8619	Non-linear Enhancement	q(A+B)<q(A∩B)
X3	X5	0.40	0.82	1.22	0.8583	Bivariate Enhancement	max(A,B)<q(A∩B)
X4	X5	0.34	0.82	1.16	0.8553	Bivariate Enhancement	max(A,B)<q(A∩B)

1. "Dual-factor enhancement" as the dominant interaction type. Among the 21 pairs of interacting factors, most interactions exhibited "dual-factor enhancement," where the combined effect of two factors was greater than the independent effect of either factor. This highlights the importance of synergistic interactions in driving land use changes.

2. Significant interaction among socio-economic factors. Interactions among socio-economic factors showed consistently high q-values, particularly between population density (X1), secondary industry output (X5), and year-end total population (X3), with interaction q-values all exceeding 0.85. This underscores the dominant role of socio-economic factors in land use changes in Changde City.

3. Synergistic effects between socio-economic and natural factors. Although the independent influence of natural factors was relatively small, their interaction with socio-economic factors was significant. For example, the interaction q-value between

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elevation and population density was 0.8486, indicating that natural topography imposes certain constraints on population distribution and land use suitability. Similarly, the interaction q-value between slope (X7) and secondary industry output (X5) was 0.8486, reflecting that industrial land distribution is influenced by terrain, with flatter areas being more conducive to industrial development.

4. Weaker interaction among natural factors. Interactions among natural factors showed generally low q-values. For instance, the interaction q-value between elevation (X6) and slope (X7) was 0.1185. This suggests that natural factors have limited direct driving forces on land use changes, and their influence is more evident in regulating and constraining the effects of socio-economic factors.

Discussion

The spatiotemporal evolution of land use patterns in Changde City from 1995 to 2020 demonstrates significant changes in land use types and their spatial distribution under the combined influence of socio-economic development and natural conditions. This study highlights that urbanization and industrialization are the primary drivers of land use pattern changes, reflected in the significant increase in built-up areas and the reduction in arable land and grassland. The continuous growth of forest area during this period is primarily attributed to the implementation of policies such as returning farmland to forests and ecological restoration projects. In contrast, the gradual decrease in arable land and grassland reflects the impact of urban expansion and the migration of rural labor. The most notable growth was observed in built-up areas, driven largely by the expansion of urban and industrial infrastructure to meet the demands of population growth and economic development. These changes underscore the dual pressures of development and ecological conservation faced by Changde City.

Socio-economic factors are the dominant forces driving land use changes, with population density, GDP, and secondary industry output having the most significant influence. Population density is identified as the core driving factor affecting land use changes in Changde City, as the growth in population directly determines the demand for residential, production, and transportation land. Additionally, the rapid development of the secondary industry has further propelled the expansion of urban construction land, leading to the gradual conversion of agricultural spaces into urban land. The notable impact of these socio-economic factors suggests that land use planning must be closely aligned with economic development policies to achieve efficient resource allocation. In comparison, natural factors have a weaker direct influence on land use changes, but they indirectly affect land use patterns through interactions with socio-economic factors. For instance, the interaction between elevation and population density indicates that topographic factors influence the spatial distribution of land development to some extent. Future land use research should place greater emphasis on the synergistic effects of natural and socio-economic factors, exploring the complex impacts of multi-factor interactions on land use changes.

The study reveals that the spatiotemporal evolution of land use patterns in Changde City reflects the dynamic balance between urbanization and ecological conservation. A key issue for future land use planning is how to promote the efficient expansion of urban spaces while protecting the red line for cultivated land. Additionally, efforts to protect ecological spaces should continue to optimize the distribution of forests, water bodies, and grasslands, further enhancing ecosystem service functions to support

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sustainable regional development. In summary, the spatiotemporal evolution of land use patterns in Changde City results from the combined effects of socio-economic factors and natural conditions, uncovering the patterns of regional land resource utilization and management. The findings not only provide a scientific basis for land use planning and ecological conservation but also offer practical guidance for advancing regional sustainable development.

Conclusions

(1) Significant changes occurred in the land use patterns of Changde City between 1995 and 2020. Arable land area gradually decreased, impervious surfaces (primarily urban construction land) expanded significantly, while forest land and water bodies remained relatively stable. Grassland and unused land, however, showed a decreasing trend. These changes reflect the dual demands of urbanization, industrialization, and ecological conservation in Changde City. The expansion of urban areas has driven the conversion of agricultural land into urban land, while the stability of forest land and water bodies highlights the effectiveness of ecological protection policies.

(2) From 1995 to 2020, the primary land use transformation in Changde City was the conversion of arable land into impervious surfaces, especially during the rapid urbanization phases when arable land experienced significant reductions. Although forest land remained relatively stable under the influence of ecological protection measures, there was a degree of conversion into agricultural and construction land. The increase in water body area demonstrates the successes of water resource management in Changde City. However, the reduction in grassland indicates that further integration and optimization of ecological spaces remain a challenge.

(3) During the period from 1995 to 2020, both arable land and impervious surfaces showed expansion trends. Arable land shifted from concentrated distributions toward regional dispersion, while impervious surfaces rapidly expanded along transportation corridors and industrial parks as urbanization progressed. Forest land and water bodies maintained relatively stable spatial distributions, while the distribution range of grassland and unused land contracted, reflecting the results of ecological space integration and agricultural structure adjustments in Changde City.

(4) The driving factors of land use changes in Changde City from 1995 to 2020 exhibited certain variations. Socioeconomic factors were the dominant forces driving land use changes, with population density, secondary industry output, and GDP having particularly significant impacts. The direct influence of natural factors was relatively minor, but their interactions with socioeconomic factors indirectly affected land use patterns. The results of interaction detection showed that the interactions among socioeconomic factors were the most significant, especially the synergistic effects between population density and industrial output, which had a much greater explanatory power for land use changes compared to natural factors.

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