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# Land Use Changes and Their Driving Factors in the Liuchong River Basin Based on the Geographical Detector Model

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**Abstract:** Land use/cover change (LUCC) is a measure that offers insights into the interaction between human activities and the natural environment, which significantly impacts the ecological environment of a region. Based on data from the period from 2000 to 2020 regarding land use, topography, climate, the economy, and population, this study investigates the spatial and temporal evolution of land use in the Liuchong River Basin, examining the interaction between human activities and the natural environment using the land use dynamics model, the transfer matrix model, the kernel density model, and the geodetic detector. The results indicate that: (1) The type of land cover in Liuchong River Basin primarily comprises cropland, forest, and shrubs, with the land use change mode mainly consisting of an increase in the impervious area and a decrease in surface area covered by shrubs. (2) The dynamic degree for single land use of barren, impervious, and waters indicates a significant increase, with areas covered by shrubs decreasing by 9.37%. In addition, the change in the degree of single land use for other types of cover is more stable, with the degree of comprehensive land use being 7.95%. The areas experiencing the greatest land use change in the watershed went through conditions that can be described as "sporadic distribution" to "dispersed" to "relatively concentrated". (3) Air temperature, rainfall, and elevation are important factors driving land use changes in the Liuchong River Basin. The impact of nighttime lighting, gross domestic product (GDP), and normalized difference vegetation index (NDVI) on land use change have gradually increased over time. The results of the interaction detection indicated that the explanatory power of the interaction between the driving factors in each period for land-use changes was always greater than that of any single factor. The results of this study offer evidence-based support and scientific references for spatial planning, soil and water conservation, and ecological restoration in a watershed.

**Key words:** kernel density model; geographical detector; land use; driving factor; Liuchong River Basin

## 1 Introduction

Land use is a dynamic process involving changes in time and space (Cao et al., 2018), resulting from the long-term interaction between human activities and the natural environment (Liu et al., 2010). An exploration of regional land change processes and driving factors can produce crucial information on land use changes in space and time (Gaur et al., 2020). Since the 1990s, substantial research on land use has been performed in China and the rest of the world, with the International Geosphere-Biosphere Program (IGBP) and International Human Dimensions Program on Global Environmental Change (IHDP) organizations jointly developing a research plan on changes in land use and land cover in 1995. Consequently, land use has become an important

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research topic (Walker, 1987). River basins are often the sites of substantial human activities, with land use changes in the areas being readily apparent (Huang et al., 2022). Socio- economic developments and changes in the natural environment of river basins not only change the structure of regional land use/cover type but also affect the quality of the ecological environment of river basins and the sustainable use of resources (Helming et al., 2011; Sun et al., 2018). Accordingly, unplanned land use may threaten the ecological and environmental security of river basins (Yu et al., 2011; Guo et al., 2016). Therefore, it is crucial that changes in characteristics of land use in watersheds are analyzed by examining long-term series data and exploring the driving factors of land use changes to facilitate national land space planning and ecologically optimized construction in watersheds.

Recently, studies on land use have increased, investigating spatial and temporal patterns, dynamic changes, and driving factors of land use at different scales. The research areas of the studies include administrative divisions (Birhanu et al., 2019; Qiu and Ma, 2022; Peng et al., 2023), watersheds (Amelia et al., 2023; Astou Sambou et al., 2023; Wang and Zhang, 2023; Li et al., 2024), and geomorphological types (Mao and Shangguan, 2022; Guo et al., 2023). They employed the transfer matrix model to identify changes in the attitude and dynamics of land use, as well as land use evaluation indexes and other methods. Among these methods is analysis of changes in the driving factors of land use, which is usually divided into two categories: qualitative analysis and quantitative methods. Qualitative analysis employs approaches such as listing, ranking, and exposition of driving factors; however, these methods do not adequately quantify the driving factors (Lu et al., 2020; Chen and Yang, 2022). In comparison, quantitative methods primarily involve the use of empirical statistical analysis models. For example, gray correlation analysis has been used to explore the correlation between socio-economic drivers and types of land use (Deng and Chen, 2020), while hierarchical analysis has been used to investigate factors of urban land use change in the Kathmandu Valley of Nepal (Thapa and Murayama, 2010). Similarly, principal component analysis has been utilized to explore drivers of land use change in restricted development ecological zones (Wang et al., 2019), while canonical correspondence analysis has been used to explore the drivers of land use change in Liudaogou on the Loess Plateau (Bu et al., 2016). Lastly, the geographical detector model has been used to explore the magnitude of influence of various driving factors on the amount of change in the land used for construction in the Calendar City area, examining the intrinsic driving mechanisms that cause land use changes (Jiang, 2020).

In summary, current research on changes in land use is mainly characterized by the use of geographic information technology to analyze the process and driving forces of the changes in different periods, performing investigations in watersheds, administrative divisions, and geomorphological-type areas. However, the change in the amount/weight of land use or a single land use type is often selected as a dependent variable. Approaches that utilize these variables are usually not comprehensive enough to reveal the intrinsic mechanism of changes in regional land use. Additionally, empirical statistical models are often chosen to perform analyses; however, they can quantitatively explain the changes in factors of land use, but they cannot reveal the unique spatial heterogeneity of a geographic phenomenon and are patently insufficient as methods for explaining the interaction mechanism of the influencing factors.

In this study, the Liuchong River Basin, located in the highlands of western Guizhou, China, serves as the study area. This study identified areas with the greatest changes in land use by utilizing the land use dynamic attitude, transfer matrix, and kernel density models to analyze the spatial and temporal characteristics of changes in land use. Additionally, it utilized geodetic probes to explore the relationship between multi-year land use changes and elevation, slope, direction of the slope, gross domestic product (GDP), air temperature, rainfall, population density, normalized difference vegetation index (NDVI), and nighttime light. This study aims to reveal the changes in spatial and temporal land use characteristics as well as the associated driving factors in the Liuchong River Basin with a view to providing references for land-use planning, optimized allocation of land resources, and ecological restoration in the basin and similar regions.

## 2 Materials and methods

### 2.1 Study area

Liuchong River is the largest first-class tributary of Wujiang River, originating from Xingwang Village, Hezhang County, in the western plateau of Guizhou, China. The basin is oriented in the northwest-southeast direction, with the highest elevation being 2769 m and the lowest 695 m. The river flows through the Qixingguan District of Bijie City, Nayong County, Dafang County, Zijin County, joining the Wujiang River on the left bank of Huayuqi in Qianxi County (Ren et al., 2019). The length of the main stream of the river is 273.4 km, with a natural drop of 1243 m, a catchment area of about 10820 km$^2$, and the multi-year average runoff is 13.440 billion m$^3$. There are 15 major tributaries, with seven joining the main river on the left bank and eight on the right bank. Among these, the larger tributaries are the Baifu River and the Hongyan River. The middle and upper reaches of the river are warm and cool mountainous areas with low temperatures, low annual rainfall, and a late rainy season. These areas are located in a dry area that receives a low amount of rainfall in Guizhou Province. Hongjiadu Hydropower Station is located downstream of the Liuchong River, making it the only large hydropower station in the basin (Figure 1). The

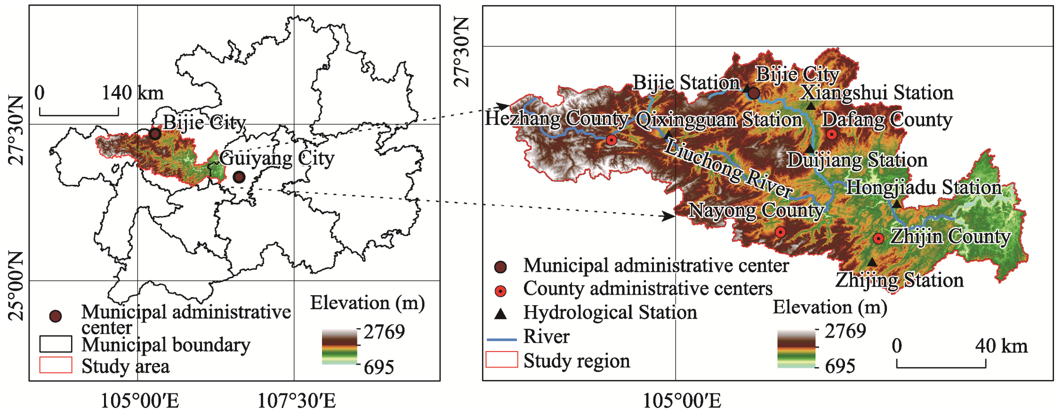


Figure 1 Location and elevation map of the study region

dam captures 91% of the rainfall received by the basin area (Zhao et al., 2021).

## 2.2 Data sources

This study utilized data from the land use dataset (Yang and Huang, 2021), with land use serving as the dependent variable, while elevation, slope, slope direction, GDP, average annual temperature, average annual rainfall, population density, nighttime lighting (Wu et al., 2022), and NDVI served as the influencing factors. Elevation, slope, and slope direction were calculated using a digital elevation model (DEM). The data sources are shown in Table 1.

## 2.3 Methods

### 2.3.1 Land-use dynamic degree

The spatial and temporal change characteristics of land use can be expressed using single land use dynamic degree and comprehensive land use dynamic degree (Feng, 2022). The two terms are calculated as follows:

Single land use dynamic degree:

$$K = \frac{U_b - U_a}{U_a} \times \frac{1}{T} \times 100\% \tag{1}$$

In the formula, $U_a$ and $U_b$ represent the area of land use types in the previous period and the later period, respectively.

Comprehensive land use dynamics degree:

$$L_c = \frac{\sum_{i=1}^{n} \Delta L_{U_{i-j}}}{2\sum_{i=1}^{n} \Delta L_{U_i}} \times \frac{1}{T} \times 100\% \tag{2}$$

In the formula, $\Delta L_{U_{i-j}}$ stands for the absolute value of the area of land use type $i$ converted to $j$ land use type; $j$ stands for non-$i$ land use types; $\Delta L_{U_i}$ denotes the area of land use type in the previous period; and $T$ represents the period of time between the intervals.

### 2.3.2 Land-use transfer matrix

The land use transfer matrix can reveal the transfer direction and transfer rate between different land use types (Huang et al., 2022). Its expression is as follows:

$$\boldsymbol{B}_{mn} = \begin{pmatrix} B_{11} & B_{12} & \dots & B_{1k} \\ B_{21} & B_{22} & \dots & B_{2k} \\ \dots & \dots & \dots & \dots \\ B_{k1} & B_{k2} & \dots & B_{kk} \end{pmatrix} \tag{3}$$

Table 1 Data sources

| Data name | Data source | Related sites | Format | Resolution |
|---|---|---|---|---|
| Land use | Wuhan University CLCD Dataset | http://doi.org/10.5281/zenodo.8176941 | Raster | 30 m |
| DEM | Geospatial Data Cloud | https://www.gscloud.cn/search | Raster | 30 m |
| GDP | Resource and Environment Science and Data Center, Chinese Academy of Sciences, China | https://www.resdc.cn/10.12078/2017121102 https://github.com/thestarlab/ChinaGDP | Raster | 1 km |
| Average annual temperature | National Tibetan Plateau Science Data Center | https://data.tpdc.ac.cn/zh-hans/data/71ab4677-b66c-4fd1-a004-b2a541c4d5bf | Raster | 1 km |
| Average annual rainfall | Earth Resources Data Cloud | Geographic data sharing infrastructure, global resources data cloud (www.gis5g.com) | Raster | 0.008°×0.008° |
| Population density | LandScan Global Population Data by ORNL | https://landscan.ornl.gov | Raster | 1 km |
| Night lights | DMSP-OLS data published by Wu Yizhen and other scholars | https://doi.org/10.7910/DVN/GIYGJU | Raster | 1 km |
| NDVI | MOD13A3 data published by NASA | https://doi.org/10.5067/MODIS/MOD13A3.006 | Raster | 1 km |

In the formula, $\boldsymbol{B}_{mn}$ represents the area of the $m$-th land type in the initial period transformed into the $n$-th land type in the termination period, and $k$ denotes the number of land use types.

### 2.3.3 Kernel density model

The kernel density model can be used to identify areas of high density or clustering where geodata activity occurs (Yuan et al., 2023). It is calculated as follows:

$$f(x) = \frac{1}{nh}\sum_{i=1}^{n} kern\left(\frac{x_i - x}{y}\right) \quad (4)$$

where $n$ stands for the number of observations; $h$ denotes the threshold value; $y$ represents the number of points within the threshold value; $x_i$ represents various land use types $i$ distributed in the region; $x$ represents the area where the land use type has not changed within a certain period, and $kern$ symbolizes the kernel density function. In this study, the higher the kernel density value of a region, the greater the intensity of land use change in the region.

### 2.3.4 Geographical detector

Geoprobe is a research model based on the characteristics of spatial heterogeneity that is used to analyze the interrelationships between dependent variables and independent variables, as well as relationships between independent variables (Wang and Xu, 2017; Che and Li, 2024). It mainly consists of four modules: factor, interaction, risk, and ecological detection. This study mainly utilizes factor and interaction detection to explore the driving factors of changes in land use in the Liuchong River Basin.

(1) Factor detection

To detect the spatially heterogeneous influence of the independent variable on the dependent variable, the result is usually expressed as $q$. If $q$ is large, the result indicates that the explanatory power of the independent variable on the dependent variable is stronger. The value of $q$ ranges from 0 to 1 and is calculated as follows:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} \quad (5)$$

where $q$ denotes the influence of the independent variable on the dependent variable，$h$=1, ⋯, $L$ stands for the categorization or partitioning of the independent or dependent variable; $N_h$ and $N$ symbolize the number of cells in stratum $h$ and the whole area, respectively; and $\sigma_h^2$ and $\sigma^2$ represent the variance of the dependent variable in stratum $h$ and the whole area, respectively.

(2) Interactive detection

Interaction probing is used to investigate whether the influence of the independent variables $x_1$ and $x_2$ on the dependent variable is enhanced or diminished when they interact, or whether the influence on the dependent variable is independent for each independent variable. It is assessed by first calculating the $q$-values of the two independent variables $x_1$ and $x_2$ on the dependent variable ($q(x_1)$ and $q(x_2)$) as well as the $q$-value of the two independent variables when they interact ($q$ ($x_1 \cap x_2$)). Then, $q(x_1)$, $q(x_2)$, and $q$ ($x_1 \cap x_2$) are compared to identify different types of interactions as shown in Table 2 (Wang et al., 2023). The delineation criteria are also shown in the table.

Table 2 Types of interactions and basis of judgment

| Interaction type | Basis of judgment |
|---|---|
| Non-linear reduction | $q(x_1 \cap x_2)$<Min($q(x_1)$, $q(x_2)$) |
| Single-factor non-linear reduction | Min($q(x_1)$, $q(x_2)$)<$q(x_1 \cap x_2)$<Max($q(x_1)$, $q(x_2)$) |
| Independent | $q(x_1 \cap x_2)=q(x_1)+q(x_2)$ |
| Bi-factor enhancement | $q(x_1 \cap x_2)$>Max($q(x_1)$, $q(x_2)$) |
| Non-linear enhancement | $q(x_1 \cap x_2)>q(x_1)+q(x_2)$ |

In Table 2, Min($q(x_1)$, $q(x_2)$) denotes the minimum of both $q(x_1)$ and $q(x_2)$; Max($q(x_1)$, $q(x_2)$) represents the maximum of both $q(x_1)$ and $q(x_2)$; $q(x_1)+q(x_2)$ stands for the sum of $q(x_1)$ and $q(x_2)$; and $q(x_1 \cap x_2)$ symbolizes the interaction of $q(x_1)$ and $q(x_2)$.

## 3 Results and analysis

### 3.1 Spatio-temporal evolution characteristics of land use

Utilizing remote sensing image interpretation data of the Liuchong River Basin, ArcGIS software was used to statistically analyze the five periods of land use (from 2000 to 2020), and the area covered by different land use types in the five periods was obtained (Table 3). As shown in Figure 2 and Table 3, the land use types in Liuchong River Basin primarily comprised cropland, forest, and shrubs, with the aggregated area of the three land use types accounting for more than 90% of the total land area of the whole region. When the spatial structure of the region was considered, impervious, grasslands, and waters in the Liuchong River Basin were found to be small in area, exhibiting sporadic distribution. In comparison, the distribution of cropland and forest was more concentrated, with cropland being mainly distributed in the northeast region of the middle and lower reaches of the basin, and forest mainly being distributed in the southwest region of the upper and lower reaches of the basin.

For the study period (2000–2020), the area covered by cropland and forest in the watershed was relatively unchanged, grassland decreased and then increased, impervious increased throughout the study period, waters increased gradually before remaining relatively stable, shrubs decreased, and barren accounted for less than 0.01% of the area in the past 20 years.

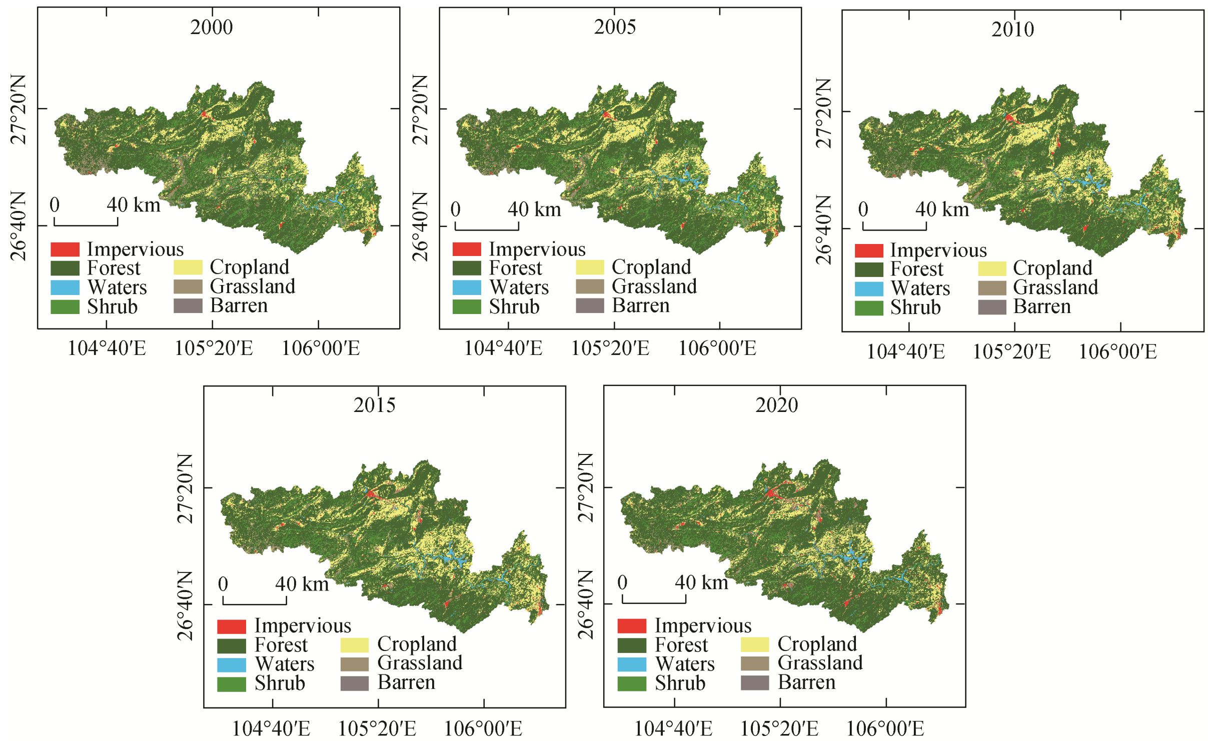


Figure 2 Spatial distribution of land use in the Liuchong River Basin during 2000–2020

Table 3 Area share of land-use types in the Liuchong River Basin (Unit: %)

| Land use type | 2000 | 2005 | 2010 | 2015 | 2020 |
|---|---|---|---|---|---|
| Cropland | 46.79 | 48.20 | 48.58 | 48.28 | 47.30 |
| Forest | 46.01 | 44.54 | 45.20 | 46.26 | 47.55 |
| Shrub | 4.97 | 5.22 | 4.25 | 3.35 | 2.64 |
| Grassland | 1.96 | 1.57 | 1.39 | 1.40 | 1.70 |
| Waters | 0.16 | 0.34 | 0.37 | 0.42 | 0.41 |
| Barren | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Impervious | 0.10 | 0.13 | 0.21 | 0.29 | 0.38 |

## 3.2 Land use dynamic degree

### 3.2.1 Single land use dynamic degree

Single land use dynamic degree was calculated using formula (1) to obtain the single-movement attitudes of all types of land cover in the Liuchong River Basin from 2000 to 2020 (Table 4). As shown in Table 4, the largest three land categories with positive single dynamic degrees for the period were barren, impervious, and waters, indicating an increase in their area. Among the land categories that decreased in area, shrubs exhibited the largest decrease, producing a single land use dynamic degree of –9.37%. The land classes with the largest single dynamic degree for each time period were waters (21.33%), impervious (12.15%), barren (59.76%), and barren (1033.15%). In comparison, land classes with the smallest single dynamic degree for each time period were barren (–14.99%), shrubs (–3.73%), shrubs (–4.23%), and shrubs (–4.25%). The magnitude of change in the single dynamic degree for each type of land use from 2000 to 2010 was relatively smooth, with the change in the single dynamic degree for barren from 2005 to 2010 being zero. The changes in the single dynamic degree for each type of land use from 2010 to 2020 were more pronounced, especially for barren, increasing from 59.76% to 1033.15%. In addition, the change in the single dynamic degree for each type of land use from 2000 to 2020 was relatively pronounced, with the exception of barren, impervious, and waters, which showed a significant increase in the single dynamic degree.

Table 4 Single dynamic degree of land use types in the Liuchong River Basin during 2000–2020 (Unit: %)

| Land use type | 2000–2005 | 2005–2010 | 2010–2015 | 2015–2020 | 2000–2020 |
|---|---|---|---|---|---|
| Cropland | 0.60 | 0.16 | –0.12 | –0.40 | 0.22 |
| Forest | –0.64 | 0.30 | 0.47 | 0.56 | 0.67 |
| Shrub | 1.05 | –3.73 | –4.23 | –4.25 | –9.37 |
| Grassland | –3.98 | –2.34 | 0.21 | 4.29 | –2.64 |
| Water | 21.33 | 2.26 | 2.33 | –0.18 | 30.90 |
| Barren | –14.99 | 0.00 | 59.76 | 1033.15 | 1032.49 |
| Impervious | 5.81 | 12.15 | 7.67 | 6.26 | 55.34 |

#### 3.2.2 Comprehensive land use dynamics degree

The comprehensive land use dynamics degree was calculated using formula (2). Table 5 shows the comprehensive land use dynamics degree for the Liuchong River Basin in the past 20 years, with the comprehensive land use dynamics degree of the basin being 7.95%. Over four different periods reflecting a "rise-fall-rise-fall" trend of change, from 2000 to 2005, the area experiencing the most change in land use type was 107898.15 ha. Concurrently, the comprehensive land use dynamics degree reached its peak at 3.92%. From 2015 to 2020, the comprehensive land use dynamics degree of the basin hit its lowest, while the land use dynamics degree reached its lowest value at 3.38%.

### 3.3 Change in the conversion direction and scale among land use types

Formula (3) was used to analyze the transfer area of land use types in the Liuchong River Basin in the four time periods from 2000 to 2020, with the results being used to create the transfer matrix scale chord diagram (Figure 3). The total change area of land use from 2000 to 2020 was 2188890.27 ha. The conversion area of cropland and forest stood as the largest. Additionally, the main direction of change for cropland was to forest, and its main sources were forest, shrubs, and grassland. Forest land primarily changed into cropland, and its main sources were cropland and shrubs. The total area of land use change from 2000 to 2005 was 107898.15 ha, of which the net conversion area of forest land was the largest. Forest land primarily changed into cropland, followed by shrubs, grassland, waters, barren, and impervious. Cropland experienced the largest net transfer in area, with the main sources of land being forest and shrubs. While land use changes from 2005 to 2010 totaled 97293.93 ha, some land categories experienced no significant changes in area. During this period, the largest areas exchanged between land types were cropland and forest, with the two land classes being converted into each other.

The total land use type changes from 2010 to 2015 were about 107578.54 ha. Among them, the land classes with the largest reductions in area were cropland, forest, and shrubs, in that order. At only 92963.78 ha, the total amount of change in land use types in the study period was the smallest from 2015 to 2020. In this period, the land type that experienced the largest decline was cropland, mainly changing into forest, while the land type experiencing the largest increase was forest, with its main sources of land being cropland and shrubs.

Table 5 Comprehensive land use dynamic degree in the Liuchong River Basin during 2000–2020

| Years | 2000–2005 | 2005–2010 | 2010–2015 | 2015–2020 | 2000–2020 |
|---|---|---|---|---|---|
| Area converted (ha) | 107898.15 | 97293.93 | 107578.54 | 92963.78 | 218890.27 |
| Comprehensive land use dynamic degree (%) | 3.92 | 3.54 | 3.91 | 3.38 | 7.95 |

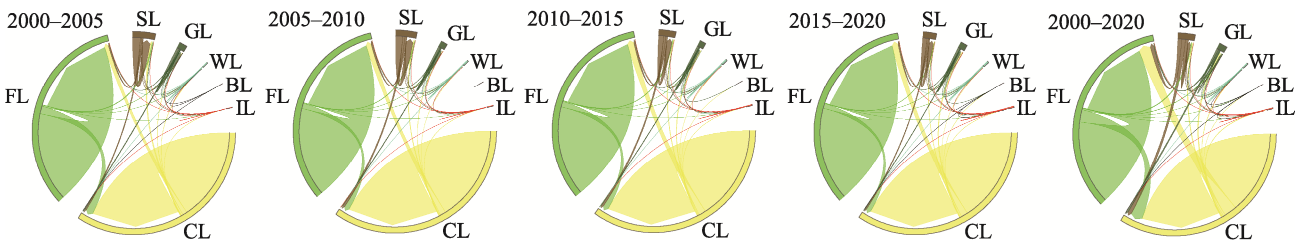


Figure 3 Proportional chord of the transfer matrix of land use types in the Liuchong River Basin during 2000–2020
Note: CL, FL, SL, GL, WL, BL and IL represent cropland, forest, shrub, grassland, waters, barren, and impervious, respectively.

### 3.4 Areas of land use exhibiting the greatest changes

Kernel density analysis of land use change was performed using Equation (4), and a distribution map was created showing areas of land use exhibiting the greatest changes in the watershed (Figure 4). As shown in Figure 4, the intensity of land use change in the Liuchong River Basin decreased trend over time in the four time periods. Among the periods, land use change intensity from 2000 to 2005 was the highest, with the changes leading to a pattern that can be described as "sporadic distribution". For the periods 2005 to 2010 and 2010 to 2015, land use change intensity was similar, being weaker than that for the period 2000 to 2005, with the distribution of land use change intensity being best described as "uniform dispersion". The land use change intensity of the basin from 2015 to 2020 was the weakest, being mainly concentrated in the middle and lower reaches of the basin. Areas experiencing the greatest land use changes in the Liuchong River Basin changed from conditions that can be described as "sporadic distribution" to "dispersion" to "relative concentration", indicating that the land use transition in the upper and middle reaches of the Liuchong River Basin occurred gradually.

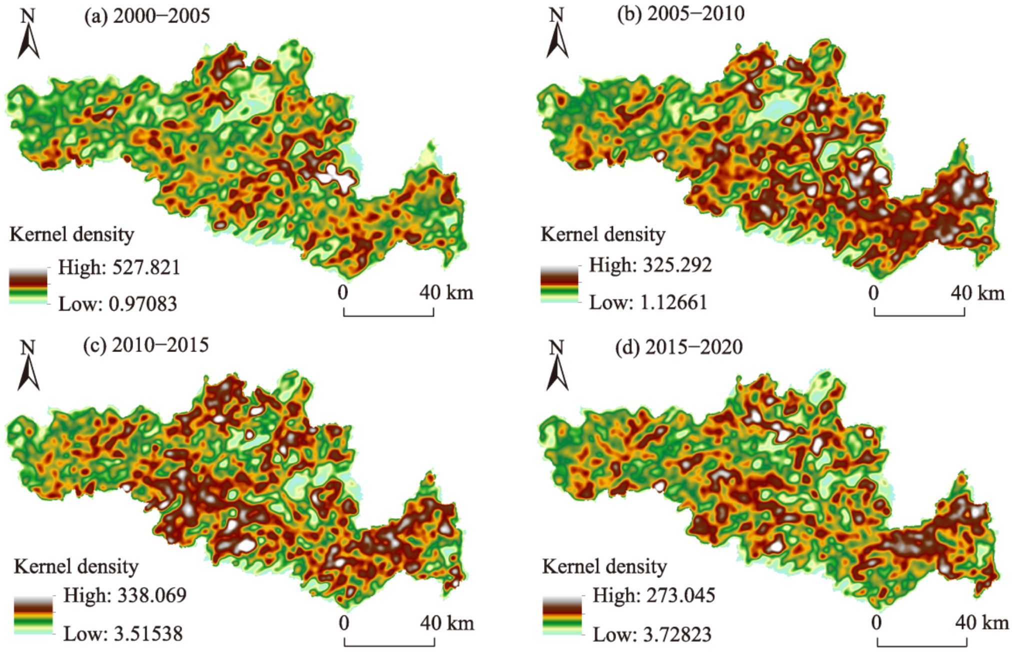


Figure 4 Regional distribution of land use change hotspots

## 3.5 Analysis of the drivers of land use change in the Liuchong River Basin

### 3.5.1 Driver selection and processing

Various studies have shown that luminous lighting data can offer insights into the production and living conditions of human society (Wang et al., 2020), while GDP provides insights into the level of local economic development (Tong and Lang, 2021). Similarly, for the watershed, the NDVI can describe the impact of policy factors of the fallow farmland reforestation and grassland return project as well as the natural forest protection project on the forest coverage rate (Wu et al., 2016). Climate and topography macroscopically determine the conditions of regional land resources and the spatial pattern of land use (Guo et al., 2016). Taking into account the accessibility and representativeness of data, nine indicators were selected as independent variables. These include elevation ($X_1$), slope ($X_2$), slope direction ($X_3$), air temperature ($X_4$), rainfall ($X_5$), population density ($X_6$), GDP ($X_7$), NDVI ($X_8$), and nighttime light ($X_9$). The intensity of land use change in the Liuchong River Basin was analyzed as the dependent variable.

Using the method adopted by Cao et al. (2013) for the categorization of each driver, elevation ($X_1$), temperature change ($X_4$), rainfall ($X_5$), population density ($X_6$), GDP ($X_7$), and nighttime lighting ($X_9$) were classified into six categories using the natural discontinuity method; slope ($X_2$) and NDVI ($X_8$) were classified into six categories using the equal spacing method; and slope direction ($X_3$) was classified into nine categories using the equal spacing method. A regular grid was used to partition the watershed extent of the Liuchong River. Accounting for the efficiency of the model calculation and the density of sampling points, the grid size was set to 750 m×750 m, and each grid raster turning point was sampled, producing 18802 sampling points. The Spatial Analyst tool in ArcGIS was used to generate the kernel density map of land use change in the Liuchong River Basin for each time period. The values of the driving factors and the corresponding intensity of land use change in each time period were extracted for the sampling points, and valid values were screened out, detected, and analyzed with the use of geographic detectors. This was used to obtain the intensity of the influence of each factor on changes in land use in the Liuchong River Basin as well as the mechanism of the interactive effect.

### 3.5.2 Factor detection analysis

The $q$-value in the Geodetector Factor Detection Module results provides information on the magnitude of influence of each driving factor. A large $q$-value indicates that the factor has a greater influence on the dependent variable. The factor detection results reveal the magnitude of the explanatory power of each factor on the change in land use in the Liuchong River Basin. Factor detection results for each time period are shown in Table 6.

Table 6 shows that the explanatory power of the driving factors for land use change in the Liuchong River Basin varied in different periods. For the period 2000 to 2005, except for slope direction, population density, and nighttime lighting, all other factors passed the hypothesis test at the 0.05 significance level. From largest to lowest, the $q$-values of the driving forces for the period were temperature, elevation, NDVI, GDP, rainfall, slope, population density, slope direction, and nighttime lighting.

For the period 2005 to 2010, all driving factors except

Table 6 Detection results of land use change drivers in the Liuchong River Basin

| Driving factors | *q*-value | | | |
|---|---|---|---|---|
| | 2000–2005 | 2005–2010 | 2010–2015 | 2015–2020 |
| Elevation | 0.048935* | 0.112041* | 0.033569* | 0.059797* |
| Slope | 0.004637* | 0.002669* | 0.002897* | 0.000587 |
| Slope direction | 0.000444 | 0.000324 | 0.000396 | 0.000567 |
| Air temperature | 0.062726* | 0.122223* | 0.038602* | 0.041786* |
| Rainfall | 0.019402* | 0.041207* | 0.031073* | 0.060689* |
| Population density | 0.003049 | 0.015999* | 0.010579* | 0.072126* |
| GDP | 0.020272* | 0.029704* | 0.039304* | 0.019554* |
| NDVI | 0.022751* | 0.073834* | 0.023649* | 0.077402* |
| Nighttime light | 0.000421 | 0.010177* | 0.037991* | 0.019375* |

Note: * indicates $P<0.05$ for the item.

slope direction passed the hypothesis test at the 0.05 significance level. From largest to smallest, the *q*-values of the driving forces were air temperature, elevation, NDVI, rainfall, GDP, population density, nighttime lighting, slope, and slope direction.

For the period 2010 to 2015, all factors except slope direction passed the hypothesis test at the 0.05 significance level. In descending order based on value, the period's *q*-values were GDP, temperature, nighttime light, elevation, rainfall, NDVI, population density, slope, and slope direction. For the period 2015 to 2020, all factors except slope and slope direction passed the hypothesis test at the 0.05 significance level. In descending order based on value, the *q*-values were NDVI, population density, rainfall, elevation, temperature, GDP, nighttime light, slope, and slope direction. Overall, from 2000 to 2010, the explanatory power of temperature and elevation on changes in land type was the strongest, while the explanatory power of GDP, population density, and nighttime light on changes in land use gradually increased over time from 2010 to 2020. Slope and slope orientation exhibited the weakest explanatory power for changes in land use in the watershed over the period under study. For the period 2000 to 2020, none of the slope orientation factors passed the hypothesis test at the 0.05 significance level.

### 3.5.3 Interactive detection analysis

The analysis of interactions reveals the differences in the effects of the factors on changes in land use when they act together versus when they act alone. The results of interaction detection for each year are shown in Figure 5. The results indicate the presence of two-factor enhancement or nonlinear enhancement, with no mutual independence or weakening being detected, indicating that the explanatory power of the interacting factors is stronger compared with that of a single factor. The results also suggest that change in land use involves a complex factor interaction process.

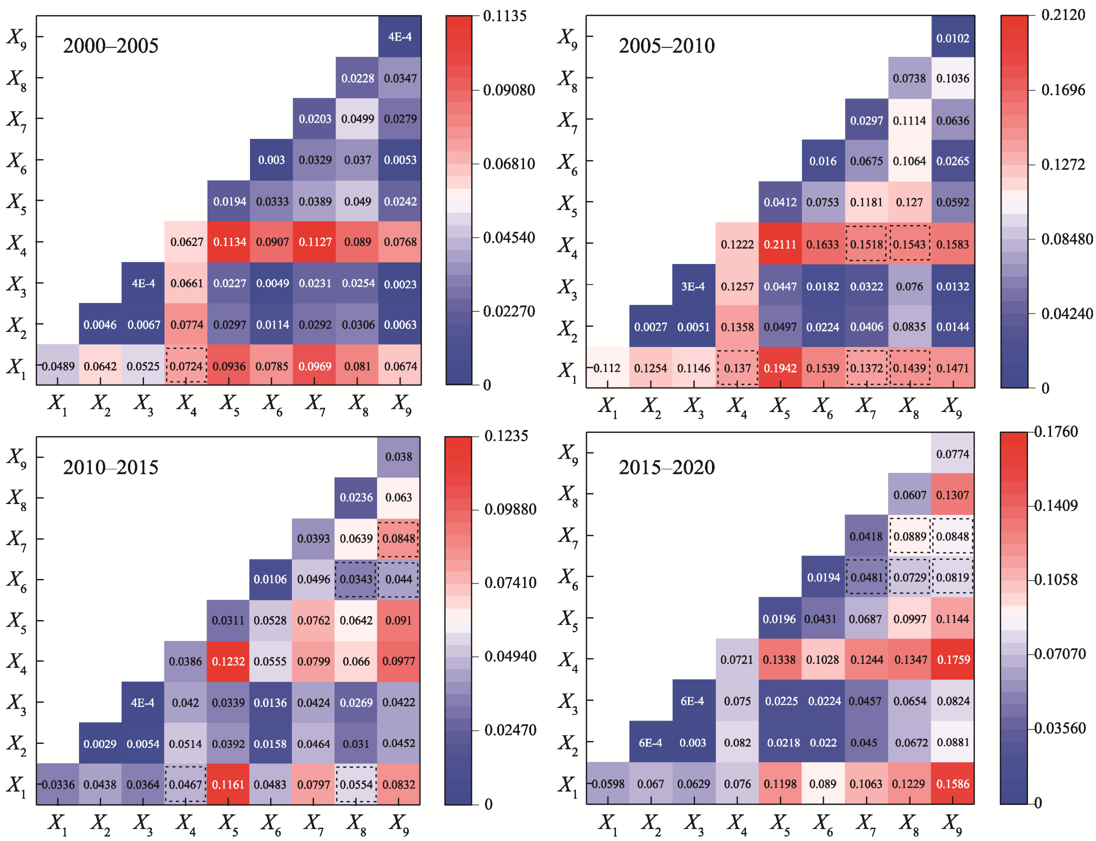


Figure 5 Interaction detection of drivers of changes in land use in the Liuchong River Basin for the period from 2000 to 2020

Note: The dashed box in the figure indicates two-factor enhancement, the rest indicate nonlinear enhancement; $X_1$: elevation; $X_2$: slope; $X_3$: slope direction; $X_4$: temperature; $X_5$: rainfall; $X_6$: population density; $X_7$: GDP; $X_8$: NDVI; $X_9$: nighttime light.

For the period from 2000 to 2005, the most significant explanatory power arises from the interaction between temperature and rainfall, as well as GDP, with the *q*-values associated with the factors exceeding the *q*-values of the interactions. The *q*-values for the interaction between temperature and rainfall, as well as GDP, exceeded 0.1. Other factors with significant explanatory power were elevation and rainfall, as well as GDP, indicating that changes in land use were mainly driven by variations in temperature, rainfall, and GDP. For the period from 2005 to 2010, except for the elevation, slope, and slope direction, the interactions between the temperature and other factors were associated with *q*-values greater than 0.1. Compared to the previous time period, the interactions of rainfall with GDP and NDVI, population density with NDVI, GDP with NDVI, and NDVI with nighttime lighting also exhibited significantly enhanced explanatory power.

For the period from 2010 to 2015, the most significant explanatory power involved interactions between temperature and rainfall, as well as elevation and rainfall, which were associated with *q*-values of 0.1232 and 0.1161, respectively. For the 2015 to 2020 period, the interactions between temperature and nighttime lighting, elevation and nighttime lighting, as well as NDVI and nighttime lighting changes were stronger, being associated with *q*-values of 0.1759, 0.1586, and 0.1307, respectively. This indicates that changes in land use in this period were governed by more factors, with changes in nighttime lighting, GDP, and NDVI gradually becoming the primary factors affecting changes in land use.

## 4 Discussion and conclusions

### 4.1 Discussion

This paper systematically examines the characteristics of changes in land use in the Liuchong River Basin by exploring variations in the area covered by specific land use types, as well as motivation and attitude, transfer characteristics, and the intensity of change, among others. Nine indicators, including elevation, slope, slope direction, GDP, temperature, rainfall, population density, NDVI, and nighttime lighting were selected as dependent variables, with the intensity of land use change serving as the most independent variable. This approach addressed the problem where the amount/portion of land use change or a single land use type as the independent variable would be insufficient to reveal the intrinsic mechanism of regional land use change. Lastly, the mechanism of land use change was investigated through single factor and factor interactions, helping to address the shortcomings of conventional methods, which are insufficient in explaining the influence mechanism of factor interactions.

Influencing factors of changes in land use, which include natural and human factors, lead to modifications in the structure and mode of land use. Considering the accessibility and representativeness of the data and referring to the existing studies (Tong and Lang, 2021; Huang et al., 2022; Wang et al., 2023), nine indicators were selected for analysis. However, the natural factors also included geological landforms and soils, and anthropogenic factors included the distance from water sources, and the distance from roads and policies, among others. Further research is needed on methods for selecting more representative factors as well as identifying dominant factors that cause changes in land use.

The geographical detector is suitable for use in case studies where the independent variable is a categorical quantity and the dependent variable is a continuous variable, whereby the study needs to categorize the continuous type of independent variables. However, the method exhibits some limitations: it cannot explain whether the effect of each factor on land use change is positive or negative. Additionally, the discretization strategy of the independent variable, the density of the grid, and the number of sampling points affect the results. Further research is needed to determine the optimal data categorization strategy, grid density, and number of sampling points.

### 4.2 Conclusions

Utilizing land-use data for the period 2000 to 2020, the characteristics of land use changes in the Liuchong River Basin were systematically analyzed by employing methods that included changes in dynamics, transfer characteristics, and the kernel density model. The drivers of land use changes in the Liuchong River Basin during the period under study were quantitatively analyzed using the geodetector model, leading to the following conclusions:

(1) In the past 20 years, the primary land use types in the Liuchong River watershed were cropland, forest, and shrubs, which collectively accounted for more than 90% of the total land area of the region. The area of impervious in the watershed has increased continuously, rising from 0.1% in 2000 to 0.38% in 2020. The area of barren in the region has consistently accounted for less than 0.01% of the total area in the past 20 years, while the area covered by shrubs has been decreasing, and the area covered by other land use types has exhibited monotonic change.

(2) From 2000 to 2020, the dynamics of other land use types in the Liuchong River Basin did not exhibit significant fluctuations in their single dynamic degree. However, there was significant growth in the single dynamic degree of barren, impervious, and waters, and a notable decline in the single dynamic degree for shrubs (9.37% decrease). The dynamic degree of comprehensive land use in the last 20 years was 7.95%. In the basin, the range of areas experiencing significant changes in land use has shifted from a “sporadic distribution” to “dispersed” to “relatively concentrated”.

(3) The drivers of each period exhibit varying explanato-

ry power regarding changes in land use in the Liuchong River Basin. However, temperature, rainfall, and elevation were found to be important factors influencing land use change, while nighttime lighting, GDP, and NDVI exhibited a gradual increase in impact on land use over time. Analysis revealed that interactions among the driving factors in each period were either two-factor or nonlinearly enhanced, with the explanatory power exhibited by interactions among the factors being always surpassing that shown by a single factor, indicating that complex factor interactions further deepened changes in land use.

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## 基于地理探测器模型的六冲河流域土地利用变化及其驱动因素分析

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**摘　要：**土地利用/覆被变化（LUCC）是人类活动与自然环境相互作用最直接的表现形式，对区域生态环境产生重要影响。本研究基于2000–2020年土地利用、地形、气候、经济与人口数据，运用土地利用动态度模型、转移矩阵、核密度模型和地理探测器探究了近20年六冲河流域土地利用时空演变特征及人类活动与自然环境因子对其影响的交互作用机理。结果显示：（1）六冲河流域土地利用类型由农田、森林与灌木占主导，土地利用变化方式主要表现为不透水面面积的上升和灌木面积的减少；（2）荒地、不透水面与水体单一动态度出现明显增长，灌木下降9.37%，其他土地利用类型单一动态度变化表现较为稳定，综合土地利用动态度为7.95%，流域的土地利用变化热点区域的范围经历了从“零星分布-扩散-相对集中”的变化过程。（3）气温、降水和高程是推动六冲河流域土地利用发生变化的重要因素，随着时间的推移，夜间灯光、GDP与NDVI逐渐成为影响土地利用变化的主要因素。交互探测结果表明各时段驱动因子间交互作用对土地利用变化的解释力始终大于单因子作用。研究结果可为流域进行国土空间规划、水土保持及生态恢复等提供数据支撑和科学参考。

**关键词：**核密度模型；地理探测器；土地利用；驱动因素；六冲河流域