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Numerical simulation of spatial-temporal coupling characteristics in the evolution of urban-rural landscape

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ABSTRACT

The change of landscape pattern is closely related to the quality of ecological environment, and the study of urban and rural landscape pattern, especially three-dimensional landscape pattern, is of great significance for urban-rural integration spatial planning. Based on the theory of landscape pattern, this study constructs a numerical simulation method for the characteristics of urban and rural three-dimensional landscape pattern, and explores the formation of optimization strategies for the three-dimensional development of urban and rural areas. Taking Chengdu City as an example, firstly, based on multi-source remote sensing data, the landscape pattern index method and gradient analysis method are utilized to explore the spatial and temporal coupling characteristics of urban and rural three-dimensional landscape patterns. Then the CA-Markov coupling model is used to predict the landscape pattern of future land use, so as to provide a reference for decision-making. The results of the study show that the landscape type changes in Chengdu City from 2005 to 2020 are dominated by the transformation between cultivated land, forest land and construction land, and the reasons for the changes are closely related to the urban development plan. In addition, the accuracy indices of the CA-Markov model all reached more than 80%, and the simulation results were reliable. The model prediction results show that construction land and cropland are the largest transformed landscape types, with a large-scale increase in the landscape area of construction land and a large-scale decrease in the landscape area of cropland. Spatially, the degree of fragmentation of the landscape pattern in Chengdu City gradually decreases, the landscape patches are more regularized, and the overall pattern shows a highly aggregated trend. The research results of this paper can be used as a reference for the optimization policy of three-dimensional landscape pattern in urban and rural areas, and provide data support and innovative ideas for the innovative development of urban and rural three-dimensional landscapes.

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Keywords: landscape pattern index method, spatio-temporal coupling characteristics, CA-Markov model, numerical simulation

1. Introduction

With the rapid development of China's economy and the acceleration of urbanization, the relationship between landscape and urbanization in contemporary China is also evolving. Urban landscape is not only the “face” of the city, but also an important symbol of urban development and the embodiment of cultural connotation [1-4]. In the process of urbanization, urban landscape reflects the direction and practice of urban development in the process of continuous change, and is also influenced by the process of urbanization, and the two interact with each other, shaping the urban landscape of contemporary China [5-6]. With the acceleration of urbanization, the scale of Chinese cities continues to expand, and the development mode, rhythm and spatial layout of cities have undergone great changes, which directly affect the evolution of urban landscape. And urban landscape has also become an important carrier for cultivating new economy and an important means for enhancing urban image [7-9].

Unlike the urban landscape, the rural landscape is a typical representative of the harmonious coexistence of natural scenery and humanistic environment. Its uniqueness lies not only in its natural beauty, tranquility and traditional flavor, but also in its functional diversity and close connection with human activities. Its composition mainly includes topography, geomorphology, hydrology, vegetation, soil and animals [10-14]. These elements interact and influence each other in the natural environment, forming the unique style of rural landscape. And with the development of rural urbanization, the rural landscape also adds urban style, and the countryside realizes a reasonable spatial layout and functional zoning, such as setting up ecological protection zones, agricultural development zones, residential zones, tourism zones, etc. [15-17].

This paper comprehensively utilizes CA-Markov landscape dynamic model, landscape transfer matrix, gradient analysis method and landscape pattern index method to explore the overall characteristics and spatial-temporal evolution trend of the landscape pattern of Chengdu City from 2005 to 2020 through numerical simulation, so as to provide reference for decision-making. First, remote sensing images are used as the data source to analyze the overall change characteristics of the three-dimensional landscape pattern in Chengdu City from 2005 to 2020 in the horizontal and vertical dimensions. The horizontal dimension explores the transformation characteristics and patterns of land use landscape types such as cropland, woodland, grassland, watershed, and construction land. The vertical dimension analyzes the landscape pattern changes in Chengdu City from the aspects of buildings and vegetation. Second, the CA-Markov model was used to simulate and predict the distribution of landscape pattern in Chengdu in 2025. The accuracy of the model was verified in terms of quantitative and spatial scales, and then the temporal and spatial evolution trends of the landscape pattern were analyzed through the prediction results.

2. Data sources and research methodology

2.1. Data sources and processing

In this paper, Chengdu City is taken as an object to study the evolution process of urban rural landscape by numerical simulation. The study uses four remote sensing images, Landsat7_ETM + in 2005, SPOT-5 in 2010, SPOT-7 in 2015 and SPOT-7 in 2020, as data sources, and after geometric correction, applies eCognition software and combines with the supervised classification for image interpretation to obtain the four phases of land use data in Chengdu City. On this basis, referring to the current land use classification, and combining the characteristics of land types in Chengdu City and the research objectives, the classification results were grouped into five landscape types: arable land, construction land, forest land, watershed and grassland. The classification accuracy of the classified data was evaluated using the function of randomly selecting points of AreGIS software, and the total accuracy reached 91.46%, which was in line with the data accuracy requirements of the deciphering. Other relevant socio-economic data were obtained from the Chengdu Statistical Yearbook (2006-2021).

2.2. Research methodology

2.2.1. Landscape pattern index method. Landscape pattern index can quantitatively reflect the information of spatial configuration and structural composition of landscape pattern, which is the digitalized embodiment of landscape pattern characteristics. In this paper, after summarizing the relevant literature and combining with the actual situation of Chengdu City, the number of patches (NP), patch density (PD), boundary density (ED), average patch area (AREA_MN), patch shape index (LSI) and aggregation index (AI) are selected from the type level, and the Shannon diversity index (SHDI) and Shannon evenness index (SHEI) are selected from the landscape level to characterize the urban-rural landscape pattern from the degree of landscape fragmentation, shape complexity and aggregation. SHEI) to analyze the urban rural landscape pattern from the characteristics of landscape fragmentation degree, shape complexity and aggregation [18].

1) Number of patches (NP):

$$NP = n \tag{1}$$

NP represents the number of all patches of a certain landscape type within the study area, the unit is one, where n is the total number of patches in the urban landscape.NP can be used to indicate the degree of fragmentation of a certain landscape type, and the number of patches has a positive correlation with the degree of landscape fragmentation.

2) Patch density (PD):

$$PD = \frac{n}{A} \tag{2}$$

PD refers to the ratio of the total number of patches to the total area of a certain landscape type, where n and A are the number of patches and the total area of patches of the urban landscape, respectively, and the larger the value indicates that the greater the number of patches, the higher the heterogeneity of the landscape, and the more serious the degree of fragmentation.

3) Average patch area (AREA_MN):

$$AREA\_MN = \frac{A}{n} \tag{3}$$

AREA_MN is the ratio of the total area of a landscape type to the total number of its patches, where A and n are the total area and total number of patches in the urban landscape, respectively. Its value is negatively correlated with the degree of landscape fragmentation, and the smaller the index value, the more serious the degree of landscape separation and fragmentation.

4) Plaque shape index (LSI):

$$LSI = 0.25E\sqrt{A} \tag{4}$$

LSI is a measure of shape complexity by calculating the degree of deviation between the shape of a patch in a region and a circle or square of the same area, where A and E represent the total area and total area perimeter of the urban landscape, respectively, and the larger the value of the LSI index, the more complex the shape of the landscape.

5) Shannon diversity index (SHDI):

$$SHDI = -\sum_{i=1}^{n} p_i \ln p_i \tag{5}$$

The Shannon Diversity Index reflects the total number of patches of different landscape types and the proportion of total area in the same period. Where p_i indicates the frequency of landscape type i patches in the study area. When the Shannon diversity index is 0, it indicates that the whole landscape consists of one patch. The larger the Shannon diversity index is, the richer the diversity of the landscape system is, the more uniform the proportion of each landscape is, and the more stable the landscape system is.

6) Shannon Homogeneity Index (SHEI):

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

The Shannon evenness index is the ratio of the Shannon diversity index to the maximum possible diversity at a given landscape abundance, and can reflect the distribution of different landscape types over an area. The Shannon evenness index value is between 0 and 1. When $SHEI = 0$, it indicates that the whole landscape system consists of one plate. When $SHEI = 1$, it indicates that each landscape type is evenly distributed in the landscape system and there is no obvious dominant landscape type.

7) Aggregation index (AI):

$$AI = \left[\frac{g_{ij}}{\max_{g_{ij}}}\right] \tag{7}$$

Aggregation index can reflect the dispersion of patches in the landscape, and its index value is taken in the range between 0 and 100. In the formula, g_{ij} is the number of nodes between the image elements of the urban landscape based on the haplotype method, and $\max_{ij}$ is its maximum number of nodes. When $AI = 0$, it indicates that the individual patches in the landscape are maximally dispersed. When $AI = 100$, it means that the whole landscape is composed of one independent patch.The value of AI index has an inverse relationship with the dispersion of the landscape, and the larger the value of AI index, the more centralized the distribution of individual patches in the landscape.

8) Boundary density (ED):

$$ED = \frac{\sum_{j=1}^{n} p_{ij}}{A} (j \neq 1) \tag{8}$$

ED is the edge length between patches of urban landscape types, which can be used to indicate the degree of landscape fragmentation. Its index value is positively related to the degree of landscape segmentation, and the greater the boundary density, the more serious the degree of urban landscape fragmentation.

Since the spatial resolution of GF-2 remote sensing image is 4m, and the difference between the spatial resolution of Landsat5 remote sensing image and 30m is too large, which may affect the results of the landscape pattern index calculation, therefore, after resampling 30m in ArcGIS 10.0 software, we imported the three-phase landscape classification raster data into Fragstats 4.0 software at the type level and the landscape level, respectively. The corresponding landscape pattern index was selected and imported into Excel software for summarization and analysis after arithmetic.

2.2.2. Gradient analysis. Spatial gradient refers to the spatial characteristics of landscape features that change regularly and gradually along a certain direction. There are 2 main gradient analysis methods: the moving window analysis method and the buffer zone method, which can be utilized to study changes in urban landscape patterns.

For a specific study area, choosing the appropriate study scale is especially important for the research results. Related studies show that the moving window method can better analyze the relationship between landscape and spatial variability, as well as determine the characteristic scale of the study area, and can fix the noise caused by small scale and local variability. The principle is to select a certain size of window to move in the study area to form a new data graph that can be calculated in the GIS, to realize the quantification of landscape indexes on the regional or district scale, and to clearly show the characteristics of landscape heterogeneity on the spatial scale.

2.2.3. Landscape spatial dynamic modeling. There are many cases in the existing literature on landscape spatial dynamics simulation, integrated multiple results of research, landscape spatial model based on ecological processes can be divided into different ways of dealing with the neighborhood rule model, random landscape model, landscape intelligence model, landscape process model, and landscape coupling model.

1) Neighborhood rule model. In the domain rule model representation of landscape dynamics emphasized by the dynamic changes of the patch will be affected by the neighboring patches of different degrees. At present, the most representative neighborhood rule model is the cellular self-organization (CA) model.

2) Stochastic landscape model. Stochastic landscape model is also called Markov model, the study is the use of Markov process in the state of the transfer is no a posteriori, the landscape of the pattern and the process of the overall dynamics both in space and in time. It combines probability distributions with spatial information and will have little connection to specific ecological processes. Stochastic landscape models incorporate modeling tools such as geometric, mechanistic, and statistical methods to introduce biofeedback principles into spatial dynamics models or to introduce spatial features into traditional ecological models. One of the most commonly used is the Markov model, the basic method is to simulate the dynamic development law and trend between the states of landscape patches through the transfer matrix.Markov model assumes that its transfer probability does not change with time, the key to the successful use of this model lies in the transfer matrix to determine the transfer matrix, which is characterized by the probability of the state of the previous point of the patch is determined. The dynamic prediction of the landscape can be represented by the following Markov model:

$$A_{(t+1)} = A(t)P_{ij} \tag{9}$$

where A_{t+1} is the landscape pattern state matrix, A_t is the corresponding landscape pattern state matrix of the landscape patch at moment t, and P_{ij} is the landscape patch state transfer matrix.

3) Landscape Intelligence Model. Due to the complex nonlinear relationship between the nature of landscape change and landscape ecology, artificial neural networks are increasingly integrated into landscape ecology, enriching the simulation methods of landscape ecology. For example, the artificial neural network approach combined with GIS technology to model and simulate landscape changes under different perturbations helps to predict future landscape change trends, etc.

4) Landscape coupling model. The coupled model can complement or verify each other's simulation results, and obtain simulation results with higher accuracy for multiple simulation variables. If the ecological process of landscape pattern contains multiple complex factors, the coupled model has better explanatory ability and stronger advantages.

2.2.4. CA models:

1) The concept of tuple. CA model is composed of tuple, tuple state, neighborhood and transition rule, the basic principle is that the state of a tuple in the next moment is a function of the state of its neighborhood in the previous moment [19].The CA model can be simply described as:

$$S_{(t+1)} = f\left(S_{(t)}, N\right) \tag{10}$$

where S is a discrete, finite set of metameric states, $t+1$ is different moments, N is a metameric neighborhood, and f is a transition rule for localized spatial metameric states.

2) Composition of CA model. The basic components of a CA model include four parts: tuple, neighborhood, tuple space and transformation rules, and any CA model can be considered as a collection of a tuple space and transformation functions defined in that space.

(1) Tuple and its state. Metacells, also called cells or primitives, are the most basic components that make up a metacell space. In geographic research, a tuple is generally considered to be a unit in a study area that is divided into units of uniform size and shape.

(2) Metacell space. The tuple space is a collection of spatial outlets composed of tuple distributions. For the most common two-dimensional tuple automata model, its two-dimensional tuple space is divided into three patterns: triangular, quadrangular and hexagonal. Triangular meshes are relatively simple but difficult to express in a computer. The quadrilateral grid is simple and intuitive, easy to implement in a computer, but lacking in practical simulations. The hexagonal grid can solve the isotropy problem well and the simulation results are more realistic, but the model expression is complicated and the modeling is difficult.

(3) Neighborhood. Neighborhood refers to the local metric space centered on a certain metric. The definition of the neighborhood of a 2D tuple automaton is more complicated, it is a 2×2 block of tuples done uniformly each time, while in the first three models, each tuple is treated separately.

(4) Transformation rules. The transition rule is a kinetic function that determines the state of a tuple in the next moment based on the current state of the tuple as well as the neighborhood condition. Transition rules allow the construction of a simple, localized tuple space that is discrete in both space and time. For a commonly used Moore neighborhood, the transformation function can be expressed as:

$$S_{ij}^{t+1} = f_N\left(S_{ij}^{t}\right) \tag{11}$$

where S denotes the state of the tuple, f is the transition function that defines the transition of tuple ij from moment t to moment $t+1$. N is the neighborhood of the tuple and is the variable of the transition function.

2.2.5. CA-Markov modeling:

1) Markov process is one of the stochastic process theories, the state that will be reached in the process in the next moment are only dependent on the current state, independent of the previous state, the study is the use of Markov process in the state of the transfer is no posteriority. The landscape pattern process is an independent being in terms of spatio-temporal relationships, thus its stochastic process is weakly correlated. Markov process is used to predict the future state by studying the probabilities between the initial system state states and the transfer probabilities determine the trend of the system state.

2) The transfer probability, which describes the probabilistic statistical properties of a Markov process, is commonly used in practice as a substitute for frequency, and thus requires a transfer frequency calculation figure, the frequency matrix. According to the transfer probability matrix of the state arrived at time t_n from time $t(n-1)$, by transferring the state to another state probability therefore has the nature of conditional probability.

3) Markov process of related to the state of the previous moment, do not see the later occurrence, i.e., $t(n-1)$ only related to t_n state of the moment state with in front of the state. The mathematical expression for the transition probability matrix landscape type is as follows:

$$P = \left(P_{ij}\right) = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ & & \cdots & \\ P_{n1} & P_{n2} & \cdots & P_{nn} \end{bmatrix} \tag{12}$$

4) State transfer probability matrix: multiple probabilities of an event P_{ij} satisfy the following conditions:

$$\begin{gathered} 0 \le P_{ij} \le 1 \\ \sum_{j=1}^{n} P_{ij} = 1 \end{gathered} \tag{13}$$

where i, j is any of the values in $1, 2, 3, \ldots n$.

5) Calculate the state transfer probability matrix: i.e., find the state transfer probability of each state transferring to any other state, which is calculated by the basic equation:

$$P_{ij}^{n} = \sum_{k=1}^{N} P_{ik} P_{kj}^{(n-1)} = \sum_{k=1}^{N} P_{ik}^{(n-1)} P_{kj} \tag{14}$$

Markov chains are usually characterized by two features: chirality and no posteriority, and satisfy the following equations:

$$E(n) = E(n-1)P_{ij} = E(0)P_{ij}^{n} \tag{15}$$

Different land use types may be converted to each other, the conversion function of multiple land use is difficult to use a concise function to be effectively expressed, in a relatively small study area within a time year, the land use structure is relatively stable, so the Markov model is equipped with the conditions of a dynamic model that can be used to predict the changes in the structure of land use.

3. Findings and analysis

In this chapter, CA-Markov landscape dynamic model, landscape transfer matrix, gradient analysis method and landscape pattern index method will be comprehensively utilized to grasp the main laws of the spatial and temporal evolution of the three-dimensional landscape pattern of Chengdu City from 2005 to 2020 from general characteristics to spatial and temporal characteristics, and to get the overall situation of the future landscape pattern of the study area under the existing development pattern, in the hope of providing a sustainable use of the land in Chengdu City. We hope to provide a scientific basis for the sustainable utilization of land in Chengdu.

3.1. Characterization of spatial and temporal coupling of three-dimensional landscape patterns

3.1.1. Overall Changing Characteristics of 3D Landscape Patterns:

1) Characteristics of overall changes in the horizontal dimension. The proportion of landscape area of non-construction land and construction land types in Chengdu City from 2005 to 2020 is shown in Table 1. The formula for calculating the dynamic change degree of which is as follows:

$$K = \frac{U_b - U_a}{U_a \times T} \times 100\% \tag{16}$$

where: K is the attitude of landscape utilization dynamics. U_a and U_b denote the area of a particular landscape type at the beginning moment *a* and the end moment *b* of the study, respectively. T is the time interval from *a* to *b* (years).

From 2005 to 2020, the area proportion of non-construction land landscape type decreased from 75.58% to 62.58%, and the degree of dynamic change of landscape type was -1.15. In contrast, the area proportion of construction land landscape type increased from 24.42% to 37.42%, and the degree of dynamic change of landscape type amounted to 3.55.

Table 1. Area proportion of construction and non-construction land

	Year	Non-construction land/%	Construction land/%
Area specific gravity/%	2005	75.58	24.42
	2010	69.66	30.34
	2015	65.78	34.22
	2020	62.58	37.42
Dynamic variation	2005-2020	-1.15	3.55

Meanwhile, the area proportion of each landscape type in Chengdu City from 2005 to 2020 is shown in Table 2.

In terms of the composition of non-construction land landscapes in different years, the dominant landscape type in the study area is cropland (area proportion >50%), whose area proportion is much higher than that of other landscape types. During the whole study period, the landscape composition of non-construction land types in the order of the size of the area proportion includes cropland, woodland, water and grassland, the area proportion of cropland, woodland and grassland shows a decreasing trend, and the area proportion of water area has increased, which has a small impact on the area proportion of the whole non-construction land landscape types due to its small actual area and small change.

By time period, from 2005 to 2010, the area proportion of cropland, grassland, and watershed decreased by 6.11%, 0.14%, and 0.03%, respectively, and the proportion of woodland and construction land increased by 0.39% and 5.92%, respectively, and the city maintained a high-speed expansion pattern.From 2010 to 2015, the area proportion of cropland and woodland decreased by 3.61% and 0.33%, respectively, and the proportion of grassland, waters, and the area share of construction land increased by 0.01%, 0.05%, and 3.88%, respectively, and the rate of urban expansion slowed down.From 2015 to 2020, the area share of arable land decreased by 3.09%, and the area share of construction land increased by 3.20%, and the city maintained a certain degree of inertia and scale of development.

Table 2. Area proportion of landscape type

	Year	Farmland/%	Woodland/%	Meadow/%	Waters/%	Construction land/%
Area specific gravity/%	2005	65.98	7.75	0.36	1.49	24.42
	2010	59.84	8.14	0.22	1.46	30.34
	2015	56.23	7.81	0.23	1.51	34.22
	2020	53.14	7.62	0.28	1.54	37.42
Dynamic variation	2005-2020	-1.30	-0.11	-1.48	0.22	3.55

In order to better observe the landscape evolution characteristics of each land use type and the position and role of each constituent landscape type of the non-construction land use landscape in the overall change of the landscape in different time periods from 2005 to 2020, this study analyzes the transfer-in and transfer-out contribution rates of each landscape type in each time period. The formula for calculating the transfer-in (transfer-out) contribution rate and retention rate is as follows:

$$T_{ij} = \frac{A_{ij}}{A_t} \tag{17}$$

$$T_{oj} = \frac{A_{ji}}{A_t} \tag{18}$$

$$R = \frac{A}{U} \times 100\% \tag{19}$$

where: T_{ij} is the specific transfer-in contribution rate. T_{oj} is the specific transfer-out contribution rate. A_{ij} is the area transferred from type i to type j. A_t is the total area where transfer of landscape types occurred. A_{ji} is the area transferred from type j to type i. R is the rate of retention of specific landscapes. A is the total area of the specific landscape that did not undergo a type shift change during the study period. U is the total area of the landscape type at the beginning of the study period.

The landscape type transfer matrix from 2005 to 2010 is shown in Table 3, with the unit of area in km^2, and the unit of transfer in (out) contribution and retention rate in %, which is the same as later.

The total area transferred out of landscape types from 2005 to 2010 was 262.77 km^2, and the transformation mainly occurred between cropland, forest land and construction land. Of the transferred area, cultivated land accounted for 215.78km^2, and the remaining landscape types accounted for only 17.88%. The transformed area of each landscape was mostly transferred to construction land, with construction land receiving 81.52% of the transferred area. Cultivated land, grassland, and water transfer out contribution is greater than transfer in contribution, and forest land and construction land transfer in contribution is greater than transfer out contribution. Of the landscape types, grassland has a much lower retention rate than the other landscape types, with a retention rate of only 61.03%. Generally speaking, during this period, the area of arable land was greatly reduced, the area of construction land was greatly increased, all kinds of landscapes changed drastically, the stability of landscape types was poor, and the disadvantages of urban sprawl appeared at the beginning.

Table 3. Transfer matrix of landscape type in 2005-2010

Type	Farmland	Woodland	Meadow	Waters	Construction land	Transfer out area	Transfer contribution rat	Retention rate
Farmland	2089.51	10.58	2.56	1.97	200.67	215.78	82.12	90.64
Woodland	3.15	245.43	0.00	0.58	4.29	8.02	3.05	96.84
Meadow	0.02	0.00	11.40	0.12	7.14	7.28	2.77	61.03
Waters	1.23	1.54	0.03	47.19	2.13	4.93	1.88	90.54
Construction land	16.94	8.25	0.26	1.31	773.35	26.76	10.18	96.66
Transferred area	21.34	20.37	2.85	3.98	214.23			
Transfer contribution	8.12	7.75	1.09	1.52	81.52			

The landscape type transfer matrix from 2010 to 2015 is shown in Table 4, and the total area transferred out of landscape types is 149.75km^2, dominated by the conversion between cultivated land and construction land, with the contribution rate of cultivated land transferring out accounting for 86.98% of the total transferring in, and mainly converting to construction land. The contribution rate of conversion out of cropland and forest land is greater than the contribution rate of conversion in, and the area continues to shrink. Grassland, watershed and built-up land have a higher transfer-in contribution rate than transfer-out contribution rate, and the landscape area tends to increase. The retention rate of all landscape types is higher than 90%, and the original built-up land even hardly participates in the conversion of landscape area. During this period, the landscape stability was high, people began to pay attention to ecological protection in the process of urban expansion, and economic construction and urban planning shifted to high-quality development.

Table 4. Transfer matrix of landscape type in 2010-2015

Type	Farmland	Woodland	Meadow	Waters	Construction land	Transfer out area	Transfer contribution rat	Retention rate
Farmland	1764.82	0.86	0.88	3.34	125.17	130.25	86.98	93.13
Woodland	1.71	244.68	0.09	1.57	9.73	13.1	8.75	94.92
Meadow	0.01	0	6.28	0.34	0.34	0.69	0.46	90.10
Waters	0.08	0.08	0.04	42.22	3.82	4.02	2.68	91.31
Construction land	0.64	0.48	0.03	0.54	959.13	1.69	1.13	99.82
Transferred area	2.44	1.42	1.04	5.79	139.06			
Transfer contribution	1.63	0.95	0.69	3.87	92.86			

The landscape type transfer matrix for 2015-2020 is shown in Table 5, with a total area of 514.03 km^2 transferred out of the landscape type, and cropland, forest land, watershed and construction land all participated in the landscape transfer in a large area during this period. Cultivated land and constructed land together constitute the main participants in the transferred landscape, accounting for a total of 83.68% of the transferred contribution. At the same time, cropland and built-up land were also the major transfer-in landscapes in each landscape, accounting for a total of 84.35% transfer-in contribution. Grassland and watershed had roughly equal transfer-out and transfer-in contributions, and the rest of the landscape types, with the exception of built-up land, had higher transfer-out contributions than transfer-in contributions. In terms of retention rate, the retention rate of cropland, woodland, watershed and built-up land is between 60% and 90%, while the retention rate of grassland is only 38.12%, which is less stable than that of the previous period. Overall, the degree of change in all types of landscapes is high in this period, and the deeper reason behind this may be the adjustment of urban and rural land use planning.

Table 5. Transfer matrix of landscape type in 2015-2020

Type	Farmland	Woodland	Meadow	Waters	Construction land	Transfer out area	Transfer contribution rat	Retention rate
Farmland	1486.44	38.04	0.31	9.72	232.75	280.82	54.63	84.11
Woodland	48.41	185.31	0.83	1.12	10.43	60.79	11.83	75.30
Meadow	0.18	2.14	2.79	0.16	2.05	4.53	0.88	38.12
Waters	9.75	4.06	0.23	29.43	4.54	18.58	3.61	60.30
Construction land	125.47	10.59	4.73	8.52	948.88	149.31	29.05	86.40
Transferred area	183.81	54.83	6.10	19.52	249.77			
Transfer contribution	35.76	10.66	1.19	3.80	48.59			

The analysis of the landscape type transfer matrix for the three time periods from 2005 to 2020 can be synthesized, and it can be concluded that the changes in landscape types are dominated by the transformation between cultivated land, forest land and construction land. At the same time, it can be seen that the change of each land use type is closely related to the planning related to urban development.

2) Overall change characteristics of vertical dimension. The changes in building indicators from 2005 to 2020 are shown in Table 6. From 2000-2020, the number of single buildings increased by as much as 60,155, the changes in floor area and building density are not very obvious, the average building height and the standard deviation of building height have increased significantly, and the floor area

ratio and spatial compactness have also increased significantly. This reflects that since 2005, new buildings in Chengdu are mainly small in size, and the space utilization rate has risen. The change in building height reflects the diversity of buildings in the urban area and the improvement of building technology. Volume ratio and spatial compactness reflect the increase in development intensity.

Table 6. Changes in architecture indicators in 2005-2020

Architecture indicators	2005	2010	2015	2020
Number of buildings	134802	171716	187469	194957
Floor area /km^2	606.3952	567.4456	570.6421	594.0636
Building density	0.1757	0.1582	0.1604	0.1637
Average building height	9.9336	10.4134	13.8509	15.3359
Standard deviation of height	9.9011	11.8212	16.6492	18.2913
Floor area ratio	0.4033	0.4260	0.5509	0.6057
Space compactness	0.0062	0.0064	0.0084	0.0089

The changes of vegetation indicators from 2000 to 2020 are shown in Table 7. From 2005 to 2020, the vegetation cover in Chengdu decreased by 10.5588km^2, the canopy cover decreased, the leaf height diversity decreased, while the average canopy height, the canopy height heterogeneity and the three-dimensional greenness were improved to different degrees. The average canopy height, canopy height heterogeneity and three-dimensional green volume were improved to different degrees. This shows that although the vegetation area has been reduced since 2005, the diversity of vegetation has been improved and the ecological effect has been compensated to a certain extent.

Table 7. Changes in vegetation indicators in 2005-2020

Architecture indicators	2005	2010	2015	2020
Vegetation coverage area km^2	301.1362	306.6679	302.447	296.1091
Canopy cover	2.9987	3.16597	3.1268	2.97536
Average canopy height /m	11.1665	11.4121	11.40998	14.27023
Canopy height heterogeneity	3.84706	3.4466	3.4584	4.8894
Leaf height diversity	1.1458	1.1725	1.1536	0.9896
Three-dimensional green quantity /km^3	3364.5667	3514.8196	3481.9101	4159.6151

3.1.2. Characteristics of spatial and temporal coupling of three-dimensional landscape patterns. This section mainly focuses on the temporal and spatial coupling characteristics of the 3D landscape pattern in Chengdu City based on the trend of the 3D landscape pattern index values from 2005 to 2020. Using ArcGIS software, urban and rural landscape types such as cropland, woodland, grassland, watershed and building land in Chengdu City were selected for analysis, resulting in the changes of landscape pattern in the four years of 2005, 2010, 2015 and 2020 as shown in Table 8.

From the data in the table and the distribution of patches, it can be seen that: from 2005 to 2020, the area of cultivated land in Chengdu City shows a decreasing trend. The area of water area increases as a whole, and the number of patches of grassland shows a decreasing trend from 2005 to 2010, and then there is a small increase from 2010 to 2020, and the area decreases a lot as a whole, which indicates that the grassland is well utilized. Building patches show a decreasing trend and remain unchanged until 2015, indicating that there has been a clustering effect of residents' settlements over the past 15 years, and the area of building patches has decreased. Woodland patches showed a positive correlation with some increase from 2005 to 2010. It started to decrease from 2010 to 2020, and the area of woodland is also decreasing, which may be mainly due to indiscriminate logging or conversion to other types of land. Meanwhile, the perimeter of grassland and the number of patches are plummeting, the perimeter of cultivated land is decreasing in general, the number of patches of water and the area of patches are obtaining a corresponding increase, while the number of patches of woodland is increasing and the area is decreasing, which indicates that people are beginning to intervene and transform the original relationship of the landscape pattern, and the original forested landscape is being destroyed, but the grassland abandonment is decreasing, which indicates that the grassland restoration has been supported.

In addition, the data in Table 8 show that the average patch area of cultivated land in Chengdu City is decreasing from 2005 to 2020, and the patch density increases in this time period, which also indicates that it is more fragmented and subject to human interference. On the other hand, the average patch area of the two landscape types, watershed and woodland, is decreasing, and the patch density is also decreasing, which indicates that the degree of fragmentation of this landscape is smaller. Comparing the size of patch density of the five landscape types, it can be seen that the patch density of arable land has been kept the largest, which indicates that arable land is more concentrated and has a larger area in Chengdu, and it is the most dominant landscape type in the study area, while the distribution of watersheds and building land is also being concentrated.

Table 8. Index values of various landscape element types in different periods

Index	Year	Farmland	Woodland	Meadow	Waters	Construction land
Patch number	2005	548	289	58	12	494
	2010	468	346	57	12	392
	2015	362	334	19	19	372
	2020	264	311	28	21	372
Patch type area /km^2	2005	2089.51	245.43	11.4	47.19	773.35
	2010	1895.07	257.78	6.97	46.24	960.82
	2015	1767.26	246.1	7.32	48.01	1098.19
	2020	1670.25	240.14	8.89	48.95	1198.65
Perimeter of plaque type /km	2005	64246.364	85592.711	24.483	13000.372	54915.8311
	2010	50016.093	90601.139	8445.757	10000.105	64458.9015
	2015	44473.799	86289.009	3043.926	12733.043	62323.9935
	2020	28514.692	83269.336	2069.781	13023.128	63468.592
Mean patch area /km^2	2005	3.813	0.849	0.197	3.933	1.565
	2010	4.049	0.745	0.122	3.853	2.451
	2015	4.882	0.737	0.385	2.527	2.952
	2020	6.327	0.772	0.318	2.331	3.222
Patch density	2005	0.115	0.022	0.0056	0.059	0.068
	2010	0.132	0.021	0.0101	0.056	0.059
	2015	0.111	0.024	0.013	0.072	0.064
	2020	0.149	0.02	0.0166	0.042	0.075
Fractal dimension	2005	1.418	1.32	1.223	1.37	1.343
	2010	1.41	1.294	1.311	1.469	1.341
	2015	1.37	1.268	1.216	1.268	1.33
	2020	1.339	1.317	1.269	1.375	1.315

3.2. Land use landscape pattern simulation projections

3.2.1. Accuracy verification of simulation results. In this section, the accuracy of the simulated land use landscape pattern simulation in Chengdu City is validated from two dimensions, namely, quantitative and spatial scales, respectively, to prove the effectiveness of the model.

1) Quantitative accuracy validation. For the CA-Markov model simulated landscape type area of Chengdu City in 2020 in the quantitative accuracy test using precision error test method, the predicted landscape type area is compared with the actual landscape type area, the formula is as follows:

$$K = \frac{S_{ij} - S_{it}}{S_{ij}} \times 100\% \tag{20}$$

where: K indicates the simulated quantitative error for landscape type i, and when $K > 0$, it indicates that the actual area of landscape type i is larger than the predicted area. When $K < 0$, the actual area of category i landscape type is smaller than the predicted area. The smaller the absolute value of K, the higher the accuracy of the simulation results. S_{ij} and S_{it} indicate that the actual area of the ith landscape type is the same as the predicted area of the model.The accuracy of the simulation results of the number of landscape types and the actual area of Chengdu in 2020 is shown in Table 9.

As can be seen from Table 9, the largest error is mainly in the cultivated landscape, which is 0.12%. The errors of construction landscape, cultivated land landscape and woodland landscape are mainly affected by policy factors, and the error of water landscape is also affected by factors such as enclosure of lakes in the region and constant change of water level, which lead to unpredictability in the process of making transformation rules, and it is not possible to analyze the trend of various types of landscapes from a deeper level. Overall the simulated quantitative error and the actual error is small, are less than 0.2%, can be carried out the next step of prediction research.

Table 9. Quantitative precision analysis of landscape type simulation

Landscape type	Landscape area in 2020 /km²	Simulated area in 2020 /km²	Area error /%
Farmland	1670.25	1671.78	-0.12
Woodland	240.14	239.97	0.07
Meadow	8.89	8.88	0.11
Waters	48.95	48.99	-0.08
Construction land	1198.65	1197.41	0.10

2) Spatial scale accuracy verification. The accuracy verification on the spatial scale of land use change in Chengdu City in 2020 predicted by CA-Markov model is adopted by the Kappa coefficient verification method - VALIDATE, which combines the quantity verification and spatial location verification to improve the accuracy of the verification [20]. In this paper, through the accuracy verification of the simulation results of 2020 and the actual landscape type map, the analysis results show that the value of its quantity accuracy Kquantity is 0.832, and the value of its location accuracy Klocation is 0.827, which proves that the simulation of the landscape pattern of Chengdu City in 2020 is better, with a high degree of credibility, and able to satisfy the research needs.

3.2.2. Predictive Analysis of Future Land Use Landscape Patterns:

1) Quantitative results analysis. In order to more intuitively show the quantitative changes of landscape types in Chengdu City in 2020-2025, the areas of various types of landscapes in Chengdu City in 2025 predicted in the CA-Markov model and the areas of each landscape type in 2020 were counted, and the results of the comparison of landscape type situations were obtained as shown in Table 10.

As can be seen from Table 10, the area of each landscape type in 2020-2025 has undergone some changes in different degrees, which is specifically manifested in the following: the landscape area of arable land in Chengdu City has shown a smaller trend and is the landscape with the largest reduction area. The area of construction land landscape shows an increasing trend, and the proportion of construction land landscape exceeds that of arable land landscape (47.12% > 44.58%) in 2025, becoming the first major landscape type in Chengdu. The area of woodland landscapes decreases significantly, the area of water landscapes increases slightly, and grasslands show a decreasing trend.

Table 10. The comparison of landscape type

Landscape type	Landscape type area in 2020 /km²	Landscape type area in 2025 /km²	Change from 2020 to 2025 /km²	Proportion in 2025 /%
Farmland	1670.25	1411.66	-258.59	44.58
Woodland	240.14	204.03	-36.11	6.44
Meadow	8.89	7.67	-1.22	0.24
Waters	48.95	51.21	+2.26	1.62
Construction land	1198.65	1492.31	+293.66	47.12

The changes in the area of each landscape type in Chengdu City in each historical year and forecast year were counted, and the results of the comparison of the area of each landscape type were obtained as shown in Fig. 1. Where the legend indicates different years.

As can be seen from Figure 1, the area of arable land landscape shows a decreasing trend in all years, and the construction land shows an accelerated rising trend, indicating that with the acceleration of urbanization in Chengdu City, the decrease of arable land may be mainly due to the occupation of new construction land, agricultural structure adjustment and natural disasters, etc., the area of woodland landscape rises and then decreases, the area of water landscape is small and the change is not significant, and the grass landscape accounts for a very small proportion in Chengdu City, which It indicates that Chengdu City has a high degree of land use development and insufficient reserve resources of arable land.

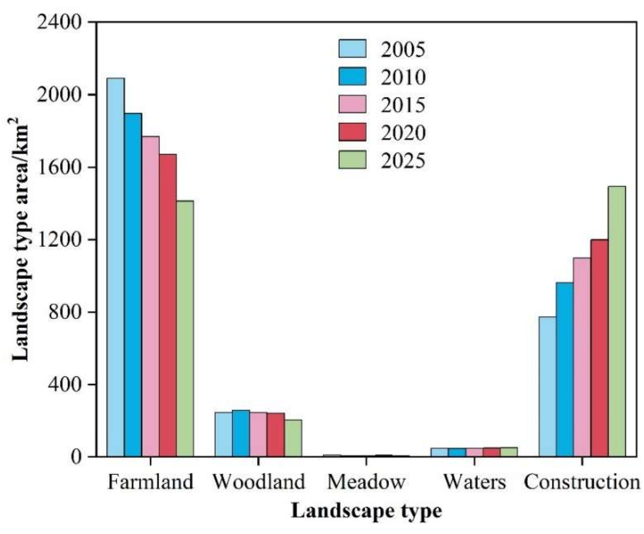

Fig. 1. The comparison chart of area of landscape types in different years

In order to have a clear understanding of the transfer of landscape types in Chengdu City, the transfer matrix generated in IDRISI 7.0 was exported to analyze the transfer of each landscape type, and the transfer area matrix and probability matrix of land use landscape were obtained as shown in Table 11 and Table 12, respectively.

According to the analysis of Table 11 and Table 12, it is concluded that in 2020-2025, the landscape of cultivated land and construction land undergoes a large change, and the landscape of cultivated land is transferred out of 443.72km², which is mainly transferred to the landscape of construction land and the landscape of forest land, and its transferred area is only 185.13km², which is nearly 42% of the transferred area. The transferred-in area of construction land is 331.43km^2, which is mainly from the transferred-out area of cultivated land and forest land. The area of forest land transferred out is larger than the area transferred in, and the area has been reduced. Waters have a small increase in their area due to setting them as a limiting factor. In the transfer matrix, the amount of grassland transferred in and transferred out is lower.

Influenced by the accelerated urbanization and rapid economic growth of Chengdu City, the landscape area of construction land in Chengdu City will show a trend of rapid growth, but the total area of construction land landscape meets the requirements of the overall plan and does not exceed its planning restriction area. Cultivated land landscape shows a decreasing trend in the whole development trend due to new construction land occupation, agricultural structure adjustment and natural disasters. Forested landscapes are slowed down by the influence of the policy of returning farmland to forests and the restriction of forest land control in Chengdu City. The water landscape shows a small increase due to the influence of regional control. Grassland landscapes show a significant decreasing trend due to their own small base, and the control of this type of landscape needs to be strengthened.

Table 11. Matrix of land use transfer area in the lower reaches in 2020-2025

Landscape type	Farmland	Woodland	Meadow	Waters	Construction land
Farmland	1226.53	123.08	0.06	3.17	317.41
Woodland	182.47	47.32	0.14	0.58	9.63
Meadow	2.24	0.12	3.21	0.18	3.14
Waters	0.17	3.86	0.84	42.83	1.25
Construction land	0.25	29.65	3.42	4.45	1160.88

Table 12. Transition probability matrix of land use in the lower reaches in 2020-2025

Landscape type	Farmland	Woodland	Meadow	Waters	Construction land
Farmland	73.43	7.37	0.01	0.19	19.00
Woodland	75.98	19.71	0.06	0.24	4.01
Meadow	25.20	1.35	36.11	2.02	35.32
Waters	0.35	7.88	1.72	87.50	2.55
Construction land	0.02	2.47	0.29	0.37	96.85

2) Analysis of spatial results. The land use landscape type map of Chengdu City in 2025 and 2020 is compared and analyzed, and the landscape level index is continued to be introduced to further analyze the predicted results of the land use landscape pattern in 2025 for the countermeasure research afterwards.The land use landscape level index of Chengdu City from 2020 to 2025 is shown in Table 13.

By analyzing the results of the simulation prediction of the landscape pattern in 2025 in Chengdu City, it can be seen that the land use landscape pattern in Chengdu City shows obvious geographical differences. In terms of distribution, cropland is mainly distributed in the three hilly valley areas of Chengdu City, and the area of cropland landscape is increasing from south to north. Forested landscapes are still mainly distributed in the mountainous type areas of Chengdu City, extending from northeast to southwest in parallel arrangement. The construction land landscape is obviously developing in an expansion trend, and the expansion trend from south to north from 2020 to 2025 is very obvious, occupying a large amount of cultivated land landscape, and the landscape patches are heavily clustered in the southern part of Chengdu City. Through Table 13, it can be seen that the landscape pattern in 2025 is less fragmented, the shape of the patches is more regularized, the spread and connectivity between the landscape patches increase, and a high degree of agglomeration is shown.

Table 13. Landscape index in land level of land use in 2020-2025

Year	NP	LSI	CONTAG	SPLIT	SHDI
2020	41265	131.4283	48.6254	16.2837	1.3562
2025	22438	76.5147	55.3167	13.5214	1.3328

4. Conclusion

Based on the CA-Markov landscape dynamic model, landscape transfer matrix, gradient analysis method and landscape pattern index method, this paper realizes the numerical simulation of the spatio-temporal coupling characteristics in the process of urban-rural landscape evolution, taking Chengdu city as an example.

The overall change characteristics of the three-dimensional landscape pattern in Chengdu City from 2000 to 2020 are shown as follows: the change of landscape type in the horizontal dimension is dominated by the transformation between cultivated land, forest land and construction land, and its change is closely related to the urban development plan. The vertical dimension landscape pattern is mainly discussed in terms of architecture and vegetation, in which architecture is mainly characterized by the increase of average building height, the increase of building height diversity, and the increase of land development intensity reflected by the increase of plot ratio and spatial compactness, while vegetation is characterized by the decrease of vegetation cover area and the increase of vegetation diversity.

The CA-Markov model was used to simulate and predict the landscape pattern of Chengdu City in 2025 both spatially and quantitatively. In terms of quantity, the landscape area of construction land increased massively, the landscape area of arable land decreased massively, and the forested landscape did not change much. Spatially, the landscape pattern of Chengdu City in the future shows a trend of reduced fragmentation, more regular landscape patches, and a high degree of aggregation in the overall pattern. The simulation results can be used to propose recommendations for the sustainable development of land use.

First, the regional land use master plan should be strictly implemented. Secondly, the spatial layout of land use and functional zoning of land use should be optimized. Third, the control of regional construction land and arable land should be increased. Finally, the dynamic monitoring of land use and law enforcement supervision should be strengthened.

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