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Simulation Analysis of Spatiotemporal Evolution of Land Use in Yangchun City using Markov-PLUS Model

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***Abstract*— *This article is based on CLCD (China Land Cover Dataset) and employs the Markov-PLUS model to simulate and configure land use structure, predict future trends, deepen the understanding of the causes and mechanisms of land use change, provide a scientific foundation for the formulation of city land policies, and promote scientific planning, efficient utilization, and sustainable development of land resources. The key result is that forests and cropland are the majority of land types in Yangchun City, accounting for over 90%, with cropland distributed northeast to southwest strip. From 2015 to 2020, the dynamic degree of single land use in grassland was -6.39%, with the fastest drop rate. The dynamic degree of comprehensive land use is relatively small, at 0.13%, indicating that the overall changes in land use types are minor, but there are still changes, primarily the conversion of forests to cropland, with 7926.75 hectares of forest converted to cropland and 5669.37 hectares of cropland converted to forest. These variations are impacted by various factors such as building distance, GDP, slope, elevation, and annual average temperature. Prediction shows that urban growth would increase impermeable surfaces and harm the ecological environment; maintaining cropland can increase cropland area while slowing urbanization; and ecological conservation helps to safeguard water bodies and forests while reducing bare land. Therefore, it is suggested that Yangchun City should protect forests and farmland, implement appropriate land use policies, promote ecological agriculture and forestry, optimize land use structure, strengthen grassland and shrub land management, control the expansion of bare land and impermeable surfaces, implement ecological protection measures, establish monitoring systems, and strengthen public participation and publicity education to achieve sustainable use of land resources as well as social sustainable development.*

***Keywords*— Markov-PLUS model, CLCD (China Land Cover Dataset), Land use evolution, Landscape configuration, Yangchun City, Multi scenario simulation**

I. INTRODUCTION

Land use and cover change (LUCC) plays a central role in shaping the appearance of the Earth's land surface. This change not only profoundly affects the local environment but also has a significant impact on climate change and sustainable development strategies on a global scale [1]. As a result, in-depth studies on LUCC and prediction of future trends have become a major concerned issue worldwide [2]. In other words, when changing the way land is utilized and covered, it actually affects the environment and future development path of the earth. This impact cannot be ignored from the local level to the global level. Therefore, research and prediction of LUCC have gained a global focus of attention, and people hope to better understand and manage land resources through this approach to achieve sustainable development.

In the field of land use change simulation research, model selection and implementation are crucial for effectively predicting and planning future land use patterns. As technology advances and models become more perfect, more and more land use change models are being proposed and applied in practice. Among these, PLUS (Patch generating Land Use Simulation) model and Markov model have attracted a lot of attention in the field of land use modeling. The PLUS model is a novel type of land use change simulation model, characterized by the ability to simulate patch level changes of multiple land use types at different time scales and deeply explore the driving mechanisms of land use change. By employing random seed generation and threshold decreasing mechanisms, the PLUS model combines the benefits of transformation analysis strategy (TAS) and pattern analysis strategy (PAS), enabling the model to more accurately reflect the complexity and diversity of land use change during simulation. However, the PLUS model requires input of land use demand as a prerequisite for simulating future spatial distribution of land use. The Markov model, as a traditional method for predicting future land use quantities, has no aftereffect and excellent prediction accuracy. The Markov model predicts the future trend of land use type changes by analyzing the transition probability matrix between land use types.

Therefore, integrating the PLUS model with the Markov model can achieve comprehensive simulation of future spatial and temporal changes in regional land use. Specifically, the Markov model is first used to predict future land use demand, and then the predicted results are used as input parameters for the PLUS model to simulate the spatial distribution of land use. This integration method not only fully utilizes the advantages of the PLUS model in simulating patch level changes, but also ensures the accuracy of predicting the number of simulation results, making the simulation results more comprehensive and accurate [3-4].

As one of the important cities in Guangdong Province, Yangchun City is also facing severe challenges in terms of land use and structural transformation. With the acceleration of urbanization, the demand for urban land is rapidly increasing, while rural land is continuously decreasing, and the land use structure is undergoing significant changes. This change not only affects the ecological environment and food security but also puts forward higher requirements for coordinated urban-rural development. Based on this, this study conducted an in-depth analysis of the spatiotemporal evolution characteristics of land use types in Yangchun City, and simulated the fine configuration of land use landscape structure applying CLCD (China Land Cover Dataset) and Markov PLUS models, providing scientific and reasonable suggestions for the optimization of future land use layout.

II. STYDY AREA AND DATA SOURCES

2.1 Study Area

Yangchun City (21°50′36″N—22°41′01″N , 111°16′27″E—112°0′22″E) is located in the southwest of Guangdong Province, serving as a transportation hub for the Pearl River Delta (PRD) and western Guangdong regions. The terrain and landforms of Yangchun are primarily mountainous and hilly, extending diagonally from northeast to southwest, approximately rectangular in shape (Figure 1). The city is 104 kilometers long from north to south and 91 kilometers wide from east to west, with a total area of 4054.7 square kilometers.

In recent years, significant progress has been made in the infrastructure construction of Yangchun. In terms of railways, a total length of 178.2 kilometers of ordinary railways has been built, and the construction of the Yangchun section of the Guangzhou Zhanjiang high-speed railway with a speed of 350 kilometers per hour is being promoted. It is expected to greatly shorten the distance to the core area of the Greater Bay Area (GBA) after its opening in 2025, achieving fast access within one hour. The development of highways is particularly rapid, with a significant increase in the length of service to 194 kilometers. The Yangchun section of the Yangchun Xinyi Expressway is expected to open by the end of 2024, further consolidating its leading position in highway density in the eastern and western wings of the province.

In addition, both main and rural roads have been comprehensively improved, with a total length of 487.787 kilometers for main roads and 4127 kilometers for rural roads, all of which have been graded and hardened, significantly improving the level of transportation services in urban and rural areas. With the continuous improvement of infrastructure, urban areas are gradually expanding, which also brings significant changes in land use distribution.

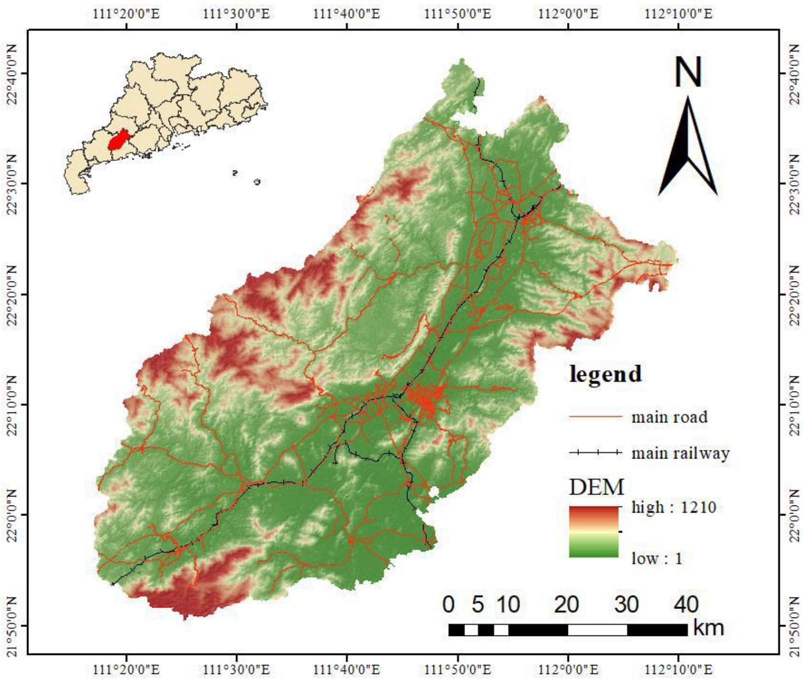

Fig.1 Overview of Yangchun Research Area

2.2 Data Sources

The land use data in this article is CLCD (China Land Cover Dataset). It is a geographic information resource carefully created by Professor Huang Xin from Wuhan University based on Landsat data on the Google Earth Engine (GEE) platform. This dataset covers the annual land cover situation in China from 1985 to 2020 with a total of 335709 scenes. Through the post-processing techniques of random forest classifiers, spatiotemporal filtering, and logical reasoning, accurate classification of land cover is achieved, with an overall accuracy rate of 80%. The CLCD dataset covers land use classification results at a resolution of 30 meters per year for 30 consecutive years, which is superior to other datasets in terms of temporal resolution but may be slightly inferior in spatial resolution and is currently limited to China.

In addition, this study also utilized four natural geographic data, namely elevation, slope, annual average temperature, and annual precipitation, as well as four socio-economic data, namely GDP, highways, railways, and buildings (Table 1).

Table 1 Required Data and Sources

Data requirements	Data sources	Application
CLCD Land Use Data	ZENODO Research Data Repository. https://zenodo.org/records/8176941	Analyzing the spatiotemporal evolution of land use types
Elevation Slope	Geospatial Data Cloud https://www.gscloud.cn/	Create a summary map of the research area; As a driving factor

Annual precipitation Annual mean temperature GDP	Resource and Environmental Science Data Platform, https://www.resdc.cn/	As a driving factor
Distance to highway Distance to railway Distance to buildings	OpenStreetMap https://www.openstreetmap.org/	Create a summary map of the research area; As a driving factor

III. METHODOLOGY

3.1 Study Method

The research route of this article (Figure 2) is as follows:

1. Collect CLCD (China Land Cover Dataset), elevation data, basic data of highways and railways, as well as natural and social data required for the Markov PLUS model for two scenes in Yangchun City in 2015 and 2020.

2. Reclassify the numbering of land use data in ArcGIS to meet the requirements of the input model; Using the Euclidean distance tool in ArcGIS to process road and other data.

3. Calculate the land dynamic degree based on the formula of land dynamic degree in terms of time, and at the same time create and analyze the land use transfer matrix; In terms of space, using ArcGIS to create a land status map and analyze it.

4. Extract the land expansion part through the Extract Land Expansion module in the model and combine it with driving factor data to generate various land development probabilities and contribution values in the LEAS (Land Expansion Analysis Strategy) module for analysis.

5. Use the Markov module in the model to predict land use quantity, simulate land use in 2020 using the CARS (CA based on Multiple Random Seeds) module, and test the accuracy through Confusion Matrix & Fom.

6. Simulate four scenarios of natural development, urban development, farmland protection, and ecological protection in 2030. Finally, draw a conclusion.

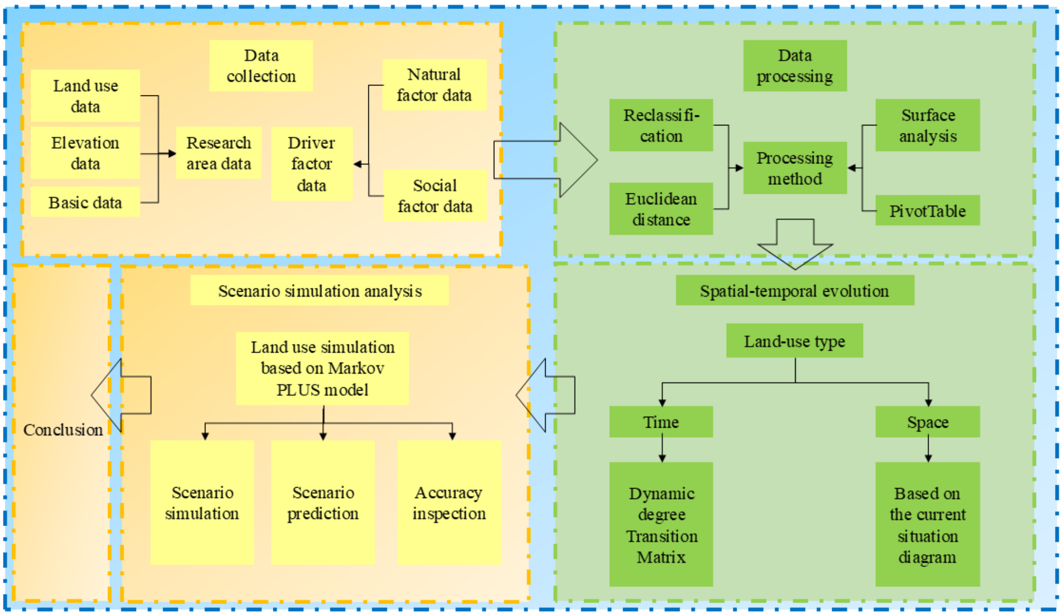

Fig.2 the Schema of the Study

3.2 Dynamic Degree of Land Use

The Land Use Dynamics Index is a quantitative evaluation tool that not only reveals the dynamic changes in land use types, but also accurately captures the degree of local land changes. Its importance lies in simplifying the complex process of land use change, predicting the future evolution trend of regional land use, and comparing the differences in land use change in different regions [5].

The dynamic degree of single land use mainly focuses on the dynamic evolution or change of the quantity of a specific land use type in a research area within a specific time span[6].The calculation formula is:

$$K=(U_A-U_B)/U_A\times 1/T\times 100\% \quad (1)$$

Among them, K represents the rate of change in the dynamic degree of a single land use, while UA and UB are the quantity (usually area) of a certain land use type in the early and late stages of the study, respectively; T is the research time scale, usually measured in years. This indicator helps to understand the rate of change in specific land use types, such as the expansion or reduction rate of forests, cropland, or urban land.

The comprehensive land use dynamic degree is a key indicator for evaluating the severity of land use changes in a specific region. The magnitude of its value directly reflects the severity of land use changes in the region, with larger values indicating more significant and drastic changes in land use [7].The calculation formula is:

$$B=\left[\sum_{i=1}^{n}(\Delta LU_{i-j})/2\sum_{i=1}^{n}LU_i\right]\times 1/T\times 100\% \quad (2)$$

During the monitoring process, LU_i represents the area size of the *i*-th land use type at the beginning of the monitoring. ΔLU_{i-j} represents the absolute value of the area occupied by the transition from the i-th land use type to a non-i land use type during the monitoring period. And T is the length of the monitoring period.

3.3 Land Use Transfer Matrix

The land use transformation matrix is a two-dimensional matrix constructed based on the transformation relationship of land cover status at different time points in the same region. By analyzing the transition matrix, it is possible to gain a clear insight into how various land types transform into each other between two different time points. This matrix provides a detailed description of the land types that have undergone changes in different land use types in different years, the specific locations of the changes, and the size of the changed areas. In addition to displaying static, specific regional and temporal data on the area of various land types, it can also reveal richer information, including the initial transfer of various land areas and the final transfer of various land areas, providing a comprehensive perspective on land use change analysis **Error! Reference source not found.**.The calculation formula is:

$$S_{ij}=\begin{bmatrix} S_{11} & \cdots & S_{1n} \\ \vdots & \ddots & \vdots \\ S_{n1} & \cdots & S_{nn} \end{bmatrix} \quad (3)$$

Among them, S represents area, which is a universal and core parameter used to measure and calculate the scope or scale of land; I and j respectively, refer to the land use types in two different periods before and after, and these two variables can track and compare the land use status at different time points; N represents the total number of land use types, which gives the range of possible land use categories; S*ij* is the area parameter under specific circumstances, specifically referring to the land use area of type i in the early stage, which transforms into type j after a period of time. This variable reveals in detail the conversion relationship between land use types to provide specific data on land use change **Error! Reference source not found.**.

3.4 Markov Model

Markov models are mainly divided into two types: Markov chains and hidden Markov models. The former has visible states, while the latter has hidden states that can be inferred through observing sequences. The state transition process in the model is based on a predefined probability distribution, which is concise and efficient, capable of processing large amounts of data and quickly providing predictions. However, it also has certain limitations, such as a limited ability to handle long-term dependency relationships. The calculation formula is as follows:

$$P_{ij}=\begin{bmatrix} P_{11} & \cdots & P_{1N} \\ \vdots & \ddots & \vdots \\ P_{N1} & \cdots & P_{NN} \end{bmatrix} \quad (4)$$

$$S_{(t+1)}=P_{ij}S_t \quad (5)$$

$$P_{ij}\in[0,1),\sum_{N=1}^{N}P_{ij}=1(i,j=1,2,3,\cdots,N) \quad (6)$$

In the formula, $S_{(t+1)}$ and S_t represent the land use status at time t+1 and t, respectively; P_{ij} is the probability matrix for land use type transition; N is the land use type [10,11].

3.5 PLUS Model

In the academic field, the PLUS model demonstrates unique advantages, which are reflected in its two core modules: the rule mining method for integrated land expansion analysis and the cellular automaton model (CARS) with multi-type random seed mechanism. This integration strategy makes the PLUS model more in-depth in explaining the influencing factors of various land use changes and also significantly improves the accuracy of simulation results [12]. The model extracts land change data, uses a random forest algorithm to calculate development probability, and then uses a CA model with multiple types of random patch seeds to simulate and predict future landscape patterns [15].

The random forest algorithm extracts random samples from the original dataset and uses multiple decision tree ensemble learning to calculate the probability P of k types of land use on cell i. This probability is expressed by the following formula:

$$P_{i,\ k}^{d}(x)=\frac{\sum_{n=1}^{M} I=[h_n(x)=d]}{M} \quad (7)$$

Among them, d is a binary variable, where d=1 indicates that the land use type has changed to the k category, and d=0 indicates that it has changed to the non-k category; X is a vector containing multiple driving force factors; I is the indicator function of the decision tree set; H(x) represents the prediction type of the nth decision tree for vector x; M is the total number of decision trees [11].

The analysis principle of the CARS module is based on a cellular automata model combined with multi-type random patch seeds and a threshold-decreasing mechanism to achieve dynamic simulation of ground-like patches. In the simulation, the land use demand is fed back through a self-regulation mechanism to obtain the adaptive coefficient of land use type competition in order to achieve the future demand target for land use area. The relevant formulas are as follows:

$$OP_{i,k}^{d=1,t}=P_{i,k}^{d=1}\times\Omega_{i,k}^{t}\times D_k^t \quad (8)$$

$$\Omega_{i,k}^{t}=\frac{con\left(c_i^{t-1}=k\right)}{n\times n-1}\times w_k \quad (9)$$

$$D_k^t=\begin{cases} D_k^{t-1} \text{ if} \left|G_k^{t-1}\right|\leq\left|G_k^{t-2}\right| \\ D_k^{t-1}\times\frac{G_k^{t-2}}{G_k^{t-1}} \text{ if} 0>G_k^{t-2}>G_k^{t-1} \\ D_k^{t-1}\times\frac{G_k^{t-1}}{G_k^{t-2}} \text{ if} G_k^{t-1}>G_k^{t-2}>0 \end{cases} \quad (10)$$

In equation (8), $P_{i,k}^{d=1}$ represents the expansion probability of the i-th unit's land use type; $\Omega_{i,k}^{t}$ is the neighborhood effect of land unit i, which refers to the coverage ratio of k types of land use within the neighborhood. Its expression is formula (9); D_k^t is the degree of impact of future land use demand on k types of land use, expressed as formula (10) [14].

3.6 Markov-PLUS Model

The Markov-PLUS model is an innovative land use change simulation model that combines the advantages of Markov and PLUS models, providing a powerful tool for land use change research. It has the following advantages:

(1) High precision prediction: By integrating the advantages of Markov and PLUS models, the Markov PLUS model can more accurately and reliably predict future land use changes.

(2) Powerful spatial allocation capability: The idea of the PLUS model significantly improves the simulation ability of the Markov-PLUS model in spatial allocation, enabling more accurate simulation of the spatial distribution of land use types.

(3) Wide applicability: The Markov-PLUS model is not only applicable to high land cover areas such as agricultural regions and urban agglomerations, but also has good applicability for simulating land use changes in complex environments such as low vegetation cover and arid areas.

3.7 Accuracy Inspection

3.7.1Kappa Coefficient

The Kappa coefficient, as a widely used evaluation tool, is often used to quantify the accuracy of classification and the consistency between different classification results. Provide an objective perspective to evaluate the performance of classification models or manual classification, ensuring that the accuracy and consistency of classification are effectively measured [13].The Kappa coefficient not only considers the overall accuracy, but also integrates the classification accuracy of each category to more comprehensively evaluate classification performance. Its value range is between -1 and 1, with larger values indicating more reliable classification results. The calculation formula is as follows:

$$Kappa=\frac{P_o-P_e}{1-P_e} \quad (11)$$

Among them, P_o refers to the proportion of observed precise consistency, that is, the proportion of correct predictions made by the model. This value can be calculated by dividing the sum of diagonal elements in the confusion matrix by the sum of elements in the entire matrix. P_e refers to the proportion of expected exact consistency, that is, the expected accuracy under random classification. This value is calculated by multiplying the actual proportion of each category by the predicted proportion, and then dividing by the square of the total sample size.

3.7.2 Overall Accuracy（OA）

Overall accuracy refers to the proportion of samples correctly classified by the model to the total number of samples. It directly reflects the average accuracy of the model in classifying all samples. The calculation formula is:

$$OA=\frac{TP+TN}{TP+FN+FP+TN} \quad (12)$$

TP (true) refers to the positive samples correctly identified by the model, that is, both the predicted and actual results are positive; FN (false negative) refers to the model incorrectly identifying positive samples as negative, i.e., predicting them as negative but actually positive; FP (false positive) describes the situation where the model incorrectly identifies negative samples as positive, meaning that they are predicted to be positive but actually negative; TN (true negative) represents the negative samples correctly identified by the model, meaning that both the predicted and actual values are negative.

IV. ANALYSIS AND RESULTS

4.1 Temporal and Spatial Evolution of Land Use Types

Analysis shows that the main land types in Yangchun City are forests and cropland, with a combined proportion of over 90% of the total land types from 2015 to 2020. The cropland is roughly distributed in a strip shape from northeast to southwest. The bare land area is the smallest and its proportion is also very small. In 2015, it was 0.00000446%, and in 2020, it was 0.00000669% (Table 2) (Figure 3).

Table 2 Changes in Land Area and Proportion of Various Types in Yangchun City from 2015 to 2020 (hm^2, %)

		Cropland	Forest	Shrub	Grassland	Water	Barren	Impervious
2015	Area	85566.96	309807.45	187.74	120.87	3471.75	1.8	4472.73
	%	21.2	76.76	0.05	0.03	0.86	0.00000446	1.11
2020	Area	87450.3	307491.93	156.78	82.26	3190.59	2.7	5254.74
	%	21.67	76.18	0.04	0.02	0.79	0.00000669	1.3

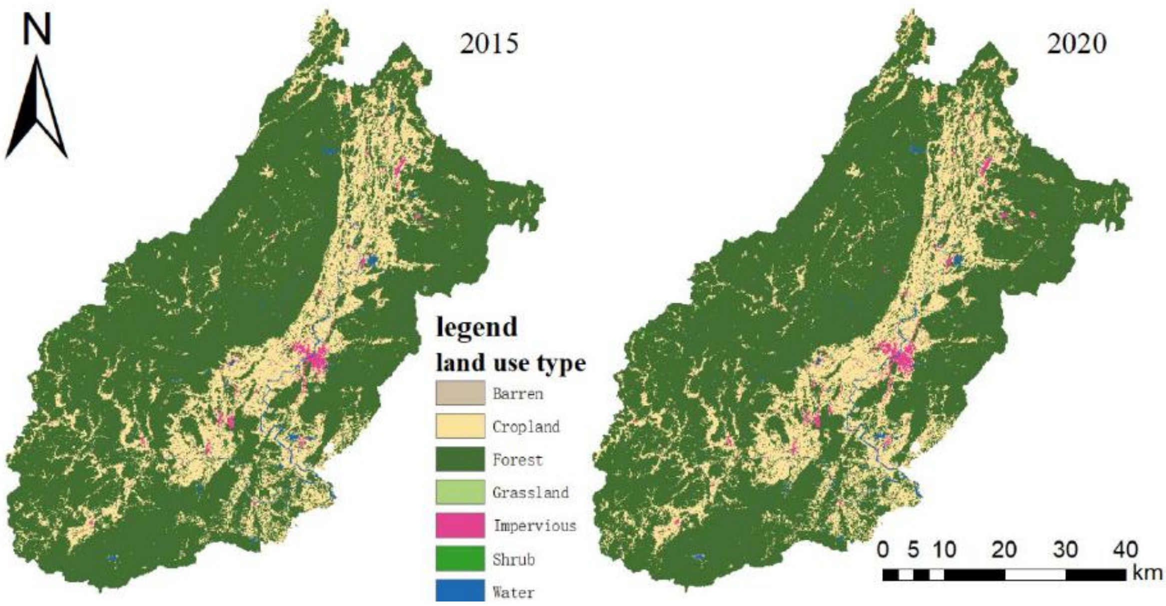

Fig.3 Spatial Evolution of Land Use in Yangchun City from 2015 to 2020

The single land use dynamic degree (K) of cropland, bare land, and construction land between 2015 and 2020 is positive, with bare land having the highest value, indicating the fastest growth rate of bare land. Meanwhile, the dynamics of forests, shrubs, grasslands, and water bodies are all negative, with grassland having the highest value, indicating the fastest rate of grassland decline. The comprehensive land use dynamic degree (B) is relatively small, indicating that the changes in land use types have been relatively gentle in the past 5 years (Table 3).

Table 3 Land Use Dynamics in Yangchun City from 2015 to 2020 (%)

years	Dynamic degree	Cropland	Forest	Shrub	Grassland	Water	Barren	Impervious
2015-2020	K	0.44	-0.15	-3.3	-6.39	-1.62	10	3.5
	B	0.13						

During the period from 2015 to 2020, the area of forest transfer was the largest, reaching 8047.35hm^2; Following closely behind is cropland, with a transfer area of 6439.14 hectares. In the forest transfer land category, cropland and impermeable surfaces dominate, with transfer areas of 7926.75 hectares and 108.45 hectares, respectively. The types of cropland transferred out are forests and impermeable surfaces, with transfer areas of 5669.37 hectares and 667.35 hectares, respectively. It is worth noting that during this period, except for shrubs and bare land, all other land types were transferred to impermeable surfaces, with a total transfer area of 802.71 hectares (Table 4).

Table 4 Land Use Transfer Matrix of Yangchun City from 2015 to 2020 (hm2)

	2020						
2015	Barren	Cropland	Forest	Grassland	Impervious	Shrub	Water
Barren	0.9	0.09	0	0.81	0	0	0
Cropland	0.18	79127.82	5669.37	25.65	667.35	2.07	74.52
Forest	0	7926.75	301760.1	0.27	108.45	11.79	0.09
Grassland	1.62	41.04	2.61	53.28	5.67	11.43	5.22
Impervious	0	0.54	0	0	4452.03	0	20.16
Shrub	0	21.06	33.3	1.89	0	131.49	0
Water	0	333	26.55	0.36	21.24	0	3090.6

4.2 Selection and Contribution Analysis of Driving Factors for Land Use Change

Table 5 shows the names and numbers of driving factors in Yangchun, and Figure 4 shows the driving factors of land use change in Yangchun. According to Table 5, Figure 4, and Figure 5, it can be seen that GDP has the highest contribution to the expansion of cropland, approaching 0.16, and the lower the GDP, the faster the expansion of cropland. When it grows slowly or is in a declining stage, it may mean that the development speed of non-agricultural industries such as industrial production and service industry slows down. This may lead to a decrease in demand for construction land, as slower economic growth is often accompanied by a decrease in the efficiency of land resource utilization. In this situation, as a relatively stable basic industry, the demand for land in agriculture may increase. Farmers may choose to expand their cropland area to increase agricultural output and income.

The expansion of impermeable surfaces is mainly influenced by the distance between buildings, approaching 0.2, and the closer to the building, the more severe the expansion of impermeable surface area. With the development of cities, especially in urban centers or densely built areas, the increase in their area indicates that land use is moving towards more intensive and compact directions. This may be because more buildings, roads, and other infrastructure are being constructed near existing buildings to improve land utilization. Secondly, the elevation and distance from the railway are both between 0.1-0.15, and the lower the elevation, the closer it is to the railway, and the faster the expansion of the impermeable surface area. Areas with lower elevations are more suitable for the expansion of urban construction land, as these areas often have flat terrain that facilitates infrastructure construction and land development. As an important transportation infrastructure, the construction and operation of railways have a significant impact on the land use and urban development of surrounding areas. The land near railway lines is often more easily developed for urban construction due to convenient transportation, leading to rapid expansion of impermeable surface area.

The annual average temperature is the key driving factor for forest expansion, approaching 0.16, and the higher the annual average temperature, the more intense the expansion. The rise in temperature is a significant feature of climate change, and when temperatures rise, areas that were originally unsuitable for forest growth may become suitable, thus potentially promoting its expansion. Next are the average annual precipitation and distance from buildings, with the former around 0.15 and the latter close to 0.14. And it is the less annual precipitation and the closer to the building, the more intense the expansion. The forest area can still expand even with a decrease in annual precipitation, which may be related to its internal species composition and ecological structure. The increase of some drought-tolerant species may have promoted its expansion. The closer to the building, the more intense the area expansion, which may be related to greening projects and ecological restoration projects around the city or building.

Table 5: Names and Numbers of Driving Factors in Yangchun City

Driver type	Driver Name	Number
Physiographic factor	Elevation	(a)
	Slope	(b)
	Annual average precipitation	(c)
	Annual temperature	(d)
Socio economic factors	GDP	(e)
	Distance to the highway	(f)
	Distance to railway	(g)
	Distance to building	(h)

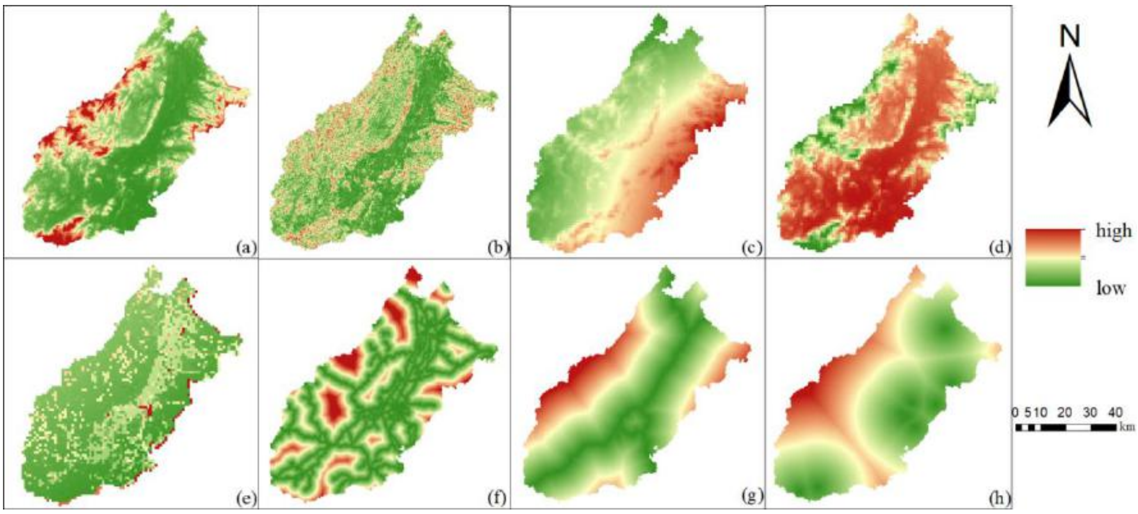

Fig.4 Driving Factors of Land Use Change in Yangchun City

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Fig.5 Contribution of Various Driving Factors to Different Land Use Types in Yangchun City

4.3 Simulation of Landscape Configuration of Land Use Structure

4.3.1 Probability of Development of Various Types of Land Use

When conducting in-depth study on the dynamic changes of land use in Yangchun, this study used CLCD land use status data maps from 2015 and 2020 for exploration. To analyze the patterns and trends behind the data graph, use the LEAS module in the PLUS model. Through precise data analysis and algorithm support, this module calculates the development probability map of each land type based on data files from 2015 to 2020 (Figure 6).

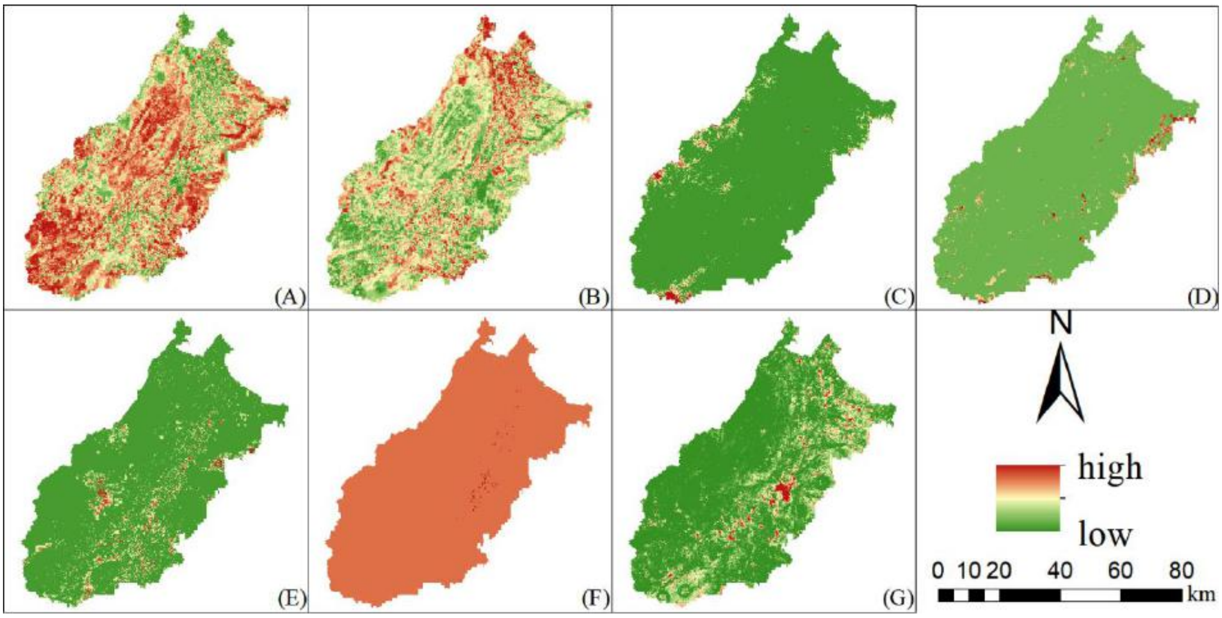

Fig.6 Development Probabilities of Various Types of Land in Yangchun City
(A)Cropland (B) Forest (C) Shrub (D) Grassland (E)Water (F)Barren (G)Impervious

4.3.2 Simulation and Accuracy Testing in 2020

The domain weight references and empirical settings for the CARS module in PLUS are shown in Table 7, and all simulations have the same weight parameters [15]. Applying the confusion matrix and formal module of the PLUS model, the actual land use map and simulation map of Yangchun in 2020 were overlaid and analyzed to obtain the confusion matrix (Table 8) and comparison chart (Figure 7) of the actual land use pattern and simulation pattern. By applying formula (11) for calculation, the Kappa value for simulation accuracy is 0.89. Meanwhile, using formula (12) for calculation, the overall accuracy is 0.96. By combining the accuracy and comparison chart, it can be clearly seen that the PLUS model simulation results have high accuracy and credibility, and can be used for predictive simulation.

Table 7 Land Type Domain Weight Setting Table

	Cropland	Forest	Shrub	Grassland	Water	Barren	Impervious
Domain weight	0.7	0.4	0.3	0.3	0.2	0.5	0.9

Table 8 Confusion Matrix of Actual and Simulated Data in Yangchun City in 2020 (Pixel Count: 1=0.09 hm^2, %)

	2020 simulation									
	Land use types	Cropland	Forest	Shrub	Grassland	Water	Barren	Impervious	Row total	User Accuracy%
Actual in 2020	Cropland	176526	15951	7	47	315	1	1519	194366	90.82
	Forest	17220	666300	75	1	240	0	110	683946	97.42
	Shrub	34	672	270	4	0	0	0	980	27.55
	Grassland	84	14	37	108	6	1	6	256	42.19
	Water	722	79	0	2	6527	0	46	7376	88.49
	Barren	1	0	0	1	0	2	0	4	50.00
	Impervious	39	687	0	4	46	1	10213	10990	92.93
	Column total	194626	683703	389	167	7134	5	11894	897918	

	Producer accuracy%	90.70	97.45	69.41	64.67	91.49	40.00	85.87		

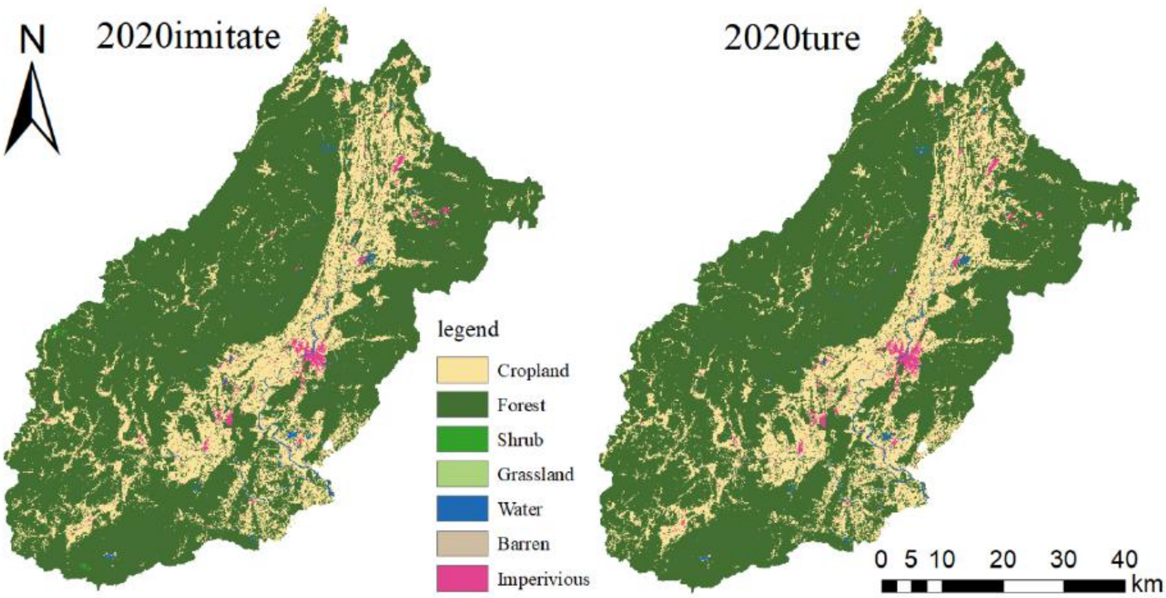

Figure 7 Comparison between Simulated and Real Situations in Yangchun City in 2020

4.3.3 Spatial Distribution of Land Types under Different Scenarios in 2030

This study adopts a combination of spatial and quantitative constraint methods to simulate four scenarios in Yangchun City in 2030: natural development scenario (NDS), urban development scenario (UDS), Cropland protection scenario (CPS), and ecological protection scenario (EPS) (Figure 8). The spatial constraint method adopts a cost matrix for land type conversion, and the quantity constraint method adopts the Markov chain method. The parameters of both methods are set based on literature and continuous testing in this study [15-17].

(1) Natural development scenario (NDS). Based on Figure 8 and Table 9, it can be seen that compared to the land use situation in 2020, the increase in cropland area is the largest under the NDS in 2030, with an increase of 3067.83 hectares, followed by an increase of 701.28 hectares in impermeable surfaces. During this period, the forest area decreased the most, by 4120.74 hectares, followed by water bodies, by 143.91 hectares. The change rate of shrubs is the highest, reaching 113.89%, and the main source is from the forests in the southwest corner. The rate of change in water bodies is the lowest, at -4.37%, and the bare land area has hardly changed.

(2) Urban development scenario (UDS). The main focus is on how urban space expands with population growth, changes in functional positioning, and economic development needs in the context of rapid urbanization, in order to predict the impact of these changes on land use structure, intensity, and ecological environment. Compared to the other three scenarios, the UDS has the largest increase in impervious surface area, at 950.85 hectares, mainly derived from the conversion of forests and cropland. The change rate of impermeable surfaces is the highest at 19.58%, which is 5.14 percentage points higher than the NDS. When only considering urban development without considering the ecological environment, cities will occupy more cropland and forests, causing damage to the ecological environment and not conducive to sustainable development.

(3) Cropland protection scenario (CPS). It is intended to evaluate the protection status of cropland resources and their impact on other land use types under specific policies or measures. Compared to the other three scenarios, the CPS has the largest increase in cropland area, at 3560.58 hectares, and the highest change rate, at 4.07%, which is 0.56% higher than the NDS. It is worth noting that in this scenario, the growth area and change rate of the

impermeable surface are the lowest, at 298.80 hm2 and 6.15%, respectively. Under the scenario of cropland protection, the cropland area will significantly increase, and at the same time, due to the increase in cropland area, the number of farmers may increase, and the urbanization process may slow down.

(4) Ecological protection scenario (EPS). The main focus is on evaluating the changes in land use structure and their impact on the ecological environment under strengthened ecological protection measures. Compared to other scenarios, the water body in this scenario increased instead of decreasing, with an increase of 180.27 hectares. The forest area decreased the least, with a decrease of 4075.29 hectares, which is 45.45 hectares less than the NDS. There is a decrease in bare ground. In this scenario, forests, water bodies, etc. are well protected.

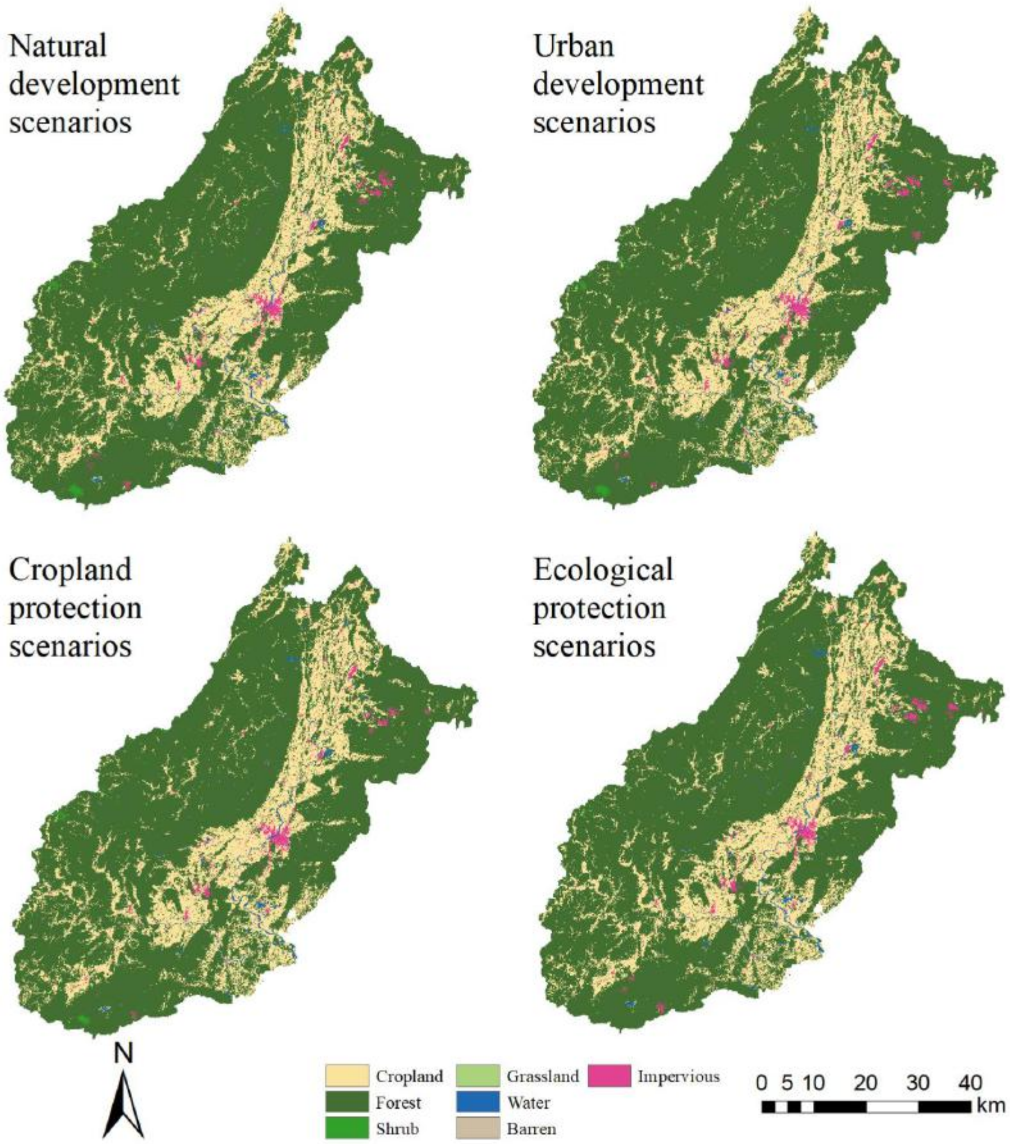

Fig.8: Simulation of Land Use Types in Yangchun City under Various Scenarios

Table 9: Changes in Land Types under Different Scenarios in Yangchun City by 2030 (hm^2,%)

Land use types	Cropland	Forest	Shrub	Grassland	Water	Barren	Impervious
2020 true	87450.3	307491.93	423.09	115.29	3291.48	1.89	4855.32
NDS	90518.13	303371.19	904.95	128.97	3147.57	1.89	5556.6
Variation	3067.83	-4120.74	481.86	13.68	-143.91	0	701.28
Change rate%	3.51	-1.34	113.89	11.87	-4.37	0	14.44
UDS	90387.9	303341.22	891.18	122.58	3078.36	1.89	5806.17
Variation	2937.6	-4150.71	468.09	7.29	-213.12	0	950.85
Change rate%	3.36	-1.35	110.64	6.32	-6.47	0	19.58
CPS	91010.88	303406.74	786.87	121.59	3147.21	1.89	5154.12
Variation	3560.58	-4085.19	363.78	6.3	-144.27	0	298.8
Change rate%	4.07	-1.33	85.98	5.46	-4.38	0	6.15
EPS	90713.7	303416.64	187.74	120.87	3471.75	1.8	5716.8
Variation	3263.4	-4075.29	-235.35	5.58	180.27	-0.09	861.48
Change rate%	3.73	-1.33	-55.63	4.84	5.48	-4.76	17.74

V. CONCLUSIONS

From 2015 to 2020, the main types of land in Yangchun City were forests and cropland, accounting for over 90% of the total, with cropland distributed in a strip shape from northeast to southwest. During this period, the dynamic degree of single land use in grassland was -6.39%, with the fastest reduction rate. The dynamic degree of comprehensive land use is relatively small, at 0.13%, indicating that land use changes are relatively flat, but there are still some land types that have undergone significant transformation. The land transfer situation shows that forests and cropland are the main types of land transferred out, with forests mainly converted to cropland and a transfer area of 7926.75 hectares. And the cropland is primarily converted into forests, with a transfer area of 5669.37 hectares. Grassland expansion is significantly affected by building distance, farmland expansion is negatively correlated with GDP, shrub expansion is driven by slope and elevation, impermeable surface expansion is closely related to building distance, forest expansion is positively correlated with temperature, and water expansion is greatly affected by elevation. Looking ahead to 2030, land changes vary under different scenarios. UDS may lead to a reduction in forests and cropland, while cropland protection scenarios promote cropland growth. EPS can help protect forests and water bodies.

Based on the above conclusions, Yangchun City should maintain the protection of forests and farmland, implement appropriate land use policies and plans, and promote ecological agriculture and forestry to ensure that these two main land types are not overexploited or illegally occupied, while improving land use efficiency and protecting the ecological environment.

Furthermore, it is also vital to optimize the land use structure, appropriately plan industrial, commercial, and residential property, stimulate intensive land use, and improve land use efficiency and production benefits. Meanwhile, increase grassland and shrub management and maintenance, and make effective use of these resources to develop industries like as ecotourism and leisure agriculture. For the expansion of bare land and impermeable surfaces, it is necessary to strengthen urban planning and construction management and promote green buildings and ecological city concepts to improve the quality of the urban ecological environment. Meanwhile, implement ecological protection measures to protect natural resources such as forests and water bodies and reduce the damage of agricultural production to the environment. Establish a comprehensive land use monitoring system, regularly monitor and evaluate land use changes, adjust land use policies and plans in a timely manner based on the results, and ensure the sustainable use of land resources.

Finally, strengthen public participation and education, raise public awareness of land use change and ecological environment protection, promote democratic and scientific decision-making, and create multi scenario development strategies for different development goals and scenarios to achieve sustainable use of land resources and social sustainable development.

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