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Landscape Dynamics, Succession, and Forecasts of *Cunninghamia lanceolata* in the Central Producing Regions of China

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Abstract: *Cunninghamia lanceolata* (Lamb.) Hook accounts for 12% of the total forest area in southern China, second only to Masson pine forests, and is an important part of the forest landscape in this region, which has a significant impact on the overall forest structure in southern China. In this study, we used kernel density analysis, landscape index calculation, variance test, and Markov prediction to analyze and forecast the evolution trend of landscape pattern in the central area of *C. lanceolata* in ten years. The objective is to investigate the change trend of the spatial pattern of *C. lanceolata* landscape in the long time series and its possible impact on zonal vegetation, as well as the macro-succession trend of *C. lanceolata* under the current social and economic background, and to make a scientific and reasonable prediction of its future succession trend. The current and future forecast results show that the landscape fragmentation degree of *C. lanceolata* is intensified, the erosion of bamboo forest is continuously intensified, and the landscape quality is continuously low. These results provide a reference for the future development direction of *C. lanceolata* and emphasize the need for targeted *C. lanceolata* management strategies in the future development of *C. lanceolata*, emphasizing the strengthening of monitoring, controlling harvesting, and managing bamboo competition in order to balance wood production with landscape quality and ecosystem stability.

Keywords: *C. lanceolata*; landscape dynamics; spatiotemporal evolution; landscape types; forecasts

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1. Introduction

Planted forests are becoming increasingly important in global forestry, natural resource conservation, and climate change policies [1]. They play a critical role in restoring forest functionality at the landscape level [2]. While the total forest area decreased from 4.28 billion hectares to 3.99 billion hectares between 1990 and 2015, with percent global forest cover dropping from 31.85% to 30.85%, the area of planted forests increased from 167.5 million hectares to 277.9 million hectares, representing a rise from 4.06% to 6.95% of the total forest area. This increase was most rapid in the temperate zone, particularly in East Asia, followed by Europe, North America, and Southern and Southeast Asia [3]. *C. lanceolata* is an abbreviation for *Cunninghamia lanceolata* (Lamb.). Hook is an evergreen conifer that naturally occurs in the subtropical region of central–southern China, where it has been cultivated as a timber species for over 1000 years [4]. *C. lanceolata* is a unique wood species in China, with a wide distribution range extending from the Qinling Mountains and the Huaihe River basin in the north to the Nanling Hills in the south. *C. lanceolata* used to be the main tree species in the forestry economy of south China. With the diversification of China's forestry economy and the replacement of *C. lanceolata* wood by artificial materials, the economic status of *C. lanceolata* is gradually declining [5,6]. It is very important for the future development of *C. lanceolata* to explore the macro-succession trend in this social and economic background.

C. lanceolata is an evergreen conifer and one of China's most significant commercial tree species [7]. It is among the most preferred plantation timber species in China, recognized for its high wood quality, rapid growth, straight stems, and strong bending resistance [8]. With the rapid expansion of *C. lanceolata*, the practice of establishing consecutive plantations on harvested *C. lanceolata* lands has been adopted [9]. Current research on *C. lanceolata* primarily focuses on its carbon sequestration capacity [10–12], site quality [13,14], site conditions [15,16], nutrient cycling [17–19], and other micro-level aspects. The Ninth National Forest Inventory indicates that *C. lanceolata* covers an area of 98.667 million hectares and has a volume of 755 million cubic meters, accounting for one-fourth and one-third of China's total plantation area and volume, respectively. As part of sustainable forest management, forest managers must incorporate visual landscape management into their plans [20]. With forest plantations often established on harvested lands, forest harvesting represents a significant change in land use types worldwide [21]. Understanding the future changes in land use types of changes and forest landscape patterns of *C. lanceolata* in the central production region of southern China is essential for effective policy-making and management of these plantations.

Landscape dynamics is a scientific field that studies changes in landscape patterns over time, involving the effects of natural processes and human activities on the spatial structure and function of landscapes [22]. As the global environment changes and human activities intensify, understanding landscape dynamics becomes increasingly important for ecosystem conservation and sustainable land use. *C. lanceolata* occupies 12% of the total forest area in southern China, second only to Masson pine forests, and constitutes a major component of the forest landscape in the region. It is very important to study the dynamic evolution of the *C. lanceolata* landscape pattern in the central production area of South China for the ecology and sustainable development of this area. In recent years, the research of landscape dynamics mainly focuses on the following aspects: analyzing the spatial pattern of landscape change through remote sensing technology and GIS [23,24], establishing simulation models to predict the future trend of change [25–27], and assessing the impact of human activities on natural ecological processes [28,29]. These studies not only reveal the complex mechanisms of landscape change but also provide important references for ecological protection and environmental planning. The in-depth study of landscape dynamics not only helps to reveal the long-term effects of natural and human factors on the ecosystem but also provides an important scientific basis for coping with global environmental changes and formulating regional development plans and ecological protection policies [30,31]. This paper aims to explore the process of landscape change and its driving factors in the study area through the comprehensive use of remote sensing data and simulation models, so as to provide a scientific basis for ecological protection and land use planning in the region.

Landscape succession is an important concept in ecology, which refers to the natural evolution of landscape patterns and the structure and function of ecosystems over time. The succession process can be a primary succession dominated by natural factors, such as the growth of new vegetation after a volcanic eruption, or a secondary succession, such as the restoration of ecosystems after deforestation. This process involves the gradual reconstruction and stabilization of ecosystems and is an important basis for understanding the dynamic changes in the natural environment [32]. In recent years, the study of landscape succession has made important progress in forest, grassland, wetland, and other ecosystems [33–35]. The research methods have gradually expanded from the traditional field survey to the integrated application of remote sensing technology, geographic information systems (GISs), and ecological models [36–38], which provide support for large-scale and long-term landscape succession monitoring and analysis [39]. Based on remote sensing data, the process of landscape succession in the southern central producing area of *C. lance-*

olata was analyzed, and the Markov model was used to predict it in order to provide a reference for ecosystem management in this area.

The central production regions of *C. lanceolata* include Zhejiang, Fujian, Jiangxi, Hunan, Guizhou, and the Guangxi Zhuang Autonomous Region. The spatiotemporal evolution trends of landscape types and landscape patterns associated with *C. lanceolata* in these six provinces (and autonomous regions) merit further exploration and study. Previous research has predominantly concentrated on the conversion of natural forests to plantations [40–42], with limited investigation into the transitions of landscape types between *C. lanceolata* and the surrounding landscapes.

The purpose of this study was to explore the change trend of the landscape spatial pattern of *C. lanceolata* in long time series and its possible impact on zonal vegetation, and to explore the macro-succession trend of *C. lanceolata* under the current socio-economic background. In this research, ArcGIS, IDRISI CA-Markov, Fragstats, and other analysis tools were employed to analyze and predict the spatio-temporal evolution of landscape pattern change in the central region of *C. lanceolata*. These results provide a scientific basis for the sustainable management and landscape management of *C. lanceolata* in the future.

2. Materials and Methods

2.1. Data and Processing

2.1.1. *C. lanceolata* Database

The primary data for this study are derived from the Forest Second Type Inventory, which is conducted by the China National Forestry and Grassland Administration. This inventory aims to assess the distribution, quantity, quality, and ownership of forests, providing an objective representation of forest conditions across China. Our research primarily utilizes the attribute named "dominant tree species" and the spatial information of the subcompartment. The database includes data from the years 2010, 2015, and 2020, covering all 31 provinces of China, excluding Hong Kong, Macao, and Taiwan.

For this study, the central production regions of *Cunninghamia lanceolata* (Lamb.). Hook were selected, including six provinces: Zhejiang, Fujian, Jiangxi, Hunan, Guizhou, and Guangxi. According to the data of the ninth national forest resources inventory, the area of *C. lanceolata* in the six provinces was 104,475.64 km^2, and the area of *C. lanceolata* in the country was 127,331.68 km^2. The *C. lanceolata* in the study area accounts for 82.05% of the *C. lanceolata* in China, which is widely representative. Using the forest resources database, vector data of *C. lanceolata* in these six provinces were extracted based on the condition "dominant species = 310,000" (310,000 being the species code for *C. lanceolata* in the forest resources database) for the years 2010, 2015, and 2020. The vector data for *C. lanceolata* in these six provinces for the years 2010 to 2020 were then merged to obtain the distribution data for the central production regions of *C. lanceolata*. The study area is mainly distributed from 21° N to 31° N latitude and 27° E to 30° E longitude. (see Figure 1).

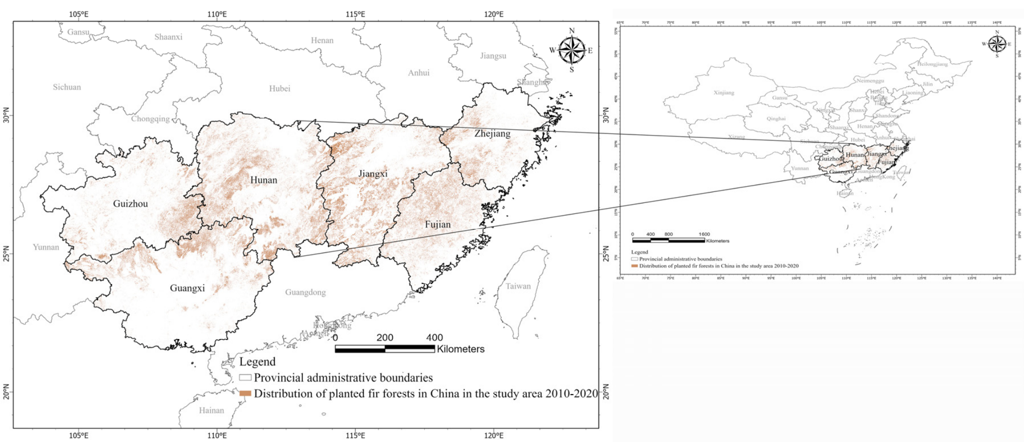


Figure 1. The study area of *Cunninghamia lanceolata* (Lamb.). Hook distribution.

2.1.2. Forest Structure Index Selection

Tree chest diameter, referred to as DBH (Diameter at Breast Height), refers to the diameter of the trunk from the ground surface of the chest height, one of the most basic factors in the determination of standing trees. Standing tree volume in forested areas, quantified as HOST (Hectare Of Standing Tree) per unit area, serves as an indicator of local wood productivity under the ecological conditions of the forest. Trees are crucial both economically and ecologically. As trees age, the growth of all forests follows predictable overall trends [43].

DBH is an important index to evaluate forest health and tree growth status, which can reflect the age structure and growth process of the stand. In general, as the stand ages, the DBH of the trees gradually increases. In economic forest management, DBH is the key index to predict wood yield. A higher DBH means a larger wood size and higher economic value for forestry operators and decision makers, helping to make sound harvesting plans. In forest management, HOST is an important reference index for making cutting plans, regeneration plans, and evaluating the effect of forest restoration. The sustainable utilization of forest resources can be ensured by controlling cutting intensity reasonably and maintaining a certain amount of HOST. AG (Age Group) refers to the classification of trees into different groups according to their age, which helps to understand the structural characteristics and dynamic changes in forests. The three indexes of DBH, HOST, and AG were selected to comprehensively understand the growth state, productivity, and structural characteristics of *C. lanceolata*. These indicators provide a key reference for scientific management, optimization of management strategies, and sustainable utilization of *C. lanceolata* in the study area and are also an important means to maintain the ecosystem function of *C. lanceolata*.

2.2. Research Methods

2.2.1. ArcGIS Kernel Density Analysis

Kernel density analysis is a spatial statistical method that can effectively reveal the spatial distribution characteristics of forest indicators, such as tree species density, tree diameter distribution, biomass, etc. Through kernel density analysis, the discrete forest plot data can be transformed into a continuous density distribution map so as to visually show the distribution of indicators in different regions. Kernel density analysis can help identify "hot spot" areas of certain forest indicators, that is, areas with higher or more concentrated indicator values. For forest resource managers, this helps to identify areas of focus for conservation or management. Kernel density analysis has the advantages of revealing spatial distribution characteristics, identifying hot spots, eliminating spatial inhomogeneity, applying multiple indicators, providing decision support, and simple operation in forest index research. It has been widely used in spatial ecology and forest management and is an important tool to analyze the spatial structure and dynamic changes in forest ecosystems.

Let f be its probability density function. The kernel density estimation [44] is as follows:

$$\hat{f}_h(x) = 1/n\sum_{i=1}^{n} K_h(x - x_i) = 1/nh\sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right) \tag{1}$$

Here, K represents the kernel function (which satisfies the properties: non-negative, integrates to 1, conforms to the properties of probability density, and has a mean of 0); h > 0 is a smoothing parameter.

In this study, kernel density analysis was used to visualize the southern *C. lanceolata* so that the distribution and aggregation degree of each selected index (DBH, HOST, AG) in the study area could be seen more intuitively.

2.2.2. Landscape Pattern Index Selection

C. lanceolata is the main body of the forest landscape in the study area, and the change in its landscape pattern index will have a great impact on the forest landscape in the study area. The study of landscape patterns holds significant practical implications for land use types of planning [45]. Landscape pattern indices can comprehensively reflect the ecological system of a region; thus, the selection of landscape pattern indices is a crucial step in landscape pattern research. Based on the scale of the study area and practical considerations, our research ultimately selected five landscape pattern indices: patch density (PD), number of patches (NP), Largest Patch Index (LPI), Landscape Shape Index (LSI), and Aggregation Index (AI). The calculation formulas and ecological significance of PD, NP, LPI, LSI, and AI are as follows [46]:

(1) PD represents the density of a certain type of patch in the landscape, reflecting the overall heterogeneity and fragmentation of the landscape as well as the degree of fragmentation of a particular type, indicating the heterogeneity per unit area of the landscape. Its formula is as follows:

$$PD = NP/A \tag{2}$$

In the equation, NP represents the number of patches; A represents the total area of the landscape or patches; PD represents patch density.

(2) NP reflects the spatial pattern of the landscape and is often used to describe the heterogeneity of the entire landscape. Its value is significantly positively correlated with the fragmentation of the landscape; generally, a larger NP indicates higher fragmentation, while a smaller NP indicates lower fragmentation. Its formula is as follows:

$$NP = n(NP \geq 1) \tag{3}$$

At the class level, NP equals the total number of patches of a specific patch type in the landscape, while at the landscape level, NP equals the total number of all patches in the landscape.

(3) LPI helps to identify the modal or dominant types within a landscape. Its magnitude determines the dominant species in the landscape and ecological characteristics such as internal abundance. Changes in its value can alter the intensity and frequency of disturbances, reflecting the direction and strength of human activities. Its formula is as follows:

$$LPI = (a_{max}/A) \times 100 \quad (0 < LPI \leq 100) \tag{4}$$

where LPI represents the proportion of the total landscape area occupied by the largest patch of a particular patch type.

(4) LSI is a shape index of patches within landscape patterns. It measures the complexity of shapes by calculating the deviation between the shape of a patch within an area and that of a circle or square of the same area, with a circle chosen as the reference in this study. Its formula is as follows:

$$LSI = E/2\sqrt{\pi A} \tag{5}$$

where E represents the total length of all patch boundaries in the landscape, and A denotes the total area of the landscape.

(5) AI examines the connectivity between patches of each landscape type. A smaller value indicates a more fragmented landscape. Its formula is as follows:

$$AI = [g_{ii}/(max \rightarrow g_{ii})](100) \tag{6}$$

where "gii" represents the number of similar adjacent patches for the corresponding landscape type.

This study conducted a change analysis of five landscape indices, namely patch density (PD), number of patches (NP), Largest Patch Index (LPI), Landscape Shape Index (LSI), and

Aggregation Index (AI), for *C. lanceolata* in the study area from 2010 to 2020, using Fragstats 4.2 and ArcGIS 10.8.2. The change data of its landscape index in ten years were obtained.

2.2.3. One-Way Analysis of Variance

One-way analysis of variance (ANOVA), also referred to as one-dimensional analysis of variance, is employed to determine whether significant differences exist in the mean values of dependent variables when a single control factor is examined at various levels. One-way ANOVA operates under the assumption that the variances of observations are equal across groups of independent normal samples and different levels of control variables.

This study used one-way analysis of variance to determine whether there were significant differences between various indicators in the study area. Finally, all the data in this study conform to normal distribution. We chose a p-value of 0.05 to test whether there were significant differences in the indicators.

2.2.4. GM (1,1) Gray Forecasting and IDRISI CA-Markov Forecasting

Many forecasting methods require a large number of samples to generate reliable predictions. If the sample size is small, it will often lead to significant errors, rendering the predictive model ineffective. The gray model is suitable for modeling and forecasting in the case of limited information and has the advantage of high computational efficiency. The sample size of our study was small, so we adopted a gray prediction model. This approach allowed our study to make reasonable predictions about DBH and HOST of *C. lanceolata* in the study area in 2025 and 2030.

Let $X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n))$ and $X^{(1)} = (x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n))$ be termed as the original form of the GM(1,1) model.

$$X^{(0)}(K) + ax^{(1)}(k) = b \tag{7}$$

The original sequence $X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n))$ must be non-negative, where $x^{(0)}(k) \geq 0$ for $k = 1, 2, \ldots, n$.

The Markov model is a mathematical model that describes the transition probability of the system between different states, which can reflect the evolution trend of the system in time [47]. It is very suitable for predicting the trend of forest landscape types over time, such as the conversion between different forest types. Through the Markov model, we can quantitatively describe the distribution of landscape types at a certain point in the future so as to understand the long-term change trend. Forest landscapes are typically composed of multiple vegetation types that involve complex ecological processes and human disturbances. Markov prediction model can effectively predict the dynamic changes in forest landscape in time and space and provide scientific basis for long-term ecological management and planning. It not only has the advantages of simple model structure and low data requirement but also reflects the complex transformation relationship between different landscape types through transition probability, so it is a common forecasting tool in landscape ecology research [48].

The classification of landscape types in our research adheres to the "Technical Regulations for Forest Resource Planning and Design Survey" (GB/T 26424-2010) [49], integrating existing classification systems with the specific conditions of the study area. The land classes in our research area are categorized into seven types: "Coniferous Forest" (CF), "*C. lanceolata*" (CL), "Deciduous Broad-leaved Forest" (DBF), "Evergreen Broad-leaved Forest" (EBF), "Bamboo Forest" (BF), "Non-Wood Forest" (NWF), and "Shrubbery" (S). Using ArcGIS tools, we overlaid the raster data for land classes from 2010 to 2015 with the "Raster Calculator" tool. The results of the overlay analysis were processed to generate the land transfer matrix for the period 2010–2015. The same methodology was applied to obtain the land transfer matrix for 2015–2020. A landscape types heatmap was created using Origin. Applying the calculation method of Markov chain to Markov analysis, the main purpose is to predict the possible changes in some variables in a certain interval in the future according to the current situation and the trend of change as a basis for some decisions. In line with the research on the future change trend of *C. lanceolata* in our research, it provides a decision-making basis for the future *C. lanceolata*, guides the planting of *C. lanceolata*, optimizes the landscape pattern, and improves the impact of ecological service systems. The Markov model has been widely used as a mature forecasting method in past landscape prediction [50].

In this study, a GM model is selected to predict the small sample data (DBH and HOST), and whether the maximum relative error is less than 0.1 is selected to test whether the prediction accuracy meets the requirements. The Markov model is used to predict large sample data (AG). Moreover, select whether the Kappa coefficient is greater than 0.95 to test whether the prediction accuracy meets the requirements.

3. Results

3.1. Changes from 2010 to 2020

The distribution area of *C. lanceolata* was calculated to be 104,475.64 km^2 in 2010, 114,183.12 km^2 in 2015, and 107,393.80 km^2 in 2020 (see Table 1). The results showed that from 2010 to 2015, the area of *C. lanceolata* trees initially decreased and then increased, resulting in an overall upward trend. The nuclear density analysis method was used to obtain Figure 2 (see Figure 2), and the results showed that the *C. lanceolata* was mainly distributed in the provincial junction. The analysis of variance showed that the variance was small, and the data showed a central trend. The ANOVA test showed that the p-value (see Table 2) < 0.05, indicating significant differences among the data.

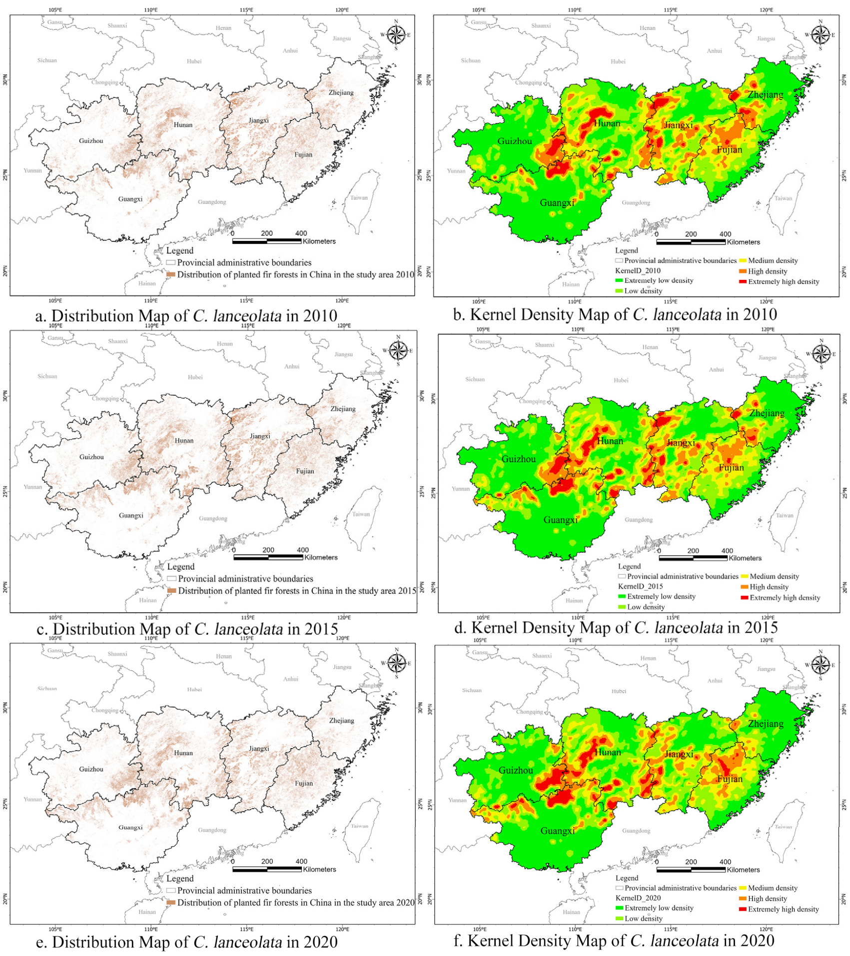


Figure 2. Distribution and kernel density of *C. lanceolata*, 2010–2020.

Table 1. Descriptives of *Cunninghamia lanceolata* (Lamb.). Hook area in the study area.

Time	Provinces	Sum (km^2)	Std. Deviation	Std. Error
2010	Zhejiang	9219.63	0.0429	0.0001
	Fujian	16,250.92	0.0355	0.0001
	Jiangxi	24,707.67	0.0864	0.0002
	Hunan	28,141.20	0.0412	0.0000
	Guizhou	12,130.24	0.0571	0.0001
	Guangxi	14,025.98	0.0444	0.0001
	2010 Total	**104,475.64**	**0.0529**	**0.0000**
2015	Zhejiang	8907.98	0.0382	0.0001
	Fujian	16,953.60	0.0338	0.0000
	Jiangxi	26,364.50	0.0692	0.0001
	Hunan	31,139.69	0.0269	0.0000
	Guizhou	13,275.22	0.0526	0.0001
	Guangxi	17,542.13	0.0356	0.0000
	2015 Total	**114,183.12**	**0.0417**	**0.0000**
2020	Zhejiang	5120.78	0.0288	0.0001
	Fujian	17,835.89	0.0309	0.0000
	Jiangxi	20,500.36	0.0591	0.0001
	Hunan	30,833.88	0.0254	0.0000
	Guizhou	13,918.27	0.0445	0.0001
	Guangxi	19,184.61	0.0175	0.0000
	2020 Total	**107,393.80**	**0.0323**	**0.0000**

Table 2. ANOVA of *C. lanceolata* area in the study area.

Time		Mean Square	F	Sig.
2010	Between Groups	222.020	92,606.776	0.000
	Within Groups	0.002		
2015	Between Groups	116.565	73,016.865	0.000
	Within Groups	0.002		
2020	Between Groups	106.528	112,542.614	0.000
	Within Groups	0.001		

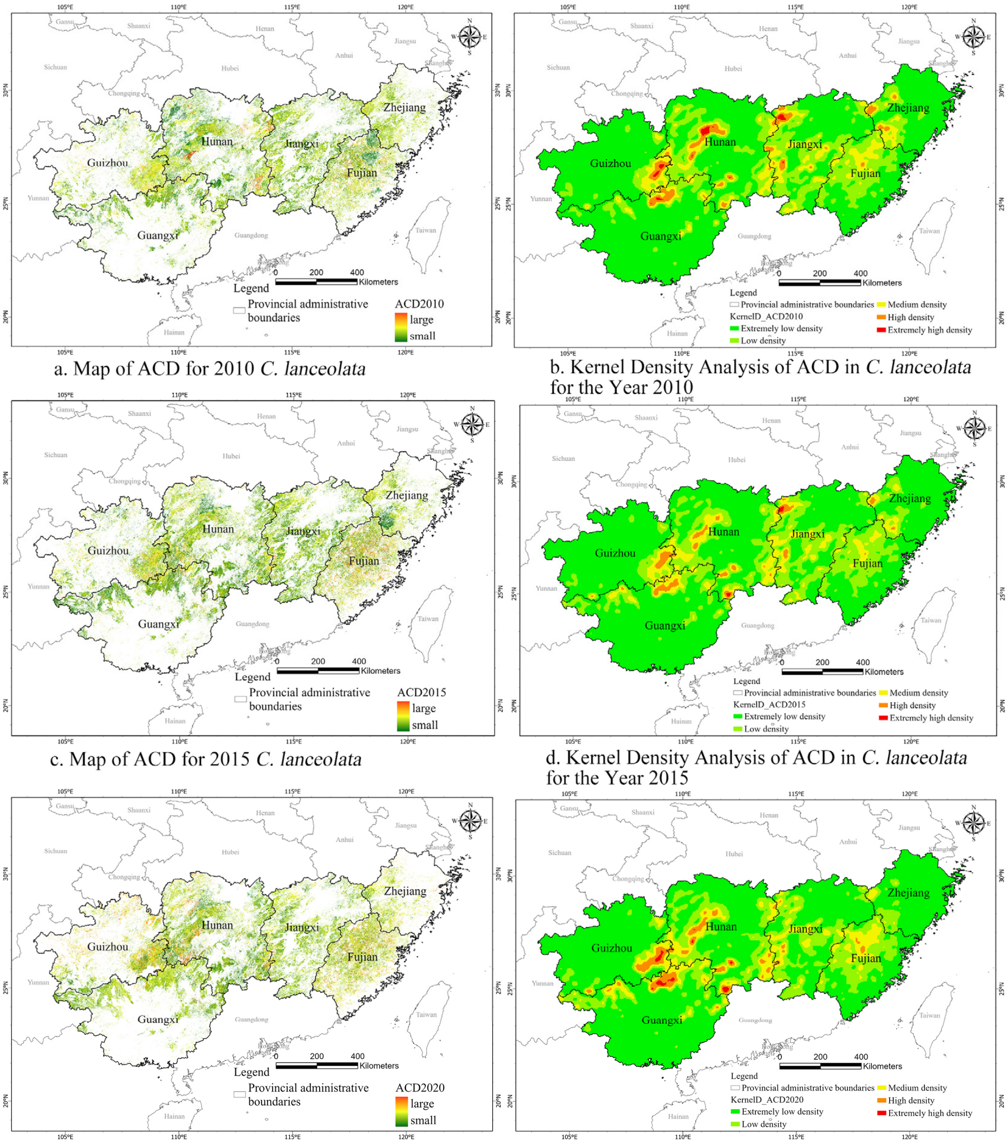
The results of variance analysis and descriptive statistics (see Table 3) show that over the span of a decade, Fujian Province exhibits the highest DBH among *C. lanceolata*, followed by Guizhou Province and Zhejiang Province. As shown in Table 3, the DBH of *C. lanceolata* in Zhejiang, Jiangxi, Hunan, and Guizhou Provinces decreased from 2010 to 2020. In contrast, the DBH of *C. lanceolata* increased in Fujian Province and Guangxi Province. The results obtained using nuclear density analysis show a growing concentration of *C. lanceolata* at the junction of Hunan Province, Guizhou Province, and the Guangxi Zhuang Autonomous Region. Conversely, dispersion tendencies are noted at the boundary of Hunan Province and Jiangxi Province, while the western regions of Hunan Province exhibit an increasing clustering of plantations (see Figure 3). The ANOVA test showed that the p value (see Table 4) < 0.05, indicating significant differences in DBH data.

Table 3. Descriptives of DBH (Diameter at Breast Height) of *C. lanceolata* from 2010 to 2020.

Time	Provinces	Mean (cm)	Std. Deviation	Std. Error
2010	Zhejiang	10.9747	7.0826	0.0177
	Fujian	10.8885	11.4197	0.0169
	Jiangxi	8.6142	5.1496	0.0100
	Hunan	8.8383	6.4960	0.0061
	Guizhou	11.9981	5.0687	0.0093
	Guangxi	8.2638	6.1404	0.0088

Table 3. *Cont.*

Time	Provinces	Mean (cm)	Std. Deviation	Std. Error
2015	Zhejiang	9.3255	5.5730	0.0099
	Fujian	12.9501	7.8988	0.0109
	Jiangxi	7.7304	5.2170	0.0078
	Hunan	8.2975	6.2981	0.0050
	Guizhou	10.0713	6.3404	0.0099
	Guangxi	7.0161	6.2784	0.0069
2020	Zhejiang	10.8303	5.3241	0.0117
	Fujian	12.3165	6.2370	0.0076
	Jiangxi	8.5330	4.9624	0.0073
	Hunan	8.7075	6.4787	0.0050
	Guizhou	10.6292	6.9666	0.0088
	Guangxi	9.1259	5.3860	0.0038



a. Map of ACD for 2010 *C. lanceolata*

b. Kernel Density Analysis of ACD in *C. lanceolata* for the Year 2010

c. Map of ACD for 2015 *C. lanceolata*

d. Kernel Density Analysis of ACD in *C. lanceolata* for the Year 2015

e. Map of ACD for 2020 *C. lanceolata*

f. Kernel Density Analysis of ACD in *C. lanceolata* for the Year 2020

Figure 3. DBH (Diameter at Breast Height) and kernel density, 2010–2020.

Table 4. ANOVA of DBH.

Time		Mean Square	F	Sig.
2010	Between Groups	905,849.8115	17,099.8198	0.0000
	Within Groups	52.9742		
2015	Between Groups	2,660,814.7543	65,654.7089	0.0000
	Within Groups	40.5274		
2020	Between Groups	1,642,293.9479	45,852.5832	0.0000
	Within Groups	35.8168		

The results of variance analysis and descriptive statistics (see Table 5) show that there was an initial decrease in HOST, followed by an overall increase throughout the study period. Furthermore, the kernel density analysis highlights the highest concentrations of HOST at the junction of Hunan Province, Guizhou Province, and the Guangxi Zhuang Autonomous Region, with a notable concentration observed in the western regions of Hunan Province (see Figure 4). Similarly, the ANOVA test showed that the p value (see Table 6) < 0.05, indicating significant differences in HOST data.

Table 5. Descriptives of HOST (Hectare of Standing Tree) of *C. lanceolata* from 2010 to 2020 (m^3/ha).

Time	Provinces	Mean (m^3/ha)	Std. Deviation	Std. Error
2010	Zhejiang	53.3572	50.9612	0.1273
	Fujian	69.1531	88.1475	0.1307
	Jiangxi	51.7211	54.6548	0.1061
	Hunan	43.5043	48.4025	0.0455
	Guizhou	66.5043	56.4866	0.1035
	Guangxi	56.1886	61.2703	0.0880
2015	Zhejiang	16.0943	28.0921	0.0497
	Fujian	28.7024	31.3702	0.0434
	Jiangxi	24.7725	27.8304	0.0415
	Hunan	29.0762	30.8306	0.0246
	Guizhou	30.3879	26.6103	0.0415
	Guangxi	45.5262	27.3487	0.0300
2020	Zhejiang	81.7874	58.6021	0.1292
	Fujian	98.2726	72.9156	0.0893
	Jiangxi	64.0243	61.1007	0.0898
	Hunan	44.0280	43.3374	0.0333
	Guizhou	87.2493	82.0854	0.1038
	Guangxi	77.8488	68.5524	0.0483

Table 6. ANOVA of HOST.

Time		Mean Square	F	Sig.
2010	Between Groups	55,878,087.8300	15,368.1212	0.0000
	Within Groups	3635.9739		
2015	Between Groups	26,222,084.5636	30,572.9058	0.0000
	Within Groups	857.6903		
2020	Between Groups	461,796,762.5213	114,641.2038	0.0000
	Within Groups	4028.1918		

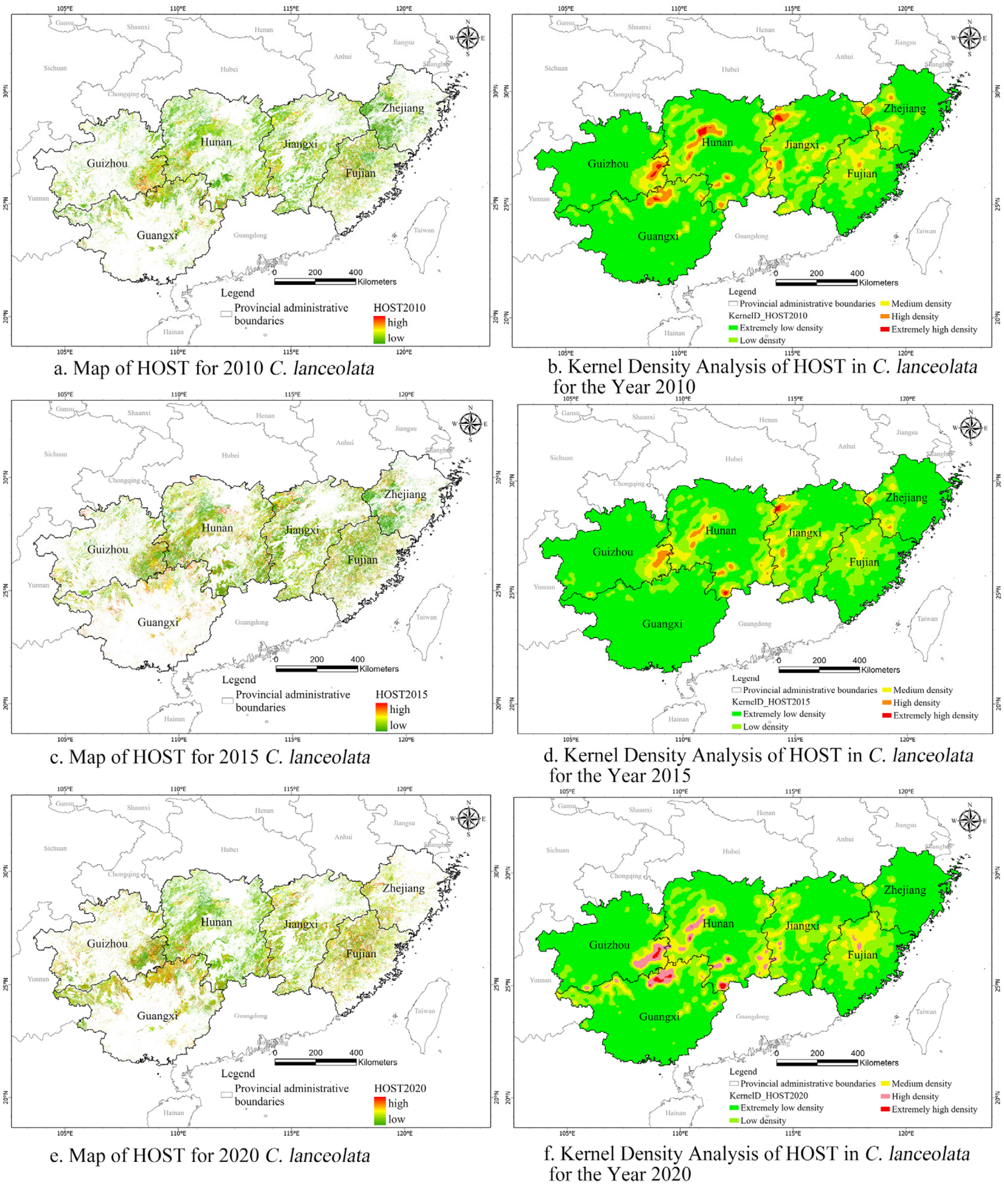
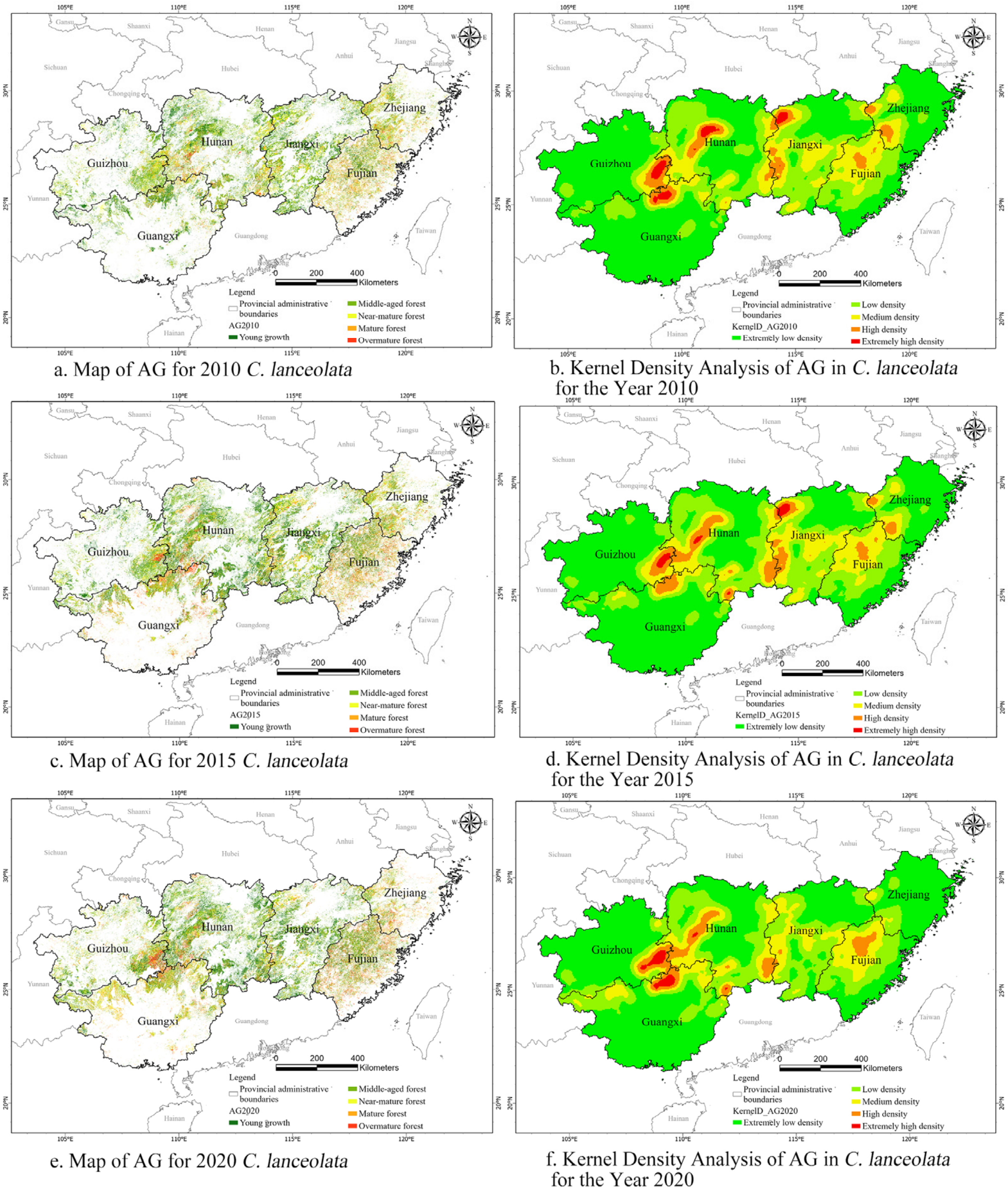


Figure 4. HOST (Hectare Of Standing Tree) and kernel density, 2010–2020.

From 2010 to 2020, the proportion of AG, in descending order, was middle-age, young, mature, near-mature, and overly mature. Middle-age forests represented the largest proportion, which decreased annually, while overly mature forests constituted a very small proportion, which increased annually. (see Table 7) The kernel density analysis indicates that the concentration of AG at the junction of Hunan Province, Guizhou Province, and the Guangxi Zhuang Autonomous Region is steadily increasing. In contrast, the concentration at the boundaries of Hunan Province and Jiangxi Province, as well as between Jiangxi Province and Zhejiang Province, is consistently decreasing (see Figure 5).

Table 7. Area change of *C. lanceolata* AG (Age Group) from 2010 to 2020 (km^2).

Time	2010	2015	2020
Young forests	23,395.05	29,511.20	27,199.76
Middle-aged forests	36,234.15	33,494.16	30,942.68
Near-mature forests	18,146.54	16,704.48	16,019.92
Mature forests	16,182.93	20,268.36	19,183.04
Overly mature forests	2858.58	5595.96	6565.92



a. Map of AG for 2010 *C. lanceolata*

b. Kernel Density Analysis of AG in *C. lanceolata* for the Year 2010

c. Map of AG for 2015 *C. lanceolata*

d. Kernel Density Analysis of AG in *C. lanceolata* for the Year 2015

e. Map of AG for 2020 *C. lanceolata*

f. Kernel Density Analysis of AG in *C. lanceolata* for the Year 2020

Figure 5. AG (Age Group) and kernel density, 2010–2020.

3.2. Landscape Pattern Analysis

The results of the landscape index calculation show that the patch density (PD) in the Zhejiang and Jiangxi Provinces exhibited significant variations, whereas the patch density in Guizhou, Fujian, Hunan, and the Guangxi Zhuang Autonomous Region showed minimal changes. The number of patches (NP) varied considerably in the Guangxi Zhuang Autonomous Region and Jiangxi Province but experienced little change in Hunan, Fujian, Guizhou, and Zhejiang Provinces. The Largest Patch Index (LPI) demonstrated substantial changes in Guizhou, Hunan, Jiangxi, and Zhejiang Provinces, while Fujian Province and the Guangxi Zhuang Autonomous Region exhibited only minor changes. Regarding the Landscape Shape Index (LSI), the Guangxi Zhuang Autonomous Region experienced significant changes while the other provinces showed only slight variations. For the Aggregation Index (AI), the changes in Zhejiang and Jiangxi Provinces were more pronounced, whereas Fujian, Hunan, Guizhou, and the Guangxi Zhuang Autonomous Region experienced smaller changes (see Table 8).

Table 8. Changes in PD, NP, LPI, LSI, and AI indices of *C. lanceolata* in each province.

		PD	NP	LPI	LSI	AI
2010	Zhejiang	27,478,845,737	25,330	7.4055	218.0021	54.6594
	Fujian	31,811,233,532	51,693	1.0974	329.6525	48.3455
	Jiangxi	13,830,726,039	34,229	6.6019	271.6493	65.5297
	Hunan	32,375,079,383	91,151	11.2396	412.357	50.9083
	Guizhou	32,338,620,289	39,212	19.1478	272.5236	50.5562
	Guangxi	33,000,974,703	46,317	12.9958	279.6785	52.8619
2015	Zhejiang	29,144,787,038	25,975	5.9629	217.5481	53.9803
	Fujian	30,911,166,626	52,365	1.1617	334.1866	48.7055
	Jiangxi	15,467,268,336	40,830	7.7604	294.76	63.7886
	Hunan	29,025,755,433	90,397	4.934	416.8057	52.8168
	Guizhou	32,293,578,811	42,855	17.6564	283.9271	50.7931
	Guangxi	27,329,992,026	47,986	13.7886	309.2127	53.3764
2020	Zhejiang	49,515,257,097	25,353	2.8022	204.4358	42.9447
	Fujian	29,642,668,643	52,793	1.22	339.1266	49.2328
	Jiangxi	22,431,985,973	45,953	1.7076	301.868	57.8779
	Hunan	29,559,731,307	91,214	4.7844	418.6568	52.3838
	Guizhou	32,376,130,978	45,087	27.8926	288.873	51.0907
	Guangxi	27,839,775,931	53,436	13.7517	330.0671	52.4077

The results showed that the fragmentation of *C. lanceolata* landscape was intensified, which led to the deterioration of landscape quality. The landscape heterogeneity was higher in the west and lower in the east. The landscape stability was stronger in the west, and the landscape dynamics were stronger in the east.

3.3. Gray Prediction and CA-Markov Prediction

3.3.1. GM Model DBH and HOST Prediction

The maximum relative errors for the forecasted DBH and HOST were 0.06% and 4.68%, respectively, both of which are less than 0.1. This indicates a high level of model fitting accuracy. As depicted in Figure 6, from 2020 to 2030, *C. lanceolata* in the study area is expected to exhibit an increasing trend in both DBH and HOST.

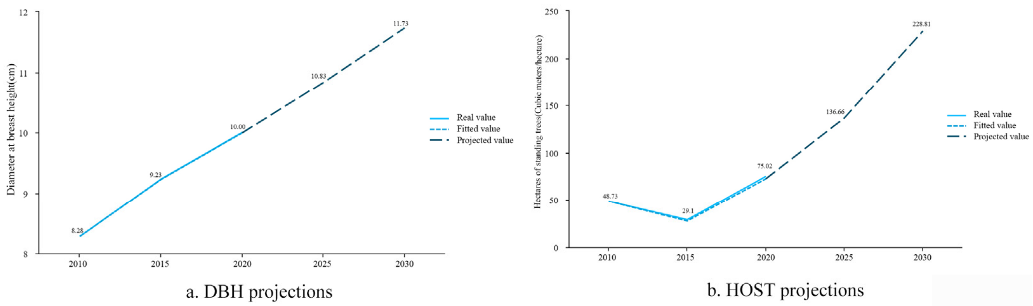


Figure 6. Gray prediction.

From 2020 to 2030, the DBH of *C. lanceolata* increased from 10.00 cm to 11.73 cm, resulting in a growth rate of 17.30%. Additionally, the HOST volume rose from 75.02 cubic meters per hectare to 228.81 cubic meters per hectare, demonstrating a growth rate of 205.00% (see Table 9).

Table 9. Predicted values of GM model.

Time	2010	2015	2020	2025	2030
DBH (cm)	8.28	9.23	10.00	10.83	11.73
HOST (m^3/ha)	48.73	29.10	75.02	136.66	228.81

From 2020 to 2030, *C. lanceolata* in the study area exhibited a slight upward trend in DBH, while the HOST demonstrated a significant upward trend with a considerable increase (see Figure 6).

The predicted results showed that the DBH and HOST of *C. lanceolata* would increase to different degrees in the future. This indicates that our management of *C. lanceolata* is expected to be a process of continuous improvement.

3.3.2. Land Transfer Matrix Analysis and Forecasting

The results showed that the main landscape type of *C. lanceolata* was the conversion between *C. lanceolata* and other coniferous forests, followed by the conversion of evergreen broad-leaved forests (see Table 10). The invasion degree of bamboo forest to *C. lanceolata* was the largest, and the relationship between shrub and *C. lanceolata* was the weakest (see Figure 7). More attention should be paid to the intrusion of bamboo forests into *C. lanceolata*.

Table 10. Landscape types of transfer matrices, 2010–2020 (km^2).

	2010–2015							
	CF	**CL**	**DBF**	**EBF**	**BF**	**NWF**	**S**	**TA**
CF	70,385.1	6727.2	1131.36	2600.32	796.24	2500	844.56	84,984.8
CL	4312.24	81,342.48	1344	3109.4	2217.7	2055.9	888.12	95,269.84
DBF	381.92	1240.52	11,276.2	1029.4	91.56	275.2	95.36	14,390.16
EBF	2468.72	5695	2515.44	40,013.64	875.8	927.64	658.92	53,155.16
BF	351.56	1531.68	178.4	470.04	24,633	284.32	127.44	27,576
NWF	656.92	1517.2	87.6	563.76	187.92	14,876	72.96	17,961.88
S	442.84	460.6	190.64	756.32	60.24	266.36	8773.4	10,950.44
TA	78,999.3	98,514.68	16,723.64	48,542.88	28,862	21,185	11,461	304,288.3
				2015–2020				
CF	57,713.4	6636.12	717.12	5278.04	1142.72	1920.1	519.44	73,927
CL	4282.64	82,257.2	691.72	4296.12	2583.36	1951.5	373	96,435.52
DBF	769.68	1335.56	10,056.04	1900.2	343.28	451.68	160.88	15,017.32
EBF	2272.92	4134.88	912.8	36,268.44	1111.52	788.56	346.6	45,835.72
BF	327.56	1217.44	120.6	769.4	26,353.5	297.96	106.08	29,192.56
NWF	1274.56	2558.92	157.16	903.44	765.04	21,453	311.4	27,423.2
S	1232.6	1044.12	432.36	1412.6	134.76	753.08	7021.6	12,031.12
TA	67,873.4	99,184.24	13,087.8	50,828.24	32,434.2	27,616	8839	299,862.4

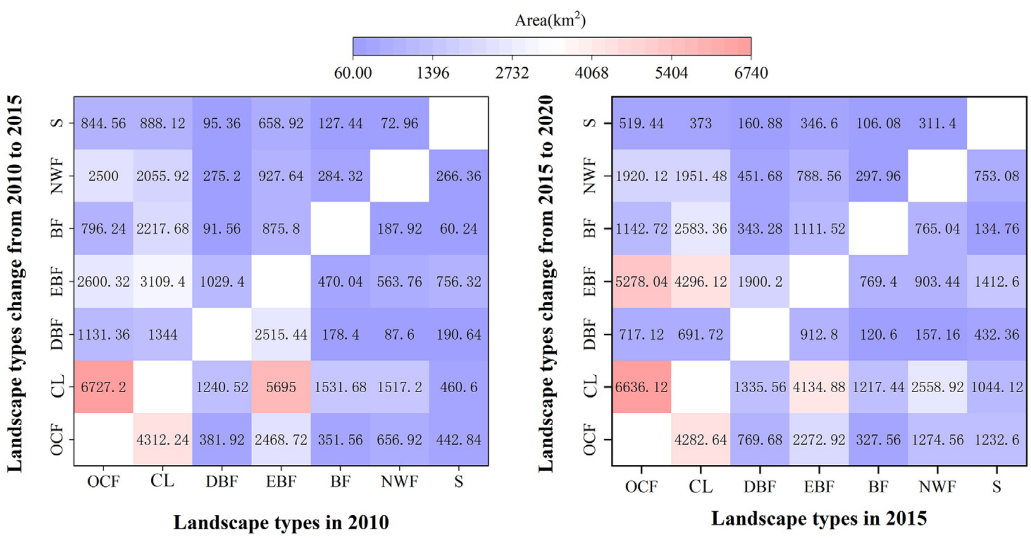
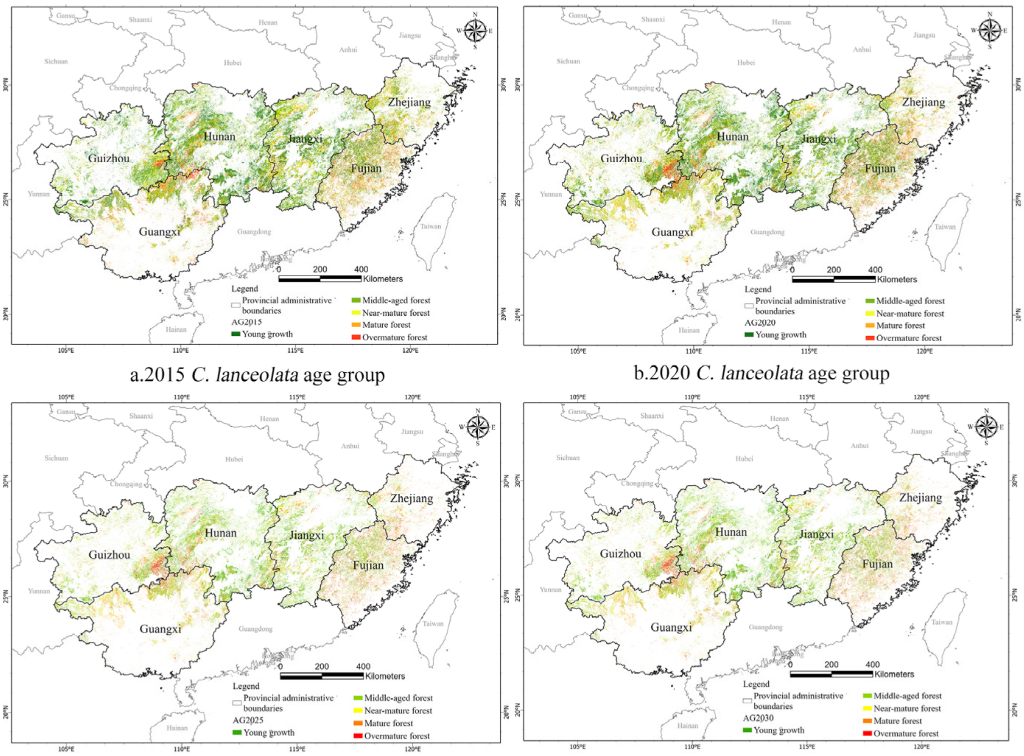


Figure 7. Landscape types change from 2010 to2020 in the study area.

3.3.3. CA-Markov AG Prediction

Kappa coefficient is 0.9803 for the AG prediction in 2025 and 0.9924 for 2030, indicating a high level of consistency in the CA-Markov model's simulation results and demonstrating its feasibility.

Figure 8 (see Figure 8) illustrates a notable shift in the AG distribution of *C. lanceolata* within the study area from 2020 to 2025, whereas the changes observed from 2025 to 2030 are less pronounced. The results show that the AG structure changes greatly during 2020–2025, while the AG structure changes little and tends to be stable during 2025–2030.



a.2015 *C. lanceolata* age group b.2020 *C. lanceolata* age group

c.2025 *C. lanceolata* age group forecasts d.2030 *C. lanceolata* age group forecasts

Figure 8. AG changes and forecasts.

The result (see Table 11) shows that during 2020–2030, *C. lanceolata* in the study area would undergo a process of replacement. It will be dominated by young and middle-aged forests, which will lead to its *C. lanceolata* landscape quality continuing to show a low state.

Table 11. Changes in area of *C. lanceolata* AG (km^2).

Time	2015	2020	2025	2030
Young forests	29,511.20	27,199.76	27,182.76	28,227.36
Middle-aged forests	33,494.16	30,942.68	31,345.84	31,481.76
Near-mature forests	16,704.48	16,019.92	18,386.96	18,198.20
Mature forests	20,268.36	19,183.04	20,201.48	19,238.60
Overly mature forests	5595.96	6565.92	6682.24	6653.36

4. Discussion

4.1. The Distribution of C. lanceolata Tends to Be Concentrated, and the Area, DBH, and HOST Increase

Our research indicates that *C. lanceolata* is primarily distributed along the borders of several provinces. Such as, the border region between Fujian and Jiangxi Provinces is characterized by the Wuyi Mountain range, while the Luoxiao Mountain range marks the boundary between Jiangxi and Hunan Provinces. Additionally, the Longji Ravi Mountains delineate the border between Hunan, Guizhou, and Guangxi Provinces. These mountainous areas experience a subtropical monsoon climate and are typically situated at altitudes between 1000 and 2000 m above sea level. This aligns with previous studies suggesting that the most suitable habitat for *C. lanceolata* includes subtropical monsoon climates, abundant rainfall, moderate temperatures, and predominantly cultivated vegetation, coniferous forests, and shrubs [51]. Furthermore, the altitude range of 1000 to 2000 m is consistent with earlier findings [52]. This distribution pattern is largely influenced by China's administrative divisions, which are often defined by natural terrain features. In the southern provinces of China, provincial boundaries are frequently marked by mountainous regions. Consequently, these border areas are predominantly mountainous, underscoring that *C. lanceolata* remains a key species for afforestation species in the southern mountainous regions.

From 2010 to 2020, the area of *C. lanceolata* increased from 104,475.64 km^2 to 107,393.80 km^2, an increase of 2.79%. The mean DBH increased from 8.28 cm to 10.00 cm by 20.77%. Ha of active wood increased from 48.73 m^3/ha to 75.02 m^3/ha, with an increase of 53.95%. The results showed that the area, DBH, and HOST of *C. lanceolata* increased to different degrees in the study area. The average DBH and HA of active wood of *C. lanceolata* increased obviously when the area increased little. This indicates that the management level of *C. lanceolata* has been continuously improved during this period. This trend aligns with previous proposals advocating for the intensive cultivation of *C. lanceolata* in future afforestation efforts [53].

4.2. Succession of Landscape Pattern of C. lanceolata *from 2010 to 2020*

From 2010 to 2020, the study area experienced significant landscape fragmentation, characterized by increased fragmentation, decreased aggregation, and greater landscape heterogeneity in the western region compared to the east. This indicates a higher degree of habitat diversity and biological richness in the western landscapes, which contributes to overall landscape diversity and stability. In contrast, the lower landscape heterogeneity in the eastern region suggests reduced habitat diversity, relative biological scarcity, and a more uniform landscape, resulting in increased landscape instability. The intensification of landscape fragmentation in the study area aligns with previous findings, attributing to shifts in land use. Specifically, from 2010 to 2015, *C. lanceolata* transitioned from economic forests and non-forest land to a predominance of economic forests and non-forest land, turning into *C. lanceolata* plantations. Then, from 2015 to 2020, *C. lanceolata* shifted from being encroached upon by evergreen broad-leaved forests to encroaching upon them [54]. This cyclical trend in the *C. lanceolata* area correlates with forestry management practices in southern China. Following reforms in land tenure systems, land was allocated to individual households, leading to a decline in large-scale afforestation efforts. Instead, afforestation became the responsibility of individual households, resulting in a reduction in large-scale *C. lanceolata* establishment observed in the 1980s. Overall, the exacerbation of landscape fragmentation in the study area was anticipated, given the expansion of urban development associated with urbanization. Urbanization is expected to expand construction land, resulting in a more fragmented and irregular landscape [55]. Furthermore, the acceleration of urbanization in the study area, driven by China's urbanization strategy, has substantially increased urbanization levels and rates [56], exacerbating landscape fragmentation. Regional disparities in urbanization and economic development between eastern and western regions [57] contribute significantly to differences in habitat diversity within the study area. However, forest fragmentation is not a unique trend in *C. lanceolata*. Globally, over half of the temperate broadleaf and mixed forest biome and nearly one quarter of the tropical rainforest biome have been fragmented or removed by humans, as opposed to only 4% of the boreal forest. Overall, Europe had the most human-caused fragmentation and South America the least [58]. Despite many improvements in legislation to better protect biodiversity, urban sprawl is still increasing in Europe, and new transport infrastructure is being constructed at a rapid pace. Fragmentation has significant effects on various ecosystem services and wildlife populations [59]. The grasslands of southern South America were rapidly converted to croplands, starting a fragmentation process that is still ongoing [60]. Whether it is Europe or South America, the landscape fragmentation phenomenon deserves our research attention in order to put forward relative solutions for the landscape fragmentation phenomenon in order to delay the worsening trend of the landscape fragmentation phenomenon. The research of the landscape fragmentation trend of *C. lanceolata*, which is greatly affected by human activities, can provide guidance for landscape restoration in the future planting policy.

The AG structure of the forests shows no significant changes, with young and middle-aged forests comprising approximately 58%, indicating a low landscape quality of *C. lanceolata*. Land transfer matrix results reveal that from 2010 to 2020, *C. lanceolata* interconverted with other coniferous and evergreen broad-leaved forests, with bamboo forests being the most invasive. In southern China, *C. lanceolata* and Masson pine plantations have traditionally dominated artificial forests, but *C. lanceolata* has shown greater advantages in investment, profitability, and timber yield compared to the predominantly Masson pine plantations [61]. Additionally, the rotational intercropping of *C. lanceolata* and Masson pine in common southern artificial forests contributes to soil fertility improvement and increased forest growth [62]. Thus, despite the ongoing interconversion between *C. lanceolata* and other coniferous forests, the overall planting area of *C. lanceolata* continues to slowly increase. Economic forests transitioning into *C. lanceolata* have increased, while intrusion into *C. lanceolata* has remained relatively stable. This is largely due to China's emphasis on ecological civilization construction and sustainable development, where the forestry sector has begun to focus on long-term ecological benefits and address conflicts between short-term economic benefits for farmers and the multifunctional stability of *C. lanceolata* [63]. Looking at the results for 2010 and 2020 in Figure 7, *C. lanceolata* continues to alternate between other coniferous and evergreen broad-leaved forests, showing a slow overall upward trend. Bamboo forest areas continue to steadily increase, maintaining stable intrusion into *C. lanceolata*, consistent with previous research findings [64,65]. From the above studies, it can be concluded that the *C. lanceolata* and the surrounding tree species in the study area are basically stable, but further attention should be paid to the trend of the more invasive bamboo forest invading the *C. lanceolata*.

Our study finally showed that the landscape pattern of *C. lanceolata* showed a trend of increasing fragmentation in the long time series. In the surrounding zonal vegetation, the erosion trend in bamboo forest to *C. lanceolata* was intensified. All these will have a negative impact on the *C. lanceolata*, which is the main body of forest landscape in southern China, and further affect the overall forest landscape structure in southern China. Therefore, in the management of *C. lanceolata* and the formulation of intervention policies, we should pay attention to the fragmentation of the *C. lanceolata* landscape and the intensification of the erosion trend in bamboo forests.

4.3. Predicting Forest Landscape Dynamics for Improved Management Using GM and CA-Markov Models

The implementation of ecosystem services by plantations largely depends on effective management [66]. Effective management strategies require better reporting and investigation [67]. With the continuous progress of science and technology, the use of remote sensing and GIS technology to help understand the spatial distribution and change in forest land has become a new technical means [68–70]. The survey is a scientific detection of the current situation of forest resources, and the prediction of forest landscape changes can understand the dynamic changes in forest pattern and structure and maintain the stability of ecosystems. The prediction of forest landscape change can provide the future trend and change direction for forest managers, so as to help formulate scientific management plans, optimize forest management, and rationally allocate land resources. Forest landscape dynamic model prediction technology is also constantly developing [71–73].

In our study, the GM model and the CA-Markov model are used to obtain prediction results with the required accuracy. The prediction results of the GM model show that, based on the data from 2010 to 2020, the DBH and HOST of *C. lanceolata* will increase steadily during the decade from 2020 to 2030. The results showed that the *C. lanceolata* in the study area was healthy, stable, and productive. Management is effective. This will help to enhance the ecological service functions of forests, including the provision of wood and other forest products, the conservation of biodiversity, the maintenance of water and soil, and the enhancement of carbon sink capacity.

4.4. Limitation and Future Direction

Using a variety of tools, our research is the first to examine the landscape dynamics and succession of a wide range of *C. lanceolata* over the past decade and to predict landscape changes for the next ten years. In terms of data sources, the Chinese Forestry and Grassland Administration employed a method that combines field investigations with remote sensing interpretation to ensure the accuracy of the forest inventory. Previous studies primarily relied on remote sensing data [74], whereas the data in this study are comparatively more rigorous and accurate. In this study, the most accurate data and a variety of methods were used to investigate the changes in spatial distribution and landscape pattern of *C. lanceolata* from 2010 to 2020, the changes in stand characteristics of *C. lanceolata*, and the alternate evolution of *C. lanceolata* and surrounding tree species. The spatial distribution and landscape pattern changes in *C. lanceolata* in the next 10 years were predicted. It is important to acknowledge the limitations of this study. Due to constraints in data acquisition, our research is confined to a ten-year timeframe, which is relatively brief. Subsequent research endeavors could explore longer time series and more precise data analysis by incorporating high-resolution remote sensing imagery and national forest inventory data.

Due to extensive data processing and the partial absence of data in certain provinces, our research prioritizes selecting the most representative central production regions of *C. lanceolata* as the focus area. We hope that this study will contribute to the future development of *C. lanceolata* and encourage further research in this field. For the continued advancement of this research, it is essential to address the data gaps from the missing provinces and to apply more accurate predictive models.

5. Conclusions

This study analyzed the spatial distribution changes, age structure dynamics, and interactions with other forest types of *C. lanceolata* from 2010 to 2030. The main conclusions are as follows:

(1) **2010–2020: Intensified concentration and fragmentation:** Kernel density analysis was used to analyze the spatial distribution trend of *C. lanceolata* during this period. The results showed that the degree of artificial concentration and fragmentation of *C. lanceolata* trees intensified during this period. The distribution of *C. lanceolata* is more concentrated near the provincial boundary, and the landscape fragmentation is intensified, resulting in the overall landscape quality decline. Landscape heterogeneity is high in the west and low in the east, stable in the west and dynamic in the east, which is influenced by both natural factors and human activities. In the future, it is necessary to adjust planting structure, improve landscape connectivity, manage according to local conditions, reasonably control cutting intensity, and strengthen monitoring and research, which can effectively alleviate the problems of *C. lanceolata* distribution concentration and landscape fragmentation and improve the overall landscape quality and ecosystem stability.

(2) **2020–2030: Stable age structure and low landscape quality:** The landscape index method and Markov prediction method were used to analyze the landscape quality and age structure of *C. lanceolata*. The results showed that the landscape quality of *C. lanceolata* was low continuously during this period. Due to continuous cutting and renewal for economic purposes, the age structure of *C. lanceolata* is still dominated by young forest and mature forest, which has little change. This practice maintains

high timber yields but leaves the landscape of very low quality, raising concerns about the long-term stability of the ecosystem. In the future, the landscape quality of *C. lanceolata* can be effectively improved by optimizing harvesting and renewal strategies, increasing tree species diversity, strengthening ecological monitoring, and implementing ecological compensation policies so as to achieve long-term stability and sustainable development of the ecosystem while ensuring wood production.

(3) **2020–2030: Improved intensive management:** The variance test method and GM prediction method were used to analyze the changes in DBH, HOST, and AG forest structure indexes of *C. lanceolata* during this period. The results showed that the artificial intensive management of *C. lanceolata* was improved continuously. Although the total area increased slowly, the DBH and HOST of *C. lanceolata* increased significantly, indicating improved management measures. These strategies can increase wood yields and have a positive impact on growth and stand structure. In the future, through continuous optimization of intensive management measures, increasing the application of scientific and technological means, and promoting diversified management, the wood yield of *C. lanceolata* can be further improved, and the forest structure and ecological function can be improved to achieve double improvement of economic and ecological benefits.

(4) **Forest conversion and bamboo invasion:** Land transfer matrix and Markov prediction method were used to analyze the transformation trend of *C. lanceolata* and surrounding zonal vegetation. The results showed that from 2010 to 2020, *C. lanceolata* was mainly converted to other coniferous forests and evergreen broad-leaved forests, and bamboo forest was the most invasive. From 2020 to 2030, the area of *C. lanceolata* will gradually increase, and the area of bamboo forests will continue to expand, maintaining pressure on *C. lanceolata*. This indicates that managing bamboo competition is still a key challenge to improving the landscape quality of *C. lanceolata*. In the future, the competitive pressure of bamboo forest on *C. lanceolata* can be effectively reduced, and the landscape quality of *C. lanceolata* can be improved by strengthening the expansion management of bamboo forest, optimizing the stand structure of *C. lanceolata*, scientifically planning land use, and formulating long-term management plans.

These findings provide a scientific basis for the sustainable management of *C. lanceolata*, emphasizing the need for monitoring eastern regions, controlling cutting intensity, and managing bamboo expansion to enhance landscape quality and ecosystem stability. Of course, there are some limitations in this study. For example, the lack of data in some provinces led us to select only the most representative central producing areas as study areas. In the future, a larger and more comprehensive study can be conducted according to the improvement of subsequent data. According to the evolution trend in landscape patterns explored in this study, more solutions can be sought to solve the problems of landscape fragmentation of *C. lanceolata* and the intrusion of bamboo forest. Of course, more accurate prediction models are also a research direction.

Author Contributions: Z.L.: writing—original draft, software, resources, methodology, investigation, formal analysis, and conceptualization. Y.Z.: writing—review and editing, supervision, project administration, and funding acquisition. J.W.: writing—review and editing, visualization, validation, and data curation. D.L.: validation and writing—review and editing. Z.C.: writing—review, editing, and supervision. S.Z.: writing—review and editing. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The data presented in this study are available on request from the corresponding author. The primary data for this study are derived from the Forest Second Type

Inventory, which is conducted by the China National Forestry and Grassland Administration. When we obtained the data, we signed a confidentiality agreement, and it was only available for academic research.

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Conflicts of Interest: The authors declare no conflicts of interest.

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