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Original Paper

Spatiotemporal Evolution and Early Warning for the Non-Agriculturalization of Cultivated Land Based on Multi-Scenario Simulation in Guizhou Province

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Abstract

The non-agriculturalization of cultivated land (NACL) poses a serious threat to food security and sustainable development. This study aims to reveal the spatiotemporal evolution of NACL in Guizhou Province, construct a hierarchical early-warning system, and propose recommendations for optimal land resource allocation. First, geospatial statistical analysis (2000-2020) revealed that the spatial pattern of NACL evolved from a scattered to a contiguously expanding one, with its rate increasing markedly from 2.7% (2000-2005) to 9.65% (2015-2020). This process was primarily driven by four key factors: population density, GDP, road network density, and cultivated land area. Second, the PLUS model was employed to conduct multi-scenario simulations and early warnings for 2035. The results indicate that the early-warning pattern exhibits a significant spatial differentiation, with higher levels in the west and lower in the east. Under the natural development (NDS) and urban expansion scenarios (UES), the risk of cultivated land loss in the western region is intensified, with most areas classified at or above the moderate warning level. In contrast, the cultivated land conservation (CCS) effectively curbs NACL and built-up land expansion, thereby not only reducing warning levels but also aligning more closely with sustainable development goals. This study provides a scientific basis for refining cultivated land conservation policies and promoting sustainable land use.

Keywords

The non-agriculturalization of cultivated land, Spatiotemporal evolution, Driving mechanisms, PLUS model, early warning levels

1. Introduction

Cultivated land is a vital resource for human survival and development, serving not only as the foundation for food production but also as a crucial link in maintaining ecosystem balance (GUO, JIN, YANG et al., 2024; MA, WANG, & ZHONG, 2024). The non-agriculturalization of cultivated land (NACL) refers to the conversion of land originally dedicated to agricultural production toward non-agricultural purposes (CAI, YANG, & XU, 2013). In this study, NACL is defined as the process through which land use changes from agricultural to other types of land uses. With the rapid advancement of global urbanization and industrialization, NACL has become a significant form of land use change. This process not only alters the land's ecological functions (DENG, HUANG, ROZELLE et al., 2006) but also indirectly disrupts ecosystem balance, exacerbating issues such as soil erosion and agricultural non-point source pollution (ZHANG, SONG, & GAO, 2025; ZHANG, LONG, MA et al., 2018; A W L, A D W, B S L, et al., 2019). These changes pose a potential threat to national food security and ecological stability (CHIEN, 2015; COHEN-SHACHAM, EMMANUELLE, GUERRA, et al., 2017). Consequently, studying this conversion process is crucial for providing a theoretical basis for ensuring food security and promoting sustainable development.

As the world's second-most populous developing nation with relatively scarce cultivated land resources, China has undergone rapid urbanization and economic development over the past four decades. During this period, the area of built-up land has expanded nearly tenfold, leading to significant encroachment of cultivated land by construction activities (FANGFANG, & LIJIE, 2014; WU, QIU, OU et al., 2024). This phenomenon is particularly pronounced in the southeastern coastal regions (RAMANKUTTY, FOLEY, & OLEJNICZAK, 2002; JIYUAN, MINGLIANG, DAFANG et al., 2003), where some areas are experiencing critical trends of land fragmentation and the disappearance of large, contiguous tracts of cultivated land. Consequently, the scale and pace of NACL have been steadily increasing (CHIEN, 2015; WEI & YE, 2014). Although NACL has, to some extent, promoted economic development, rural revitalization, and agricultural restructuring (SU, 2020), excessive conversion leads to problems such as the waste of land resources and the infringement on farmers' rights and interests. This poses a threat to food security and sustainable development (MAESTRE, LE, DELGADO-BAQUERIZO et al., 2022). Research on the impact of urbanization on land use has confirmed that economic and population growth reliant on the consumption of agricultural resources are unsustainable and hinders the process of rural development (GUASTELLA & PAREGLIO, 2014). As a populous nation and a major food consumer, China finds the conservation of its cultivated land increasingly vital (YI et al., 2016). The government places great emphasis on food security, explicitly mandating that limited cultivated land resources be prioritized for grain production and that their conversion to other agricultural or non-agricultural uses be strictly controlled (HAIPING, JUNLIAN, & XIANWEI, 2023). In 2019, the Ministry of Natural Resources and the Ministry of Agriculture and Rural Affairs jointly issued the "Notice on Strengthening and Improving the Protection of Permanent Basic Farmland." This notice strictly prohibits the use of permanent basic cultivated land for non-grain-producing activities, such as establishing fruit and forestry plantations, digging ponds for aquaculture, creating green belts, or building livestock and poultry facilities, thereby curbing NACL (Notice of the Ministry of Natural Resources and the Ministry of Agriculture and Rural Affairs on Strengthening and Improving the Protection of Permanent Basic Farmland, 2019). Currently, Current academic research on NACL primarily focuses on its spatiotemporal evolution (YIN, LI, X., LI, G., et al., 2020; CHEN, WANG, S. Y., & WANG, Y. H., 2022), driving mechanisms (LIU, Y. X., LIU, S, L., SUN, Y. X. et al., 2021; HUANG, ZHU, & LIU, n.d.), impacts on the ecological and socio-economic environment (WANG, LIU, CAI et al., 2021; QU, HU, LI et al., 2020), and predictions of future trends (WU, TAO, YANG et al., 2019; ZHANG & LU, 2021). The study areas have included the three major grain-producing functional zones (ZHAO, XIAO, & YIN, 2023) and northwestern China (YAN, CHEN, WANG et al., 2025). While the body of research on this topic is generally rich, there is a notable lack of studies on the spatiotemporal evolution and multi-scenario early warning of NACL in karst mountainous areas. Guizhou Province, characterized by its typical karst landform, presents a critical case. The restrictive terrain in these areas results in highly fragmented and poor-quality cultivated land, which is unsuitable for large-scale farming and is consequently more vulnerable to NACL. To address these challenges, this study employed a land use transition matrix to describe the spatiotemporal evolution of NACL and a Geodetector model to identify its driving factors. Furthermore, the PLUS model was used to predict future land use patterns under three distinct scenarios: natural development, urban expansion, and cultivated land conservation. A hierarchical early warning analysis is further conducted on NACL based on the predicted results. The findings are intended to provide a scientific reference for cultivated land management and optimal land resource regulation in similar ecologically fragile areas.

2. Materials and Methods

2.1 Study Area

Guizhou Province is situated in southwestern China, spanning from 103°36′E to 109°35′E and 24°37′N to 29°13′N (Figure 1). It borders Hunan Province to the east, the Guangxi Zhuang Autonomous Region to the south, Yunnan Province to the west, and Sichuan Province and Chongqing Municipality to the north. The region experiences a humid subtropical monsoon climate characterized by mild winters, cool summers, abundant precipitation, and concurrent rain and heat periods, with an average annual temperature of approximately 15°C. Topographically, Guizhou lies on the northeastern part of the Yunnan-Guizhou Plateau. Its terrain slopes from higher elevations in the west to lower ones in the east, with a general descent from the central area toward the north, east, and south. The average elevation is about 1,100 meters. The landscape is predominantly mountainous and hilly, which together constitute about 92.5% of the total area, and can be categorized into the eastern hilly region and the western plateau-mountain region. Guizhou Province is one of the most typical regions for karst landform development in southern China. Karst areas, which exhibit significant spatial heterogeneity, are extensively distributed across the province, covering approximately 61.9% of its total land area.

Cultivated land, however, constitutes only about 18% of the provincial total and is predominantly located in intermountain basins and river valleys. This distribution pattern, dictated directly by the complex topography, results in the inherent scarcity and high fragmentation of cultivated land resources in the region.

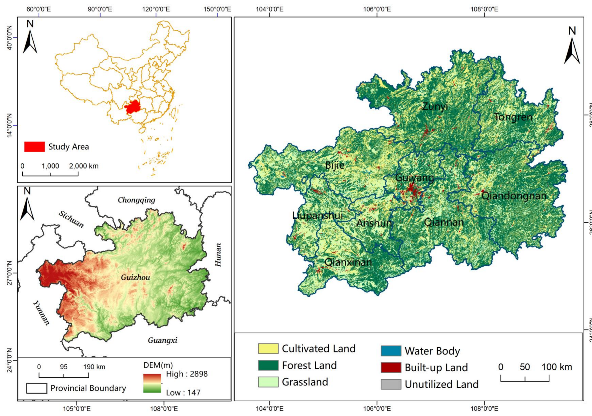


Figure 1. The Location and Land Use of the Study Area

2.2 Data Source and Processing

The data used in this study were obtained from the following sources. Land use data with a spatial resolution of 30 m × 30 m were derived from the Resource and Environment Science and Data Center, Chinese Academy of Sciences (RESDC; http://www.resdc.cn), with an overall accuracy of over 90% (JIYUAN, JIA, WENHUI et al., 2018). Digital Elevation Model (DEM) data were acquired from Geospatial Data Cloud (http://www.gscloud.cn); elevation data for Guizhou Province were extracted via ArcGIS's Extract by Mask tool, with slope and aspect subsequently derived using the platform's Spatial Analyst tools. Road and river network data were sourced from OpenStreetMap (http://www.openstreetmap.org), and Euclidean distances to these features were calculated using ArcGIS's Euclidean Distance tool. Spatially distributed kilometer-grid data for Gross Domestic Product (GDP) and population (POP) were also obtained from RESDC.

2.3 Methods

2.3.1 The Rate of NACL

The intensity of NACL in Guizhou Province was quantified using the cultivated land conversion rate. This metric, defined as the proportion of cultivated land converted to non-agricultural uses over a specified period relative to the cultivated land area at the period's start, is calculated as follows:

$$R_t = S_t / L_t \times 100\% \quad (1)$$

Where t is the time period, Rt is the NACL rate (%) during a certain period; St is the NACL area (km2) in the research region during a certain period; Lt is the cultivated land area (km2) in the research region at the beginning of a certain time period.

2.3.2 Land Use Ransfer Matrix

The land-use transfer matrix captures the quantitative changes and directions of transfers between different land-use types from an initial to a final period, presented as a two-dimensional matrix. It is used to analyze the mutual conversions between land-use categories over time, The calculation is as follows:

$$S_{ij}=\begin{bmatrix} S_{11} & S_{12} & \cdots & S_{1n} \\ S_{12} & S_{22} & \cdots & S_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ S_{n1} & S_{n2} & \cdots & S_{nn} \end{bmatrix} \tag{2}$$

Where Sij represents the area of land converted from type i to type j; n is the number of land use types; Each row of the matrix S represents the land use type at the current moment, and each column represents the land use type at the next moment.

2.3.3. Spatial Analysis Method of NACL

Spatial autocorrelation analysis, which quantifies the dependency of spatial features based on their attributes and locations, was employed to investigate the clustering of cultivated land conversion. This analysis is primarily categorized into global and local spatial autocorrelation. The Global Moran's I index was used to determine whether cultivated land conversion exhibits a clustered distribution in the study area. The value of Moran's I ranges from -1 to 1: a value greater than 0 indicates positive spatial correlation (clustering), a value less than 0 indicates negative spatial correlation (dispersion), and a value of 0 suggests no spatial correlation. The formula is expressed as follows

$$I=\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(y_i-\bar{y})(y_j-\bar{y})}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \tag{3}$$

In this equation, I represents the Global Moran's I, n is the total number of spatial units, y_i and y_j are the rates of NACL for units i and j, respectively, $\bar{y}$ is the mean rate, W_{ij} is the spatial weight, and S^2 is the sample variance.

The Global Moran's I is limitations in capturing local spatial patterns and heterogeneity. To address this, the Local Moran's I* statistic is employed to detect spatial correlations at specific locations and their neighboring units. This measure helps identify spatial agglomeration patterns of NACL, which can be categorized into five types: high-high, high-low, low-high, low-low, and non-significant clusters. The formula is as follows:

$$I^* = \frac{x_i-\bar{x}}{\frac{1}{n}\sum(x_i-\bar{x})2}\sum_{j\neq i}^{n} w_{ij}(x_i-\bar{x}) \tag{4}$$

Where I* is the Local Moran's I; W_{ij} is the spatial weight value; n is the total number of study units; is the rate of NACL for each study unit, and is the average non-agriculturalisation rate for all study units.

2.3.4 The Geodetector Model

The geodetector is a statistical tool that identifies the driving forces behind a phenomenon by detecting the effects of multiple factors and their interactions, based on the principle of spatial heterogeneity[34].

(1) Factor Detector

The factor detector is employed to quantify the spatial heterogeneity of cultivated land non-agriculturalization NACL and to assess the explanatory power of a given in-fluencing factor. Its calculation formula is as follows:

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

In the formula: q represents the explanatory power of the factor with respect to NACL, ranging from 0 to 1. with a value range of [0,1]. A higher q value indicates stronger explanatory power, whereas a lower value denotes weaker explanatory power. L stands for the number of strata (or categories) of the factor. Nh is the number of spatial units in stratum h; N is the total number of spatial units across the study area; σ_h^2 denotes the variance of NACL within stratum h; σ2 is the overall variance of NACL across the entire study area.

(2) Selection of Driving Factors

Changes in cultivated land use generally result from the interactions among natural environmental conditions, socioeconomic factors, and agricultural location characteristics. In this study, nine influencing factors (table 1) were selected across three dimensions: natural environment, socioeconomic conditions, and locational attributes. Within the natural environment dimension, elevation, slope, and aspect were chosen as key topographic factors. Variations in elevation create a vertical zonation of climate, leading to differences in crop types and growing seasons. Differences in slope and aspect affect sunlight exposure, moisture availability, nutrient distribution, and temperature. Steep slopes and north-facing slopes often require greater labor and material inputs, making such areas more prone to conversion to other land uses or abandonment (QIANQIAN, ZHEN, XIAORUI et al., 2024). Agricultural location conditions are also critical, as the proximity of cultivated land to roads and water bodies affects soil fertility, product transportation, and irrigation. Furthermore, socioeconomic factors significantly influence farming decisions; key elements include the level of regional economic development, governmental policies, cultivation costs, and transportation convenience. However, due to limitations in data availability, this study selected three representative socioeconomic drivers: Gross Domestic Product (GDP), population density, and road network density.

Table 1. Indicators of Influencing Factors for NACL

Influencing factors	Indicators	Explanation of indicators
Natural environment	Elevation(X1)	Mean elevation of the study unit
	Slope(X2)	Mean slope of the study unit

	Aspect(X3)	Mean aspect of the study units
Socioeconomic factors	GDP(X4)	Total GDP of the study unit
	Population density (X5)	Total population total of the study unit
	Road network density(X6)	The road lengths total of the study unit divided by the area of the study unit
Agricultural location conditions	Cultivated land area(X7)	Total cultivated land area of the study unit
	Distance from the road(X8)	Distance to major roads
	Distance from the water(X9)	Distance to water bodies

2.3.5 The PLUS Model

The PLUS model, introduced by Liang (LIANG, GUAN, CLARKE et al., 2021), represents an advanced framework for land use simulation, engineered to achieve superior simulation fidelity and a more authentic quantification of landscape pattern evolution. The model's architecture, illustrated in Figure 2, is founded upon three integral modules (Figure 2). First, the Land Expansion Analysis Strategy (LEAS) module is dedicated to extracting the underlying rules of land use transition. Second, the Cellular Automata (CA) component employs a multi-type random patch seeding mechanism (CARS) to generate spatial patches. Third, the pre-dictive simulation module projects future land use distributions based on the outputs of the preceding modules.

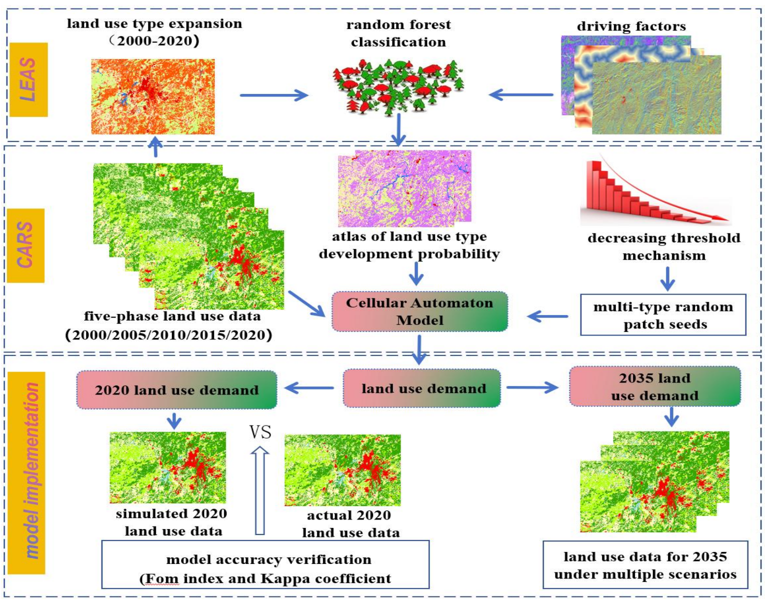


Figure 2. Schematic Diagram of the PLUS Model Structure

(1) The LEAS module first identifies the land use expansion areas from the initial to the final period. Subsequently, based on the Random Forest Classification (RFC) algorithm, it derives the transition and inertia probabilities for each land use type to reveal the associations between driving factors and land

use change. The probability is calculated as follows:

$$P_{i,k(X)}^{d}=\frac{\sum_{n=1}^{M} I[h_n(X)=d]}{M} \tag{6}$$

Where the parameters are defined as: X denotes a vector composed of multiple driving factors.hn(X) represents the predicted land use type from the n-th decision tree; d takes a value of 0 or 1, with 1 indicating a transition from other land use types to type k, and 0 indicating no transition to type k; M is the total number of decision trees; $P_{i,k(X)}^{d}$denotes the expansion probability of land use type k at spatial unit i under the given value of d; I[·] is the indicator function of the decision tree ensemble

(2) The CARS module is a Cellular Automata (CA) model based on a multi-type random patch seeding mechanism, designed for the dynamic simulation and spatial allocation of land use change. The model determines the overall transition probability for each land use type by coupling three key factors: (1) the basic development probability derived from the LEAS module; (2) the neighborhood effect, which reflects local spatial interactions; and (3) the land use demand constraint, which ensures the total quantity aligns with predefined targets. The probability is calculated using the following equation：

$$OP_{i,k}^{d=1,t}=P_{i,k}^{d}\times\Omega_{i,k}^{t}\times D_{k}^{t} \tag{7}$$

$OP_{i,k}^{d}$ is the overall transition probability for land use type k at spatial unit I; $P_{i,k}^{d}$ is the basic development probability for land use type *k* at unit i; $\Omega_{i,k}^{t}$is the neighborhood effect at time t; is the demand constraint factor at time t.

(3) To evaluate the reasonability of the model's parameter settings and its ap-plicability in the study area, a simulation accuracy validation was conducted. The Kappa coefficient was used to measure the overall consistency between the simulated and actual results, while the Figure of Merit (FoM) coefficient focused on quantita-tively testing the location accuracy at the cellular scale. The validation process in-volved simulating the 2020 land use pattern based on 2015 data and comparing it with the actual 2020 map. The results show an overall accuracy of 92% and a Kappa coeffi-cient of 0.86. According to the Kappa evaluation standard (0.81-1.00 is "excellent"), the simulation met the accuracy requirements. Concurrently, the calculated FoM coeffi-cient of 0.20 falls within its common effective range (0.01-0.25), further confirming the model's spatial locational accuracy. In summary, the simulation demonstrated high accuracy and good performance, indicating that the model can be reliably used for predicting future land use change in the study area.

(4) To investigate the characteristics of land use change under different develop-ment pathways, this study simulated the land use patterns for 2035 under three dis-tinct scenarios, using the 2020 land use data as a baseline. The objective is to provide a scientific basis for regional land use planning and policy optimization. The specific parameterizations for each scenario are as follows: Natural Development Scenar-io (NDS): This scenario assumes that historical land use change trends from 2015-2020 will continue without any additional policy intervention, serving as a baseline refer-ence. Urban Expansion Scenario (UES): Informed by the national new-type urbaniza-tion plan, this scenario prioritizes urban development. Based on the historical transi-tion probabilities, the probability of

conversion from cultivated land, forest, and grassland to built-up land was increased by 30%, while the probability of conversion from built-up land to other types was decreased by 30%. Cultivated land conservation Scenario (CCS): This scenario is based on strict cultivated land use control policies aimed at implementing the permanent basic cultivated land conservation system. Consequently, the probability of conversion from cultivated land to built-up land was reduced by 40%, and the probability of conversion to grassland and forest land was also reduced by 20%. Integrating these scenario objectives with historical data, the land use transition matrix parameters for simulating the 2035 multi-scenario land use patterns in Guizhou Province were established (Table 2).

Table 2. Parameters for the Multi-scenario Land Use Transition Matrix

Land use type	Natural Development						Urban Expansion						CultivatedLand Conservation					
	a	b	c	d	e	f	a	b	c	d	e	f	a	b	c	d	e	f
a	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
b	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
c	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
d	1	1	1	1	1	1	0	0	0	1	0	0	0	0	0	1	0	0
e	1	1	1	1	1	1	0	0	0	0	1	0	0	0	0	0	1	0
f	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Note. (a-f: represent cultivated land, forest land, grassland, water body, built-up land, and unutilized land respectively; 1 indicates convertible, and 0 indicates non-convertible.)

The neighborhood weight (Table 3) is a key parameter that quantifies the intrinsic ex-pansion capacity of each land use type, thereby influencing land use transitions. This weight, ranging from 0 to 1, indicates a land use type's expansion tendency: values closer to 1 signify a stronger tendency, while those closer to 0 signify a weaker one. In this study, the weight is calculated via range normalization, as follows：

$$X^* = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{8}$$

Where X* denotes the range-normalized value, X represents the changed area of a given land use type between two periods, Xmax is the maximum area change among all land use types, and Xmin is the minimum area change among all land use types.

Table 3. Neighborhood Weight in Land Use Simulation

	Cultivated land	Forest land	Grassland	Water body	Built-up land	Unutilized land
NDS	0.42	0.01	1.00	0.80	0.98	0.64
UES	0.30	0.01	0.82	0.69	1.00	0.56
CCS	0.93	0.01	1.00	0.90	0.97	0.76

3. Results

3.1 Temporal Evolution Characteristics of NACL

To investigate the characteristics of NACL in Guizhou Province across different periods, a quantitative analysis of its outflow dynamics was conducted using a land use transition matrix. This approach precisely quantified the area converted from cultivated land to other land types in each period, thereby identifying the primary conversion pathways, their proportional areas, and their evolutionary trends, as presented in Table 4. Overall, from 2000 to 2020, NACL in Guizhou Province was predominantly to forest and grassland, with forest accounting for the largest share. The conversion peaked during the 2015-2020 period, reaching 2789.29 km2 and 1101.30 km2 for forest and grassland, respectively. This shift can be largely attributed to national ecological conservation policies and agricultural restructuring. A key driver was the implementation of two phases of the "Grain for Green" program, under which the government provided free seedlings and per-mu planting subsidies to encourage farmers to restore cultivated land that was unsuitable for cultivation or ecologically vulnerable to grassland and forest. During the study period, the area of cultivated land converted to built-up land exhibited a sharp increasing trend, rising from 16.23 km² in 2000-2005 to 693.61 km² in 2015-2020—a net increase of 677.38 km². This dramatic expansion is primarily attributed to national policies such as the "Western Development Program" and "Targeted Poverty Alleviation," implemented since 1999, which accelerated urbanization and infrastructure construction in Guizhou Province and resulted in the encroachment of cultivated land by built-up land. In contrast, conversion to water bodies reached its highest proportion in 2010-2015, accounting for 10.51% of total NACL, while conversion to unutilized land remained minimal across all four periods, with proportions consistently close to 0%.

The non-agriculturalization rate was calculated for each period using Formula (1). During 2000-2005, the area of NACL was 1,342.31 km², corresponding to a rate of 2.70%. In the subsequent period (2005-2010), the converted area decreased slightly to 990 km², with a rate of 1.99%. From 2010 to 2015, the converted area rose to 1,054.76 km² and the rate increased to 2.13%. During 2015-2020, however, the extent of conversion increased markedly: the converted area reached 4,735.94 km² and the rate rose sharply to 9.65%. In this most recent period, the proportions of converted cultivated by receiving land type, in descending order, were forest land, grassland, built-up land, water body, and unutilized land. With the exception of unutilized land, the areas converted to all other types increased substantially in this phase. Overall, NACL in Guizhou Province exhibited a trend from relatively stable development during the earlier periods to a rapid surge in the final period.

Table 4. Area and Proportion of NACL in Guizhou Province

Time Period	Area(km^2) Proportion (%)	Foret Land	Grassland	Water Body	Built-up Land	Unutilized Land	Sum	Rate of NACL
2000-2005	Area	1076.32	245.34	4.3	16.23	0.12	1342.31	2.7%
	proportion	80.18	18.28	0.32	1.2	0	100	
2005-2010	Area	517.34	218.44	104.09	150.06	0.07	990	1.99%
	proportion	52.26	22.06	10.51	15.16	0	100	
2010-2015	Area	571.9	189.69	8.75	283.82	0.6	1054.76	2.13%
	proportion	54.22	17.98	0.83	26.91	0.06	100	
2015-2020	Area	2789.29	1101.3	151.12	693.61	0.62	4735.94	9.65%
	proportion	58.9	23.25	3.19	14.65	0.01	100	

3.2 Spatial Evolution Characteristics of NACL

Based on land use change data from 2000 to 2020, the spatial differentiation pattern of NACL rates across counties in Guizhou Province was visualized, as shown in Figure 3. During the study period, the spatial pattern of NACL underwent significant phased evolution: in the 2000-2005 period, NACL exhibited a south-high-north-low pattern, with areas having a non-agriculturalization rate exceeding 5% mainly distributed in Leishan, Majiang, Jianhe, and Ziyun counties, among which Jianhe County's rate surpassed 7%. Between 2005 and 2010, NACL was concentrated in western regions; from 2010 to 2015, it was scattered. Over 2000-2015, the overall pattern of NACL exhibited "low-value contiguous, high-value scattered" spatial differences, with high-value areas concentrated in a few regions of central Guizhou (Guiyang and its surrounding areas), and most counties having rates below 3%. However, by 2015-2020, the area and extent of NACL expanded dramatically: the minimum county-level NACL rate rose to over 5%, the coverage of high-value areas (>7%) broadened significantly, and a "high-value clustering" spatial pattern emerged. Overall, the spatial pattern of NACL in Guizhou Province exhibited an evolutionary trajectory transitioning from a "localized, scattered" pattern to a "contiguous, widespread" one. In the early stage, it occurred sporadically around the core of central cities; in the later period, both the intensity and scope of NACL increased significantly.

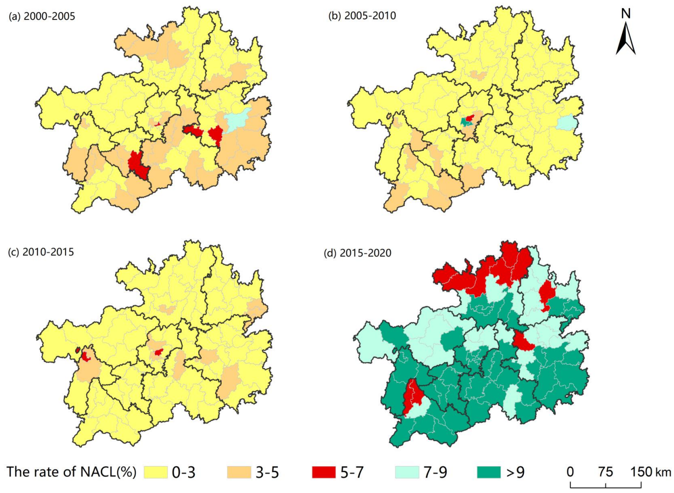


Figure 3. The Spatial Distribution Pattern of NACL in Guizhou Province

The spatial agglomeration characteristics of the rate of NACL in Guizhou Province were examined using GeoDa software. The calculated global Moran's I* indices for the four study periods were 0.283, 0.334, 0.245, and 0.506, all of which passed the signifi-cance test at $p < 0.05$. These results indicate a statistically significant positive spatial autocorrelation in the distribution of NACL across the province. Identifying local spa-tial clusters of NACL plays a critical role in optimizing land resource management and addressing practical issues related to cultivated land protection. According to Fig-ure 4, during 2000-2005, High-High clusters were primarily distributed in eastern counties and Luodian County in the south, while Low-Low clusters were mainly con-centrated in parts of Guiyang City, Bijie City, and Wuchuan County in Zunyi City. From 2005 to 2010, High-High clusters shifted toward the central region, forming a concentration centered on Guiyang City; concurrently, Low-Low clusters expanded northward, reaching northern Bijie City and Zunyi City. Between 2010 and 2015, High-High clusters exhibited a scattered distribution, primarily in Tongren urban area, Guiyang urban area, and Hezhang County in Bijie City. In contrast, Low-Low clusters extended from Zunyi City to parts of Tongren City, with scattered occurrences in Liu-zhi County and Qinglong County. During 2015-2020, the spatial pattern of NACL was most concentrated: High-High clusters aggregated in Guiyang City, while Low-Low clusters clustered in Zunyi City.

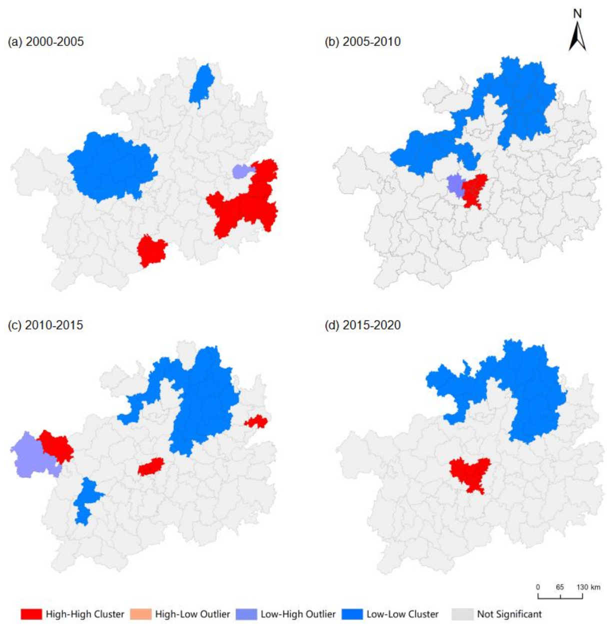


Figure 4. The Spatial Agglomeration Characteristics of NACL Rates in Guizhou Province

3.3 Drivers of NACL

3.3.1 Factor Detection Analysis

The results of the factor detector are shown in Figure 5. During 2000-2005, culti-vated land area, population density, and GDP were the primary driving factors of NACL, with explanatory powers exceeding 0.1. In contrast, slope had the minimal im-pact, with an explanatory power of 0.028, indicating that this period was predomi-nantly influenced by agricultural and economic factors. From 2005 to 2010, population density, GDP, road network density, and cultivated land area exhibited explanatory powers above 0.1, where population density and GDP exerted the greatest influence and became the dominant factors. Between 2010 and 2015, the explanatory powers of road network density, population density, cultivated land area, and GDP increased compared to the preceding two periods, reaching values above 0.2. During 2015-2020, the explanatory power of all driving factors increased significantly relative to the three preceding periods, with population density and cultivated land area reaching 0.445 and 0.35, respectively. Taken together, cultivated land area, population density, road net-work density, and GDP consistently constituted the most influential factors across all four periods. The underlying mechanisms for these persistent drivers are twofold. First, population expansion substantially increased the demand for built-up land (for resi-dential, public service, and infrastructure uses), thereby driving urban spatial expan-sion and the consequent occupation of cultivated land. Second, high-density road net-works enhanced regional accessibility. This improvement not only reduced transporta-tion and transaction costs for land development, making even average-location culti-vated land more accessible, but also stimulated land value appreciation along the routes. The resulting capital accumulation in land development further accelerated NACL.

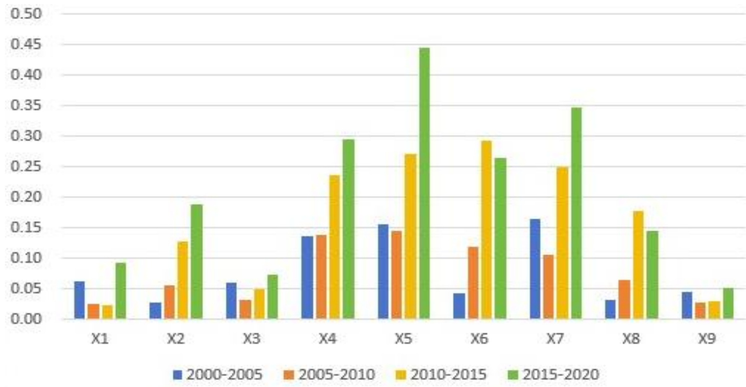
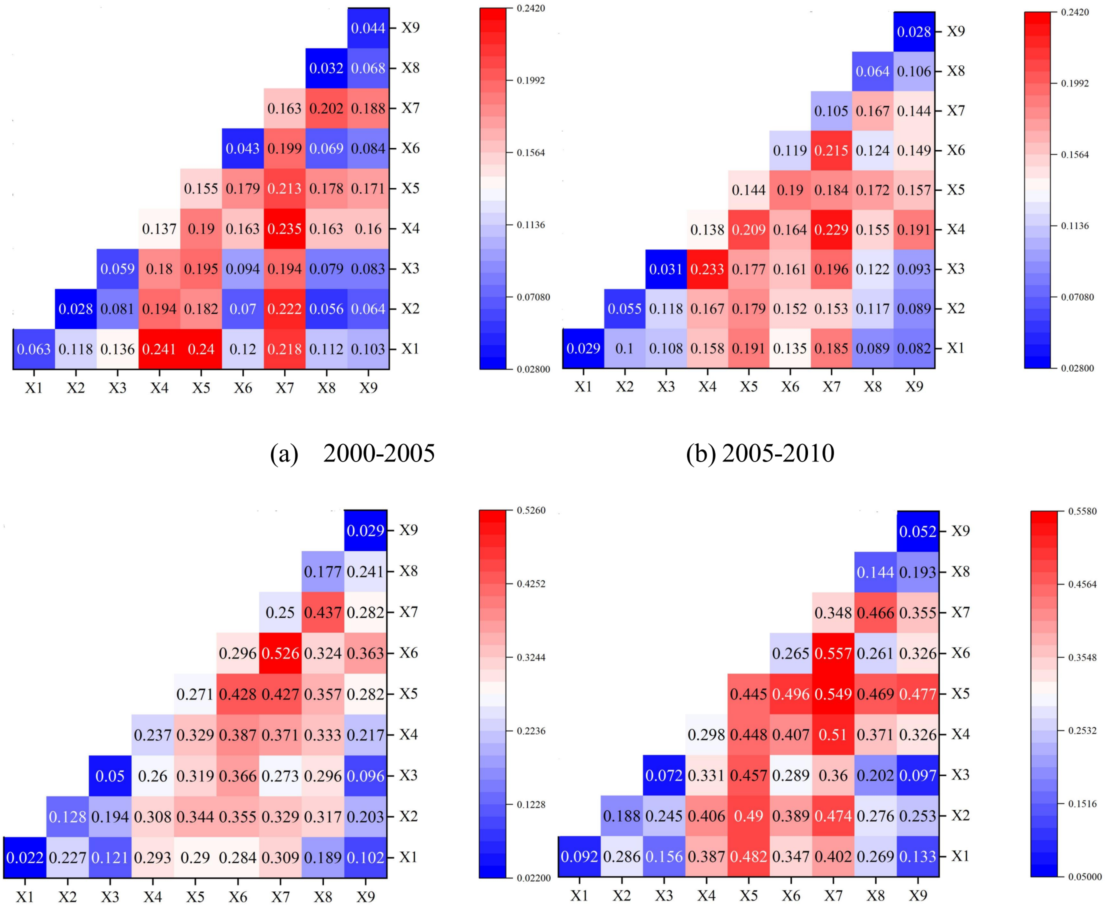


Figure 5. Results of NACL Factor Detector

3.3.2 Interaction Detection Analysis

The interaction detector within the Geodetector model was used to examine how the interplay between any two factors influences their explanatory power regarding NACL. The results (Figure 6) show that all pairwise interactions led to either bivariate or nonlinear enhancement. This indicates that the spatial pattern of NACL in Guizhou Province did not result from any single factor but emerged from the synergistic inter-play of natural environmental, socio-economic, and agricultural location conditions. during the first two periods, the interaction between GDP and natural environment factors substantially amplified their combined impact on NACL. During 2000-2005, the interaction between GDP and elevation had the strongest explanatory power for NACL, with a q-value of 0.241. By 2005-2010, the dominant interaction shifted to GDP and aspect, which yielded a q-value of 0.233. In the latter two periods, the role of culti-vated land area became prominent, as its interactive effects with both population den-sity and road network density were significantly enhanced. Specifically, the interaction between cultivated land area and road network density reached its peak in both peri-ods, with q-values as high as 0.526 and 0.557, respectively. This was followed by its in-teraction with population density, with corresponding q-values of 0.427 and 0.549.



(a) 2000-2005 (b) 2005-2010

(c)2010-2015 (d)2015-2020

Figure 6. Detection of Interaction Effects among Driving Factors

3.4 Multi-Scenario Simulation of Land Use in Guizhou Province

3.4.1 Spatial Distribution of Land Use in 2035 under Different Scenarios

This study employed the PLUS model to simulate the 2035 land-use patterns of Guizhou Province under three scenarios: NDS, UES, and CCP, comparing them with the 2020 baseline (Figure 7). The results reveal that the spatial patterns under the NDS and UES are similar, both characterized by extensive conversion of cultivated land to built-up land, with new built-up areas scattered sporadically across the province. In contrast, the CCS effectively curbs this conversion trend. Under this scenario, scattered built-up land and other agricultural plots adjacent to existing cultivated land are reclaimed and consolidated, resulting in a more contiguous cultivated land distribution pattern.

Differences were also observed in the quantitative structure of land-use patterns across the scenarios (Figure 8). Under the NDS, forest land was the primary land use type (49.92%), followed by cultivated land (26.34%) and grassland (19.41%). Compared to 2020, cultivated land, forest land, and unutilized land decreased by 1883.61 km², 5281.33 km², and 3.37 km², respectively, with forest land experiencing the largest reduction. Conversely, grassland, water bodies, and built-up land increased by 3174.51 km², 1252.7 km², and 2741.1 km², respectively. This suggests that, without policy constraints, the expansion of built-up land and grassland would exacerbate the loss of cultivated land. Under the UES, urban sprawl became the dominant driver, leading to a rapid increase in built-up land. This scenario resulted in severe cultivated land loss, with an area reduction of 2114.36 km². This highlights the immense pressure of urban expansion on cultivated land resources. In the CCS, the implementation of strict cultivated land retention constraints curbed the trend of cultivated land loss. This scenario led to a net increase in cultivated land area of 4488.63 km². The results confirm that strict governance over the quantity and use of cultivated land is an effective approach to achieving cultivated land protection goals.

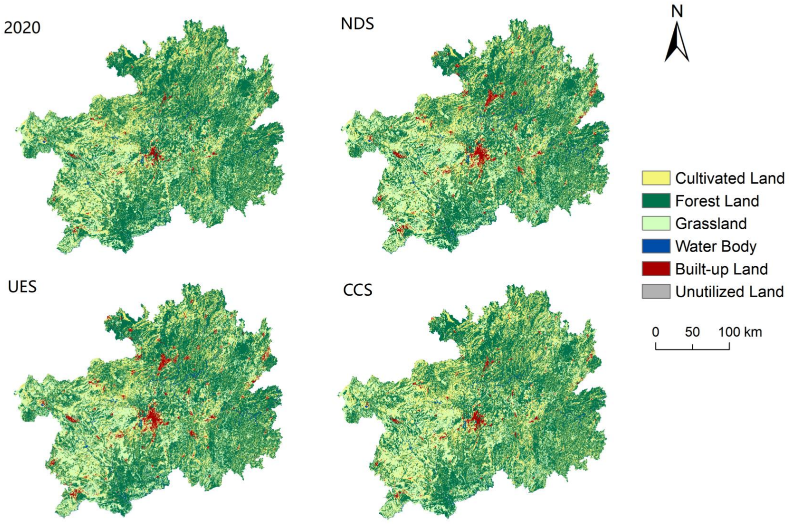


Figure 7. Simulated Land Use Patterns under Different Scenarios

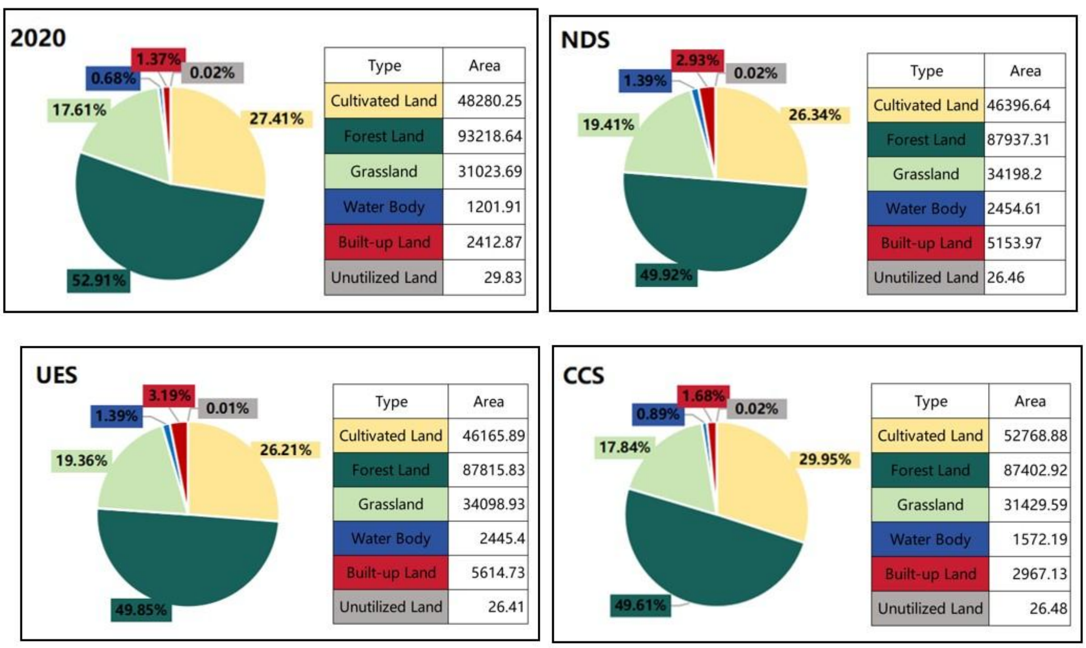


Figure 8. Proportion Chart of Different Land Use Types (Area:km^2)

3.4.2 Graded Early Warning of NACL under Different Scenarios in 2035.

The early warning levels for NACL in 2035 are classified into five tiers: Mild (0%-5%), Moderate (5%-10%), High-level (10%-15%), Severe (15%-20%), and Extreme (20%-100%). As shown in figure 9, Overall, the early-warning pattern for NACL exhibits a distinct east-west spatial disparity. Warning levels in the western counties are generally higher than those in the eastern counties. Specifically, areas with moderate-to-severe warnings are predominantly concentrated in the west, whereas low-level warnings are continuously distributed across the eastern region. Under the NDS, 2 counties are at an Extreme level and 1 at a Severe level, with an additional 10 counties classified as High. The UES exhibits a largely similar warning pattern. In contrast, under the CCS, the trend of NACL is effectively mitigated. The highest warning level is High, affecting only a single county; ten counties in the southwest remain at a Moderate level, while all others are classified as Mild.

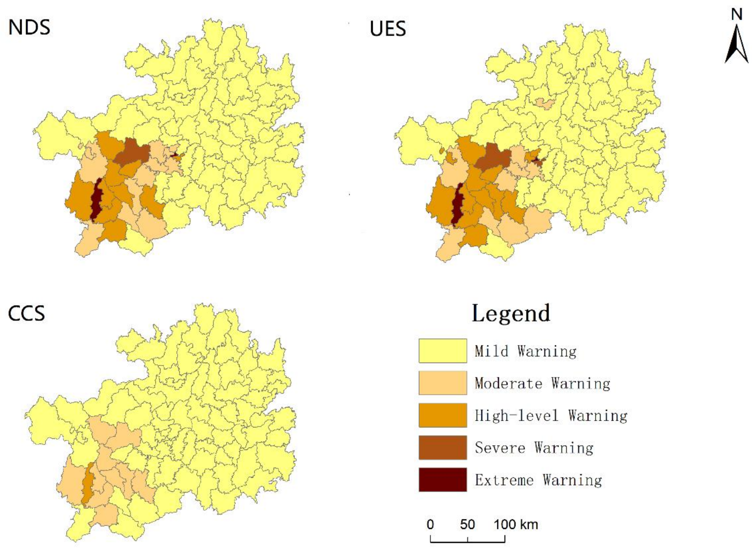


Figure 9. Graded Early Warning of NACL under Different Scenarios

4. Discussion

4.1 Spatiotemporal Characteristics of NACL

This study indicates that the rate of NACL in Guizhou Province exhibited an accelerating trend from 2000 to 2020, increasing from 2.7% to 9.65%, which suggests that this process has not been effectively curbed. The period from 2015 to 2020 was the most intense, driven by a combination of factors. During this time, China poverty alleviation strategy prompted large-scale relocation programs, rural population decline, and infrastructure improvements. Concurrently, investment in the tertiary sector increased, with its share of GDP rising from 46.3% in 2015 to 52.1% in 2020. These interconnected dynamics collectively led to the extensive occupation of cultivated land. Our research further indicates that a significant portion of cultivated land loss is due to conversion to forest land and grassland, a trend largely driven by policy-led ecological restoration. Confronted with mounting ecological pressures from economic and urban expansion, the government enacted stringent protection measures.

Consequently, local authorities have rezoned marginal some cultivated land for ecological purposes[37] to align with the national mandate for “ecological civilization,” which has directly spurred the conversion of cultivated land to forests. Another key driver is the passive process of cultivated land abandonment followed by natural regeneration (QIANQIAN, XIE, XIAORUI et al.. 2024). The inherent marginality of land in the Karst region, characterized by rugged terrain, thin soils, and severe fragmentation that worsens with elevation and slope (LIANG, PAN, CHEN et al., 2021; B W X A, C X J A B, B J L A, et al., 2020), renders cultivation economically unviable. This forces farmers to abandon the most challenging plots. Subsequently, aided by the region’s favorable water and heat conditions, these abandoned lands naturally succeed to grassland or forest over time.

4.2 Multi-scenario Early Warning of NACL for 2035

Using the PLUS model, we simulated and analyzed the spatial patterns of land use under three scenarios for 2035: NDS, UES, and CCS. The results indicate that under the NDS and UES, cultivated land and forestland areas would experience significant reduction, while built-up land would expand rapidly. This phenomenon suggests that the current land use regulation model, which relies on a natural development approach, is inadequate for balancing the multiple demands of ecological protection, agricultural production, and urban development during rapid urbanization. This leads to the increasingly prominent issue of NACL, necessitating the optimization of land use allocation through targeted regulatory measures. In contrast, the CCS exhibits a more optimal land use pattern. By implementing measures such as strengthening cultivated land protection constraints, enforcing the requisition-compensation balance policy, and strictly controlling built-up land expansion, this scenario achieves a significant increase in regional cultivated land area, effectively ensuring food security. Concurrently, the expansion of built-up land is curbed, and the early warning level for NACL is reduced from “severe” to “moderate” or lower. These simulation results are more aligned with the requirements of sustainable development and are consistent with previous research findings (WANG, ZHENG, TANG et al., 2021; ZHOU, JOHNSON, SHI et al., 2025).

4.3 Suggestions

To effectively curb NACL, several measures are recommended. Firstly, a stricter land use approval system should be implemented to control, at the source, the encroachment of urban expansion onto high-quality cultivated land. Secondly, to address the issue of cultivated land abandonment caused by high fragmentation, advanced equipment such as small-scale agricultural machinery can be introduced to promote large-scale farming, thereby reducing cultivation costs and increasing yields. Concurrently, financial subsidy policies should be utilized to attract and retain agricultural technical talent, enhancing farmers’ motivation for cultivation and their overall profitability. Finally, given the significant spatial heterogeneity in hydrothermal conditions and cultivated land suitability caused by Guizhou Province’s complex terrain, the implementation of a differentiated, zonal management strategy is essential. for flat, contiguous cultivated land areas, the priority should be to develop large-scale modern agriculture and high-yield grain crops, reclaim converted cultivated land back to grain production, and construct supporting infrastructure such as reservoirs and roads. For gentle-slope cultivated land areas, the promotion of terracing is recommended to reduce soil and water loss, coupled with the moderate development of specialty cash crops. For steep-slope areas, which are of poor quality and unsuitable for cultivation, the policy should be to implement the “Grain-for-Green” program (reforestation and grassland restoration) or to develop under-forest economies.

5. Conclusions

Between 2000 and 2020, the spatial pattern of NACL in Guizhou Province evolved from scattered patches to large-scale, contiguous expansion. This process markedly accelerated during 2015-2020, with a converted area of 473,593.77 hm² and a rate of 9.65%. Spatial statistics confirmed a significant clustering effect in the NACL distribution. Analysis using the geodetector revealed that the spatial pattern of NACL is the result of combined effects from multiple factors, including natural environment, socioeconomic conditions, and agricultural location. Among these, population density, GDP, road network density, and cultivated land area were identified as the primary driving factors. Furthermore, multi-factor interactions, particularly between socioeconomic and agricultural factors, further enhanced the explanatory power for NACL. Multi-scenario simulations based on the PLUS model indicate that the early-warning pattern for NACL exhibits a distinct east-west disparity, with higher warning levels in the western counties than in the east. Areas with moderate or higher warnings are primarily concentrated in the west, while mild warnings are continuously distributed in the east. Under the NDS and UES, cultivated land loss is projected to intensify, leading to higher warning levels; moderate-or-higher warning areas will be concentrated in southwestern Guizhou Province. In contrast, the CCS effectively curbs cultivated land loss and significantly reduces the warning grades.

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