
Research article

Multi-Scenario prediction of land use change and soil conservation in Yunnan province based on the PLUS-InVEST model

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Abstract: Assessing soil erosion dynamics plays an important role in maintaining global soil resource security, ensuring stable food production, and achieving the Sustainable Development Goals. However, intensive human activities have continuously reshaped land use patterns, and considerable uncertainty remains regarding the responses of land use patterns and soil conservation services (SCS) under future development scenarios. As Yunnan Province serves as an essential ecological security barrier in Southwest China, investigating the dynamics of land use and soil conservation across scenarios and identifying their key driving factors is of great significance. In this study, the PLUS-InVEST model was coupled to evaluate the spatiotemporal distribution of land use and SCS in Yunnan Province from 2010 to 2020. Future climate data were incorporated to simulate changes in land use and SCS under three scenarios (natural development (ND), economic construction (EC), and ecological protection (EP)) by 2030, and the Geodetector model was used to identify the driving mechanisms. The results showed that: (1) From 2010 to 2020, land use change in Yunnan Province was mainly characterized by mutual conversions among cultivated land, forest land, and grass land, reflecting the combined effects of ecological land adjustment and human disturbance. By 2030, the expansion of cultivated land and building land was most pronounced under the EC scenario, whereas the EP scenario exhibited the greatest increase in forest land and grass land. (2) From 2010 to 2020, SCS in Yunnan Province showed a spatial pattern of higher values in the west and lower values in the east, with an overall increasing trend. Compared with 2020, SCS increased under all three scenarios by 2030, with the smallest increase under the EC scenario and the largest increase under the EP scenario. (3) Land use expansion was jointly affected by climate, population, and locational factors, while slope was the dominant factor influencing SCS in Yunnan Province. Factor interactions significantly enhanced

explanatory power, with the interaction between slope and annual precipitation being the most prominent. These findings indicated that SCS in Yunnan Province is controlled by a coupled mechanism involving terrain, climate, vegetation, and land use. This study provides scientific support for land use optimization, soil erosion prevention and control, and the coordination of ecological protection with socioeconomic development in ecologically critical regions.

Keywords: land use; soil conservation services (SCS); PLUS-InVEST model; Yunnan province

1. Introduction

Soil erosion is a dynamic process involving the detachment, transport, and deposition of surface materials driven by external forces such as hydraulic and aeolian power [1]. This phenomenon not only results in soil quality degradation, diminished agricultural productivity, and impaired ecosystem functions, but also exacerbates the risk of geohazards, establishing it as a critical global environmental challenge [2]. Accurate assessment and prediction of soil conservation dynamics are essential for maintaining global soil resource security, ensuring stable food production, and achieving the Sustainable Development Goals [3]. As a fundamental driver of soil erosion, land use change significantly modulates regional hydrological processes and sediment transport mechanisms by altering land cover types, surface morphology, and soil structure [4]. Therefore, elucidating the relationships and evolutionary patterns of land use change and soil conservation under diverse development scenarios is importance for optimizing land resource management strategies and refining soil erosion control systems.

As key tools for evaluating erosion processes, soil erosion models play a critical role in quantifying erosion intensity and analyzing its spatiotemporal patterns [5]. Empirical and physical models, which integrate parameters such as vegetation, soil, and meteorology, primarily focus on historical and current soil erosion assessments. However, their application in future scenario prediction remains limited [6,7]. Therefore, studies on soil erosion prediction generally follow two approaches: one integrates algorithms such as machine learning and cellular automata (CA) to perform direct prediction based on historical erosion data, but faces limitations in elucidating physical mechanisms [8], the other employs multi-model coupling to simulate future environmental changes and then applies these outputs as input parameters to drive erosion models for indirect prediction [9]. To predict soil erosion under different future scenarios, the coupling of the Revised Universal Soil Loss Equation (RUSLE) with land use simulation models such as CA-Markov, CLUE-S, and FLUS has been widely applied. However, these models have limitations in explaining complex transition relationships among historical land use types and simulating patch-scale spatial expansion, which may affect the reliability of land use input data for multi-scenario soil erosion prediction [10–12]. The Patch-generating Land Use Simulation (PLUS) model integrates the Land Expansion Analysis Strategy (LEAS) rule-mining framework and a cellular automata model based on multi-type random patch seeds (CARS). It not only accurately quantifies the expansion potential of different land use types and the relative contributions of their driving factors, but also achieves patch-scale simulation under different scenarios based on expansion dominance, thereby providing more reliable land-use input data for soil erosion prediction [13,14]. As a vital tool for ecosystem service assessment, the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model has been widely used to analyze the spatiotemporal distribution of ecosystem services. Specifically, its

Sediment Delivery Ratio (SDR) module, due to its unique modeling framework, has performed prominently in soil erosion risk assessment and related environmental impact studies [15]. In recent years, the coupled use of the PLUS and InVEST models has increased. However, most researchers have focused on the spatiotemporal evolution and prediction of ecosystem services such as carbon storage, habitat quality, and water yield, while less attention has been given to the multi-scenario response of soil conservation services (SCS) [16–18]. In addition, driving factor analyses have mostly focused on the effects of individual factors, whereas the interactive effects of driving factors on the spatial differentiation of SCS remain insufficiently explored [19,20]. Overall, studies have several limitations: (1) The mechanisms of historical land use transitions remain insufficiently explained; (2) future multi-scenario land use simulation under policy-related development pathways and its integration with SCS prediction remain underdeveloped; and (3) the interactive effects among the driving factors of SCS have not been fully clarified. Therefore, coupling the PLUS model with the InVEST SDR module can improve the understanding of historical land use transition mechanisms and enhance the simulation of land use patterns and SCS responses under different future development scenarios. Moreover, exploring the interactions among driving factors can further reveal the mechanisms underlying the spatial differentiation of SCS [21]. This study can provide scientific support for optimizing regional land use structure, preventing soil erosion, and balancing ecological protection with economic development, particularly in ecologically critical regions such as Yunnan Province.

Yunnan Province is on the southwestern frontier of China [16]. It is the source region of “six major river systems” and “four giant international rivers” (the Red River, the Lancang (Mekong) River, the Nujiang (Salween) River, and the Irrawaddy River), making it a cornerstone of ecological security and biodiversity conservation in Southwest China [22]. The province plays a crucial role in maintaining the three major ecological security barriers of the Western Plateau, the Yangtze River Basin, and the Pearl River Basin, and in safeguarding ecological security at regional, national, and even international scales [23]. However, with the rapid advancement of the Western Development Strategy, together with its steep terrain and ecological sensitivity, ecological issues in Yunnan Province, particularly soil erosion, have become increasingly prominent [22]. Concurrently, the uneven spatiotemporal distribution of precipitation exacerbates local soil erosion, while anthropogenic disturbances, such as inappropriate land use, further heighten the instability and vulnerability of ecosystem structures and functions [24]. These factors have weakened the soil conservation function, as vegetation degradation leads to a decline in soil retention capacity, making the spatiotemporal distribution of soil conservation more complex and significantly increasing uncertainty in its dynamics [25]. Given the complex terrain of Yunnan Province and the long-term and time-lagged effects of land use change, 2030 was selected as the target year for scenario prediction.

Overall, we took Yunnan Province as the study area and employed the PLUS and InVEST models as the main methods. Three development scenarios, namely natural development (ND), economic construction (EC), and ecological protection (EP), were established and combined with future climate data from the Coupled Model Intercomparison Project Phase 6 (CMIP6). Our objectives of this study were as follows: (1) To analyze the spatiotemporal characteristics of land use and SCS in Yunnan Province from 2010 to 2020; (2) to simulate land use and SCS under three development scenarios for 2030, and to analyze their spatiotemporal variation; and (3) to identify the dominant driving factors of land use change and SCS in Yunnan Province, and to explore the interactions among factors influencing SCS. The results of this study can provide a theoretical basis for assessing soil erosion

risks under different development scenarios in Yunnan Province and support land use allocation optimization, ecological protection, and balanced socioeconomic development.

2. Study area and methods

2.1. Study area

Yunnan Province ($21^{\circ} 08'32''\sim 29^{\circ} 15'08''\text{N}$, $97^{\circ} 31'39''\sim 106^{\circ}11'47''\text{E}$) is on the southwestern frontier of China, covering a total area of approximately 394000 km^2 (Figure 1a). The topography is characterized by higher elevations in the north and lower elevations in the south, exhibiting significant altitudinal relief (Figure 1b) [26]. The land use structure of the province is dominated by forest land and grass land (Figure 1c). The soil type is red soil, and the complex and diverse geological conditions result in significant spatial variations in soil depth (Figure 1d) [27]. The climate of Yunnan integrates subtropical and tropical monsoon characteristics, with a distinct seasonal distribution of precipitation. The wet season, lasting from May to October, accounts for 85% of the total annual precipitation (AP), whereas the dry season from November to April contributes only 15% [28]. AP varies substantially across the province, ranging from 560 mm to 2300 mm, while the mean annual temperature (MAT) ranges from 6.9 to 27.1°C [29]. The combination of complex topography and uneven precipitation distribution has resulted in severe soil erosion within the region.

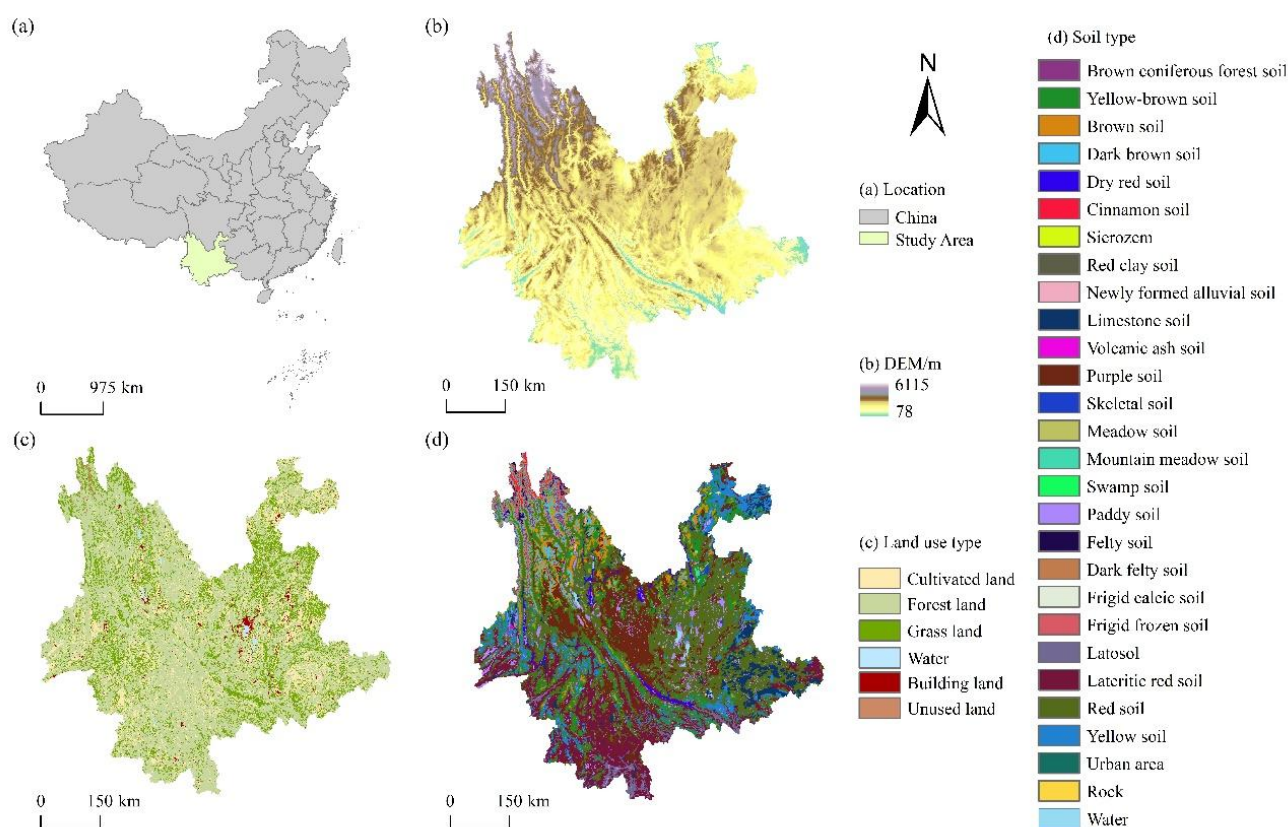


Figure 1. Location (a), elevation (b), land use in 2020 (c), and soil type (d) of the study area.

2.2. Data sources

In this study, we incorporated datasets encompassing land use, socioeconomic factors, and natural variables, with specific descriptions provided in Table 1. Specifically, land use data, soil types, GDP, population, MAT, and AP were acquired from the Resource and Environmental Science and Data Center (RESDC), Chinese Academy of Sciences. The land use dataset was referenced to the WGS_1984 coordinate system. According to the first-level classification standard described on the RESDC website, the land use data were classified into six categories: cultivated land, forest land, grass land, water, building land, and unused land. This dataset had relatively high accuracy, and these land use categories have been widely adopted in related studies [23,30]. Infrastructure data, such as railways and highways, were obtained from OpenStreetMap (OSM). Slope data were extracted from a Digital Elevation Model (DEM).

Table 1. Data list.

Data type	Data name	Resolution/m	Source
Land use data	Land use	30	RESDC (https://www.resdc.cn/)
Natural factors	DEM	90	Geospatial Data Cloud (https://www.gscloud.cn)
	Slope	90	Based on DEM extraction
	MAT	1000	RESDC (https://www.resdc.cn/)
	AP	1000	
	Soil type	1000	
	Distance to water	30	Open Street Map (https://www.openstreetmap.org/)
Socioeconomic factors	GDP	1000	RESDC (https://www.resdc.cn/)
	Population	1000	
	Distance to trunk road	30	Open Street Map (https://www.openstreetmap.org/)
	Distance to highway	30	
	Distance to primary road	30	
	Distance to secondary road	30	
	Distance to tertiary road	30	
	Distance to railway	30	
	Distance to county center	30	

2.3. Methods

2.3.1. PLUS model

The PLUS model was employed to simulate and predict land-use changes in Yunnan Province. Initially, 15 influencing factors, including AP, MAT, DEM, slope, GDP, population, and distances to roads, county centers, and water, were projected to a unified coordinate system. Subsequently, the Land Expansion Analysis Strategy (LEAS) was applied to extract transition rules and determine the development probabilities for six land use categories. Finally, a Markov model was utilized to forecast future land use demand, yielding the target pixel counts for each type. Combined with the land use

transition matrix, a transition cost matrix was established, and parameters for neighborhood weights and random patch seed probability were configured. Neighborhood weights represent the expansion intensity of each land use type relative to other types (Table 2) [31,32]. The random patch seed probability, which reflects the difficulty of generating new patches for various land use categories, was set to 0.01 [31]. Accuracy assessment was performed by simulating the 2020 land use pattern based on 2000–2010 data and comparing it with the actual 2020 land use. A Kappa coefficient of 0.69 was achieved, indicating high simulation accuracy and consistency.

Table 2. Neighborhood weights of various land use type in three scenarios.

Scenario Type	A	B	C	D	E	F
ND scenario	0.12	0.12	0.32	0.1	0.28	0.06
EC scenario	0.24	0.12	0.12	0.1	0.85	0.1
EP scenario	0.12	0.24	0.32	0.1	0.05	0.1

Note: A: Cultivated land, B: Forest land, C: Grass land, D: Water, E: Building land, F: Unused land.

Human activities drive changes in the quantity and spatial distribution of land use, reflecting trade-offs between ecological conservation and economic development. Therefore, based on research and relevant policies such as the Territorial Spatial Planning of Yunnan Province (2021–2035) and the Territorial Spatial Ecological Restoration Planning of Yunnan Province (2021–2035), we established three development scenarios: the ND, EC, and EP scenarios [32,33]. The transition cost matrix is presented in Table 3. Under the ND scenario, no conversion constraints were applied except for the restriction on converting building land to other types. The EC scenario restricted the conversion of cultivated land and building land to other categories, while increasing the transition probabilities from forest land, grass land, and unused land to building land by 20%, and from forest and grass land to cultivated land by 20%. In the EP scenario, the conversion probabilities from forest land and grass land to building land and unused land were reduced by 20%, whereas the transition probability from unused land to forest and grass land was increased by 20% [34].

Table 3. Land use type transition matrix under three scenarios.

	ND scenario						EC scenario						EP scenario					
	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	0	0	0	0	0	1	1	1	1	1	1
B	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	0	0	0
C	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0	0	0
D	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1
E	0	0	0	0	1	0	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: 1 indicates that the land use type can be transformed, while 0 indicates that the land use type cannot be transformed.

2.3.2. InVEST model

The calculation of soil conservation was implemented using the Sediment Delivery Ratio (SDR) module of the InVEST model. This module simulates hillslope erosion and catchment sediment transport processes based on the RUSLE [35]. The formula is as follows:

$$RUSLE = R \times K \times LS \times C \times P \quad (1)$$

where RUSLE represents the soil erosion modulus, $t/(hm^2 \cdot a)$; R is the rainfall erosivity factor, $(MJ \cdot mm)/(hm^2 \cdot h \cdot a)$; K is the soil erodibility factor, $(t \cdot hm^2 \cdot h)/(M \cdot mm \cdot hm^2)$; LS denotes the topographic factor; C is the vegetation management factor; and P is the support practice factor.

2.3.3. CMIP6

CMIP6 is an international initiative driven by the World Climate Research Program, aimed at enhancing global climate system understanding and prediction capabilities [36]. Within the CMIP6 multi-model ensemble framework, precipitation data under the SSP245 (moderate-emission) scenario were adopted and integrated with three land use scenarios, including ND, EP, and EC. By synthesizing future land use patterns across scenarios, the spatiotemporal responses of SCS were systematically evaluated.

2.3.4. Driving factor analysis

The Optimal Parameters-based Geographical Detector was employed to analyze 15 individual factors and their interactions to identify the primary driving forces behind the spatial evolution of SCS. Specifically, factor detection was used to measure the impact of individual driving factors on SCS, while interaction detection evaluated whether the combined effects of two factors significantly influenced SCS and identified the strength of factor interactions [37]. The results for both are expressed by the q value, calculated as follows:

$$q = 1 - \frac{1}{N\delta^2} \times \sum_{h=1}^L N_h \delta_h^2 = 1 - \frac{SSW}{SST} \quad (2)$$

$$SSW = \sum_{h=1}^L N_h \delta_h^2 \quad (3)$$

$$SST = N\delta^2 \quad (4)$$

where q represents the explanatory power of a factor; h represents the factor's stratification; N_h and N are the number of units in stratum h and the entire region, respectively; δ_h^2 and δ^2 are the variances of Y values for stratum h and the entire region; and SSW and SST denote the sum of within-strata variances and the total sum of squares, respectively. The value of q ranges from 0 to 1, where a larger q indicates stronger explanatory power.

2.3.5. Software and technical implementation

Data preprocessing and spatial analysis were mainly conducted using ArcGIS 10.8. All spatial data were projected as WGS_1984_UTM_46N, and resampled to a spatial resolution $1\text{ km} \times 1\text{ km}$ to ensure spatial consistency among datasets. The PLUS model was used to analyze the drivers of land use change and to simulate land use patterns under different development scenarios. The InVEST SDR module was employed to assess SCS for historical and future periods. For future assessments, CMIP6 climate data were integrated with land use simulation results under different development scenarios. The Geodetector model was implemented in Python to identify the driving factors of SCS and to analyze interactions among these factors. ArcGIS and Origin were used for map visualization and figure preparation. The spatial resolution of the final output maps for land use simulation and SCS was $1\text{ km} \times 1\text{ km}$.

3. Results

3.1. Spatiotemporal changes in land use in Yunnan Province from 2010 to 2030

3.1.1. Spatiotemporal evolution characteristics of land use from 2010 to 2020

The analysis of the overall land use composition revealed that forest land was the dominant land use type in Yunnan Province during 2010–2020, accounting for more than 50% of the total area. This was followed by grass land and cultivated land, while water, building land, and unused land occupied relatively small proportions (Figure 2). Between 2010 and 2020, cultivated land, grass land, and unused land in Yunnan Province exhibited a decrease by 939, 2705, and 575 km^2 , respectively. Conversely, forest land, water, and building land showed an increasing trend, with increments of 954, 814, and 2451 km^2 , respectively. Regarding spatial distribution, cultivated land was predominantly concentrated around building land. Significant land use changes were observed in eastern Yunnan, whereas the southwestern region remained relatively stable.

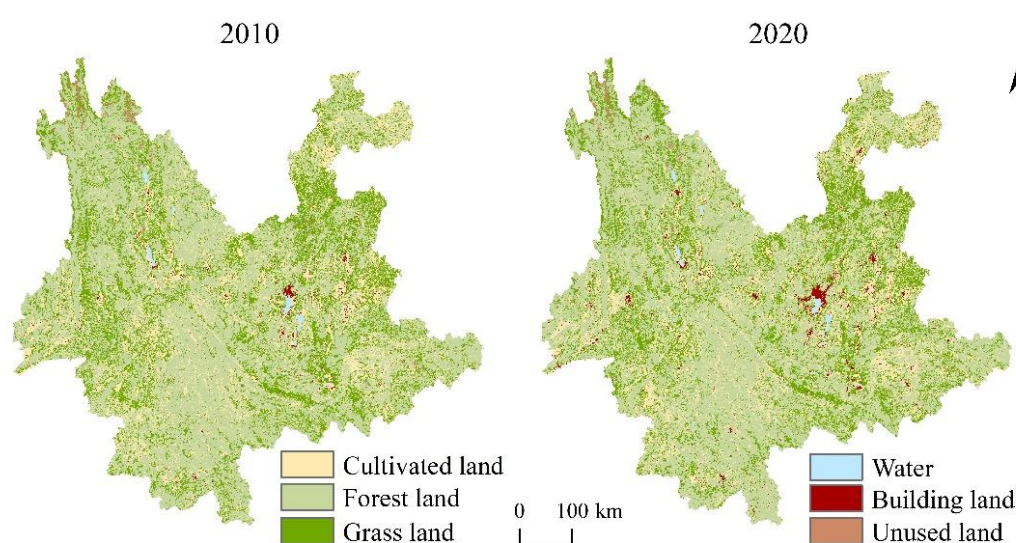


Figure 2. Land use in Yunnan Province from 2010 to 2020.

From the perspective of land transfer characteristics, the land use change in Yunnan Province from 2010 to 2020 was primarily characterized by mutual conversions among forest land, grass land, and cultivated land (Figure 3). The land types transferred in were mostly cultivated land, forest land, and grass land, with transfer-in areas of 45442, 36086, and 31289 km², accounting for 38.13%, 30.28%, and 26.26% of the total transfer-in area, respectively. Specifically, the increase in cultivated land, grass land, and water in Yunnan Province in 2020 primarily originated from forest land; the increase in forest land and unused land mainly came from grass land; and the increase in building land was primarily derived from cultivated land. This indicated that ecological land and agricultural land were the most active components in land use transitions in Yunnan Province, and that urban expansion exerted pressure on agricultural land. Overall, this transition pattern reflected the combined impacts of ecological land conversion and human development activities.

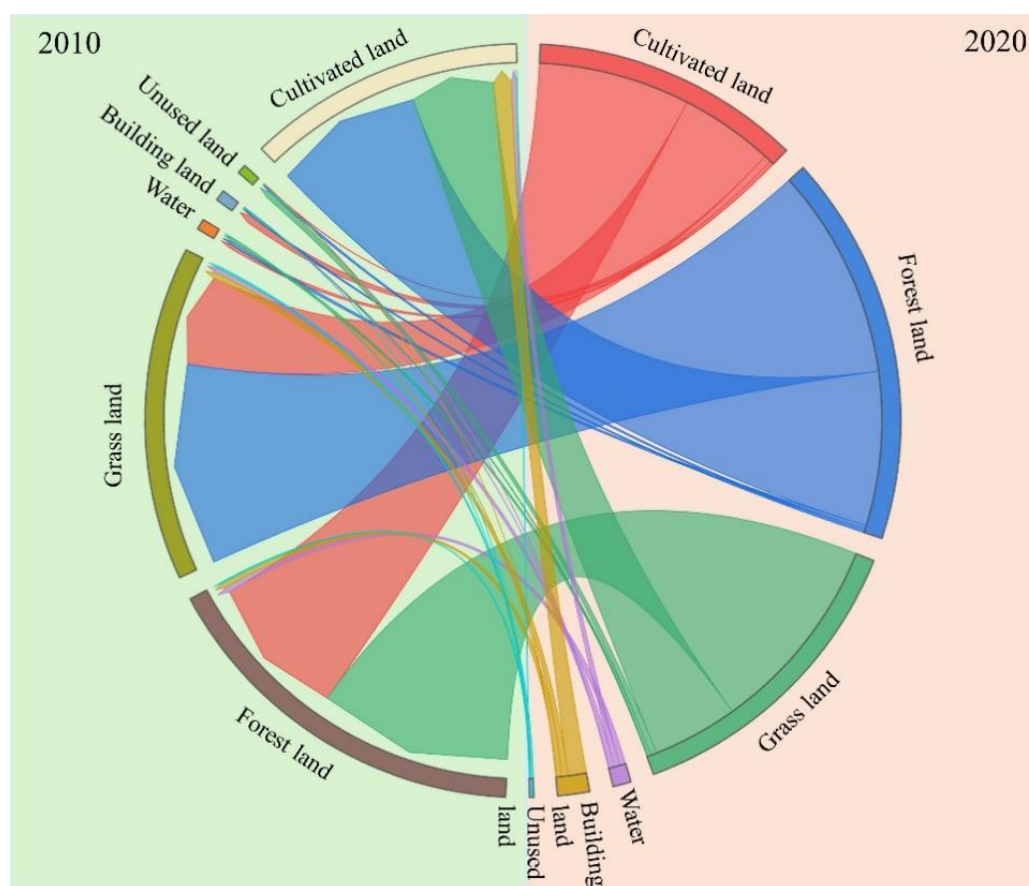


Figure 3. Land use transition on Yunnan Province from 2010 to 2020. Note: This chart shows only the transitions between land use types. When the land use type remained the same in 2010 and 2020, it is not displayed.

3.1.2. Spatiotemporal changes in land use in Yunnan Province under multiple scenarios

By 2030, the land use patterns in Yunnan Province were projected to exhibit significant scenario-based differentiation, with pronounced variations in area changes across the three simulated scenarios (Figure 4). Compared with 2020, under the ND scenario, building land, water, and cultivated land increased by 564, 470, and 222 km², respectively; conversely, forest land, grass land, and unused land

decreased by 225, 753, and 278 km². Under the EC scenario, cultivated land, water, and building land increased by 6154, 437, and 1071 km², while forest land, grass land, and unused land decreased by 4376, 2996, and 290 km². In the EP scenario, cultivated land and unused land decreased by 3556 and 500 km², respectively, whereas forest land, grass land, water, and building land increased by 8, 3112, 468, and 468 km², respectively. Under the EP scenario, cultivated land exhibited a decreasing trend while it showed an increasing trend under the other two scenarios, with the largest increase occurring in the EC scenario. Forest land and grass land showed an increasing trend under the EP scenario but decreased under the other two scenarios. Water and building land increased across all three scenarios, with building land experiencing the most significant growth under the EC scenario. In contrast, unused land showed a decreasing trend in all three scenarios. A cross-comparison of the three scenarios revealed that the ND scenario followed historical trends; the EC scenario prioritized economic development at the expense of ecological protection; and the EP scenario promoted ecological restoration but resulted in the loss of cultivated land.

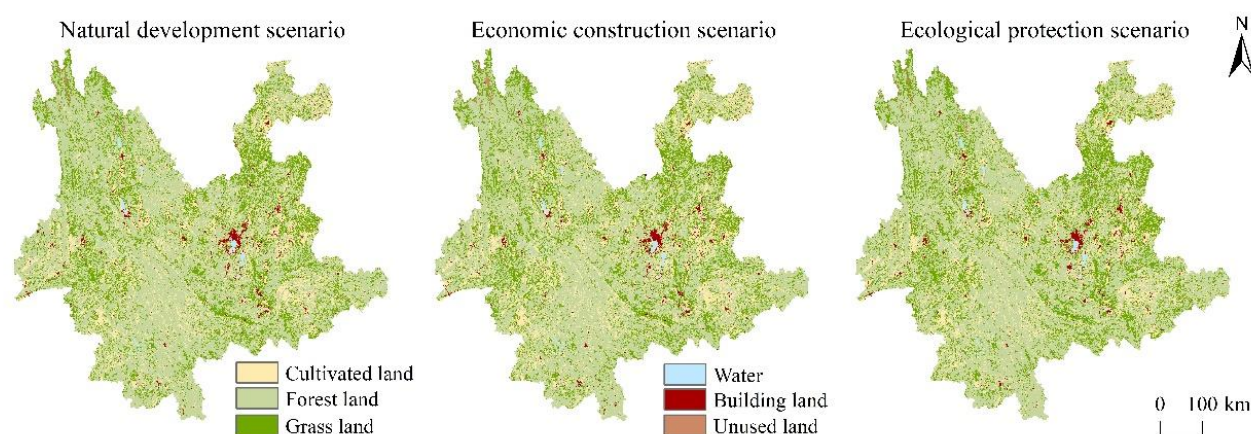


Figure 4. Land use in three scenarios for Yunnan Province in 2030.

3.2. Spatiotemporal changes in SCS in Yunnan Province from 2010 to 2030

3.2.1. Spatiotemporal evolution of SCS from 2010 to 2020

From 2010 to 2020, SCS in Yunnan Province exhibited a spatial distribution characterized by higher values in the west and lower values in the east (Figure 5). Temporally, the average soil conservation showed an increasing trend, rising from 4804.31 t/km² in 2010 to 4903.63 t/km² in 2020. Regarding soil conservation by land use type, forest land maintained the highest soil conservation capacity from 2010 to 2020, with its total soil conservation increasing from 1177.84×10^6 t to 1199.12×10^6 t. This was followed by grass land, where soil conservation decreased from 428.78×10^6 t to 423.82×10^6 t, and then by cultivated land, which saw an increase from 213.1×10^6 t to 227.5×10^6 t. Building land and unused land each accounted for less than 1% of the total soil conservation, with the soil conservation of building land increasing from 3.14×10^6 t to 7.56×10^6 t.

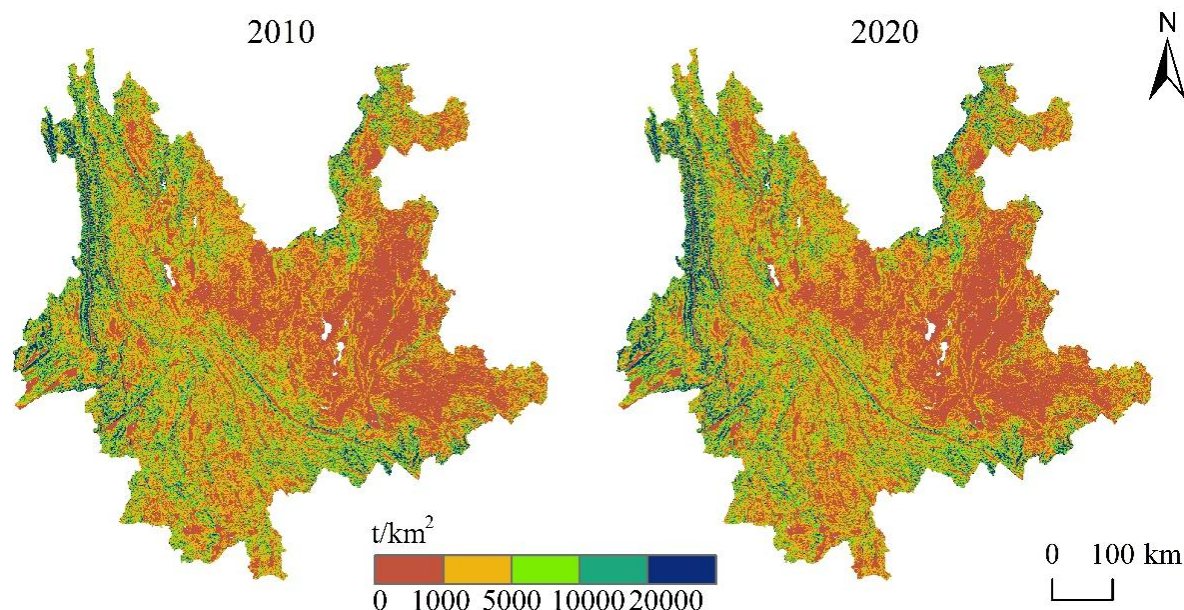


Figure 5. SCS in Yunnan Province from 2010 to 2020.

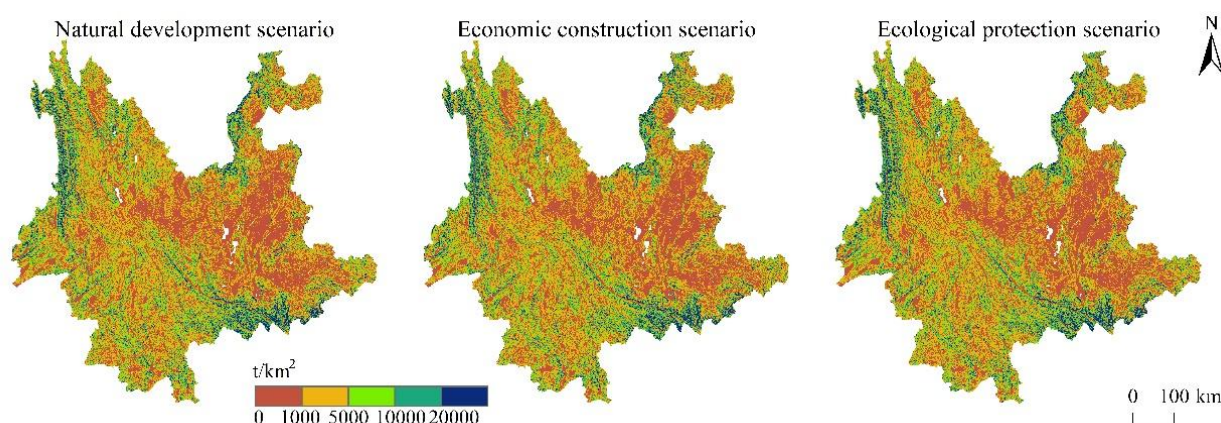


Figure 6. SCS in the three scenarios of Yunnan Province in 2030.

3.2.2. Spatiotemporal prediction of SCS under multiple scenarios

In 2030, SCS in Yunnan Province under the three scenarios exhibited a spatial pattern of higher values in the west and lower values in the east (Figure 6). Compared with 2020, the average soil conservation under all three scenarios showed an increasing trend. Specifically, the average soil conservation increased by 395.26 t/km² to 5,298.89 t/km² under the ND scenario, by 381.44 t/km² to 5285.07 t/km² under the EC scenario, and by 402.91 t/km² to 5306.54 t/km² under the EP scenario, with the highest increase occurring under the EP scenario. Regarding soil conservation across land use types, the soil conservation of cultivated land exhibited a decreasing trend under the EP scenario, while it demonstrated an increasing trend under the other two scenarios. Soil conservation for forest land, grass land, and building land increased across all three scenarios. Among them, the soil conservation of forest land and grass land was highest under the EP scenario, at 1286.04×10⁶ t and 489.03×10⁶ t,

respectively, and lowest under the EC scenario, at 1266.52×10^6 t and 462.49×10^6 t, respectively. Soil conservation for building land was highest under the EC scenario (12.09×10^6 t) and lowest under the EP scenario (9.29×10^6 t). A cross-comparison of the three scenarios indicated that the EP scenario effectively prevents soil erosion, whereas the EC scenario leads to a relative worsening of soil erosion.

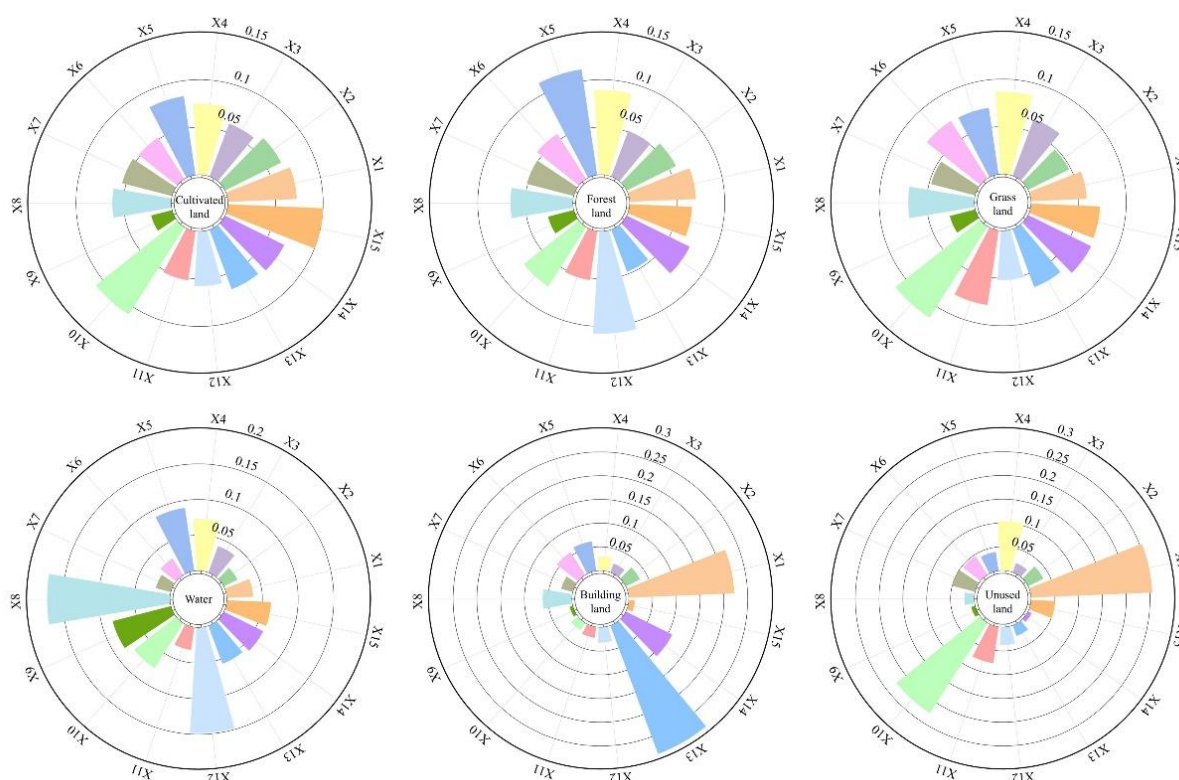


Figure 7. Contribution degree of driving factors for land use expansion. X1: DEM; X2: distance to secondary road; X3: distance to highway; X4: GDP; X5: population; X6: AP; X7: distance to tertiary road; X8: slope; X9: Soil type; X10: MAT; X11: distance to railway; X12: distance to water; X13: distance to county center; X14: distance to primary road; X15: distance to trunk road

3.3. Analysis of driving factors for land use and SCS

3.3.1. Analysis of driving factors for land use change

The analysis error of the PLUS model for the driving forces of land types in Yunnan Province from 2010 to 2020 was below 0.2, indicating high simulation accuracy. Between 2010 and 2020, grass land and building land experienced the most significant changes in Yunnan Province. The driving factors with the highest contributions to these changes were MAT (X10) and distance to county center (X13), respectively (Figure 7). Specifically, the factors affecting grass land were ranked as MAT (X10), GDP (X4), and distance to railway (X11). The driving factors for building land were distance to county center (X13), DEM (X1), and distance to primary road (X14). The driving factors for grass land and building land indicated that the evolution of land use patterns was

jointly shaped by natural constraints and human interference. The driving factors with the highest contributions to cultivated land, forest land, water, and unused land were MAT (X10), population (X5), slope (X8), and DEM (X1), respectively.

3.3.2. Analysis of driving factors for SCS

Since slope was extracted from the DEM, only the slope factor was incorporated into the driving factor analysis to avoid collinearity. Topographic factors, specifically slope (X8), emerged as the dominant driver for SCS in Yunnan Province, followed by the distance to primary road (X14) (Figure 8). The interactions among the 15 factors influencing SCS consistently exhibited bi-factor enhancement relationships. Notably, interactions involving slope consistently displayed the highest explanatory power, with q value ranging from 0.29 to 0.39 (Figure 8). Among these, the interaction between slope (X8) and AP (X6) exerted the most significant explanatory power on SCS, followed by the interactions of slope (X8) with soil type (X9) and slope (X8) with distance to primary road (X14), respectively. While interactions between socioeconomic factors (such as GDP (X4) and population (X5)) and other environmental variables were relatively weak, their explanatory power increased substantially when interacting with the slope. These results indicated that the superposition of key driving factors significantly enhances the explanatory power for the spatial distribution patterns of SCS.

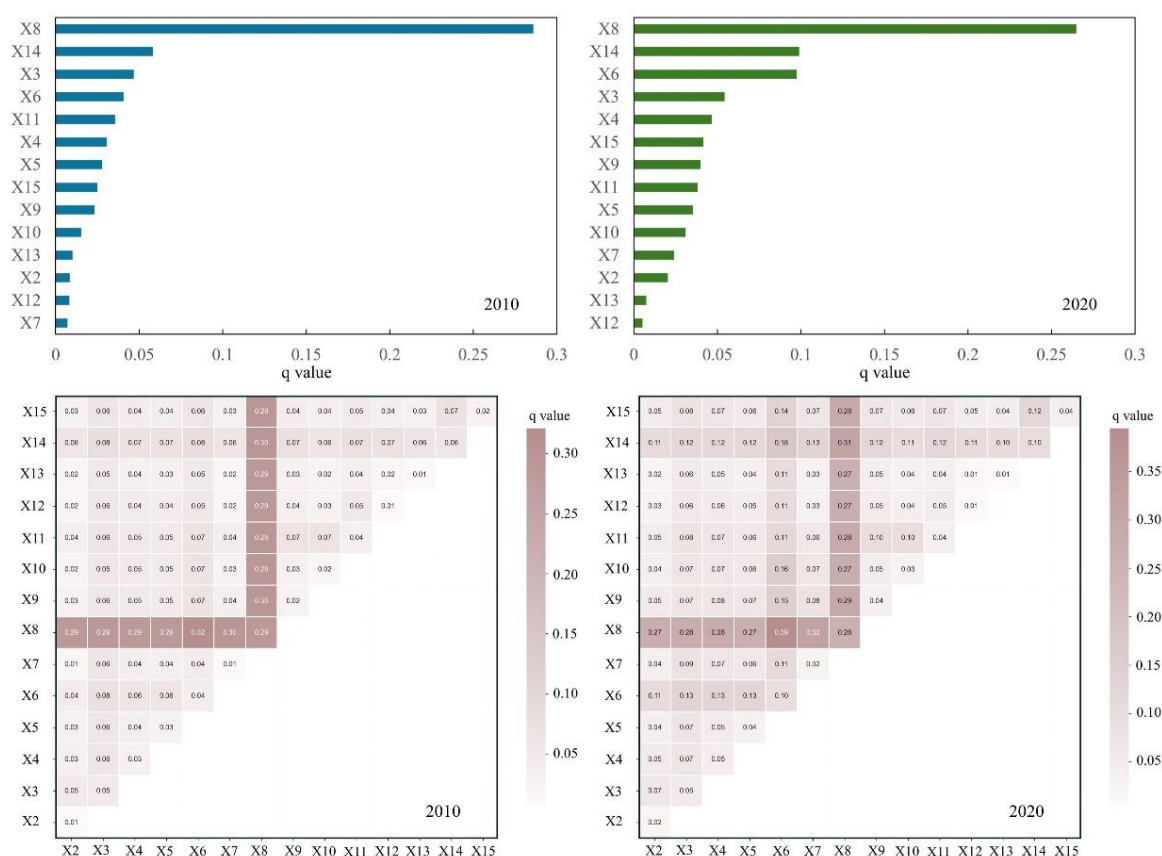


Figure 8. Analysis of factors affecting SCS in 2010 and 2020.

4. Discussion

4.1. Response of SCS to land use change

Land use directly modulates ecosystem soil conservation processes by altering surface conditions and the ecological environment [38]. Furthermore, SCS as a critical indicator of ecosystem function, reflects the structure and status of regional land use to a certain extent [39]. Between 2010 and 2020, the implementation of policies such as the New-type Urbanization Plan of Yunnan Province (2014–2020) and the Industrial Transformation and Upgrading Plan of Yunnan Province (2016–2020) accelerated urbanization and industrialization in the province. The rapid increase in demand for building land led to the substantial occupation of cultivated land, forest land, and grass land, thereby altering the original ecosystem structure and function. Reduced vegetation cover consequently weakened soil and water conservation functions [40]. Studies have demonstrated that vegetation effectively mitigates soil erosion through multi-layered mechanisms, including canopy interception of precipitation, soil reinforcement by root networks, and surface protection by the litter layer [41]. In cultivated areas, farming activities reduce vegetation cover; furthermore, frequent tillage disturbances disrupt soil structural stability and increase the formation of surface runoff, thus exacerbating erosion processes [42]. Conversely, forest land and grass land mitigate soil erosion due to the soil-binding effects of plant root systems.

Scenario-based projections for 2030 indicated that soil conservation capacity reaches its minimum under the EC scenario and peaks under the EP scenario. In the EC scenario, excessive expansion of cultivated land and building land resulted in the loss of forest land and grass land, reducing the total soil conservation. Although the significant expansion of forest land and grass land under the EP scenario effectively enhances soil conservation, the current context of rapid economic development highlights the potential conflict between ecological land preservation and urbanization demands. This suggests that economic policies should be implemented in synergy with ecological protection regulations, transcending single-objective policy constraints to build a collaborative governance system that balances development and conservation. Systematic regulation is essential for achieving an overall equilibrium between economic growth and ecological stability [43]. Furthermore, analysis of the influencing factors of SCS indicated that the combined effects of steep slopes and precipitation exacerbates erosion risks [44]. This is consistent with the findings of Li et al., who indicated that the primary driving factors of SCS were vegetation cover, precipitation, and topographic factors, and that multi-factor interactions further enhanced the spatial heterogeneity of soil erosion [19]. These findings suggest that the complex mountainous terrain and concentrated precipitation in Yunnan Province may jointly amplify the nonlinearity of soil erosion processes. Specifically, in mountainous regions, small changes in slope gradient (LS), rainfall intensity (R), or vegetation cover may lead to disproportionate changes in surface runoff, flow velocity, soil detachment, and sediment transport capacity. Therefore, soil erosion does not respond linearly to topographic, precipitation, or land-use changes; instead, erosion risk may increase rapidly once certain topographic-hydrological thresholds are exceeded. Particularly in areas with low vegetation cover, the superposition of steep slopes and intense rainfall may substantially weaken soil conservation capacity and generate localized erosion-risk hotspots. This is also consistent with the findings of Yu et al., who showed that in alpine regions, SCS may decline sharply when vegetation cover decreases below a certain threshold [3]. In Yunnan Province, the superposition of steep slopes, concentrated seasonal precipitation, and inappropriate land

use conversion may further increase local soil erosion risks. Therefore, future land use planning in Yunnan Province should not rely solely on regional average soil erosion levels, but should focus on sensitive areas where steep slope, strong rainfall erosivity, and low vegetation cover overlap. Inappropriate cultivation and construction on steep slopes should be restricted, and ecological restoration and soil and water conservation measures should be prioritized in areas where steep slope, intense precipitation, and low vegetation cover overlap [45].

4.2. Applicability and limitations

In this study, we constructed a soil conservation prediction framework based on the integration of the PLUS and InVEST SDR models. By coupling dynamic land use simulation with conservation process assessment, this approach enables systematic modeling of regional soil conservation evolution. The PLUS model, incorporating a random forest-based LEAS, accurately identifies driving factors and their relative contribution rates, effectively capturing spatiotemporal patterns of land use change and significantly enhancing simulation accuracy [46]. These improvements provide robust data support for soil conservation forecasting, demonstrating good adaptability, particularly when addressing complex land use conversions in mountainous terrains [47]. By establishing three representative scenarios (ND, EC, and EP), we systematically examined soil conservation response mechanisms across development pathways, effectively reflecting the synergistic impacts of policy interventions, economic growth, and environmental management. The results demonstrated that rational land use planning, especially under the EP scenario, can significantly mitigate regional soil erosion risks by optimizing vegetation cover and landscape configurations [23].

Despite the scientific grounding of these findings, several limitations remain. The lack of higher temporal resolutions in land use data, such as data at 5-year intervals, may obscure short-term fluctuations or intermediate nonlinear shifts in regional development trajectories. In future studies, researchers should incorporate multi-period, higher-frequency historical data to further refine temporal transition mechanisms and enhance the precision of long-term ecological simulations. The spatial resolution of fundamental datasets, such as precipitation and socioeconomic indicators, may constrain model precision; furthermore, latent factors such as micro-topographic variations, sub-regional economic disparities, and geohazards were not fully integrated into the erosion simulations. Additionally, the selection of limited climate models from CMIP6 introduces unavoidable uncertainties into rainfall erosivity projections. Researchers could enhance predictive capabilities in complex environments by adopting higher-resolution remote sensing data, optimizing spatial interpolation methods, incorporating multi-model ensemble comparisons, and refining driving mechanisms that synthesize natural and socioeconomic variables. Such advancements will provide more reliable scientific support for optimizing regional soil conservation measures and making sustainable development decisions.

5. Conclusions

We coupled the PLUS model with the InVEST SDR module to analyze the spatiotemporal evolution of land use change and SCS in Yunnan Province from 2010 to 2020, and to predict their responses under different development scenarios for 2030. The dominant driving factors and their interactions were also identified. The main conclusions are as follows:

- (1) Land use change in Yunnan Province was mainly characterized by mutual conversions among

cultivated land, forest land, and grass land, reflecting the combined influence of natural terrain constraints and human activities. Forest land and grass land, as major ecological land types, played a fundamental role in maintaining regional SCS. In contrast, changes in cultivated land and building land affected soil erosion risk by altering vegetation cover, surface disturbance, and runoff processes. Therefore, land use structure acted as an important mediator linking human development activities with soil erosion processes in mountainous regions.

(2) SCS in Yunnan Province showed clear spatial differentiation, and this spatial pattern was not controlled by a single factor. Instead, it resulted from the combined effects of terrain, precipitation, vegetation cover, and land use structure. As such, complex mountainous terrain affects slope runoff velocity and sediment transport capacity, thereby enhancing the spatial heterogeneity of soil erosion processes. Concentrated precipitation further strengthens erosion dynamics, whereas forest and grassland vegetation improve soil conservation capacity through rainfall interception, root reinforcement, and runoff reduction. These findings indicated that SCS in Yunnan Province is regulated by a coupled terrain-climate-vegetation-land use mechanism.

(3) The three development scenarios reflected different land use transition pathways and ecological effects. The EC scenario was mainly characterized by the expansion of cultivated land and building land, which may intensify surface disturbance, reduce local vegetation cover, and increase local soil erosion risk. The EP scenario maintained and restored ecological land, especially forest land and grass land, thereby improving vegetation cover, slope stability, and soil conservation capacity. The ND scenario generally followed historical development trends, with relatively moderate changes in land use structure and SCS. These results suggested that future soil conservation outcomes depend not only on the magnitude of land use change, but also on the direction, spatial location, and ecological function of land conversion.

(4) The driving factor analysis showed that slope was the key factor affecting the spatial differentiation of SCS in Yunnan Province, and its interaction with precipitation further enhanced the explanatory power. This indicated that terrain-climate coupling is an important mechanism shaping soil erosion and soil conservation patterns in Yunnan Province. In areas where steep slopes, strong rainfall erosivity, and low vegetation cover overlap, soil erosion risk may be nonlinearly amplified. Therefore, future land use planning should focus on these erosion-sensitive areas, restrict inappropriate cultivation and construction on steep slopes, and prioritize ecological restoration and soil and water conservation measures to support land use optimization, soil erosion prevention, and the coordination of ecological protection with economic development.

Author contributions

Yuqing Zhang: ormal analysis, investigation, writing-original draft; Genyu Xu: Conceptualization, methodology, software, resources, supervision, writing-review & editing.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

The authors declare no conflict of interest.

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