

Article

Predicting Soil Erosion Using RUSLE and GeoSOS-FLUS Models: A Case Study in Kunming, China

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Abstract: Revealing the relationship between land use changes and soil erosion provides a reference for formulating future land use strategies. This study simulated historical and future soil erosion changes based on the RUSLE and GeoSOS-FLUS models and used a random forest model to explain the relative importance of natural and anthropogenic factors on soil erosion. The main conclusions are as follows: (1) From 1990 to 2020, significant changes in land use occurred in Kunming, with a continuous reduction in woodland, grassland, and cropland, being converted into construction land, which grew by 195.18% compared with 1990. (2) During this period, the soil erosion modulus decreased from 133.85 t/(km²·a) in 1990 to 130.32 t/(km²·a) in 2020, with a reduction in soil loss by 74,485.46 t/a, mainly due to the conversion of cropland to construction and ecological lands (woodland, grassland). (3) The expansion of construction land will continue, and it is expected that by 2050, the soil erosion modulus will decrease by 3.77 t/(km²·a), 4.27 t/(km²·a), and 3.27 t/(km²·a) under natural development, rapid development, and ecological protection scenarios, respectively. However, under the cropland protection scenario, the soil erosion modulus increased by 0.26 t/(km²·a) compared with 2020. (4) The spatial pattern of soil erosion is influenced by both natural and anthropogenic factors, and as human activities intensify in the future, the influence of anthropogenic factors will further increase. Traditionally, the expansion of construction land is thought to increase soil loss. Our study may offer a new perspective and provide a reference for future land use planning and soil loss management in Kunming.

Keywords: soil erosion; urbanization; cropland; land use strategy



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1. Introduction

Soil erosion occurs extensively around the world, causing significant damage to human production and life [1]. Globally, soil erosion damages 50,000 km² of land annually, with the continental United States alone suffering direct economic losses of USD 6 billion each year due to soil erosion [2–4]. The essential process of soil erosion involves the destruction and detachment of soil by external forces, with types including wind erosion, water erosion, gravitational erosion, and compound erosion, among which water erosion is particularly widespread and destructive [5–7]. Under the backdrop of intensified human activities and climate change, soil erosion has undergone noticeable changes. Whether these changes are beneficial or detrimental remains unclear, making in-depth study of their impact on soil erosion of great practical significance.

Currently, domestic and international research on soil erosion primarily focuses on the mechanisms of the erosion process and the construction of prediction models, which include empirical, semi-empirical, and physically based models [8–10]. In the late 1950s, the Universal Soil Loss Equation (USLE) was first introduced, incorporating six major factors of soil erosion, and the Revised USLE (RUSLE) was later developed based on subsequent research [11,12]. The USLE/RUSLE model, as an empirical model for predicting soil erosion, has received significant attention due to its simple structure and ease of use [13–15].

Many domestic scholars have conducted in-depth studies on soil erosion based on the USLE/RUSLE model, achieving numerous research results at various scales, including plot, watershed, and administrative levels [16–18]. The occurrence of soil erosion is the result of multiple factors interacting, and extensive experimental and observational research has shown that rainfall and land use are the two main influencing factors [19–21]. Building upon the USLE/RUSLE model, studies have been conducted using scenarios, SWAT (Soil and Water Assessment Tool), MMF (Morgan, Morgan, and Finney), and mathematical statistics (such as double cumulative curves, linear regression, and elasticity coefficients) to explore the extent of rainfall and land use impacts on soil erosion, yielding various conclusions [22–24]. This variation may be due to the scale effects apparent when the model is used across different temporal and spatial scales, as well as uncertainties introduced by model parameters. Land use refers to the way humans exploit the natural properties of the land. Land use changes can alter the physical and biological characteristics of the surface, such as the conversion of cropland to grassland and woodland, reduced human activity, and increased vegetation cover, all of which directly affect soil erosion [25,26].

Kunming, as the capital of Yunnan Province, is also a free trade zone. Due to the impacts of economic and population growth, human activities have intensified, placing significant pressure on the regional ecological environment and causing marked changes in land use [27]. Currently, some scholars have made achievements in research on soil erosion in Kunming. For example, Chen et al. [28] illustrated that soil erosion of cropland in Kunming is much higher than that of other land use types, and they further verified the effect of soil and water conservation measures on the reduction in flow and sand on sloping cropland. Gu et al. [29] analyzed the spatial pattern of rainfall erosivity and seasonal differences in soil erosion in Kunming. Rao et al. [30] evaluated the effects of rainfall and vegetation cover changes on soil erosion through sensitivity analysis and predicted the risk of soil erosion in the different periods of the future based on the random forest model. Yu et al. [31] considered the effects of various drought scenarios on soil erosion management and regional ecological security. Some research on soil erosion in Kunming has focused primarily on the impact of climate change on soil erosion, with few studies considering the impact of land use changes independently of climate change. Additionally, research on soil erosion changes should not be limited to the past; studying soil erosion under future land use changes has more practical significance. The CA-Markov model is widely used in future simulations of land use, but it is limited in handling complex competition and interactions between different types of land use [32,33]. To overcome these deficiencies, the GeoSOS-FLUS model has been improved based on the CA-Markov model by incorporating artificial neural network algorithms, enhancing adaptive inertia and competition mechanisms, and significantly improving simulation accuracy and adaptability [34–36]. The RUSLE model is specifically used for assessing soil erosion, while the GeoSOS-FLUS model focuses on simulating future changes in land use. Although both are widely used in their respective fields, there are few studies attempting to combine them to predict soil erosion under different future land use change scenarios. By integrating these two models, research can more comprehensively consider the direct impact of land use changes on soil erosion, thereby providing a dynamic and comprehensive environmental assessment framework.

This study aims to propose a rapid and efficient method to predict future trends in soil erosion under various land use management strategies, offering guidance for the formulation of future land management policies and soil and water conservation governance. Given the current research applications of the GeoSOS-FLUS and RUSLE models, there is uncertainty in the future spatial patterns of land use. Based on remote sensing imagery, this research decoded the spatial distribution of land use in Kunming from 1990 to 2020 and calculated the soil erosion modulus for this period by integrating topographic, rainfall, and soil data. Utilizing the GeoSOS-FLUS model, predictions for land use distribution from 2030 to 2050 were made, forming the basis for deriving future vegetation cover measures and cultivation practice factors. These were used to comprehensively explore future soil erosion conditions under scenarios of land use changes, reflecting the extent and process

by which land use changes impact soil erosion and providing a scientific basis for the formulation of land use strategies.

2. Overview of the Study Area

Kunming is the capital of Yunnan Province, covering an area of 21,000 km². The average elevation of Kunming is 1870 m, with mountainous terrain predominating, accounting for 84% of the study area, while plateaus and hills comprise the remaining 16% (Figure 1). The urban area is built around Dian Lake, making it a typical plateau lake city. With the advancement of urbanization and tourism development, construction land has rapidly expanded, heavily encroaching on productive and ecological lands, intensifying competition for land resources. Particularly around Dian Lake, the landscape is fragmented, and the spatial distribution of land use types is severely imbalanced.

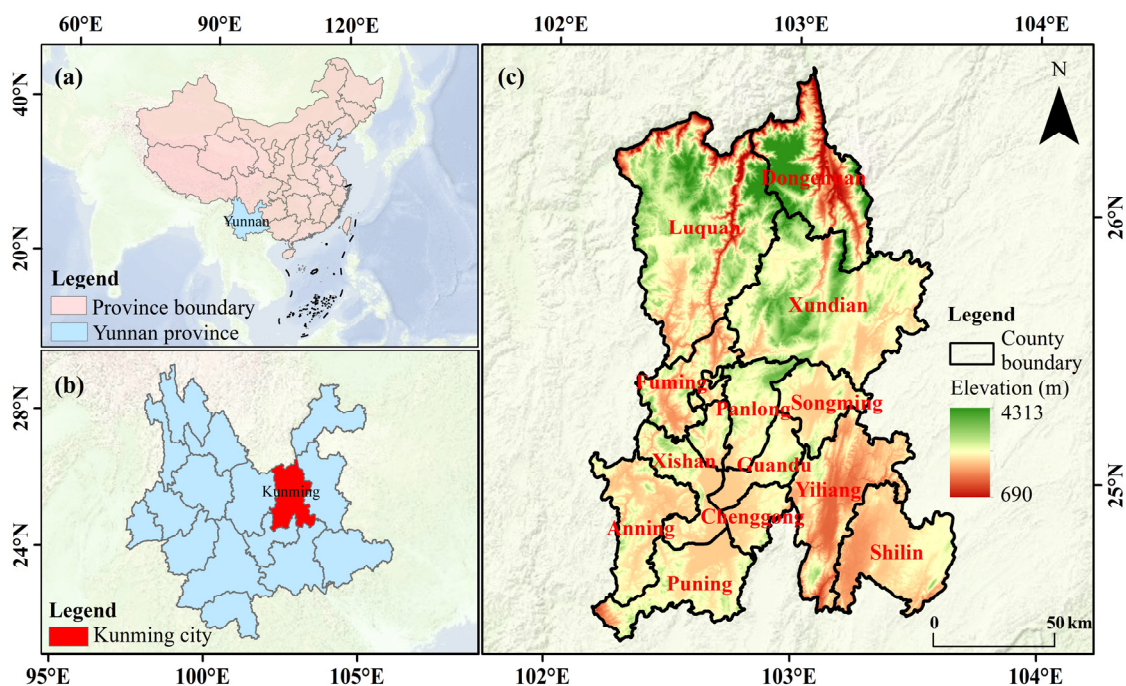


Figure 1. Geographic location map: (a) China's boundary; (b) Yunnan province's boundary; (c) Kunming city's boundary.

3. Data Sources and Methods

3.1. Data Sources

Land use data: The remote sensing images used in this paper are sourced from the Geospatial Data Cloud, including seven phases of Landsat 5/Landsat 8 images from 1990 to 2020. These images were preprocessed using ENVI 5.1 and classified through manual visual interpretation to obtain land use data. The overall accuracy is above 90%, and the Kappa coefficient is above 0.89.

Driving factors: To predict the patterns of land use change and the driving forces of soil erosion, the study selected natural factors such as elevation, slope, rainfall, temperature, normalized difference vegetation index, and soil erodibility, along with human activity factors such as population density and human footprint, as drivers. Detailed information about these data is provided in Table 1.

Table 1. Sources of analyzed data.

Categories	Variables	Abbreviations	Resolution	Website
Land use type		Lut	30 m	https://www.gscloud.cn , accessed on 18 March 2024
Natural factors	Elevation	Ele	30 m	https://www.gscloud.cn , accessed on 20 March 2024
	Slope	Slop	30 m	https://www.gscloud.cn , accessed on 20 March 2024
	Temperature	Tem	30 m	https://data.cma.cn , accessed on 20 March 2024
	Rainfall	Rain	30 m	https://data.cma.cn , accessed on 20 March 2024
	Normalized difference vegetation index	NDVI	250 m	https://www.geodata.cn , accessed on 20 March 2024
	Soil erodibility factor	Se	30 m	https://www.geodata.cn , accessed on 20 March 2024
Anthropogenic factors	Population density	Pop	100 m	https://www.resdc.cn , accessed on 25 March 2024
	Human footprint	Hf	500 m	Haowei et al. [37]

3.2. Methods

3.2.1. RUSLE Model

The RUSLE model was used to calculate the soil erosion modulus (SEM), expressed as [38,39]:

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

where A is the SEM, $t/(hm^2 \cdot a)$; R is the rainfall erosivity factor, $MJ \cdot mm/(hm^2 \cdot h \cdot a)$; K is the soil erodibility factor, $t \cdot hm^2 \cdot h/hm^2 \cdot MJ \cdot mm$; LS is the slope length and steepness factor; C is the vegetation cover and management factor; P is the soil conservation practices factor.

(1) R factor

Rainfall directly contributes to the formation of soil erosion and reflects its potential erosivity. The study calculates the rainfall erosivity using daily rainfall data from 12 meteorological stations around Kunming. The expression is [40]:

$$R_i = \alpha \sum_{j=1}^k (D_j)^\beta \quad (2)$$

$$\beta = 0.8363 + \frac{18.114}{P_{(d12)}} + \frac{24.455}{P_{(y12)}} \quad (3)$$

$$\alpha = 21.586\beta^{-7.1891} \quad (4)$$

In the formula, R_i represents the rainfall erosivity for the i -th half-month; D_j is the daily cumulative rainfall on the j -th day of the half-month; k is the number of days with erosive rainfall during that half-month; α and β are model parameters; $P_{(d12)}$ and $P_{(y12)}$ represent the daily average and annual average rainfall amounts for days with rainfall greater than 12 mm, respectively.

(2) K factor

The K factor is calculated using the erosion-productivity impact calculator (EPIC). The expression is [41]:

$$K = \left\{ 0.2 + 0.3 \exp \left[0.0256 SAN \left(1 - \frac{SIL}{100} \right) \right] \right\} \left(\frac{SIL}{CLA + SIL} \right)^{0.3} \left[1.0 - \frac{0.25C}{C + \exp(3.72 - 2.95C)} \right] \left[1.0 - \frac{0.7SN}{SN + \exp(-5.51 + 22.9SN)} \right] \quad (5)$$

In the formula, *SAN*, *SIL*, and *CLA* represent the sand, silt, and clay content (%), respectively; *C* is the organic carbon content (%); $SN = 1 - SAN/100$.

(3) *LS* Factor

The *LS* factor effectively reflects the surface characteristics of the study area and significantly influences soil erosion. The expression is [42]:

$$L = \left(\frac{\lambda}{22.13} \right)^m \quad (6)$$

$$m = \begin{cases} 0.2, \theta \leq 1^\circ \\ 0.3, 1^\circ < \theta \leq 3^\circ \\ 0.4, 3^\circ < \theta \leq 5^\circ \\ 0.5, \theta > 5^\circ \end{cases} \quad (7)$$

$$S = \begin{cases} 10.8\sin\theta + 0.3, \theta \leq 5^\circ \\ 16.8\sin\theta - 0.5, 5^\circ < \theta \leq 10^\circ \\ 20.204\sin\theta - 0.1204, 10^\circ < \theta \leq 25^\circ \\ 29.585\sin\theta - 5.6079, \theta > 25^\circ \end{cases} \quad (8)$$

In the formula, *L* represents the slope length factor; λ is the unit slope length; *m* is the slope length exponent; *S* is the slope steepness factor, and θ is the slope angle. The study conducted the *LS* factor calculation using a 30 m resolution DEM.

(4) *CP* factor

The vegetation cover and management factor (*C*) reflects the reduction in soil erosion under vegetation cover, with values ranging from 0 to 1, typically determined by modeling, experimental, and assignment methods for the *C* factor. In this study, the *C* factor was obtained using the assignment method based on the research findings by Chen et al. [43,44] (Table 2). The soil and water conservation practices factor (*P*) reflects the reduction in erosion after implementing conservation measures, with values ranging from 0 to 1, assigned according to land use types based on the research findings by Qiao et al. [45] (Table 2).

Table 2. Assignment of *C* and *P* factors.

Land Use Types	Cropland	Woodland	Construction Land	Grassland	Waters	Bare Land
<i>C</i>	0.10	0.003	0.20	0.005	0.00	1.00
<i>P</i>	0.35	0.80	0.00	1.00	0.00	1.00

3.2.2. GeoSOS-FLUS Model

The GeoSOS-FLUS model proposed by Liu et al. [46] uses historical land use data and driving factors to simulate future land use patterns under the influence of various natural and anthropogenic factors. The driving factors selected for this study include elevation, slope, precipitation, temperature, normalized difference vegetation index, soil erodibility factor, population density, and human footprint, totaling eight factors. The main simulation process includes the following aspects:

- (1) Suitability probability calculation: The artificial neural network (ANN) algorithm is used to train and estimate the occurrence probabilities of various types of land use. The ANN includes three types of layers: input layer, hidden layer, and output layer. In the input layer, each neuron corresponds to an input variable, i.e., the selected driving factor. Its expression is:

$$X = [x_1, x_2, \dots, x_n]^T \quad (9)$$

where x_i is the i th neuron in the input layer. In the hidden layer, the signal received by neuron j at time t from all input neurons on grid cell p is estimated using the following formula:

$$net_j(p, t) = \sum_j W_{jk} \times x_i(p, t) \quad (10)$$

where $net_j(p, t)$ is the signal received by neuron j in the hidden layer; $x_i(p, t)$ is the i th variable associated with input neuron i at grid cell p at time t ; w_{jk} is the adaptive weight between the input layer and the hidden layer; the hidden layer is connected to the output layer by an activation function. The calculation is as follows:

$$p(p, k, t) = \sum_j W_{jk} \times \frac{1}{1 + e^{-net_j(p, t)}} \quad (11)$$

In the formula, $p(p, k, t)$ is the suitability probability for land use type k at time t on grid cell p .

- (2) The adaptive inertia coefficient adapts to the iterative process, reducing the gap between the expected demand and actual amount of land use types, adjusting the quantities of each land use type to the predefined targets to simulate spatial changes in land use types. The formula is as follows:

$$Interia_k^t \begin{cases} Interia_k^{t-1} & |D_k^{t-2}| \leq |D_k^{t-1}| \\ Interia_k^{t-1} \times \frac{|D_k^{t-2}|}{|D_k^{t-1}|} & 0 > |D_k^{t-2}| > |D_k^{t-1}| \\ Interia_k^{t-1} \times \frac{|D_k^{t-1}|}{|D_k^{t-2}|} & |D_k^{t-1}| > |D_k^{t-2}| > 0 \end{cases} \quad (12)$$

In the formula, $Interia_k^t$ is the inertia coefficient t for type k land during iteration; D_k^{t-1} represents the area difference between the land demand at time $t - 1$ and the actual quantity of land type k .

- (3) Scenario settings: Based on the natural conditions and socioeconomic development status of Kunming and in accordance with the “Yunnan Provincial Territorial Spatial Planning (2021–2035),” this study sets up four scenarios including natural development (NDS), rapid development (RDS), cropland protection (CPS), and ecological protection (EPS). Initially, land use changes from 2010 to 2020 are used as a reference to predict future land use demand using the Markov chain method and to obtain land use type transition probabilities. NDS: based on land use transitions from 2010 to 2020, without restrictions. RPS: in this scenario, transfers from impervious surfaces to other types are restricted in the transition matrix; the probabilities of transferring cropland, woodland, and grassland to construction land are increased by 20%, and the probability of transferring construction land to other types is decreased by 30%. EPS: the probabilities of transferring woodland and grassland to construction land are reduced by 50%, the probability of transferring cropland to construction land is reduced by 30%, and the probabilities of transferring cropland and grassland to woodland are increased by 30%. CPS: the probability of transferring cropland to construction land is reduced by 70%.

3.2.3. Random Forest Model

The random forest model is a machine learning algorithm that includes multiple decision tree classifiers. It is advantageous for its convenience in handling large datasets, fast computation speed, robust results, and its ability to overcome issues of multicollinearity. The study is based on the *R* language platform, with tuned parameters: the number of decision trees in the model ($ntree$) = 750 and the number of variables tried at each node ($mtry$) = 5, with other settings as default. The accuracy of the model is validated by the coefficient of determination (R^2) and mean absolute error (MAE); a higher R^2 and a lower MAE indicate a higher explanatory accuracy of the model [47–49].

4. Results and Analysis

4.1. Spatiotemporal Characteristics of Land Use Changes in Kunming

4.1.1. Spatial Patterns of Land Use Types

Woodland and grassland were the main land use types in Kunming, widely distributed and accounting for more than 70% of the study area (Figure 2). Cropland was the next major type, covering more than 20% of the study area, primarily distributed in low-altitude regions such as Songming and Yiliang. Waters accounted for more than 2.20%, primarily consisting of Dian Lake. Influenced by natural geographical patterns, construction land was mainly concentrated around the Dian Lake area. Bare land had a low proportion, scattered in spots throughout the study area. From 1990 to 2020, the areas of cropland, woodland, and grassland showed a decreasing trend, with cropland decreasing the most by 382.74 km², followed by woodland and grassland, which decreased by 104.38 km² and 339.41 km², respectively. Waters, construction land, and bare land showed an increasing trend, with construction land increasing significantly from 403.45 km² in 1990 to 1190.90 km² in 2020. This increase was due to the rapid development of the economy and tourism, resulting in urban expansion. The areas of waters and bare land grew less, by 36.73 km² and 2.47 km², respectively.

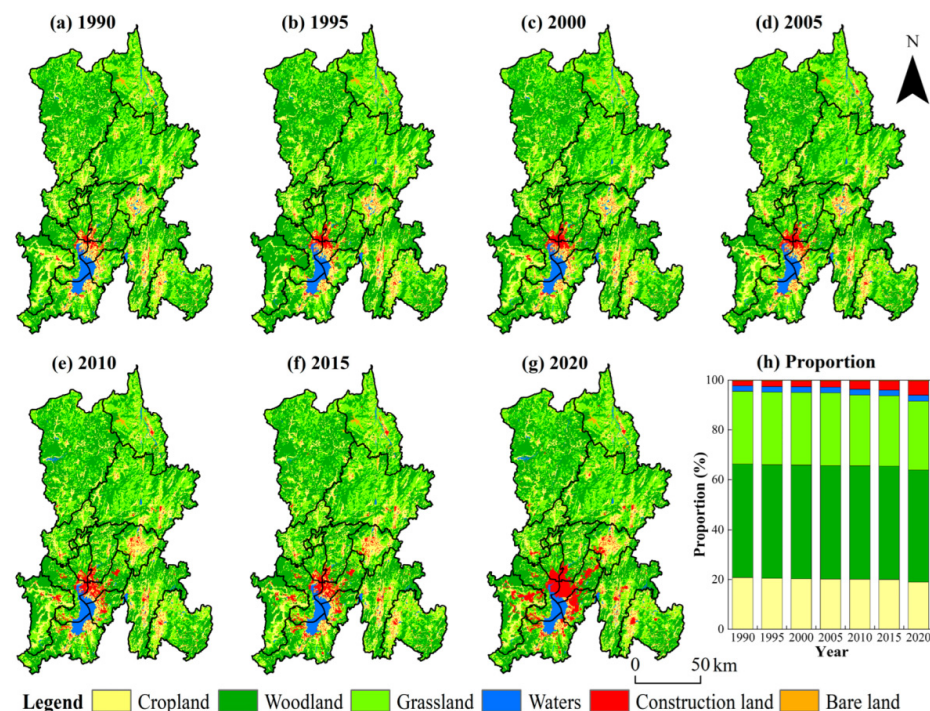


Figure 2. Spatial distribution of land use types in (a) 1990, (b) 1995, (c) 2000, (d) 2005, (e) 2010, (f) 2015, (g) 2020; (h) area proportion.

4.1.2. Land Use Change Trajectory from 1990 to 2020

From 1990 to 2020, land use types in Kunming underwent significant changes, characterized mainly by a substantial reduction in ecological and productive land and the expansion of construction land (Figure 3). Over the 30 years, 861.29 km² of cropland was converted, primarily into woodland (206.47 km²), grassland (174.98 km²), and construction land (452.88 km²). A total of 636.03 km² of woodland was converted, transforming into cropland (188.88 km²), grassland (329.12 km²), and construction land (118.03 km²). A total of 839.27 km² of grassland was converted, transforming into cropland (246.82 km²), woodland (355.32 km²), and construction land (237.13 km²). Land use changes mainly involved mutual conversions among cropland, woodland, and grassland, primarily scattered in Luquan and Xundian, which mostly occurred between 2000 and 2010. Second, the conversion of cropland, woodland, and grassland to construction land became more prominent, especially

after the beginning of the 21st century, primarily concentrated in areas around Dian Lake with high levels of human activity.

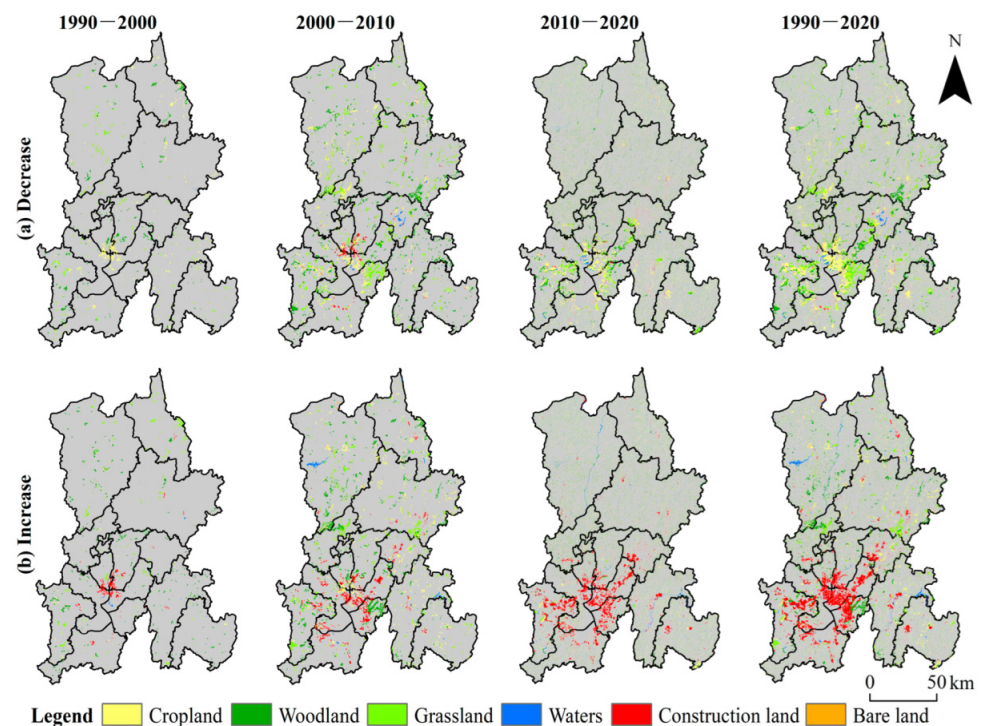


Figure 3. Land use change trajectory: (a) represents land transferred out, and (b) represents land transferred in.

4.2. Spatiotemporal Characteristics of Soil Erosion in Kunming

4.2.1. Spatiotemporal Changes in SEM from 1990 to 2020

Over the past 30 years, the spatial distribution of SEM has been relatively consistent, with low-value areas being dominant, particularly concentrated around Dian Lake; high-value areas are mainly scattered in the northern part of the study area and high-altitude regions of Yiliang (Figure 4). Temporally, the SEM in the study area has shown a decreasing trend, with the average decreasing from $133.85 \text{ t}/(\text{km}^2 \cdot \text{a})$ in 1990 to $130.32 \text{ t}/(\text{km}^2 \cdot \text{a})$ in 2020. In the first 10 years, the decline was slight, about $0.75 \text{ t}/(\text{km}^2 \cdot \text{a})$. After entering the 21st century, the decline became more pronounced, with a decrease of $2.78 \text{ t}/(\text{km}^2 \cdot \text{a})$ from 2000 to 2020. The areas where the SEM decreased were mainly concentrated around Dian Lake where the terrain is generally flat and densely populated, due to the expansion of construction land and surface hardening. The areas where the SEM increased were relatively small in proportion and were mainly concentrated in the southern part of Xundian.

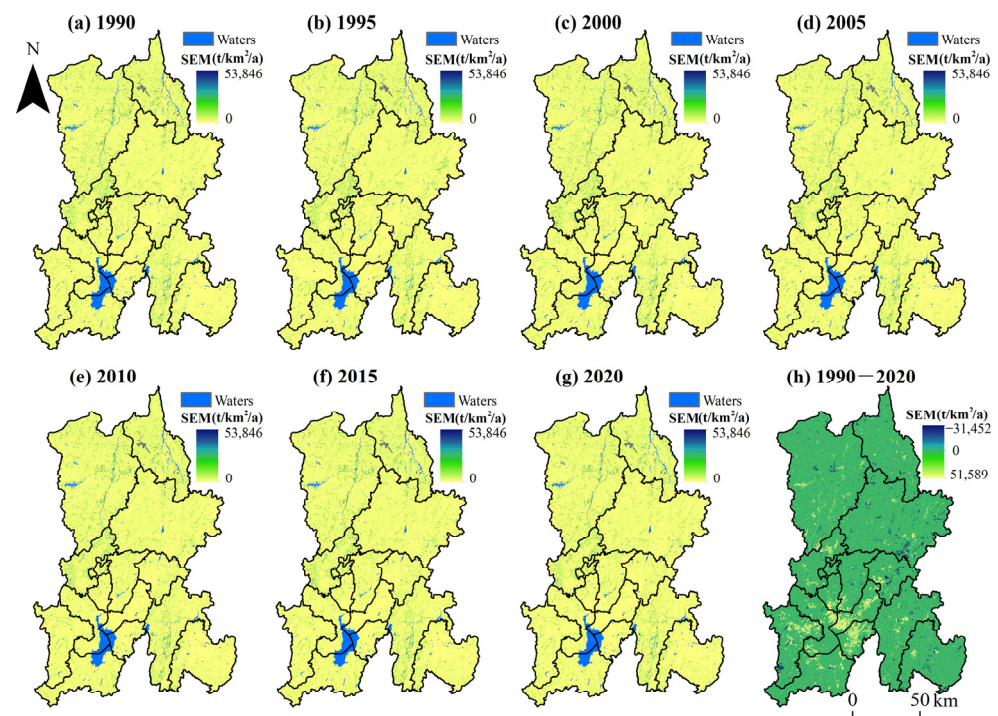


Figure 4. Spatial distribution of SEM in (a) 1990, (b) 1995, (c) 2000, (d) 2005, (e) 2010, (f) 2015, (g) 2020; (h) SEM change from 1990 to 2020.

4.2.2. Soil Loss under Land Use Change from 1990 to 2020

The study used the ArcGIS zonal statistics tool to calculate the changes in SEM caused by land use changes from 1990 to 2020 and combined this with the area of land use changes to calculate soil loss (Figure 5). Overall, soil loss due to land use changes decreased by 74,485.46 t/a, with the changes in cropland causing the most significant soil loss variations. Cropland conversion to other land use types reduced soil loss by 225,824.03 t/a, with cropland conversion to construction land reducing soil loss the most, by 93,099.56 t/a, followed by conversion to woodland and grassland, reducing soil loss by 69,113.88 t/a and 58,292.14 t/a, respectively. The conversion of other land use types to cropland increased soil loss by 144,073.72 t/a, with the conversion of woodland and grassland to cropland increasing soil loss the most, by 73,504.54 t/a and 65,983.86 t/a, respectively. Additionally, it is noteworthy that the conversions between bare land and ecological land (woodland and grassland) also significantly affect soil loss.

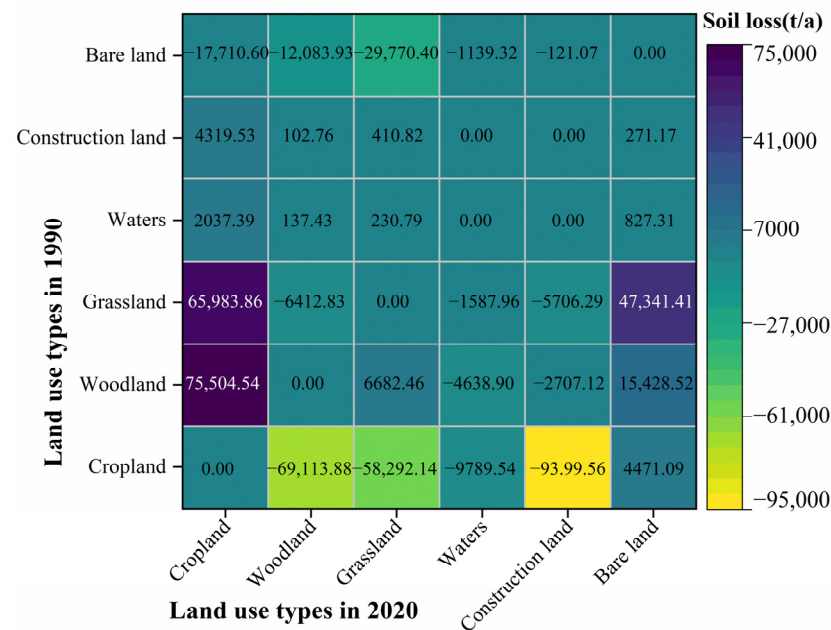


Figure 5. Soil loss due to land use changes from 1990 to 2020.

4.3. Future Land Use Change Simulation

4.3.1. Spatial Patterns of Land Use Types from 2030 to 2050

The land use in 2020 was simulated by GeoSOS-FLUS based on the land use data in 2010 and compared with the actual land use data in 2020; it showed an overall accuracy and kappa coefficient of 90.26% and 0.87, respectively, indicating that the simulation was effective and the results are highly credible.

The study further simulated the spatial patterns of land use from 2030 to 2050 under different scenarios (Figure 6). Under the NDS, without explicit policy constraints, the proportion of construction land in 2050 will increase by 5.71%, doubling from 2020. This increase comes from the conversion of cropland, woodland, and grassland, expected to decrease by 2.26%, 1.69%, and 1.97%, respectively. Under the RDS, the expansion of construction land intensifies, with the proportion increasing by 7.14% compared with 2020, leading to decreases in cropland, woodland, and grassland by 2.78%, 2.08%, and 2.46%, respectively. Under the CPS, the expansion of construction land is effectively controlled, with the proportion increasing by 3.09% compared with 2020, mainly occupying woodland and grassland, which decrease by 1.52% and 1.84%, respectively, while the cropland proportion slightly increases by 0.10%. Under the EPS, the proportion of construction land is expected to increase by 2.79% compared with 2020, mainly converted from cropland, which leads to a 2.26% reduction in the cropland proportion. The conversion of woodland and grassland to construction land is restrained, with their areas decreasing by only 0.22% and 0.61%, respectively.

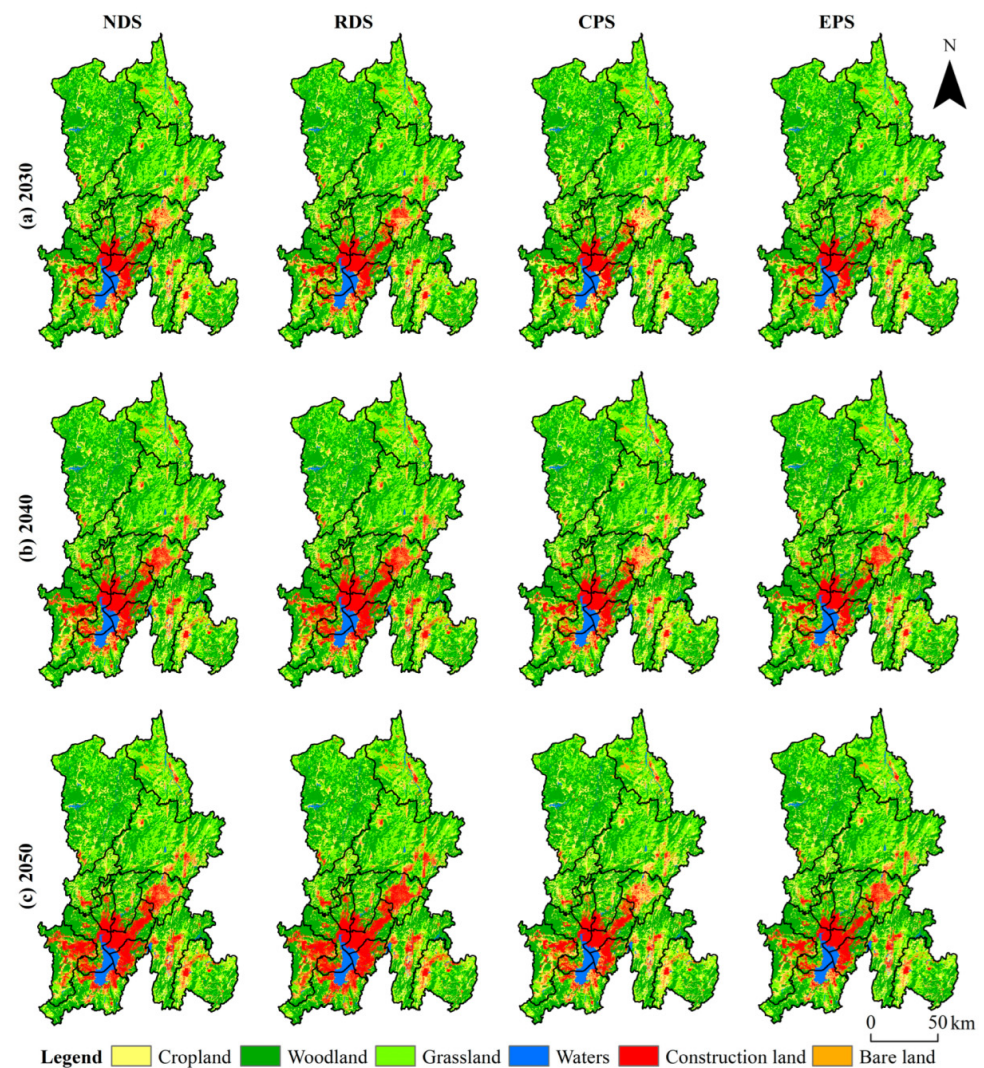


Figure 6. Spatial distribution of land use under different scenarios in (a) 2030, (b) 2040, (c) 2050. Note: natural development scenarios (NDS), rapid development scenarios (RDS), cropland protection scenarios (CPS), and ecological protection scenarios (EPS).

4.3.2. Land Use Change Trajectories from 2020 to 2050

The expansion of construction land is the main driving force of land use change, with cropland, woodland, and grassland being the primary areas of expansion (Figure 7). The evolution of construction land centers around Dian Lake, extending toward the southeast and northwest, particularly under the NDS and RDS. Under the EPS and CPS, although construction land shows an increasing trend, the areas of expansion change. Under the CPS, the primary areas of expansion are woodland and grassland, with an increase in cropland, mainly occurring in Luquan and Xundian. Under the EPS, the primary area of expansion is cropland.

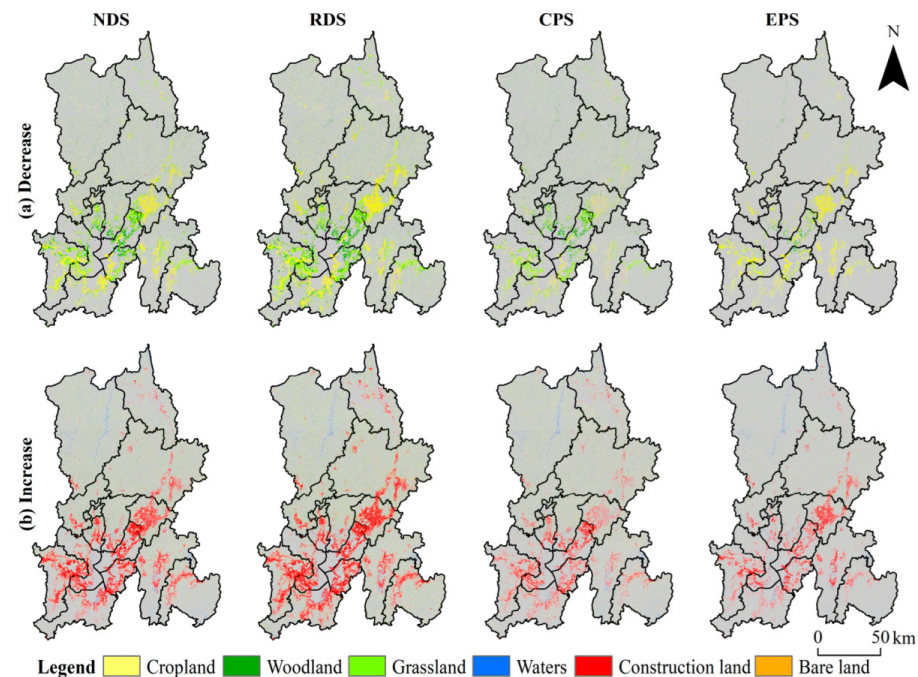


Figure 7. Land use change trajectories under different scenarios from 2020 to 2050; (a) represents land transferred out and (b) represents land transferred in. Note: natural development scenarios (NDS), rapid development scenarios (RDS), cropland protection scenarios (CPS), and ecological protection scenarios (EPS).

4.4. Future Soil Erosion Changes

4.4.1. Spatiotemporal Changes in SEM from 2030 to 2050

Under the NDS, continuing the historical trend, the expansion of construction land leads to a gradual annual decrease in the average SEM, dropping by $3.77 \text{ t}/(\text{km}^2 \cdot \text{a})$ in 2050 compared with 2020 (Figure 8). Under the RDS, the intensification of construction land expansion results in a greater decrease in the SEM, declining by $4.27 \text{ t}/(\text{km}^2 \cdot \text{a})$ from 2020 to 2050. Under the EPS, the expansion of construction land is restricted, but due to the increase in the conversion area from cropland to woodland and grassland, the SEM decreases by $3.27 \text{ t}/(\text{km}^2 \cdot \text{a})$. However, under the CPS, due to the increase in cropland area from 2030 to 2050, the SEM shows a slight increase, rising by $0.26 \text{ t}/(\text{km}^2 \cdot \text{a})$ in 2050 compared with 2020. Due to the expansion of construction land, the areas with reduced SEM are primarily located around Dian Lake. Overall, under the NDS, RDS, and EPS, the SEM decreases due to urban expansion and ecological restoration. However, under the CPS, the increase in cropland area leads to an increase in SEM.

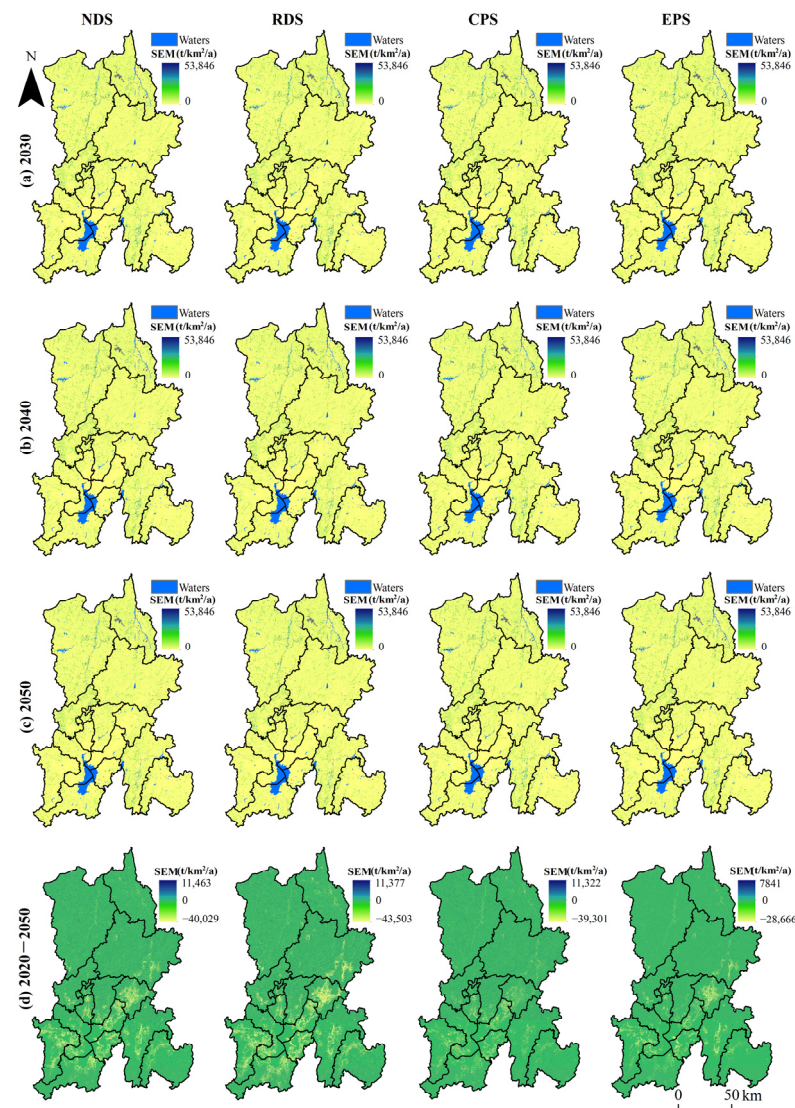


Figure 8. Spatial distribution of SEM under different scenarios in (a) 2030, (b) 2040, (c) 2050; and (d) SEM change from 2020 to 2050. Note: natural development scenarios (NDS), rapid development scenarios (RDS), cropland protection scenarios (CPS), and ecological protection scenarios (EPS).

4.4.2. Soil Loss under Land Use Changes from 2020 to 2050

Overall, under the NDS, RDS, and EPS, soil loss shows a decreasing trend, with reductions of 79,556.95 t/a, 89,902.13 t/a, and 68,632.72 t/a, respectively (Figure 9). However, under the CPS, soil loss increases by 4187.02 t/a. The conversion of cropland remains the primary factor influencing changes in soil loss. The conversion of cropland to construction land results in the greatest reduction in soil loss, followed by woodland and grassland. Conversely, the conversion of woodland and grassland to cropland significantly increases soil loss. Compared with other scenarios, the increase in soil loss under the CPS is mainly attributed to the restricted conversion of cropland to construction land. Additionally, the conversion of woodland and grassland to cropland leads to an increase in cropland area, which, in turn, increases soil loss.

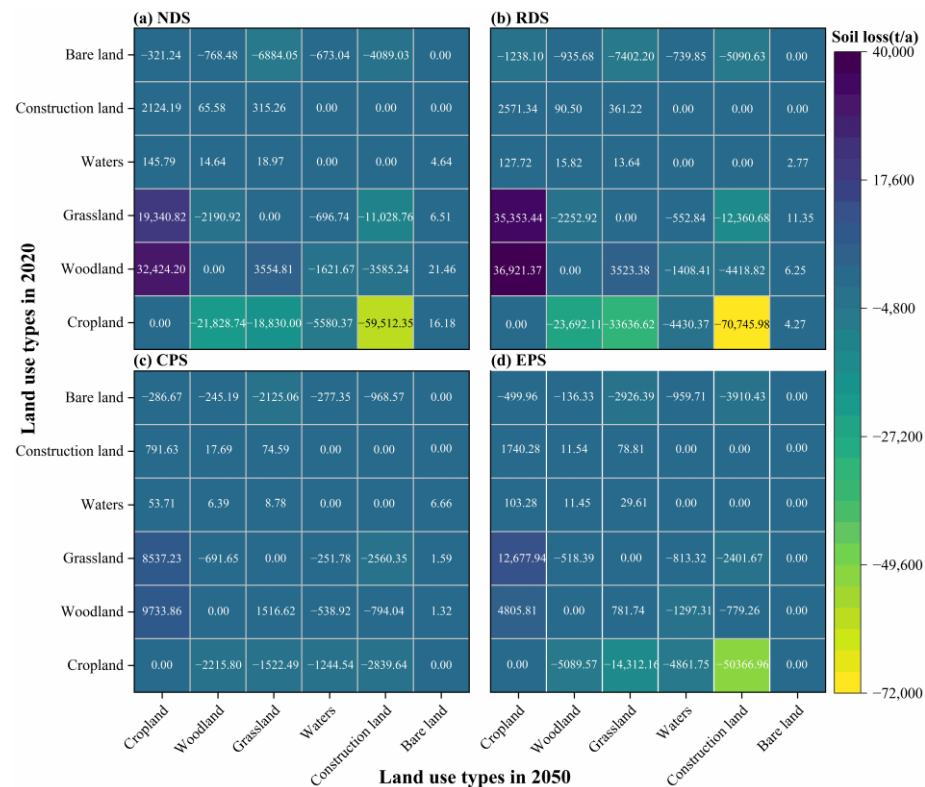


Figure 9. Soil loss due to land use change under different scenarios from 2020 to 2050. Note: natural development scenarios (NDS), rapid development scenarios (RDS), cropland protection scenarios (CPS), and ecological protection scenarios (EPS).

4.5. Analysis of Factors Influencing Soil Erosion

The accuracy test results for the random forest regression show that the adjusted R^2 values are all above 0.90, and the MAE values are all below 0.05, indicating that the random forest model has a good fit and is suitable for analyzing the importance of driving factors.

From 1990 to 2020, the importance of land use types consistently ranked first although their significance slightly decreased (Figure 10). Changes in land use, particularly the expansion of urban areas and the increase in agricultural activities have had a significant impact on soil erosion patterns. Slope and elevation have always been important natural factors in soil erosion, with little change in their importance over time. Following this, the importance of the human footprint has increased, reflecting the acceleration of population growth and industrialization and the corresponding rise in the impact of human activities. Future scenarios show clear differences in the importance of driving factors. Under the NDS and RDS, the importance of natural factors tends to decrease, while the importance of human activities increases. Conversely, under the CPS and EPS, future soil erosion management strategies need to comprehensively consider the interaction between human activities and natural conditions, especially in the context of climate change and population growth, which makes these factors more complex.

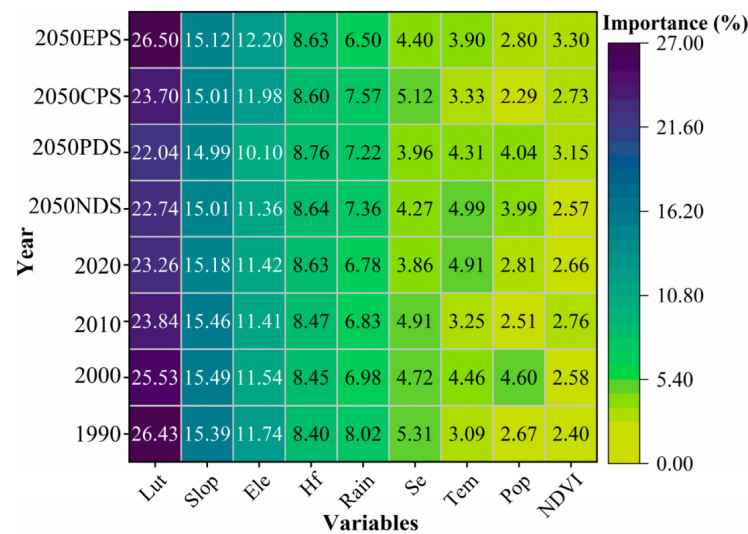


Figure 10. Importance of factors influencing soil erosion. Notes: natural development scenarios (NDS), rapid development scenarios (RDS), cropland protection scenarios (CPS), ecological protection scenarios (EPS), land use type (Lut), slope (Slop), elevation (Ele), human footprint (Hf), rainfall (Rain), soil erodibility factor (Se), temperature (Tem), population density (Pop), and normalized difference vegetation index (NDVI).

5. Discussion

5.1. Impact of Land Use Changes on Soil Erosion

From 1990 to 2020, the SEM varied significantly between different land use types in Kunming. One reason for this phenomenon is the difference in vegetation cover between land use types [50,51]. Vegetation cover can effectively slow down water flow, increase water infiltration, and reduce surface runoff. This helps control soil erosion and determines the soil erosion status to some extent [52,53]. Another reason is the impact of human activities. For example, tillage in cropland causes soil layer disturbance, weakening soil resistance to erosion [54–56]. Additionally, exposed surfaces easily generate surface runoff, which increases surface erosion and exacerbates erosion, resulting in a higher SEM for cropland [28,57,58]. However, construction land with poor vegetation cover has a lower SEM. During development, this land often undergoes surface hardening, such as paving roads and buildings, reducing the exposure of soil to rainfall and runoff, thus lowering erosion potential [59]. During the study period, the SEM showed a decreasing trend, especially after entering the 21st century, with a significant increase in the rate of decrease, similar to the findings of Rao et al. [30] using the CSLE model. The primary reason for the decrease in the SEM is the large-scale expansion of urban construction land since 2000, driven by economic development and population pressure in Kunming. This expansion has reduced cropland and, consequently, soil erosion. Statistics show that from 2000 to 2020, Kunming's GDP increased nearly tenfold, and the population doubled [60]. On the other hand, the conversion of cropland with a high SEM to woodland and grassland with a lower SEM, due to the implementation of the national policy of returning farmland to forest and grass, has significantly reduced soil loss [61,62]. Additionally, rural population loss, cropland quality, and economic benefits have led to frequent abandonment of cropland. According to surveys, 80% of villages have abandoned 15% of their cropland area, with some converting to grassland, thus reducing soil loss [63–65]. This fully illustrates that soil erosion is a complex phenomenon influenced by various factors, such as topography, vegetation cover, and human activities.

This study used the RUSLE and GeoSOS-FLUS models to assess the impact of land use changes on soil erosion. In the model setup, the R , K , and LS factors remained unchanged, and changes in soil erosion under different land use scenarios were simulated by adjusting the C and P factors related to land use changes [66,67]. The results show that in the NDS

and RDS, although the expansion of construction land occupied a large amount of other land use types, this change did not lead to more severe soil erosion. On the contrary, the expansion of construction land resulted in reductions in soil loss amounting to 25,477.32 t/a and 32,726.54 t/a, respectively. In the EPS, although the total soil loss decreased, it was reduced to 20,668.45 t/a, a lesser reduction compared with the first two scenarios due to less expansion of construction land. Additionally, due to ecological protection policies, the conversion of woodland and grassland to cropland was controlled, resulting in a smaller increase in soil loss compared with the NDS and RDS, amounting to 6289.12 t/a. However, under the CPS, because cropland protection policies restricted the conversion of cropland to construction land, the reduction in soil loss due to this restricted expansion was only 7162.60 t/a. In this scenario, the increase in cropland area has encroached upon woodland and grassland, resulting in an increase in soil loss of 18,271.09 t/a. This is the main reason for the overall increase in soil loss in the study area under this scenario. Overall, the expansion of construction land remains the main driver for the reduction in soil loss in the future.

5.2. Future Soil Erosion Control Strategies

Changes in land use are one of the key factors affecting soil erosion and an important means for policymakers to effectively improve regional soil erosion conditions at a lower cost [68–70]. Although the rapid expansion of construction land may reduce soil loss in the short term, this phenomenon is neither positive nor sustainable [71]. The expansion of construction land often involves converting natural surfaces such as forests and grasslands into hard structures like buildings and roads, which reduces the likelihood of soil weathering or erosion but also deprives the land of its original ecological value [72]. Ecosystem services provided by natural surfaces, such as maintaining biodiversity, regulating the water cycle and climate, and promoting soil nutrient cycling, are significantly reduced after the expansion of construction land, thereby causing long-term negative impacts on the environment [73]. The increase in hard surfaces reduces the ground's ability to absorb rainwater, leading to lower groundwater levels and increased runoff. This may exacerbate urban flooding risks and water scarcity during droughts [74,75]. Additionally, urban areas with extensive hard surfaces and a lack of green spaces typically experience higher temperatures than surrounding areas. This creates the so-called "urban heat island effect", which not only affects living comfort but may also alter the climatic conditions within the city [76,77]. From a long-term and overall environmental impact perspective, uncontrolled expansion of construction land may pose challenges to sustainable urban development, such as overconsumption of resources, deterioration of environmental quality, and a decrease in the quality of life [78–80]. In contrast, under the EPS, planting trees and other plants not only effectively stabilizes the soil and reduces water erosion but also provides habitats for wildlife, increases biodiversity, and improves microclimatic conditions, offering a sustainable way to reduce soil loss [81]. Additionally, under the CPS, although the transfer of cropland is restricted and the area increases, the soil loss is higher compared with other scenarios due to low vegetation cover on cropland and significant human disturbance.

The future expansion of construction land may temporarily reduce regional soil loss; however, this effect is not sustainable. Therefore, it is crucial to develop and implement scientific land use planning policies. While ensuring that economic development needs are met, it is essential to also consider ecological protection. This includes integrating more ecological elements, clearly delineating economic development zones, and establishing ecological protection areas to limit the unchecked expansion of construction land. It is recommended to establish a comprehensive ecological monitoring network, using advanced tools such as satellite remote sensing and geographic information systems to continuously monitor ecological lands in real time. This allows for timely policy adjustments and optimizations in response to ecological changes. Additionally, there is an urgent need to reduce soil loss from cropland. Effective maintenance of land health and productivity can

be achieved by employing soil conservation measures, optimizing cultivation techniques, and enhancing vegetation cover, which, in turn, reduces soil loss.

5.3. Research Limitations and Future Prospects

Although the simulation results show high accuracy, they overlook the impact of other economic factors on land use changes. Our study considered differences in the *C* and *P* factors among various land use types, but did not account for variations within the same land category. Additionally, rainfall significantly affects soil erosion development, the *R* factor in this study was based on the average from 1990 to 2020, without considering the actual impact of future climate change. Therefore, future studies should integrate climate change and more detailed land use data to comprehensively explore the evolution of soil erosion.

6. Conclusions

The study analyzed the historical and future changes in SEM and its driving forces in Kunming, with the key findings as follows: (1) The primary land use types in Kunming are woodland, grassland, and cropland. From 1990 to 2020, land use changed significantly, with woodland, grassland, and cropland continuously decreasing, being converted to construction land, which increased by 195.18% compared with 1990. (2) During this period, the regional SEM decreased from 133.85 t/(km²·a) to 130.32 t/(km²·a), and soil loss was reduced by 74,485.46 t/a. This reduction was mainly due to the conversion of cropland to construction land and ecological land (woodland and grassland). (3) The expansion of construction land is expected to continue. By 2050, the SEM under the NDS, RDS, and EPS scenarios is anticipated to decrease by 3.77 t/(km²·a), 4.27 t/(km²·a), and 3.27 t/(km²·a), respectively. However, under the CPS, the SEM is expected to increase by 0.26 t/(km²·a) compared with 2020. (4) The spatial pattern of soil erosion in Kunming is influenced by both natural and anthropogenic factors. As human activities intensify, the importance of anthropogenic factors will further increase. The decrease in soil erosion attributed to the growth of construction land is not a sustainable solution. Future land use planning must strike a balance between the demands of economic development and the need for ecological preservation. This involves integrating more ecological components and curbing the unregulated expansion of construction land to some extent, ensuring the preservation of ecological land areas.

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References

1. Xiong, M.; Leng, G. Global Soil Water Erosion Responses to Climate and Land Use Changes. *CATENA* **2024**, *241*, 108043. [[CrossRef](#)]
2. Takhellambam, B.S.; Srivastava, P.; Lamba, J.; McGehee, R.P.; Kumar, H.; Tian, D. Projected Mid-Century Rainfall Erosivity under Climate Change over the Southeastern United States. *Sci. Total Environ.* **2023**, *865*, 161119. [[CrossRef](#)] [[PubMed](#)]

3. Thaler, E.A.; Kwang, J.S.; Quirk, B.J.; Quarrier, C.L.; Larsen, I.J. Rates of Historical Anthropogenic Soil Erosion in the Midwestern United States. *Earth's Future* **2022**, *10*, e2021EF002396. [[CrossRef](#)]
4. Zhang, Y.; Hartemink, A.E.; Vanwalleghem, T.; Bonfatti, B.R.; Moen, S. Climate and Land Use Changes Explain Variation in the A Horizon and Soil Thickness in the United States. *Commun. Earth Environ.* **2024**, *5*, 129. [[CrossRef](#)]
5. Tuo, D.; Xu, M.; Gao, G. Relative Contributions of Wind and Water Erosion to Total Soil Loss and Its Effect on Soil Properties in Sloping Croplands of the Chinese Loess Plateau. *Sci. Total Environ.* **2018**, *633*, 1032–1040. [[CrossRef](#)]
6. Van Pelt, R.S.; Hushmurodov, S.X.; Baumhardt, R.L.; Chappell, A.; Nearing, M.A.; Polyakov, V.O.; Strack, J.E. The Reduction of Partitioned Wind and Water Erosion by Conservation Agriculture. *CATENA* **2017**, *148*, 160–167. [[CrossRef](#)]
7. Zhang, J.; Yang, M.; Deng, X.; Liu, Z.; Zhang, F. The Effects of Tillage on Sheet Erosion on Sloping Fields in the Wind-Water Erosion Crisscross Region of the Chinese Loess Plateau. *Soil. Tillage Res.* **2019**, *187*, 235–245. [[CrossRef](#)]
8. Guo, T.; Srivastava, A.; Flanagan, D.C. Improving and Calibrating Channel Erosion Simulation in the Water Erosion Prediction Project (WEPP) Model. *J. Environ. Manag.* **2021**, *291*, 112616. [[CrossRef](#)]
9. Hafen, K.C.; Blasch, K.; Gessler, P.E.; Dunham, J.; Brooks, E. Estimating Streamflow Permanence with the Watershed Erosion Prediction Project Model: Implications for Surface Water Presence Modeling and Data Collection. *J. Hydrol.* **2023**, *622*, 129747. [[CrossRef](#)]
10. Zhu, R.; Yu, Y.; Zhao, J.; Liu, D.; Cai, S.; Feng, J.; Rodrigo-Comino, J. Evaluating the Applicability of the Water Erosion Prediction Project (WEPP) Model to Runoff and Soil Loss of Sandstone Reliefs in the Loess Plateau, China. *Int. Soil Water Conserv. Res.* **2023**, *11*, 240–250. [[CrossRef](#)]
11. Laflen, J.M.; Flanagan, D.C. The Development of U. S. Soil Erosion Prediction and Modeling. *Int. Soil. Water Conserv. Res.* **2013**, *1*, 1–11. [[CrossRef](#)]
12. Wang, B.; Zheng, F.; Guan, Y. Improved USLE-K Factor Prediction: A Case Study on Water Erosion Areas in China. *Int. Soil. Water Conserv. Res.* **2016**, *4*, 168–176. [[CrossRef](#)]
13. Bensekhria, A.; Bouhata, R. Assessment and Mapping Soil Water Erosion Using RUSLE Approach and GIS Tools: Case of Oued El-Hai Watershed, Aurès West, Northeastern of Algeria. *IJGI Int. J. Geo-Inf.* **2022**, *11*, 84. [[CrossRef](#)]
14. Fenta, A.A.; Tsunekawa, A.; Haregeweyn, N.; Poesen, J.; Tsubo, M.; Borrelli, P.; Panagos, P.; Vanmaercke, M.; Broeckx, J.; Yasuda, H.; et al. Land Susceptibility to Water and Wind Erosion Risks in the East Africa Region. *Sci. Total Environ.* **2020**, *703*, 135016. [[CrossRef](#)] [[PubMed](#)]
15. Yang, C.; Fan, J.; Liu, J.; Xu, F.; Zhang, X. Evaluating the Dominant Controls of Water Erosion in Three Dry Valley Types Using the RUSLE and Geodetector Method. *Land* **2021**, *10*, 1289. [[CrossRef](#)]
16. Li, Z.; Nie, X.; He, J.; Chang, X.; Liu, C.; Liu, L.; Sun, L. Zonal Characteristics of Sediment-Bound Organic Carbon Loss during Water Erosion: A Case Study of Four Typical Loess Soils in Shaanxi Province. *CATENA* **2017**, *156*, 393–400. [[CrossRef](#)]
17. Weslati, O.; Serbaji, M.-M. Spatial Assessment of Soil Erosion by Water Using RUSLE Model, Remote Sensing and GIS: A Case Study of Mellegue Watershed, Algeria–Tunisia. *Environ. Monit. Assess.* **2024**, *196*, 14. [[CrossRef](#)] [[PubMed](#)]
18. Zeng, Y.; Meng, X.; Wang, B.; Li, M.; Chen, D.; Ran, L.; Fang, N.; Ni, L.; Shi, Z. Effects of Soil and Water Conservation Measures on Sediment Delivery Processes in a Hilly and Gully Watershed. *J. Hydrol.* **2023**, *616*, 128804. [[CrossRef](#)]
19. Huang, C.; Zhou, Z.; Teng, M.; Wu, C.; Wang, P. Effects of Climate, Land Use and Land Cover Changes on Soil Loss in the Three Gorges Reservoir Area, China. *Geogr. Sustain.* **2020**, *1*, 200–208. [[CrossRef](#)]
20. Wang, H.; Wang, X.; Yang, S.; Zhang, Z.; Jiang, F.; Zhang, Y.; Huang, Y.; Lin, J. Water Erosion Response to Rainfall Type on Typical Land Use Slopes in the Red Soil Region of Southern China. *Water* **2024**, *16*, 1076. [[CrossRef](#)]
21. Wei, W.; Chen, L.; Fu, B.; Chen, J. Water Erosion Response to Rainfall and Land Use in Different Drought-Level Years in a Loess Hilly Area of China. *CATENA* **2010**, *81*, 24–31. [[CrossRef](#)]
22. Dos Santos, F.M.; De Souza Pelinson, N.; De Oliveira, R.P.; Di Lollo, J.A. Using the SWAT Model to Identify Erosion Prone Areas and to Estimate Soil Loss and Sediment Transport in Mogi Guaçu River Basin in Sao Paulo State, Brazil. *CATENA* **2023**, *222*, 106872. [[CrossRef](#)]
23. Halecki, W.; Kruk, E.; Ryzek, M. Loss of Topsoil and Soil Erosion by Water in Agricultural Areas: A Multi-Criteria Approach for Various Land Use Scenarios in the Western Carpathians Using a SWAT Model. *Land Use Policy* **2018**, *73*, 363–372. [[CrossRef](#)]
24. Mihara, K.; Kuramochi, K.; Toma, Y.; Hatano, R. Spatiotemporal Analysis of Soil Loss in Cold Climate Upland Farming Watersheds Using SWAT: Case Study of Tokoro River Watershed, Hokkaido, Japan. *Soil. Sci. Plant Nutr.* **2024**, *70*, 65–77. [[CrossRef](#)]
25. Gusarov, A.V. The Response of Water Flow, Suspended Sediment Yield and Erosion Intensity to Contemporary Long-Term Changes in Climate and Land Use/Cover in River Basins of the Middle Volga Region, European Russia. *Sci. Total Environ.* **2020**, *719*, 134770. [[CrossRef](#)] [[PubMed](#)]
26. Wang, Y.Q.; Shao, M.A. Spatial Variability of Soil Physical Properties in a Region of the Loess Plateau of PR China Subject to Wind and Water Erosion. *Land Degrad. Dev.* **2013**, *24*, 296–304. [[CrossRef](#)]
27. Zheng, F.; Huang, J.; Feng, Z.; Xiao, C. Impact of the Kunming–Bangkok Highway on Land Use Changes along the Route between Laos and Thailand. *Land* **2021**, *10*, 991. [[CrossRef](#)]
28. Chen, G.; Zhao, J.; Duan, X.; Tang, B.; Zuo, L.; Wang, X.; Guo, Q. Spatial Quantification of Cropland Soil Erosion Dynamics in the Yunnan Plateau Based on Sampling Survey and Multi-Source LUCC Data. *Remote Sens.* **2024**, *16*, 977. [[CrossRef](#)]
29. Gu, Z.; Huang, Y.; Feng, D.; Duan, X.; Xue, M.; Li, Y.; Li, Y. Towards Mapping Large Scale Soil Erodibility by Using Pedological Knowledge. *Arch. Agron. Soil. Sci.* **2021**, *67*, 809–821. [[CrossRef](#)]

30. Rao, W.; Shen, Z.; Duan, X. Spatiotemporal Patterns and Drivers of Soil Erosion in Yunnan, Southwest China: RULSE Assessments for Recent 30 Years and Future Predictions Based on CMIP6. *CATENA* **2023**, *220*, 106703. [\[CrossRef\]](#)
31. Yu, Y.; Shen, Y.; Wang, J.; Wei, Y.; Liu, Z. Simulation and Mapping of Drought and Soil Erosion in Central Yunnan Province, China. *Adv. Space Res.* **2021**, *68*, 4556–4572. [\[CrossRef\]](#)
32. Bacani, V.M.; Machado Da Silva, B.H.; Ayumi De Souza Amede Sato, A.; Souza Sampaio, B.D.; Rodrigues Da Cunha, E.; Pereira Vick, E.; Ribeiro De Oliveira, V.F.; Decco, H.F. Carbon Storage and Sequestration in a Eucalyptus Productive Zone in the Brazilian Cerrado, Using the Ca-Markov/Random Forest and InVEST Models. *J. Clean. Prod.* **2024**, *444*, 141291. [\[CrossRef\]](#)
33. Taloor, A.K.; Sharma, S.; Parsad, G.; Jasrotia, R. Land Use Land Cover Simulations Using Integrated CA-Markov Model in the Tawi Basin of Jammu and Kashmir India. *Geosystems Geoenviroin.* **2024**, *3*, 100268. [\[CrossRef\]](#)
34. Chen, X.; He, X.; Wang, S. Simulated Validation and Prediction of Land Use under Multiple Scenarios in Daxing District, Beijing, China, Based on GeoSOS-FLUS Model. *Sustainability* **2022**, *14*, 11428. [\[CrossRef\]](#)
35. Li, Z.; Xue, W.; Winijkul, E.; Shrestha, S. Spatio-Temporal Dynamics of Non-Point Source Pollution in Jiulong River Basin (China) Using the Soil & Water Assessment Tool Model in Combination with the GeoSOS-FLUS Model. *Water* **2023**, *15*, 2763. [\[CrossRef\]](#)
36. Wang, Y.; Shen, J.; Yan, W.; Chen, C. Backcasting Approach with Multi-Scenario Simulation for Assessing Effects of Land Use Policy Using GeoSOS-FLUS Software. *MethodsX* **2019**, *6*, 1384–1397. [\[CrossRef\]](#) [\[PubMed\]](#)
37. Mu, H.; Li, X.; Wen, Y.; Huang, J.; Du, P.; Su, W.; Miao, S.; Geng, M. A Global Record of Annual Terrestrial Human Footprint Dataset from 2000 to 2018. *Sci. Data* **2022**, *9*, 176. [\[CrossRef\]](#) [\[PubMed\]](#)
38. Gao, G.; Liang, Y.; Liu, J.; Dunkerley, D.; Fu, B. A Modified RUSLE Model to Simulate Soil Erosion under Different Ecological Restoration Types in the Loess Hilly Area. *Int. Soil. Water Conserv. Res.* **2024**, *12*, 258–266. [\[CrossRef\]](#)
39. Sud, A.; Sajan, B.; Kanga, S.; Singh, S.K.; Singh, S.; Durin, B.; Kumar, P.; Meraj, G.; Sahariah, D.; Debnath, J.; et al. Integrating RUSLE Model with Cloud-Based Geospatial Analysis: A Google Earth Engine Approach for Soil Erosion Assessment in the Satluj Watershed. *Water* **2024**, *16*, 1073. [\[CrossRef\]](#)
40. Waseem, M.; Iqbal, F.; Humayun, M.; Umais Latif, M.; Javed, T.; Kebede Leta, M. Spatial Assessment of Soil Erosion Risk Using RUSLE Embedded in GIS Environment: A Case Study of Jhelum River Watershed. *Appl. Sci.* **2023**, *13*, 3775. [\[CrossRef\]](#)
41. Ma, S.; Wang, L.-J.; Wang, H.-Y.; Zhao, Y.-G.; Jiang, J. Impacts of Land Use/Land Cover and Soil Property Changes on Soil Erosion in the Black Soil Region, China. *J. Environ. Manag.* **2023**, *328*, 117024. [\[CrossRef\]](#)
42. Zhang, T.; Lei, Q.; Du, X.; Luo, J.; An, M.; Fan, B.; Zhao, Y.; Wu, S.; Ma, Y.; Liu, H. Adaptability Analysis and Model Development of Various LS-Factor Formulas in RUSLE Model: A Case Study of Fengyu River Watershed, China. *Geoderma* **2023**, *439*, 116664. [\[CrossRef\]](#)
43. Chen, Z.; Gong, A.; Ning, D.; Zhang, L.; Wang, X.; Xiang, B. Characteristics of Soil Erosion and Nutrient Loss in Yunnan Province Based on RUSLE Model. *J. Soil. Water Conserv.* **2021**, *35*, 7–14. [\[CrossRef\]](#)
44. Dong, Q.; Xun, Y.; Jiang, G.; Cheng, S.; Tang, H.; Zhang, Q. Soil erosion of Benghe watershed in Feixian county of Yimeng mountainous region. *J. Soil. Water Conserv. China* **2011**, *7*, 55–58,69. [\[CrossRef\]](#)
45. Qiao, X.; Li, Z.; Lin, J.; Wang, H.; Zheng, S.; Yang, S. Assessing Current and Future Soil Erosion under Changing Land Use Based on InVEST and FLUS Models in the Yihe River Basin, North China. *Int. Soil. Water Conserv. Res.* **2024**, *12*, 298–312. [\[CrossRef\]](#)
46. Liu, X.; Liang, X.; Li, X.; Xu, X.; Ou, J.; Chen, Y.; Li, S.; Wang, S.; Pei, F. A Future Land Use Simulation Model (FLUS) for Simulating Multiple Land Use Scenarios by Coupling Human and Natural Effects. *Landsc. Urban Plan.* **2017**, *168*, 94–116. [\[CrossRef\]](#)
47. Fernández, D.; Adermann, E.; Pizzolato, M.; Pechenkin, R.; Rodríguez, C.G.; Taravat, A. Comparative Analysis of Machine Learning Algorithms for Soil Erosion Modelling Based on Remotely Sensed Data. *Remote Sens.* **2023**, *15*, 482. [\[CrossRef\]](#)
48. He, W.; Xiao, Z.; Lu, Q.; Wei, L.; Liu, X. Digital Mapping of Soil Particle Size Fractions in the Loess Plateau, China, Using Environmental Variables and Multivariate Random Forest. *Remote Sens.* **2024**, *16*, 785. [\[CrossRef\]](#)
49. Torra, O.; Hürlimann, M.; Puig-Polo, C.; Moreno-de-las-Heras, M. Assessment of Badland Susceptibility and Its Governing Factors Using a Random Forest Approach. Application to the Upper Llobregat River Basin and Catalonia (Spain). *Environ. Res.* **2023**, *237*, 116901. [\[CrossRef\]](#) [\[PubMed\]](#)
50. Pulido-Fernández, M.; Schnabel, S.; Lavado-Contador, J.F.; Miralles Mellado, I.; Ortega Pérez, R. Soil Organic Matter of Iberian Open Woodland Rangelands as Influenced by Vegetation Cover and Land Management. *CATENA* **2013**, *109*, 13–24. [\[CrossRef\]](#)
51. Talukdar, S.; Singha, P.; Shahfahad; Mahato, S.; Praveen, B.; Rahman, A. Dynamics of Ecosystem Services (ESs) in Response to Land Use Land Cover (LU/LC) Changes in the Lower Gangetic Plain of India. *Ecol. Indic.* **2020**, *112*, 106121. [\[CrossRef\]](#)
52. Hu, Y.; Zhang, F.; Luo, Z.; Badreldin, N.; Benoy, G.; Xing, Z. Soil and Water Conservation Effects of Different Types of Vegetation Cover on Runoff and Erosion Driven by Climate and Underlying Surface Conditions. *CATENA* **2023**, *231*, 107347. [\[CrossRef\]](#)
53. Luo, J.; Zhou, X.; Rubinato, M.; Li, G.; Tian, Y.; Zhou, J. Impact of Multiple Vegetation Covers on Surface Runoff and Sediment Yield in the Small Basin of Nverzhai, Hunan Province, China. *Forests* **2020**, *11*, 329. [\[CrossRef\]](#)
54. Rapuc, W.; Giguet-Covex, C.; Bouchez, J.; Sabatier, P.; Gaillardet, J.; Jacq, K.; Genuite, K.; Poulenard, J.; Messenger, E.; Arnaud, F. Human-Triggered Magnification of Erosion Rates in European Alps since the Bronze Age. *Nat. Commun.* **2024**, *15*, 1246. [\[CrossRef\]](#) [\[PubMed\]](#)
55. Wei, C.; Dong, X.; Yu, D.; Zhang, T.; Zhao, W.; Ma, Y.; Su, B. Spatio-Temporal Variations of Rainfall Erosivity, Correlation of Climatic Indices and Influence on Human Activities in the Huaihe River Basin, China. *CATENA* **2022**, *217*, 106486. [\[CrossRef\]](#)
56. Zhao, L.; Meng, P.; Zhang, J.; Zhang, J.; Li, J.; Wang, X. The Contribution of Human Activities to Runoff and Sediment Changes in the Mang River Basin of the Loess Plateau, China. *Land Degrad. Dev.* **2023**, *34*, 28–41. [\[CrossRef\]](#)

57. Li, K.; Wang, L.; Wang, Z.; Hu, Y.; Zeng, Y.; Yan, H.; Xu, B.; Li, C.; Cui, H.; Yu, S.; et al. Multiple Perspective Accountings of Cropland Soil Erosion in China Reveal Its Complex Connection with Socioeconomic Activities. *Agric. Ecosyst. Environ.* **2022**, *337*, 108083. [\[CrossRef\]](#)
58. Wang, Y.; Qin, X.; Kong, Y.; Hou, D.; Ren, P. Temporal Variation in Soil Resistance to Rill Erosion in Cropland of the Dry—Hot Valley Region, Southwest China. *Land* **2024**, *13*, 546. [\[CrossRef\]](#)
59. Fang, H. Impact of Land Use Change and Dam Construction on Soil Erosion and Sediment Yield in the Black Soil Region, Northeastern China. *Land Degrad. Dev.* **2017**, *28*, 1482–1492. [\[CrossRef\]](#)
60. Peng, M.; Tan, L.; Li, H.; Wu, J.; Ma, T.; Xu, H.; Xu, J.; Zhao, W.; Hao, J. Energy Transitions in Yunnan Province Based on Production Function Theory. *Energies* **2023**, *16*, 7299. [\[CrossRef\]](#)
61. Shidong, L.; Moucheng, L. The Development Process, Current Situation and Prospects of the Conversion of Farmland to Forests and Grasses Project in China. *J. Resour. Ecol.* **2022**, *13*, 120–128. [\[CrossRef\]](#)
62. Wang, W.; Cui, C.; Yu, W.; Lu, L. Response of Drought Index to Land Use Types in the Loess Plateau of Shaanxi, China. *Sci. Rep.* **2022**, *12*, 8668. [\[CrossRef\]](#) [\[PubMed\]](#)
63. Gao, Y.; Yang, P. Temporal and Spatial Distribution of Soil Water Repellency in Grassland Soils and Its Relation to Soil Moisture, Hydrophobic Matter, and Particle Size. *Sci. Total Environ.* **2023**, *904*, 166700. [\[CrossRef\]](#)
64. Li, Z.; Wei, J.; Hao, R. The Constraint Effect of Grassland Vegetation on Soil Wind Erosion in Xilin Gol of China. *Ecol. Indic.* **2023**, *155*, 111006. [\[CrossRef\]](#)
65. Yang, S.; Luo, D.; Han, H.; Jin, Z. Soil Erosion Differences in Paired Grassland and Forestland Catchments on the Chinese Loess Plateau. *J. Mt. Sci.* **2023**, *20*, 1336–1348. [\[CrossRef\]](#)
66. Tonolli, A.; Pisciotto, A.; Scalenghe, R.; Gristina, L. From Grapes to Getaways: Unraveling the Residential Tourism Impact on Land Use Change and Soil Erosion Processes in Menfi District. *Land Use Policy* **2024**, *137*, 107013. [\[CrossRef\]](#)
67. Zhang, Y.; Zhang, P.; Liu, Z.; Xing, G.; Chen, Z.; Chang, Y.; Wang, Q. Dynamic Analysis of Soil Erosion in the Affected Area of the Lower Yellow River Based on RUSLE Model. *Heliyon* **2024**, *10*, e23819. [\[CrossRef\]](#) [\[PubMed\]](#)
68. Polykretis, C.; Grillakis, M.G.; Manoudakis, S.; Seiradakis, K.D.; Alexakis, D.D. Spatial Variability of Water-Induced Soil Erosion under Climate Change and Land Use/Cover Dynamics: From Assessing the Past to Foreseeing the Future in the Mediterranean Island of Crete. *Geomorphology* **2023**, *439*, 108859. [\[CrossRef\]](#)
69. Wolde, B.; Moges, A.; Grima, R. Assessment of the Combined Effects of Land Use/Land Cover and Climate Change on Soil Erosion in the Sile Watershed, Ethiopian Rift Valley Lakes Basin. *Cogent Food Agric.* **2023**, *9*, 2273630. [\[CrossRef\]](#)
70. Zhou, Y.; Yi, Y.; Liu, H.; Tang, C.; Zhang, S. Spatiotemporal Dynamic of Soil Erosion and the Key Factors Impact Processes over Semi-Arid Catchments in Southwest China. *Ecol. Eng.* **2024**, *201*, 107217. [\[CrossRef\]](#)
71. Minervino Amodio, A.; Gioia, D.; Danese, M.; Masini, N.; Sabia, C.A. Land-Use Change Effects on Soil Erosion: The Case of Roman “Via Herculia” (Southern Italy)—Combining Historical Maps, Aerial Images and Soil Erosion Model. *Sustainability* **2023**, *15*, 9479. [\[CrossRef\]](#)
72. Srejić, T.; Manojlović, S.; Sibinović, M.; Bajat, B.; Novković, I.; Milošević, M.V.; Carević, I.; Todosijević, M.; Sedlak, M.G. Agricultural Land Use Changes as a Driving Force of Soil Erosion in the Velika Morava River Basin, Serbia. *Agriculture* **2023**, *13*, 778. [\[CrossRef\]](#)
73. Mungkung, R.; Pengthamkeerati, P.; Chaichana, R.; Watcharothai, S.; Kitpakornsanti, K.; Tapananont, S. Life Cycle Assessment of Thai Organic Hom Mali Rice to Evaluate the Climate Change, Water Use and Biodiversity Impacts. *J. Clean. Prod.* **2019**, *211*, 687–694. [\[CrossRef\]](#)
74. Munir, B.A.; Ahmad, S.R.; Rehan, R. Torrential Flood Water Management: Rainwater Harvesting through Relation Based Dam Suitability Analysis and Quantification of Erosion Potential. *ISPRS Int. J. Geo-Inf.* **2021**, *10*, 27. [\[CrossRef\]](#)
75. Salem, H.M.; Valero, C.; Muñoz, M.Á.; Gil-Rodríguez, M.; Barreiro, P. Effect of Reservoir Tillage on Rainwater Harvesting and Soil Erosion Control under a Developed Rainfall Simulator. *CATENA* **2014**, *113*, 353–362. [\[CrossRef\]](#)
76. Deng, X.; Yu, W.; Shi, J.; Huang, Y.; Li, D.; He, X.; Zhou, W.; Xie, Z. Characteristics of Surface Urban Heat Islands in Global Cities of Different Scales: Trends and Drivers. *Sustain. Cities Soc.* **2024**, *107*, 105483. [\[CrossRef\]](#)
77. Donthu, E.V.S.K.K.; Kyriakodis, G.-E.; Zhang, X.; Long, Y.P.; Wan, M.P.; Bozonnet, E. Simulation Advances with EnviBatE—A Case Study on Urban Heat Island Mitigation in Singapore. *Build. Environ.* **2024**, *258*, 111580. [\[CrossRef\]](#)
78. Ding, G.; Guo, J.; Ou, M.; Prishchepov, A.V. Understanding Habitat Isolation in the Context of Construction Land Expansion Using an Ecological Network Approach. *Landsc. Ecol.* **2024**, *39*, 56. [\[CrossRef\]](#)
79. Kang, L.; Ma, L.; Liu, Y. Comparing the Driving Mechanisms of Different Types of Urban Construction Land Expansion: A Case Study of the Beijing-Tianjin-Hebei Region. *J. Geogr. Sci.* **2024**, *34*, 722–744. [\[CrossRef\]](#)
80. Zhou, B.; Hu, X.; Xiong, C. Differential Influences of High-Speed Railway Stations on the Surrounding Construction Land Expansion and Institutional Analysis: The Case of Taiwan and Hainan. *Land* **2023**, *13*, 10. [\[CrossRef\]](#)
81. Li, S.; Li, Y.; Shi, J.; Zhao, T.; Yang, J. Optimizing the Formulation of External-Soil Spray Seeding with Sludge Using the Orthogonal Test Method for Slope Ecological Protection. *Ecol. Eng.* **2017**, *102*, 527–535. [\[CrossRef\]](#)

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