

Article

The Spatiotemporal Evolution, Driving Mechanisms, and Future Climate Scenario-Based Projection of Soil Erosion in the Southwest China

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Abstract

Soil erosion is a significant environmental challenge in Southwest China, influencing regional ecological security and sustainability. This study investigates the spatiotemporal evolution, driving mechanisms, and future projections of soil erosion in Southwest China, with a focus on the period from 2000 to 2023. The RUSLE model was used to analyze the spatiotemporal variation of soil erosion intensity over the 23-year period in Southwest China. The XGBoost and SHAP models were then employed to identify and interpret the driving factors behind soil erosion. These models revealed that precipitation, temperature, vegetation cover, and land use change were the primary drivers of soil erosion in the region. Finally, future soil erosion risks were projected for 2030, 2040, and 2050 under three climate scenarios (SSP119, SSP245, and SSP585) based on the CMIP6 climate model. The results suggest that (1) the analysis of soil erosion in Southwest China from 2000 to 2023 reveals a significant decline in soil erosion intensity, with a 58.16% reduction in average erosion intensity, from 4.23 t·ha⁻¹·yr⁻¹ in 2000 to 1.77 t·ha⁻¹·yr⁻¹ in 2020. The spatial distribution of erosion in 2023 showed that 90.9% of the region experienced slight erosion, with only 4.56% of the area facing moderate to severe erosion. (2) Natural factors, particularly elevation and precipitation, are the primary drivers of soil erosion. Regions with higher elevations and greater precipitation are more susceptible to soil erosion, particularly on steep slopes with shallow soil layers. Human activities, including GDP growth, land use patterns, and population density, also significantly influence soil erosion dynamics, with higher GDP levels and increased urbanization correlating with elevated erosion risks. The interaction between natural and socioeconomic factors demonstrates a complex relationship in soil erosion processes. (3) By 2050, soil erosion intensity in southwestern China is projected to increase overall, with the most significant increase occurring under the SSP585 scenario. The spatial distribution of soil erosion will largely maintain current patterns, with high-erosion areas concentrated in the northwest and low-erosion areas in the southeast. Areas experiencing mild erosion are expected to decrease, while moderately eroded regions will expand. Projection results suggest that increased precipitation and extreme weather events will lead to the most severe soil erosion in high-altitude regions, particularly in western Sichuan. Our historical assessments and future forecasts suggest vegetation conservation, rainfall monitoring, and restoration of western Sichuan in southwest China are critical for future erosion control and regional ecological security in southwest China.



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Keywords: the southwest China; soil erosion; RUSLE model; XGBoost; CMIP6

1. Introduction

Soil erosion is a geomorphic process that detaches soil particles, rock fragments, soil aggregates, and organic matter from its primary location and then transports these to another location by various processes. As one of the most widespread forms of land degradation globally, soil erosion leads to a decline in soil fertility, increased sedimentation in rivers and reservoirs, and serious threats to food security and ecosystem stability [1,2]. In Southwest China, soil erosion, particularly water erosion, is a critical environmental issue, influenced by complex interactions between topography, land use, climate, and vegetation cover [3–6]. The temporal and spatial heterogeneity of precipitation and vegetation leads to significant intra-annual variation in soil erosion, yet most current studies have focused on long-term or annual erosion estimates, overlooking the seasonal dynamics that are crucial for understanding short-term erosion risks [7,8]. Although the Revised Universal Soil Loss Equation (RUSLE) has been widely applied for soil erosion assessment in water erosion-dominated areas [9,10], key factors such as rainfall erosivity (R) and cover-management (C) are often treated as static or annual values, failing to capture intra-annual variability [11,12]. Given that both precipitation and vegetation are temporally dynamic and are the primary drivers of seasonal erosion patterns [13–15], it is essential to assess their combined effects at finer temporal resolutions. Therefore, investigating the intra-annual spatiotemporal evolution of soil erosion and its driving mechanisms is of great importance for revealing high-risk erosion periods and optimizing seasonal soil and water conservation strategies.

A great deal of previous research into soil erosion has focused on identifying its spatial and temporal dynamics across different landscapes and climatic regions [1]. While early studies primarily addressed long-term trends and annual-scale patterns [16,17], more recent research has shifted toward uncovering finer-scale variations, including seasonal and event-based fluctuations driven by changes in rainfall regimes, vegetation cycles, and land use patterns [18]. The integration of high-resolution satellite data, such as NDVI time series and radar-based rainfall estimates, has improved erosion monitoring capabilities, particularly in complex terrain [19]. Nevertheless, erosion events triggered by extreme weather, short-term land disturbances, and subsurface processes remain insufficiently captured [20,21]. In fragmented and ecologically sensitive landscapes, terrain heterogeneity and human-induced pressures such as road construction, agricultural encroachment, and deforestation significantly complicate modeling efforts [22,23]. Furthermore, soil erosion assessments often overlook interactions among natural and human systems, such as feedback loops between vegetation degradation, soil sealing, and runoff generation. Addressing these limitations calls for process-based frameworks capable of integrating surface and subsurface hydrology, land use trajectories, and vegetation succession dynamics [24,25].

Recent advancements in soil erosion prediction have prioritized the integration of climate scenarios and high-resolution modeling frameworks to address future environmental challenges. The transition from CMIP5 to CMIP6 scenarios marks a pivotal shift, with the latter significantly improving the representation of extreme precipitation events and monsoon variability—critical drivers of erosion in subtropical regions like Yunnan [26,27]. For instance, CMIP6-based projections under SSP585 predict a 20–35% increase in rainfall erosivity (R-factor) across Yunnan’s karst basins by 2100, exacerbating sediment yields in ecologically fragile zones such as the Wumeng Mountains [28,29]. Hybrid approaches coupling RUSLE with machine learning algorithms (e.g., XGBoost) have enhanced predictive accuracy by identifying nonlinear thresholds, such as erosion surges when monsoon rainfall

exceeds $60 \text{ mm} \cdot \text{d}^{-1}$, while incorporating land-use transition probabilities derived from agent-based simulations [23,26]. Yunnan, the integration of CMIP6 outputs with the Chinese Soil Loss Equation (CSLE), has enabled spatially explicit risk mapping, revealing that intensified agricultural practices could elevate erosion rates by 15–25% in arable hotspots despite conservation measures [19,30]. However, critical gaps persist: current models inadequately resolve subsurface hydrology in karst systems, where fissure-dominated runoff redirects 30–40% of surface water to underground pathways, decoupling erosion from traditional RUSLE parameters.

Soil erosion in Southwest China has been a key focus of research due to the region's complex topography, diverse ecosystems, and significant human impacts. Studies have shown that soil erosion is highly variable across different landscapes, including the karst regions of Guizhou, the mountainous areas of Sichuan, and the fertile plateaus of Yunnan [31]. The spatial distribution of rainfall erosive force across Southwest China from 1960 to 2012 was explored, highlighting the seasonal dynamics of soil erosion in various watersheds [30]. In addition, the CSLE model was employed to assess soil erosion in the region, finding that land use changes, particularly in arable areas, significantly altered erosion patterns [32]. Empirical orthogonal function analysis and the Mann–Kendall test were used to analyze rainfall erosivity in Southwest China over the past 50 years, and the effectiveness of soil conservation practices was assessed using remote sensing data [30,33]. The role of human activities, such as deforestation and agricultural intensification, in exacerbating soil erosion, particularly in the karst landscapes of Guizhou and the steep slopes of Sichuan, was further identified [23,34]. While much of the focus has been on long-term trends, there is an increasing emphasis on examining intra-annual variations, especially in relation to seasonal precipitation and vegetation cycles, which drive short-term erosion risks [7,11]. This body of research underscores the need for more detailed, spatially and temporally refined analyses to guide effective soil and water conservation strategies in Southwest China.

However, few studies have explicitly addressed these challenges within Southwest China's diverse karst landscape. This study aims to fill these gaps by (1) incorporating temporally dynamic factors, especially the intra-annual variability of R and C ; (2) analyzing the driving forces of soil erosion patterns through advanced machine learning techniques (XGBoost) to better capture natural-human system interactions; and (3) integrating multiple climate scenarios (SSP119, SSP245, SSP585) to project future soil erosion trends under changing climate conditions. By combining the Revised Universal Soil Loss Equation (RUSLE) with machine learning and climate projections, this research offers a novel multi-method framework to comprehensively assess the spatiotemporal dynamics of soil erosion and its driving mechanisms in Southwest China. The findings provide scientific support for improved soil conservation strategies tailored to this ecologically sensitive and climatically variable region.

2. Materials and Methods

2.1. Study Area

The Southwest China is situated in the interior of southwestern China ($21^{\circ}8' - 34^{\circ}19' \text{ N}$, $97^{\circ}21' - 110^{\circ}12' \text{ E}$), encompassing Sichuan Province, Yunnan Province, Guizhou Province, and Chongqing Municipality, with a total area of approximately 1.1455 million square kilometers. The region spans the first and second tiers of China's terrain, featuring a significant elevation gradient and a topography that descends from west to east. It is characterized by diverse landforms, predominantly composed of mountains and hills, with an average elevation exceeding 4000 m. The region experiences a subtropical monsoon climate, characterized by hot and rainy summers and dry winters with limited precipitation. The annual

average precipitation is approximately 1100 mm, with the majority occurring between May and October. As China's second-largest natural forest area, land use in Southwest China is primarily dominated by forest land, followed by cropland and grassland. The region features tropical and subtropical vegetation types, including grasslands, meadows, alpine vegetation, shrublands, coniferous forests, wetlands, broad-leaved forests, cultivated vegetation, and herbaceous cover (Figure 1).

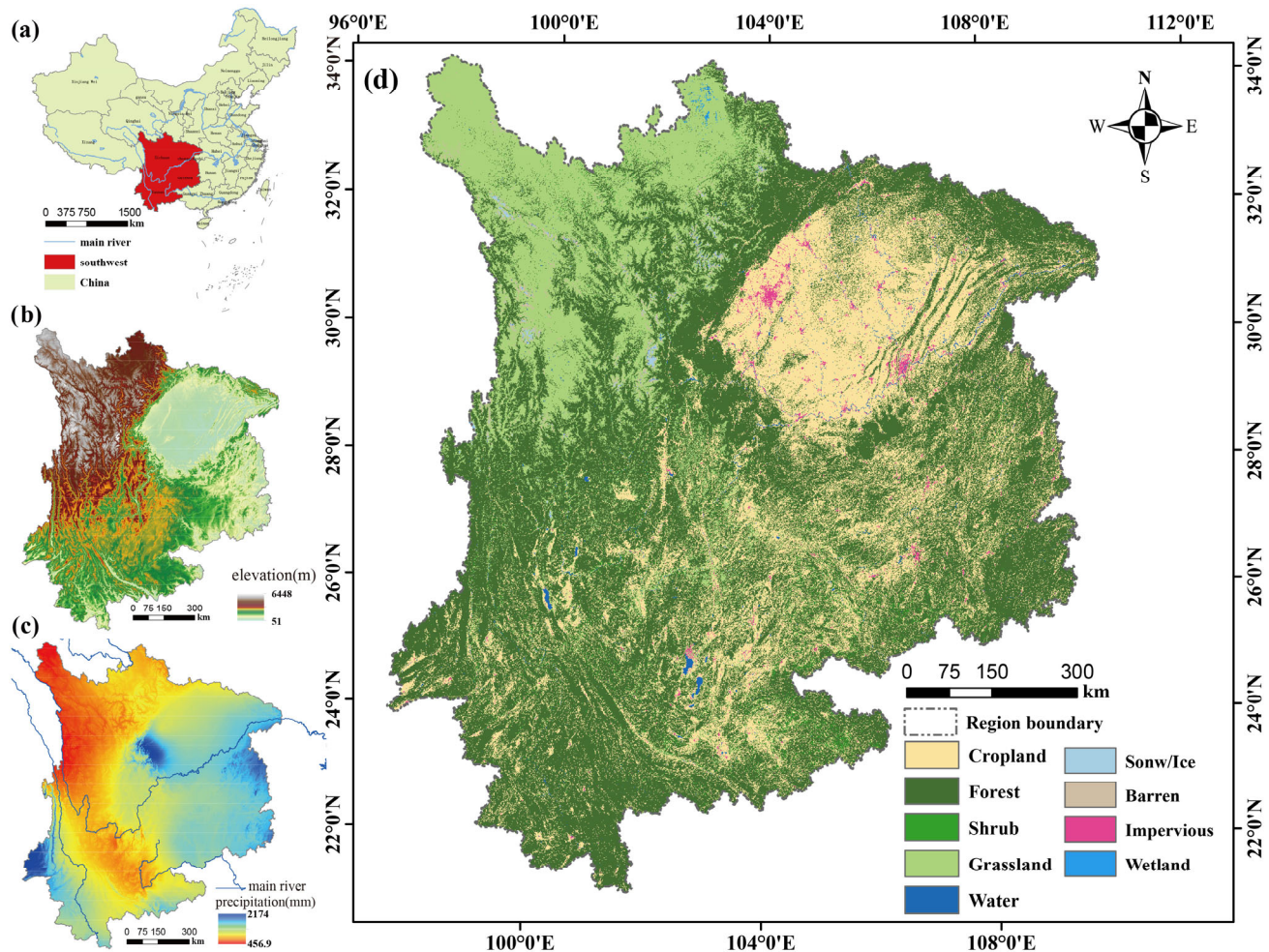


Figure 1. Geographical location (a) and elevation pattern (b), precipitation (c), and land use of the Southwest China (d).

2.2. Database

This study utilized multi-source environmental and socio-economic datasets with varying spatial resolutions to assess and predict soil erosion patterns in Southwest China. Precipitation and soil data with a spatial resolution of 1000 m and a scale of 1:1 million, respectively, were obtained from the National Earth System Science Data Center. Potential evapotranspiration (PET) and average monthly temperature data, both at 1000 m resolution, were sourced from CASEarth and the National Tibetan Plateau Data Center. Land use data with a resolution of 30 m were acquired from the In Earth System Science Data repository, while digital elevation model (DEM) data at 30 m resolution were derived from the Geospatial Data Cloud Platform. NDVI, GDP, and population datasets, all with a spatial resolution of 1000 m, were obtained from relevant national data platforms. Future climate scenario data, including three Shared Socioeconomic Pathways (SSP199, SSP245, and SSP585), were extracted from CMIP6 climate models, enabling the simulation of future rainfall erosivity (R factor) under different emission trajectories. All datasets were projected

to WGS_1984_UTM_Zone_48N and resampled to a uniform spatial resolution of 1000 m to ensure consistency in subsequent analyses, as shown in Table 1.

Table 1. Data and data sources.

Data	Resolution	Data Source
Precipitation [35]	1000 m	National Earth System Science Data Center, National Science & Technology Infrastructure of China (http://www.geodata.cn) (accessed on 19 March 2025).
Potential evapotranspiration (PET) [36]	1000 m	CASEarth: Big Earth Data for Three Poles (https://portal.casearth.cn › poles) (accessed on 19 March 2025).
Average monthly temperature (TMP) [35]	1000 m	National Earth System Science Data Center, National Science & Technology Infrastructure of China (http://www.geodata.cn) (accessed on 19 March 2025).
Soil data	1:1 million	National Earth System Science Data Center
Land use	30 m	In Earth System Science Data (https://zenodo.org/records/12779975) (accessed on 19 March 2025).
DEM	30 m	Geospatial Data Cloud Platform (http://www.resdc.cn/DOI ,
NDVI	1000 m	https://doi.org/10.12078/2018060601) (accessed on 19 March 2025).
GDP	1000 m	(http://www.resdc.cn/DOI ,
Population	1000 m	https://doi.org/10.12078/2017121102) (accessed on 19 March 2025).
CMIP6 [37–39]	1000 m	National Tibetan Plateau/Third Pole Environment Data Center (https://data.tpdc.ac.cn/zh-hans/data/f3b17306-fd3e-423c-9084-83c41f9072c0) (accessed on 19 March 2025).

2.3. Methodology

2.3.1. Soil Erosion Assessment

This study employed the Revised Universal Soil Loss Equation (RUSLE) [40,41]. This model, developed by the United States Department of Agriculture (USDA) in 1997, was built upon the original Universal Soil Loss Equation (USLE), and is as follows:

$$A = R \times K \times L \times S \times C \times P$$

where A is the soil erosion modulus ($\text{t}\cdot\text{ha}^{-1}\cdot\text{yr}^{-1}$), R is the rainfall erosivity factor ($\text{MJ}\cdot\text{mm}\cdot(\text{ha}\cdot\text{h}\cdot\text{yr})^{-1}$), K is the soil erodibility factor ($\text{t}\cdot\text{ha}\cdot\text{h}\cdot(\text{ha}\cdot\text{MJ}\cdot\text{mm})^{-1}$), L is the slope length factor, S is the slope gradient factor, C is the vegetation cover factor, and P is the soil and water conservation measures factor. L , S , C , and P are dimensionless [42].

(1) Rainfall erosivity factor (R)

Rainfall impacts the ground, leading to topsoil loss and soil erosion. High-intensity and frequent rainfall significantly increases the soil erosion risk, acting as a key driver of water-induced erosion. In this study, the rainfall erosivity factor was calculated using the empirical formula proposed by Wischmeier and modified by Arnoldus [43,44]. To improve

the accuracy, the rainfall data were adjusted by averaging the precipitation from the two years before and after the study period. The formula used is shown below:

$$R = \sum_{i=1}^{12} 1.735 \times 10^{[1.5 \times \log(\frac{P_i^2}{P}) - 0.8188]} = \sum_{i=1}^{12} 0.2633 \times 31.6228 \log(\frac{P_i^2}{P})$$

where R is the rainfall erosivity factor, and P_i and P are the average monthly and annual rainfall (mm), respectively.

(2) Soil erodibility factor (K)

K represents the soil's susceptibility to erosion by external forces. It reflects how easily the soil can be eroded, depending on its physical and chemical properties. In this study, the soil texture and organic carbon data were extracted from the study area. K was calculated using the formula proposed by Williams [45,46], as shown below:

$$K = \left\{ 0.2 + 0.3e^{[-0.0256S_d(1-\frac{S_p}{100})]} \right\} \times \left(\frac{S_p}{S_c + S_p} \right)^{0.3} \times \left[1 - \frac{0.25C}{S_n + e^{(-5.51229S_n)}} \right] \times 0.1317$$

where: S_d means sand content (%), S_p means silt content (%), S_c means clay content (%), C means organic carbon content (%), S_n means $1 - (S_d / 100)$.

(3) Slope length and slope steepness factor (LS)

L indicates the slope length from the top to the bottom. A longer slope allows for more water to accumulate, which increases the potential for erosion and leads to a higher soil loss. In this study, the calculation method for the slope length factor was adopted from Renard [47,48], where the formula used is as follows:

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

$$m = \frac{\beta}{1 + \beta}$$

$$\beta = \frac{\sin \theta / 0.0896}{3(\sin \theta)^{0.8} + 0.56}$$

where λ is the slope length, m is the slope length index, and θ is the slope ($^\circ$).

S plays a critical role in evaluating how the topography influences soil erosion. Steeper slopes lead to faster surface runoff, which increases the kinetic energy of flowing water, thereby intensifying soil erosion. In this study, the slope factor was derived from slope data extracted from the DEM. The slope factor calculation followed the methods provided by McCool [49] and Liu [50], where the formula used is as follows:

$$S = \begin{cases} 10.8 \sin \theta + 0.03 & \theta < 5^\circ \\ 16.8 \sin \theta - 0.5 & 5^\circ \leq \theta < 10^\circ \\ 21.91 \sin \theta - 0.96 & \theta > 10^\circ \end{cases}$$

where S is the slope factor and θ is the slope ($^\circ$).

(4) Vegetation cover factor (C)

C assesses how effectively different types and densities of vegetation reduce soil erosion. Its value ranges from 0 to 1, where a lower C value indicates denser vegetation, which reduces surface runoff, weakens erosive forces, and helps retain soil particles. In

this study, the method proposed by Cai [51] was adjusted to better suit the geographic conditions. The vegetation cover factor was then calculated using the following formula:

$$C = \begin{cases} 1 & f_{vc} \leq 10\% \\ 0.6508 - 0.3436 \lg f_{vc} & 10\% < f_{vc} \leq 85\% \\ 0 & f_{vc} > 85\% \end{cases}$$

$$f_{vc} = \frac{NDVI - NDVI_{soil}}{NDVI_{veg} - NDVI_{soil}}$$

where: f_{vc} means fractional vegetation cover, $NDVI_{soil}$ means NDVI value for bare soil, $NDVI_{veg}$ means NDVI value for full vegetation cover.

(5) Soil and water conservation practices factor (P)

P represents the effectiveness of various soil and water conservation practices, such as terraces, protective forest belts, and grass–shrub mulch, in preventing soil erosion. P values range from 0 to 1, where 0 indicates no soil erosion risk and 1 suggests that no conservation measures have been implemented, increasing the likelihood of erosion [52–54]. The vegetation cover is sparse and there are significant variations in slope. Therefore, in this study, the cultivated land was further classified by the slope gradient (Table 2).

Table 2. p values for different land-use types.

Land Use Type	Cropland	Forest	Shrubland	Grassland	Water	Bare Land	Built-Up Area
p value	0.6	0.3	0.5	0.4	0	1	0.8

According to the Soil Erosion Classification and Grading Standard (SL190-2008), The soil erosion intensity was classified into 6 categories: slight ($0\text{--}2 \text{ t}\cdot\text{ha}^{-1}\cdot\text{yr}^{-1}$), mild ($2\text{--}25 \text{ t}\cdot\text{ha}^{-1}\cdot\text{yr}^{-1}$), moderate ($25\text{--}50 \text{ t}\cdot\text{ha}^{-1}\cdot\text{yr}^{-1}$), strong ($50\text{--}80 \text{ t}\cdot\text{ha}^{-1}\cdot\text{yr}^{-1}$), extremely strong ($80\text{--}150 \text{ t}\cdot\text{ha}^{-1}\cdot\text{yr}^{-1}$), and severe ($>150 \text{ t}\cdot\text{ha}^{-1}\cdot\text{yr}^{-1}$). In this study, the soil erosion data for the years 2000, 2005, 2010, 2015, and 2020 were estimated using the 5-year moving average centered on each target year. For example, the 2000 soil erosion value was calculated as the average of annual values from 1998 to 2002. The same method was applied for 2005 (2003–2007), 2010 (2008–2012), 2015 (2013–2017), and 2020 (2018–2022). For the year 2023, the soil erosion value was derived directly from the data of that specific year.

2.3.2. XGBoost and SHAP Models

XGBoost (eXtreme Gradient Boosting) is an ensemble learning algorithm based on gradient-boosted decision trees (GBDT), which enhances predictive performance through iterative training of multiple decision trees [55]. The core concept involves utilizing the residuals from the preceding tree to train the subsequent tree, ultimately aggregating the predictions of all trees through weighted summation. In contrast to traditional GBDT, XGBoost incorporates regularization terms (such as L2 regularization) to control model complexity and supports parallel computation, rendering it particularly effective for modeling structured data [56]. This study employs the XGBoost algorithm to construct a soil erosion prediction model and utilizes SHAP (SHapley Additive exPlanations) analysis to quantify the contributions of driving factors. The objective function of XGBoost is formulated as:

$$L^{(t)} = \sum_{i=1}^n l\left(y_i, y_i^{(t-1)} + f_t(x_i)\right) + \Omega(f_t)$$

The regularization term $\Omega f(t)$ is defined as:

$$\Omega(f_t) = \gamma T + \frac{1}{2} \lambda \sum_{j=1}^T w_j^2$$

where $L(t)$ denotes the loss function of the model after the t -th iteration, l represents the individual loss function, y_i is the true value of the i -th sample, $\hat{y}_i$ is the predicted value of the i -th sample from the previous $t - 1$ trees, and $\hat{y}_i^t$ denotes the prediction of the t -th tree for the i -th sample, where x_i is the feature vector of the i -th sample. n represents the total number of training samples.

SHAP is grounded in the Shapley value from game theory and decomposes model predictions into the contribution values of individual features [57]. For a given sample x , the SHAP value for a feature is defined as:

$$\phi_i = \sum_{S \in F \setminus \{i\}} \frac{|S|!(|F| - |S| - 1)!}{|F|!} \left(f_{S \cup \{i\}}(x_{S \cup \{i\}}) - f_S(x_S) \right)$$

where ϕ_i represents the SHAP value of feature i , F is the set of all features used by the model, S denotes any subset of features in F that does not include feature i , $|F|$ is the total number of features in the set F , $|S|$ is the number of features in the subset S , $f_{S \cup \{i\}}$ is the model's prediction output on the feature subset $S \cup \{i\}$, f_S is the model's prediction output on the subset S that excludes feature i , and $x_{S \cup \{i\}}$, x_S represent the input feature values corresponding to subsets $S \cup \{i\}$ and S , respectively. In this study, the driving factors include precipitation, potential evapotranspiration, temperature, DEM, slope, GDP, population, cropland, and building, as they collectively influence soil erosion dynamics and ecosystem functioning in the southwestern region.

2.3.3. Statistics

Since the temporal dynamics of soil physical properties and topographic features over the next 30 years are negligible, this study focuses on the key roles of the rainfall erosivity factor (R) and vegetation cover management factor (C), while assuming that the soil conservation measures factor (P) remains constant. The R factor is derived from the Coupled Model Intercomparison Project Phase 6 (CMIP6), which provides multi-scenario predictive data, including SSP119, SSP245, and SSP585. The C factor is derived from Hateffard's research [58] and is estimated using the mean value of inter-annual variations between 2000 and 2023. By multiplying the dynamically predicted R and C factors with the constant values assumed for other factors, a predictive model for soil erosion intensity under future climate change scenarios is developed.

3. Results

3.1. Spatiotemporal Variation in Soil Erosion Forcing Factors

Figure 2a illustrates the spatial distribution of rainfall erosivity (R) across Southwest China in 2023. The average R value for the region is $2173.98 \text{ MJ} \cdot \text{mm} \cdot (\text{ha} \cdot \text{h} \cdot \text{yr})^{-1}$, with significant spatial heterogeneity observed. A distinct southeast-to-northwest decreasing trend is evident, where the highest R values are located in the southwestern region, particularly within the southern Hengduan Mountains. This area experiences intense precipitation combined with steep terrain, resulting in increased runoff and erosive potential. The maximum R value in this region reaches $4212.83 \text{ MJ} \cdot \text{mm} \cdot (\text{ha} \cdot \text{h} \cdot \text{yr})^{-1}$. In contrast, the northwestern zone, situated in the upper reaches of the Nujiang and Jinsha Rivers, is more inland and less influenced by monsoonal activity, leading to reduced precipitation and weaker rainfall intensity, with the minimum R value recorded at $566.617 \text{ MJ} \cdot \text{mm} \cdot (\text{ha} \cdot \text{h} \cdot \text{yr})^{-1}$. In the

transitional zone between the Yunnan-Guizhou Plateau and the Sichuan Basin, rainfall erosivity exhibits a decreasing pattern influenced by topographic variations. Figure 2b presents the spatial distribution of the soil erodibility factor (K), which ranges from 0.0033 to $0.0225 \text{ t} \cdot \text{ha} \cdot \text{h} \cdot (\text{ha} \cdot \text{MJ} \cdot \text{mm})^{-1}$. Areas surrounding the Sichuan Basin and parts of western Diqing Prefecture exhibit higher K values, indicating more erodible soil compositions. Conversely, lower K values are predominantly distributed across the Yunnan-Guizhou Plateau and the southern section of the Hengduan Mountains, suggesting these areas possess relatively more erosion-resistant soil types. Figure 2c shows the slope length and steepness factor (LS), derived from DEM analysis, which ranges from 0.12 to 10.76, with a regional mean of 2.75. Spatially, LS values are higher in the northwest and progressively decrease toward the southeast. This pattern corresponds with the mountainous terrain of the northern Hengduan region, where steep and extended slopes significantly increase the LS factor. In contrast, flatter areas such as the Sichuan Basin and Yunnan-Guizhou Plateau exhibit lower LS values. Overall, the distribution of LS reflects the topographic gradients captured in the DEM. Figure 2d illustrates the distribution of the cover-management factor (C). The average value across the study area is approximately 0.07, with approximately 90% of the region exhibiting a C value close to zero, indicating dense vegetation coverage and strong erosion resistance. However, localized areas of higher C values are observed in the central-northern and northern sub-regions, where sparse vegetation cover suggests greater erosion susceptibility. Figure 2e presents the support practice factor (P). The spatial distribution of P demonstrates relatively high values in the east, gradually decreasing toward the west. The mean p value is approximately 0.4, reflecting generally effective implementation of soil conservation measures. Nevertheless, elevated p values are particularly pronounced in eastern regions, such as the Sichuan Basin, suggesting extensive conservation efforts. In contrast, lower values in the Hengduan Mountains highlight the need for enhanced erosion control infrastructure in these high-risk mountainous areas.

3.2. Spatiotemporal Variation in Soil Erosion

3.2.1. Spatial Distribution of Soil Erosion

The soil erosion modulus was classified according to the Soil Erosion Classification and Grading Standards (SL190-2007), and the results are presented in Figure 3. The soil erosion moduli for Southwest China in 2000, 2005, 2010, 2015, 2020, and 2023 were 4.23, 3.18, 2.99, 2.9, 1.77 $\text{t} \cdot \text{ha}^{-1} \cdot \text{yr}^{-1}$, and 2.5 $\text{t} \cdot \text{ha}^{-1} \cdot \text{yr}^{-1}$, respectively, indicating a declining trend in soil loss.

The study revealed that the spatial distribution of soil erosion intensity in South-west China was highly significant, generally exhibiting a pattern of “higher in the northwest and lower in the southeast.” Using the spatial distribution of the soil erosion modulus in 2023 (Figure 3f) as an example, slight erosion areas accounted for 90.9% of the total study area, primarily located in the eastern and western regions of the Yunnan-Guizhou Plateau. Light erosion areas covered 4.54%, scattered throughout the region with a concentration in the Sichuan Basin. Moderate erosion areas comprised 3.84%, predominantly clustered in the northwestern part of the region near the Nujiang-Lancangjiang River basin. Severe and more intense erosion areas constituted only 0.72%, mainly occurring in the mountainous regions along the western edge of the Sichuan Basin.

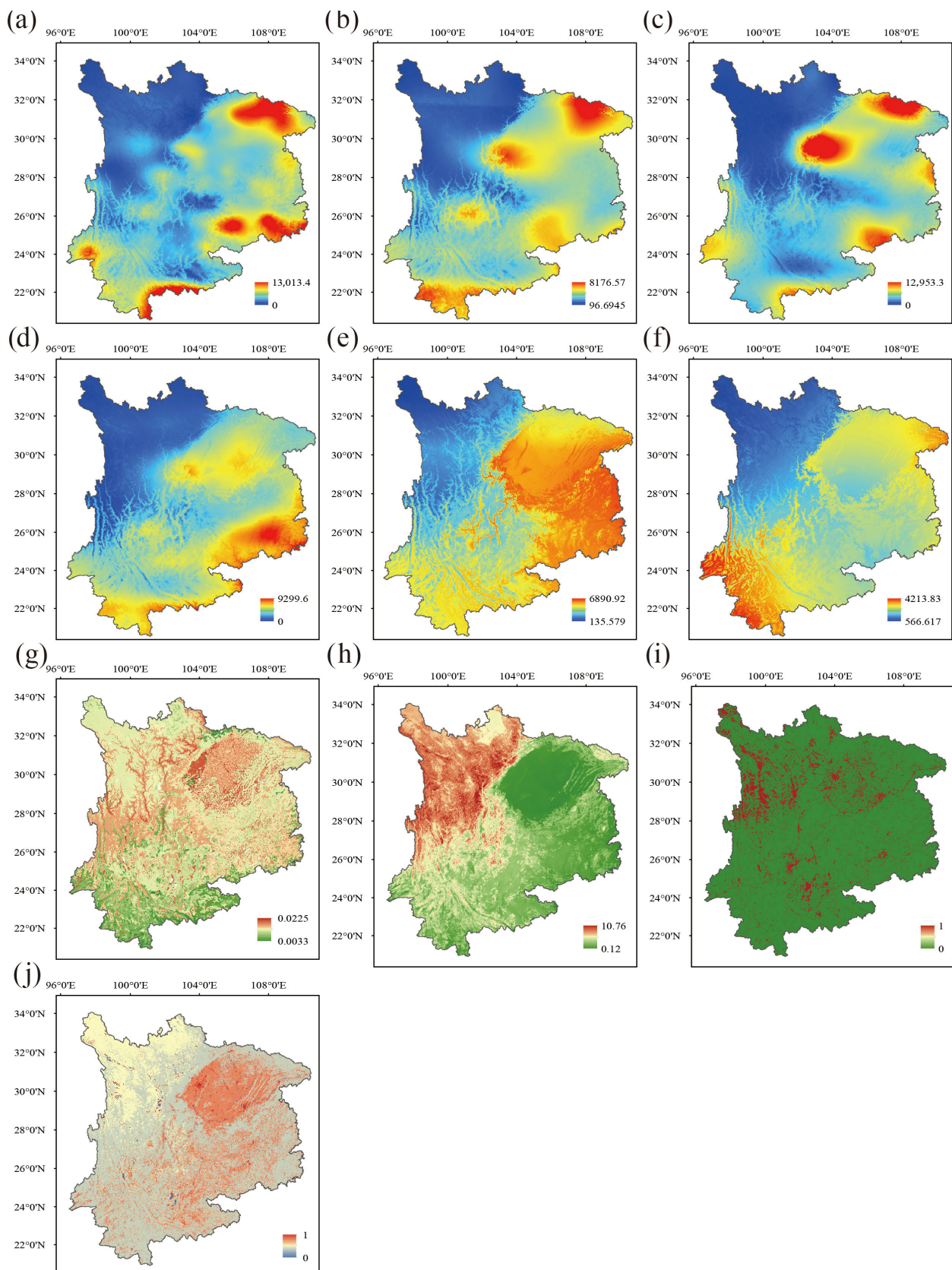


Figure 2. Temporal and spatial distribution of each RUSLE factor: (a) Rainfall erosivity factor (R) in 2000, (b) R in 2005, (c) R in 2010, (d) R in 2015, (e) R in 2020, (f) R in 2023, (g) soil erodibility factor (K), (h) slope length and steepness factor (LS), (i) vegetation cover factor (C), (j) soil and water conservation measures factor (P).

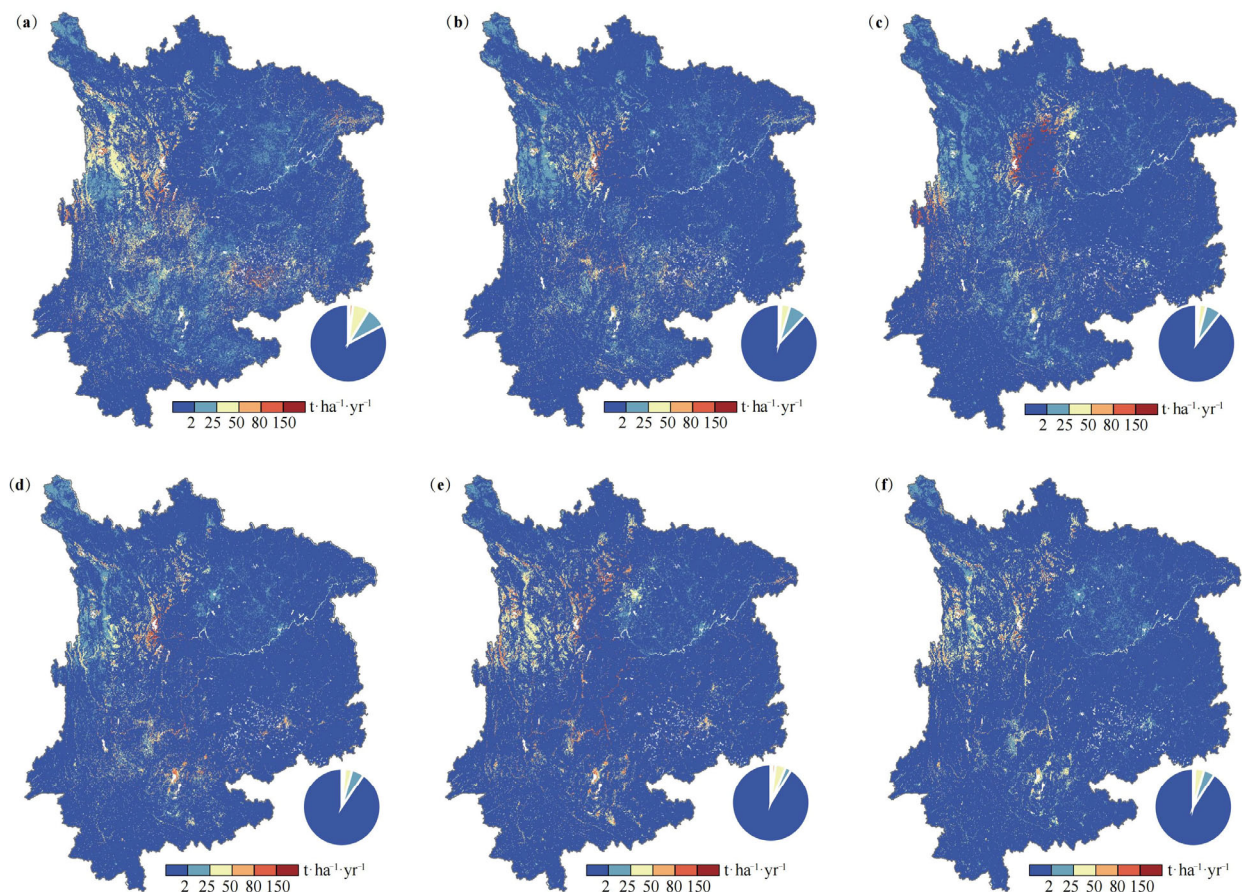


Figure 3. Spatial distribution map of soil erosion: (a) 2000, (b) 2005, (c) 2010, (d) 2015, (e) 2020, (f) 2023.

In 2000, strong soil erosion was observed in the northwest (Nujiang-Lancangjiang River basin) and the southeast (Beipan River basin). Anshun City in the southeast exhibited an average soil erosion intensity of $13.62 \text{ t} \cdot \text{ha}^{-1} \cdot \text{yr}^{-1}$, contrasting sharply with surrounding areas. The northeastern region was primarily characterized by slight and moderate erosion. From 2005 to 2020, the core area of soil erosion shifted to the mountainous regions on the western edge of the Sichuan Basin. In 2010, the average soil erosion intensity in Chengdu and Ya'an reached $9.55 \text{ t} \cdot \text{ha}^{-1} \cdot \text{yr}^{-1}$ and $8.22 \text{ t} \cdot \text{ha}^{-1} \cdot \text{yr}^{-1}$, respectively. By 2023, the overall erosion intensity in Southwest China exhibited a decelerating trend, however, the northwestern region (upper Jinsha River and Nujiang-Lancangjiang River basin) still maintained relatively high erosion levels. The average soil erosion intensity in Diqing Tibetan Autonomous Prefecture and Garze Tibetan Autonomous Prefecture remained at 6.92% and 7.81%, respectively.

3.2.2. Spatial and Temporal Trends of Soil Erosion

Figure 4 displays the boxplot of average soil erosion intensity in Southwest China from 2000 to 2023, based on the mean soil erosion intensity for each prefecture-level city and autonomous prefecture in the region. As illustrated in Figure 2e, from 2000 to 2020, the implementation of soil and water conservation measures, including the Grain-for-Green Program, resulted in a significant decrease in soil erosion intensity, declining from $4.23 \text{ t} \cdot \text{ha}^{-1} \cdot \text{yr}^{-1}$ in 2000 to $1.77 \text{ t} \cdot \text{ha}^{-1} \cdot \text{yr}^{-1}$ in 2020, representing a 58.16% reduction. Notably, a substantial increase in soil erosion intensity occurred between 2006 and 2014, rising from $1.88 \text{ t} \cdot \text{ha}^{-1} \cdot \text{yr}^{-1}$ to $3.23 \text{ t} \cdot \text{ha}^{-1} \cdot \text{yr}^{-1}$ during this period. Overall, soil erosion intensity in Southwest China has shown a marked downward trend over the past two decades,

despite some interannual fluctuations. This long-term reduction can be attributed to the continuous promotion of ecological restoration programs, such as reforestation and slope land conversion, as well as the adoption of improved land use practices and enhanced vegetation coverage, which have collectively mitigated surface runoff and reduced erosion susceptibility.

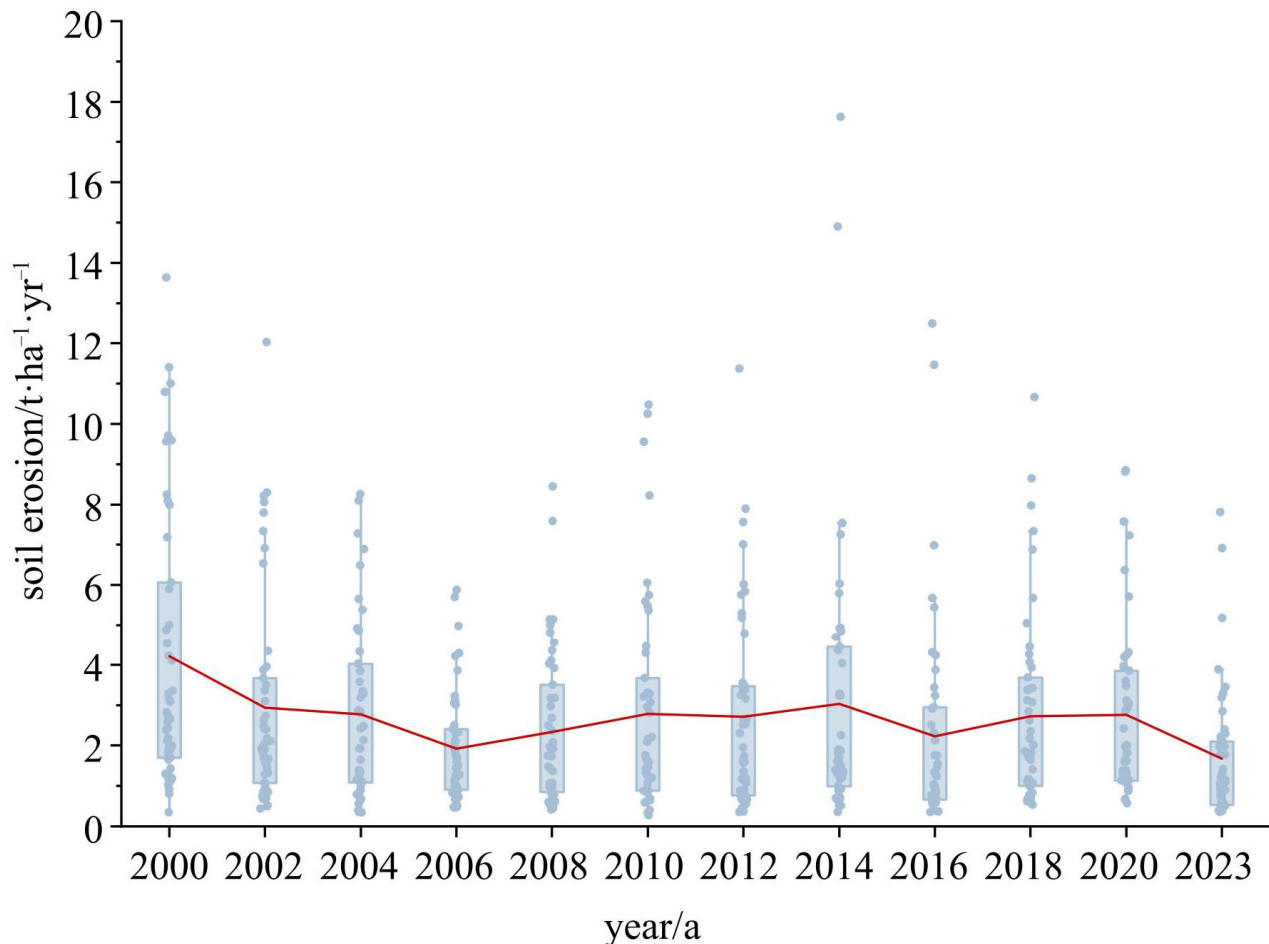


Figure 4. Average soil erosion values from 2000 to 2023.

The spatial variation of soil erosion changes is presented in Figure 5. From 2000 to 2005, the area experiencing severe or higher soil erosion intensity decreased by 46.57%, while the area with mild erosion increased by 6.34%. In the northwest, particularly in the upper reaches of the Jinsha River, and in the southeast, within the Beipan River Basin, most regions previously classified as severe or moderate soil erosion areas improved to moderate or light erosion levels. Notably, Anshun City and Liupanshui City exhibited the most substantial reductions in average soil erosion intensity, decreasing by 7.27% and 6.10%, respectively. From 2005 to 2010, soil erosion in the southeastern region demonstrated significant improvement. Areas such as Anshun and Liupanshui experienced a decrease in their average soil erosion modulus by at least $3 \text{ t} \cdot \text{ha}^{-1} \cdot \text{yr}^{-1}$. However, in the Ya'an region and surrounding areas (the western mountainous area of the Sichuan Basin), soil erosion intensified significantly, reaching severe or higher levels, with Chengdu's soil erosion increasing by $7.48 \text{ t} \cdot \text{ha}^{-1} \cdot \text{yr}^{-1}$. Between 2010 and 2015, soil erosion in Ya'an and its surrounding areas, as well as in the western regions, decreased by more than $5 \text{ t} \cdot \text{ha}^{-1} \cdot \text{yr}^{-1}$. Conversely, in the south, the soil erosion intensity in Kunming escalated from light to severe and extreme levels, with the average soil erosion modulus rising by $2.99 \text{ t} \cdot \text{ha}^{-1} \cdot \text{yr}^{-1}$. From 2015 to 2020, the overall soil erosion intensity in the region remained relatively stable,

though erosion intensity in the northwest continued to increase, with Chengdu's average soil erosion intensity rising by $4.01 \text{ t} \cdot \text{ha}^{-1} \cdot \text{yr}^{-1}$. From 2020 to 2023, the area affected by severe or higher soil erosion in Southwest China declined from 2.02% of the total area to 0.72%, while areas with mild and light erosion increased from 93.62% to 95.44%.

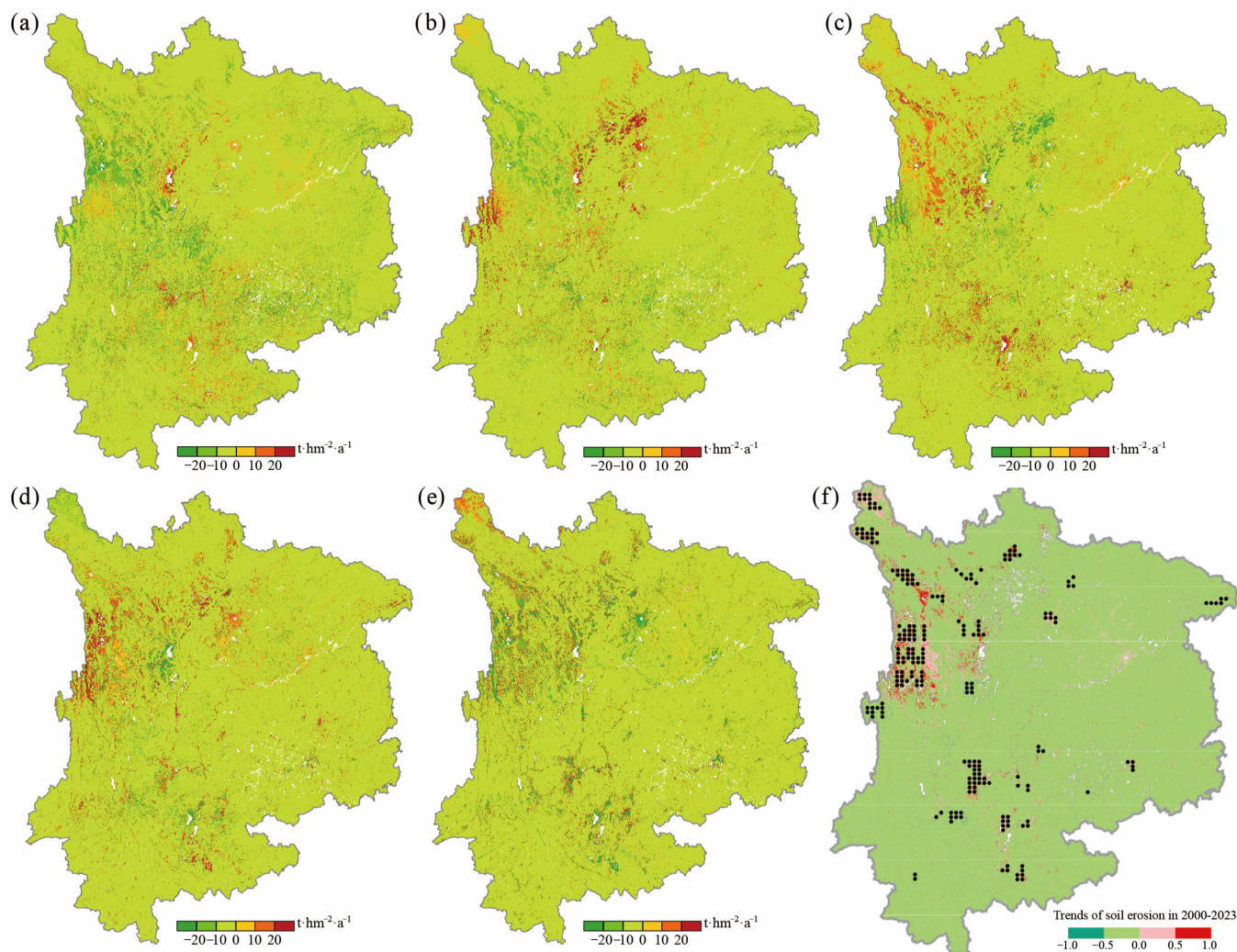


Figure 5. Spatial distribution and trend of soil erosion change: (a) 2000–2005, (b) 2005–2010, (c) 2010–2015, (d) 2015–2020, (e) 2020–2023, (f) trends of soil erosion 2000–2023. The black dots represent the significant areas ($q < 0.05$, the same below).

An analysis of soil erosion intensity trends from 2000 to 2023 is illustrated in Figure 5f, where red indicates areas with increased soil erosion intensity, green denotes decreased intensity, and black markings signify statistical significance ($q < 0.05$). Between 2020 and 2023, fewer regions exhibited significant increases or decreases in soil erosion intensity. Areas with significant increases were primarily concentrated in the southwestern part of the southern edge of the Qinghai-Tibet Plateau, while the majority of the region showed no significant reduction in soil erosion intensity, particularly in the eastern Yunnan-Guizhou Plateau, southern Sichuan Basin, and southern Heng-duan Mountains.

The erosion intensity area statistics for Southwest China from 2000 to 2023, based on six periods of data, are presented in the soil erosion intensity transfer chord diagram shown in Figure 6. From 2000 to 2005, the soil erosion intensity primarily exhibited a decreasing trend. The largest area of transfer was from light erosion to slight erosion, reaching 481.5 hm^2 . The second largest transfer was from moderate erosion to slight erosion, with an area of

250.65 hm². The total area of soil erosion intensity shifting from light or higher categories to slight erosion amounted to 927.34 hm², accounting for 57% of the total transfer area. This indicates an overall reduction in soil erosion intensity. However, transfers from slight erosion to light erosion (211.83 hm²) and from moderate erosion to light erosion (188.35 hm²) were also observed, although they were smaller in scale. Additionally, the area of transfer to strong or higher intensity erosion was only 80.11 hm², making up just 4.92% of the total transfer area, reflecting the effective control of the expansion of severe erosion. From 2005 to 2010, the top four areas of soil erosion intensity transfer were slight to slight erosion, slight to light erosion, moderate to slight erosion, and slight to moderate erosion, with areas of 350.85 hm², 237.06 hm², 185.55 hm², and 126.8 hm², respectively. Compared to the previous period, the transfer to strong or higher intensity erosion increased, with a transfer area of 118.91 hm², accounting for 9.6% of the total transfer area. This suggests an increase in localized soil erosion risk. From 2010 to 2015, soil erosion intensity transfer showed some fluctuations and reversals. The area transferred from slight or moderate to light erosion was 301.65 hm² and 150.51 hm², respectively, indicating that soil erosion intensity had decreased in some areas. However, transfers from slight to light, slight to moderate, and moderate to moderate erosion amounted to 224.22 hm², 121.85 hm², and 115.77 hm², respectively. Furthermore, the transfer area to strong or higher intensity erosion was 131.1 hm², accounting for 11.01% of the total transfer area, suggesting that some areas still faced the risk of escalation in erosion intensity. From 2015 to 2020, the area of transfer from slight and moderate erosion to light erosion decreased to 253.04 hm² and 146.04 hm², respectively, compared to the previous period. Transfers from slight to light erosion, slight to moderate, and light to moderate erosion amounted to 123.4 hm², 176.79 hm², and 165.45 hm², respectively. The transfer to strong or higher intensity erosion increased to 181.52 hm², accounting for 16.02% of the total transfer area, reflecting a potential risk of soil erosion intensity conversion from lower to higher levels in certain regions. From 2020 to 2023, soil erosion intensity transfer showed new dynamics and trends. The most significant transfer was from slight erosion to light erosion, with an area of 329.46 hm², followed by transfers from slight to moderate erosion (206.37 hm²). This indicates that the trend of increased soil erosion intensity still exists in some areas. Transfers from light and moderate erosion to slight erosion were 171.38 hm² and 256.22 hm². Compared to the previous stage, the area of transfer to strong or higher intensity erosion sharply decreased to only 4.8% of the total transfer area, reflecting the effectiveness of soil erosion control measures.

From 2000 to 2023, the overall trend of soil erosion intensity in Southwest China showed significant improvement. Notably, the transfer from moderate or higher levels of erosion to slight erosion was the most prominent, with a total area of 1445.32 hm², accounting for 66.5% of the total transfer area. Specifically, the transfer area from light erosion to slight erosion was 736.77 hm², from moderate erosion to slight erosion was 548.89 hm², and from severe erosion to slight erosion was 128.08 hm². These figures suggest that the majority of the region's soil erosion issues have been effectively controlled and managed. However, there is still a transfer of 671.7 hm² from lower to higher intensity erosion, which highlights the potential rebound risk of water and soil loss in some areas. Additionally, transfers from slight erosion to light erosion (322.47 hm²), to moderate erosion (182.53 hm²), and from light erosion to moderate erosion (621.6 hm²) reflect the ongoing influence of complex terrain, climate change, and human activities on soil erosion processes.

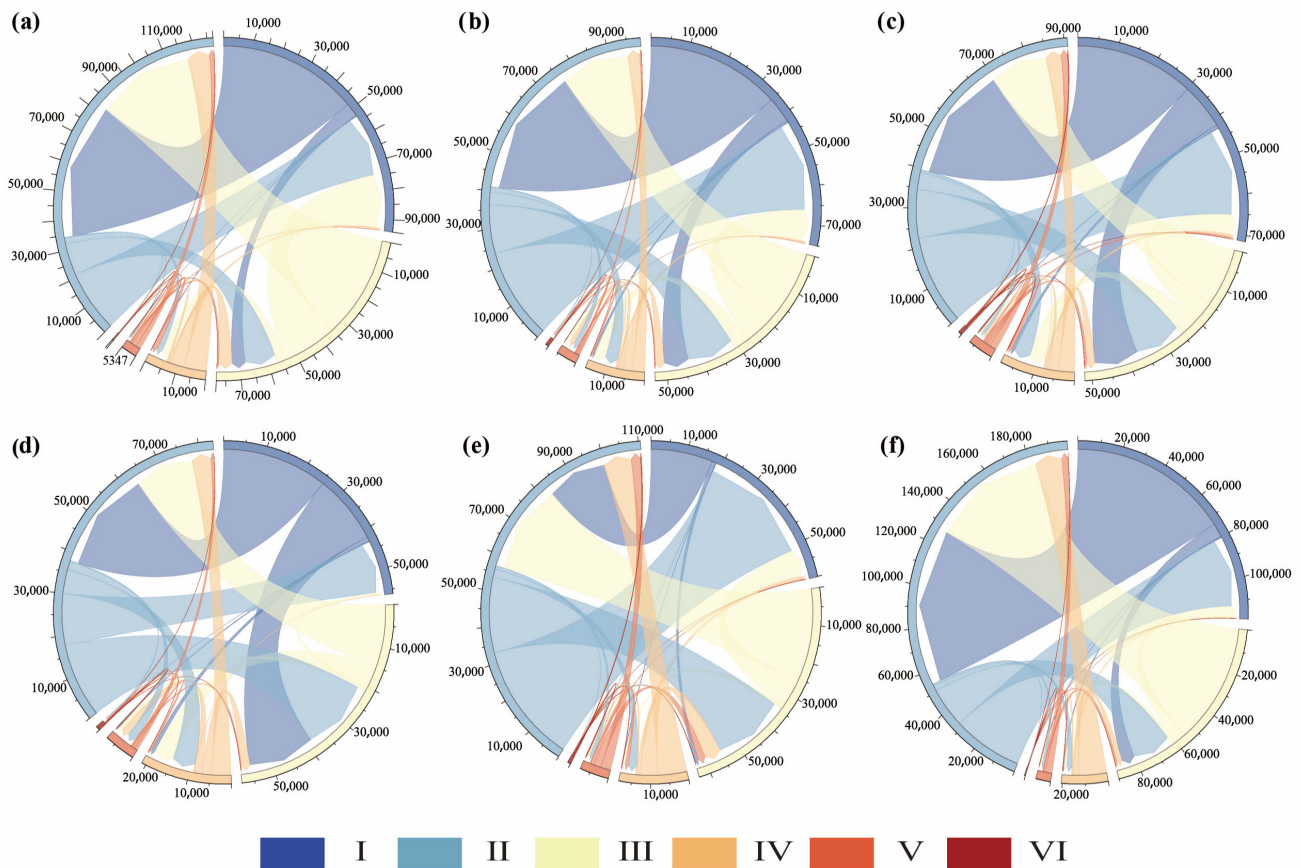


Figure 6. Transfer of different soil erosion intensities: (a) 2000–2005, (b) 2005–2010, (c) 2010–2015, (d) 2015–2020, (e) 2020–2023, (f) 2000–2023.

3.3. Effects of Driving Factors for Soil Erosion

To quantitatively assess the marginal contributions of each driving factor to soil erosion, the SHAP method was employed to interpret the prediction results derived from the XGBoost model, elucidating the relative importance and directional influence of different variables on soil erosion predictions. As illustrated in Figure 7, the magnitude of SHAP values represents the average marginal contribution of each variable to the model output, while the sign denotes the direction of its effect. DEM emerges as the most influential driving factor affecting soil erosion in the southwestern region, with predominantly positive SHAP values, indicating that areas of higher elevation are more susceptible to soil erosion. Pre ranks second in importance, exhibiting slightly lower explanatory power than elevation but generally demonstrating a positive influence across most samples, underscoring rainfall's role as a direct driver of soil erosion. GDP displays variability in its directional influence across samples but maintains an overall positive correlation, suggesting that economic activities contribute to soil disturbance and increased land use intensity, thereby elevating soil erosion risk. Tmp and PET provide moderate explanatory power to the model, while slope, despite its limited overall contribution, exhibits an amplifying effect on erosion in specific steep-slope areas. In contrast, anthropogenic factors such as cropland, built-up land, and population density demonstrate relatively minor contributions. Collectively, natural environmental factors predominantly govern the spatial differentiation of soil erosion in the southwestern region.

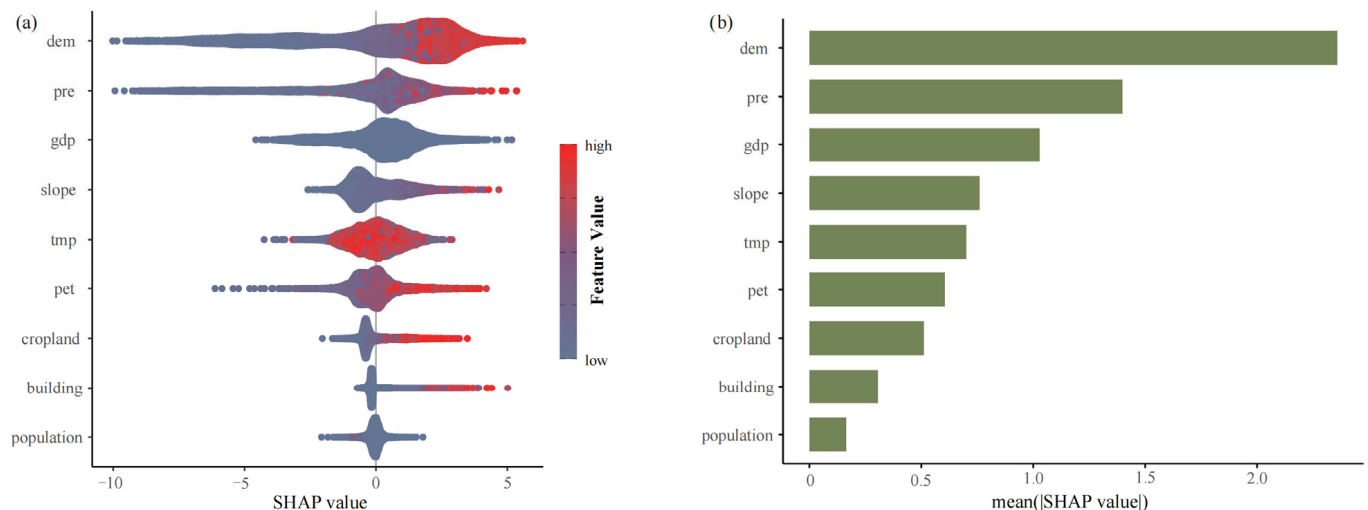


Figure 7. SHAP value impact plot of the XGBoost model (a) and bar plot showing the mean absolute SHAP value of each driving factor of soil erosion (b).

3.3.1. XGBoost Model Setup and Validation

The XGBoost algorithm in this study is configured with the following parameters: the objective function is set to “reg: squarederror” for regression tasks. The learning rate (eta) is set to 0.05, and the maximum depth of each tree (max_depth) is 7, which helps control the complexity of the model. The gamma parameter is set to 0.4 to regulate the minimum loss reduction required for a split. The subsample and colsample_bytree parameters are both set to 0.8 to reduce overfitting by randomly sampling 80% of the data and features, respectively, for each tree. Additionally, L2 regularization (lambda = 1.2) and L1 regularization (alpha = 0.3) are employed to control the complexity of the model and prevent overfitting. The model is trained using cross-validation (xgb.cv), with early stopping implemented after 30 rounds without improvement in performance. The final model is trained based on the best iteration selected from the cross-validation. SHAP (SHapley Additive exPlanations) analysis is then applied to assess and quantify the contribution of each feature to the model’s predictions.

3.3.2. Influence of Climate Factors on Soil Erosion

As Figure 8a–c show the significant non-linear characteristics of climate factors on soil erosion. Pre exhibits a clear threshold effect on soil erosion: when rainfall is below 500 mm, the SHAP values are negatively distributed, indicating a weak driving effect on erosion. Between 500–1200 mm, the SHAP values increase rapidly and remain at a high level, suggesting that rainfall in this range has a strong positive contribution to soil erosion. However, when rainfall exceeds 1200 mm, the SHAP values fluctuate more significantly, and the contribution of some samples decreases. PET shows an overall positive impact in the range of 400–1600 mm, with SHAP values gradually increasing as PET increases. The SHAP response curve for tmp exhibits a multi-peak characteristic, with notable local peaks in the ranges of approximately 0 °C, 5–10 °C, and 15–20 °C.

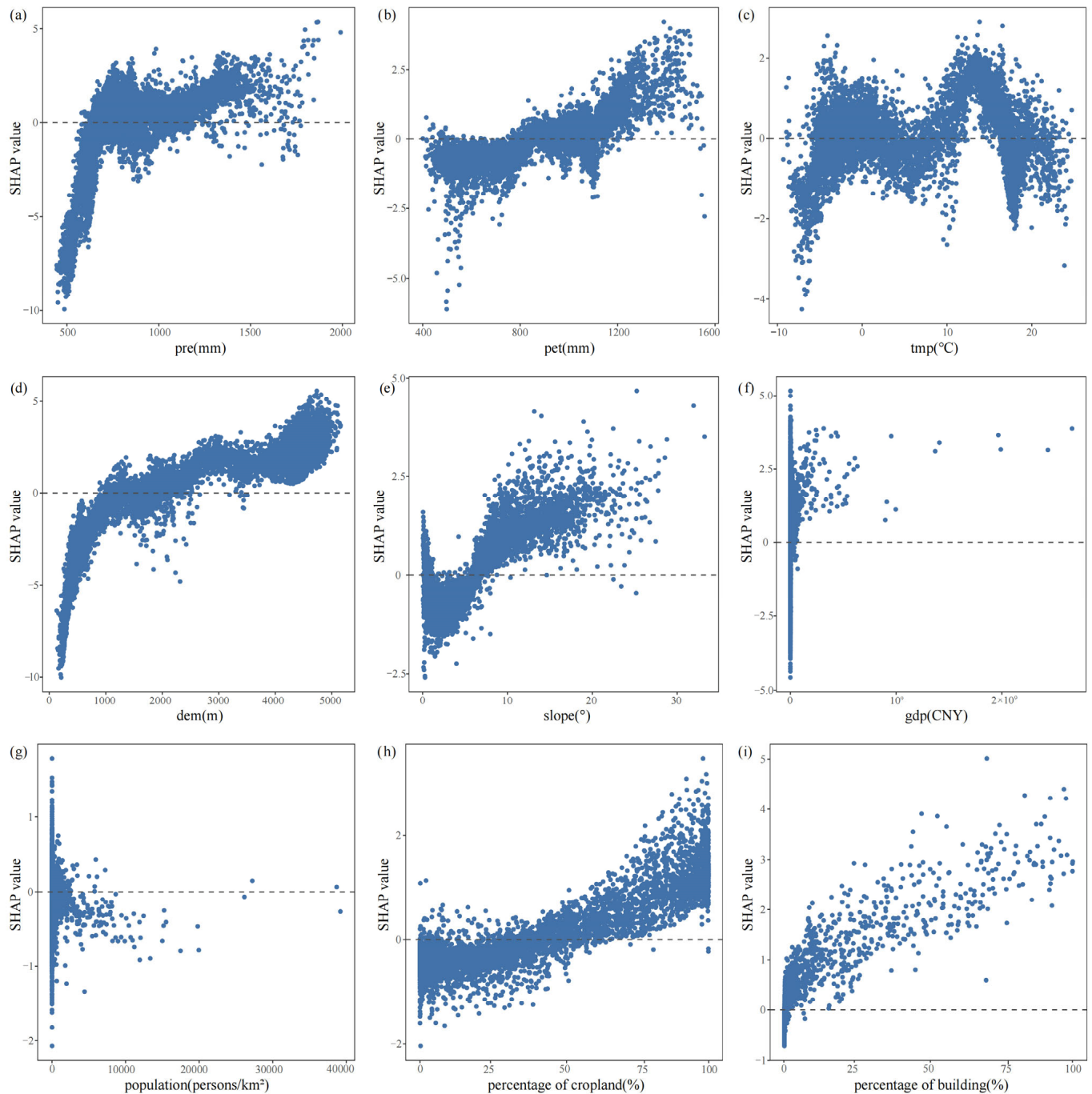


Figure 8. SHAP dependence plots of precipitation (a), potential evapotranspiration (b), temperature (c), dem (d), slope (e), GDP (f), population (g), cropland (h), and building (i).

3.3.3. Influence of Topographical Factors on Soil Erosion

As Figure 8d,e shows the significant stage-like changes in the impact of dem on soil erosion as elevation increases. In low-elevation areas (<1000 m), elevation has a clear negative contribution to soil erosion, with relatively low SHAP values. As the elevation rises, the SHAP values gradually increase, reaching a stable positive impact between approximately 2500 m and 4000 m. Above 4000 m, the contribution slightly increases but remains stable. Figure 8e illustrates the relatively complex influence of slope on soil erosion. In areas with low slopes ($<5^\circ$), the SHAP values are scattered, and the direction of influence is unstable. However, in areas with moderate slopes ($5\text{--}15^\circ$), the SHAP values show an overall increasing trend, indicating that slope in this range has a gradually enhanced

positive contribution to soil erosion. As the slope further increases ($>15^\circ$), the SHAP values become more dispersed, with increased fluctuations, suggesting that the influence of high slopes on soil erosion varies significantly, showing some uncertainty and local variability.

3.3.4. Influence of Anthropogenic Factors on Soil Erosion

Figure 8f–i present the effects of human factors on soil erosion vary in magnitude and direction. GDP has a generally positive impact on soil erosion (i.e., a beneficial effect in reducing erosion), with its SHAP values showing significant fluctuations in areas with very low GDP, indicating some uncertainty. As GDP gradually increases, the SHAP values show a clear upward trend, suggesting that areas with higher GDP tend to contribute more positively to erosion control, possibly due to better infrastructure, management practices, and investment in conservation efforts. The impact of population density on soil erosion is overall weaker. In areas with extremely low population density (<5000 people), the SHAP values are scattered, with both positive and negative values, indicating an unstable effect on soil erosion. In areas with medium-to-high population density ($>10,000$ people), the SHAP values tend to approach 0, suggesting a weakening of the marginal impact of this factor. The contribution of cropland proportion to soil erosion shows a gradually increasing trend. When the proportion of cropland is less than 50%, the SHAP values mainly distribute near 0. As the proportion of cropland increases, the SHAP values rise significantly, indicating that regions with extensive cropland tend to experience greater soil erosion, likely due to land disturbance and reduced vegetation cover. The proportion of built-up land shows the most significant impact on soil erosion, with SHAP values increasing rapidly as the proportion rises, especially between 0% and 50%. In areas with over 75% built-up land, SHAP values remain high. Although impervious surfaces themselves are not subject to traditional soil erosion, they can increase surface runoff, which may intensify erosion in surrounding areas. Thus, the positive impact reflects an indirect enhancement of erosion risk due to urban expansion.

3.3.5. The Interactive Effects of Driving Factors

The interaction between climatic and topographic factors plays a pivotal role in influencing soil erosion risk. In high-elevation regions, intense rainfall can lead to rapid surface runoff, especially on steep slopes with shallow soils, thereby exacerbating soil erosion. This suggests that elevation and precipitation often act as compounding drivers of erosion in mountainous areas. In contrast, under low precipitation conditions, elevation exerts less influence on erosion processes, likely due to limited water availability restricting runoff formation.

Similarly, the interplay between socioeconomic and environmental factors significantly affects the intensity and spatial distribution of soil erosion. Regions with intensive human activities, such as rapid urbanization or expansive agricultural development, often experience increased erosion pressure due to vegetation loss and surface disturbance. These anthropogenic changes, when coupled with complex terrain, can enhance hydrological responses, further accelerating erosion. Therefore, understanding the combined effects of natural and human-induced factors is crucial for identifying erosion-prone areas and implementing targeted soil conservation strategies (Figure 9).

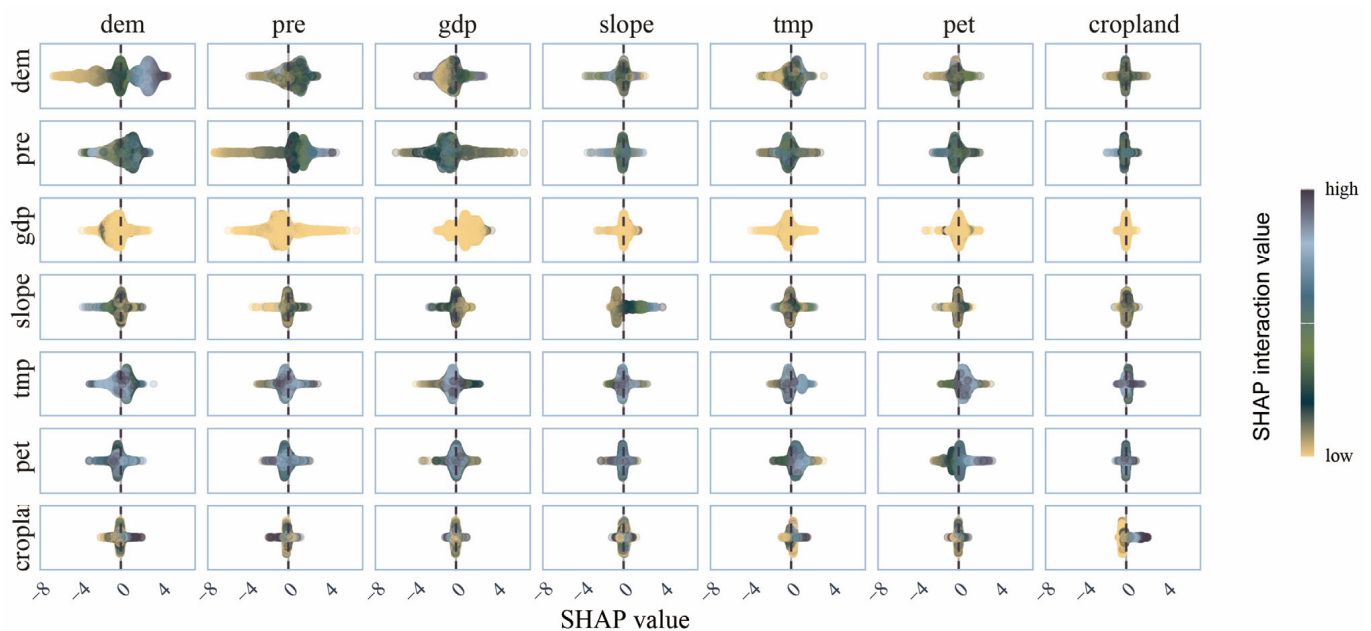


Figure 9. Interactive SHAP values for drivers of soil erosion.

3.4. Soil Erosion Projections

3.4.1. Rainfall Erosivity Factor

As shown in Figure 10, under the SSP119 scenario, the average rainfall erosivity values in 2030 (Figure 10a), 2040 (Figure 10b), and 2050 (Figure 10c) are 2784.86, 2919.40, and 3337.25 $\text{MJ}\cdot\text{mm}\cdot(\text{ha}\cdot\text{h}\cdot\text{yr})^{-1}$, respectively, indicating a continuous upward trend over time. This suggests that even under a relatively low-emission pathway, the driving force of rainfall on soil erosion is expected to intensify. Spatially, rainfall erosivity tends to be higher in high-altitude and precipitation-prone regions, and lower in flatter and lowland areas, highlighting the significant influence of topographic variation and rainfall distribution. This trend implies that erosion risks may become more pronounced in geomorphologically sensitive areas in the context of future climate change, even under conservative climate scenarios.

Under the SSP245 and SSP585 scenarios, rainfall erosivity shows different phased patterns. In SSP245, the average values are 2635.17 $\text{MJ}\cdot\text{mm}\cdot(\text{ha}\cdot\text{h}\cdot\text{yr})^{-1}$ in 2030 (Figure 10d), peaking at 3061.54 in 2040 (Figure 10e), and then decreasing to 2621.45 in 2050 (Figure 10f), reflecting a rise-then-fall trend potentially driven by interannual rainfall variability and climate regulation effects. For SSP585, the averages are 2611.44 in 2030 (Figure 10g), slightly decreasing to 2573.78 in 2040 (Figure 10h), then increasing to 2823.67 in 2050 (Figure 10i). Although the short-term variation is mild, the long-term trend still points toward increasing erosivity under the high-emissions scenario. Spatially, both SSP245 and SSP585 scenarios exhibit a general pattern of decreasing rainfall erosivity from northwest to southeast, indicating that regional differentiation of erosion risk will become more prominent, and targeted soil and water conservation strategies are urgently needed.

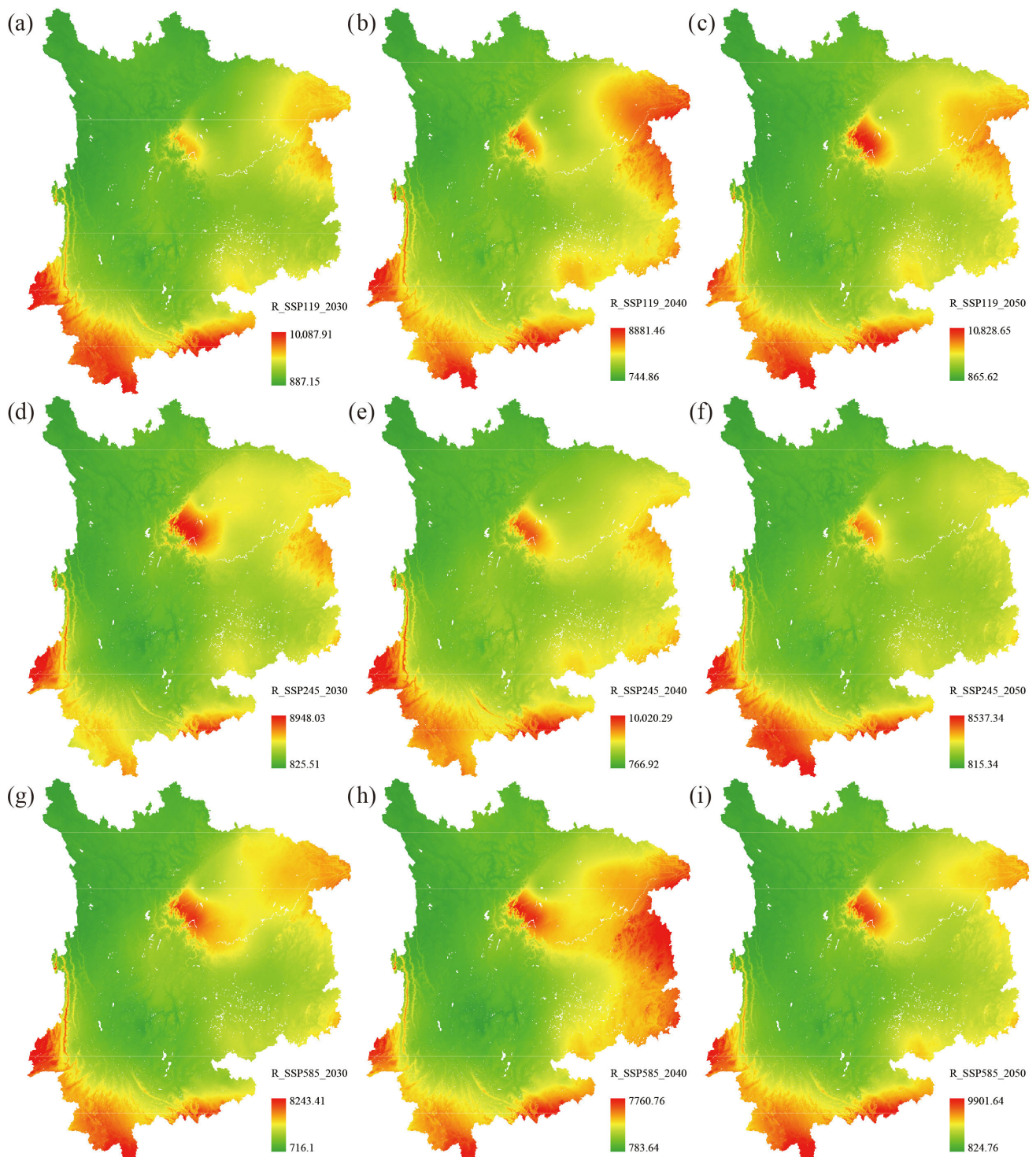


Figure 10. Rainfall erosive factors in different situations: SSP119_2030 (a), SSP119_2040 (b), SSP119_2050 (c), SSP245_2030 (d), SSP245_2040 (e), SSP245_2050 (f), SSP585_2030 (g), SSP585_2040 (h), SSP585_2050 (i).

3.4.2. Soil Erosion in Different Scenarios

Based on the RUSLE model and future climate scenarios SSP119, SSP245, and SSP585, the soil erosion intensity for the period 2030–2050 was projected (Figure 11). The spatial pattern of soil erosion intensity is expected to remain largely unchanged, still following the general trend of “high in the northwest and low in the southeast”. However, the average

soil erosion intensity will gradually increase, with the increase under the SSP585 scenario being greater than that under the SSP119 scenario.

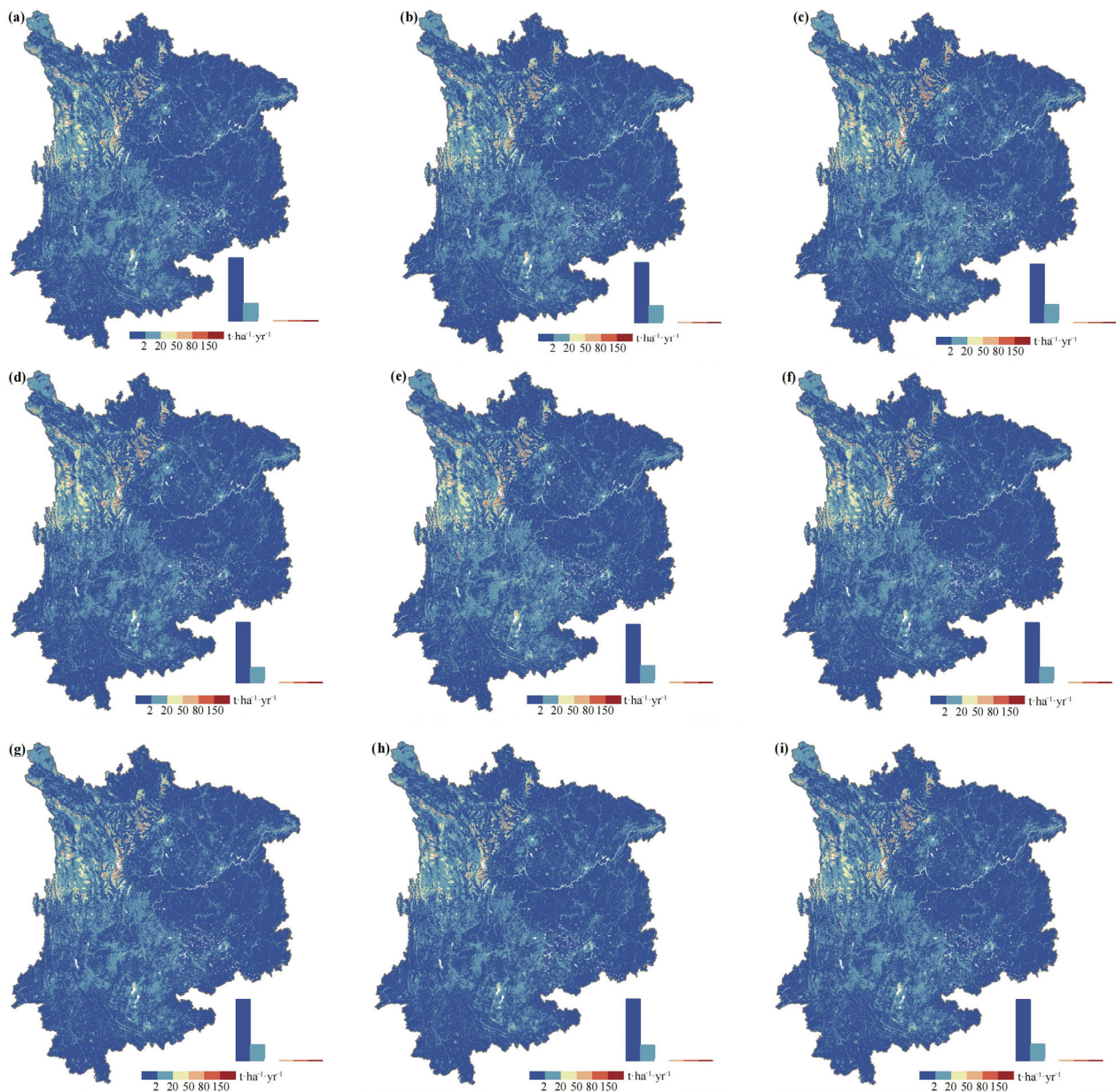


Figure 11. Predicted change in Transfer of different soil erosion intensities: (a) SSP119-2030, (b) SSP119-2040, (c) SSP119-2050, (d) SSP245-2030, (e) SSP245-2040, (f) SSP245-2050, (g) SSP585-2030, (h) SSP585-2040, (i) SSP585-2050.

Areas of slight erosion are mainly distributed in the eastern and western parts of the Yunnan-Guizhou Plateau, where lower elevations reduce the likelihood of soil erosion. Light erosion zones are sporadically distributed across the region, with concentrations in the central Sichuan Basin. Moderate erosion zones are concentrated near the Nujiang–Lancangjiang river basins in the northwest, where increasing elevation elevates the probability of soil erosion. Strong and extremely strong erosion zones are mainly found in the Ganzi Tibetan Autonomous Prefecture, Diqing Tibetan Autonomous Prefecture, and Aba Tibetan and Qiang Autonomous Prefecture, where high altitudes and dominant grassland land use make the areas more vulnerable to severe soil erosion.

Compared with the average soil erosion intensity of $1.77 \text{ t}\cdot\text{ha}^{-1}\cdot\text{yr}^{-1}$ in 2020, under the SSP119 scenario, the predicted average soil erosion intensity will increase by approximately $1.66 \text{ t}\cdot\text{ha}^{-1}\cdot\text{yr}^{-1}$ by 2030, $1.80 \text{ t}\cdot\text{ha}^{-1}\cdot\text{yr}^{-1}$ by 2040, and $2.17 \text{ t}\cdot\text{ha}^{-1}\cdot\text{yr}^{-1}$ by 2050, showing a steady upward trend. Under the SSP245 scenario, the predicted increases are about $1.74 \text{ t}\cdot\text{ha}^{-1}\cdot\text{yr}^{-1}$ by 2030, $2.11 \text{ t}\cdot\text{ha}^{-1}\cdot\text{yr}^{-1}$ by 2040, and $1.75 \text{ t}\cdot\text{ha}^{-1}\cdot\text{yr}^{-1}$ by 2050, with the average erosion intensity first increasing and then decreasing. Under the SSP585 scenario, the projected increases are about $1.49 \text{ t}\cdot\text{ha}^{-1}\cdot\text{yr}^{-1}$ by 2030, $1.34 \text{ t}\cdot\text{ha}^{-1}\cdot\text{yr}^{-1}$ by 2040, and $1.75 \text{ t}\cdot\text{ha}^{-1}\cdot\text{yr}^{-1}$ by 2050, showing a pattern of initial decline followed by an increase.

Across all three climate scenarios, the area affected by soil erosion in Southwest China is projected to expand. Comparatively, the long-term average soil erosion modulus and total erosion amount are highest under the low-emission SSP119 scenario. Relative to 2023, by 2030, the proportion of area experiencing slight erosion is expected to decrease to approximately 77.07%, while the proportion of light erosion area is projected to increase to about 20.31%, with areas of moderate and strong or more severe erosion remaining largely unchanged. By 2040, the slight erosion area proportion is anticipated to decline to around 76.23%, while light erosion is expected to rise to approximately 21.03%. By 2050, slight erosion is forecast to decrease to approximately 75.83%, with light erosion increasing to about 21.26%.

Overall, by the mid-21st century, relatively severe soil erosion in Southwest China is likely to be concentrated primarily in western Sichuan, where the increased probability of heavy rainfall events will elevate the risk of soil erosion, resulting in substantial soil loss.

The spatial patterns of soil erosion intensity under the SSP119 and SSP585 emission scenarios for 2030–2050 were calculated (Figure 12), with significant differences observed. In 2030, compared with the SSP119 scenario, soil erosion intensity under the SSP585 scenario increased by 2.5 to $6.5 \text{ t}\cdot\text{ha}^{-1}\cdot\text{yr}^{-1}$ across large areas of the central and northern regions, while decreasing by 3.5 to $7.5 \text{ t}\cdot\text{ha}^{-1}\cdot\text{yr}^{-1}$ in the southern and north-western regions. In 2040, compared with the SSP119 scenario, soil erosion intensity under the SSP585 scenario increased by 2 to $5 \text{ t}\cdot\text{ha}^{-1}\cdot\text{yr}^{-1}$ only in localized areas of the central and northern regions, while decreasing by 0.5 to $7 \text{ t}\cdot\text{ha}^{-1}\cdot\text{yr}^{-1}$ across extensive areas in the north, south, and west. In 2050, compared with the SSP119 scenario, soil erosion intensity under the SSP585 scenario increased by 2.5 to $3.5 \text{ t}\cdot\text{ha}^{-1}\cdot\text{yr}^{-1}$ only in a few localized areas in the north, while decreasing by 2.5 to $8 \text{ t}\cdot\text{ha}^{-1}\cdot\text{yr}^{-1}$ across broad areas of the north, south, and west. Overall, the differences between the SSP119 and SSP585 scenarios were more pronounced in 2030, whereas by 2050, the differences between the two scenarios became relatively smaller.

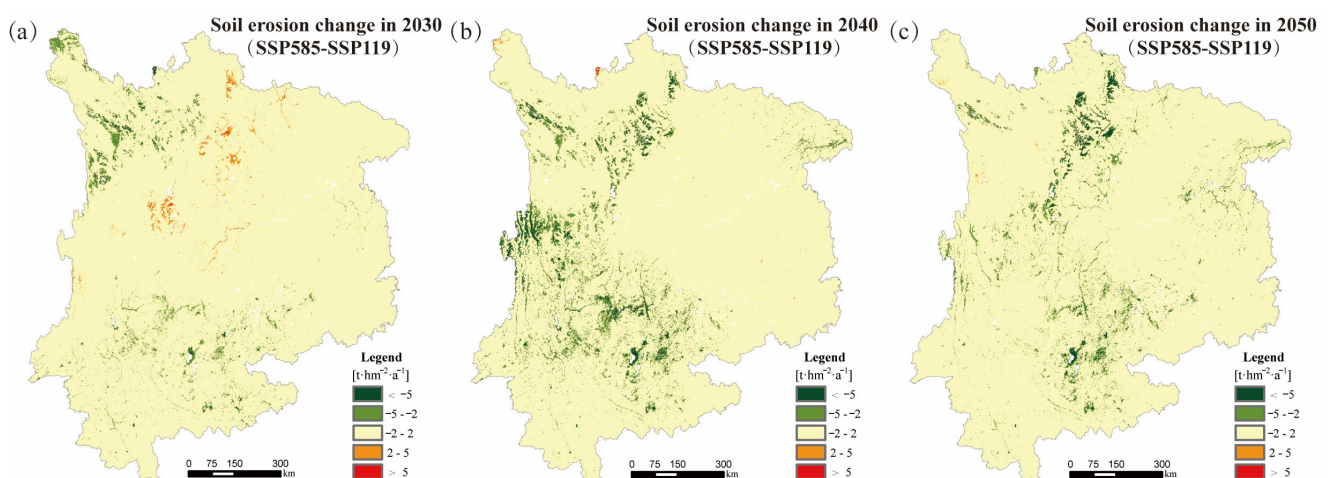


Figure 12. The spatial pattern of difference in soil erosion intensity between the two scenarios: (a) 2030, (b) 2040, and (c) 2050.

4. Discussion

4.1. Reliability and Accuracy of Estimates

This study systematically assessed the spatiotemporal evolution of soil erosion in Southwest China from 2000 to 2023 using the Modified Universal Soil Loss Equation (RUSLE) model. The results indicate a continuous decline in overall soil erosion intensity, with a spatial distribution pattern characterized by “higher in the northwest and lower in the southeast.” The overall estimates exhibit high reliability and accuracy, primarily due to the reasonable calibration of model parameters (such as R, K, LS, C, and P factors) and the high quality of data sources (including precipitation, land use, and DEM data). Previous studies have confirmed that the RUSLE model performs well in large-scale regional soil erosion simulations, demonstrating good adaptability and accuracy [48,59]. Especially in complex topography and diverse climatic conditions, such as those in Southwest China, the RUSLE model has been applied and validated multiple times [60,61]. In addition, recent improvements in the extraction and modification methods for various factors, such as the use of high-precision remote sensing data to estimate vegetation cover, have further enhanced the accuracy and reliability of the model [62]. The refinement of DEM data has improved the accuracy of the slope length and steepness factors, thereby enhancing the precision of the soil erosion estimation model [63]. Additionally, the localized modeling of the soil erodibility factor (K) has further improved the accuracy of soil erosion estimation, ensuring that the model better reflects the specific soil types and characteristics of the region [64]. These improvements have significantly enhanced the credibility of the soil erosion simulation results. The use of multi-year sequence data and high-resolution input data in this study effectively reduced errors caused by anomalous climatic conditions or human interference in any single year.

This study reveals that the overall soil erosion intensity in Southwest China has exhibited a declining trend from 2000 to 2023, with a stable spatial pattern characterized by “higher intensity in the northwest and lower intensity in the southeast.” This trend is consistent with the findings of several recent high-level empirical studies [65,66], thereby supporting the scientific validity and reliability of the present research. First, regarding temporal changes, the overall soil erosion intensity in Southwest China has decreased, primarily due to the continuous implementation of ecological restoration policies and the cumulative effect of natural recovery processes. The Grain for Green Program, implemented since 1999, has significantly improved regional vegetation coverage, resulting in a notable reduction in surface exposure and erosion risk [67]. Previous studies have demonstrated that between 2000 and 2020, the average NDVI in Southwest China exhibited a continuous increase [68], which is strongly correlated with the reduction in soil erosion intensity [69]. The observed unit-area soil erosion in this study decreased from $4.23 \text{ t} \cdot \text{ha}^{-1} \cdot \text{yr}^{-1}$ to $2.5 \text{ t} \cdot \text{ha}^{-1} \cdot \text{yr}^{-1}$, which is consistent with the nationwide trend in soil erosion control effectiveness assessments [65].

At the same time, from the perspective of driving mechanisms, the changes in erosion intensity revealed in this study are closely related to the dual driving mechanisms of climate change and human activities, which is consistent with the current mainstream understanding in soil erosion dynamics research [64,70]. Regarding climate change, the annual average precipitation in Southwest China has remained stable in recent years, however, the frequency of extreme precipitation events has increased [71]. However, due to significant vegetation restoration, which has substantially enhanced surface protection, the overall erosion risk has been effectively mitigated [72]. In terms of human activities, large-scale ecological projects and soil and water conservation measures (such as slope-to-terrace conversion and area closures for restoration) have been systematically implemented

in key watershed regions, significantly enhancing the ecological service functions of these areas [73,74].

4.2. Response Measures Under Future Scenarios

According to the analysis of driving factors and future climate scenario predictions in this study, soil erosion in Southwest China is projected to generally intensify in the future, particularly in high-altitude areas and regions with increased precipitation, where the risk of soil loss is expected to rise substantially. Although large-scale ecological projects such as the Grain-for-Green Program have been implemented and have contributed significantly to reducing soil erosion in the region, targeted measures remain essential to address the evolving challenges. Therefore, addressing future soil erosion requires a dual approach involving both environmental conservation and regulation of human activities, with regionally differentiated prevention and control strategies. Specifically, enhancing soil and water conservation infrastructure is critical in areas anticipated to experience significant increases in precipitation. Priority should be given to measures such as terracing, constructing check dams, and establishing vegetative slope protection to effectively reduce surface runoff and erosion intensity [75,76]. In high-altitude ecologically fragile areas, further efforts should focus on integrating natural restoration with artificial interventions to increase vegetation coverage, thereby reinforcing the ecosystem's resilience to erosion and enhancing ecological stability [77]. For regions characterized by steep slopes, where slope gradient strongly amplifies erosion risk, terrace construction and slope stabilization engineering are particularly crucial. These targeted interventions can effectively mitigate gravitational and runoff-induced erosion, addressing the high-risk characteristics of these areas [78]. By tailoring soil conservation measures to the region's diverse topography and climatic conditions, more effective and sustainable erosion control can be achieved.

In addition, considering the indirect effects of population growth, economic development, and land use changes on soil erosion, future efforts should focus on optimizing land use structures to regulate the impact of human activities on erosion processes. On one hand, the expansion of construction land in high-risk areas should be limited, particularly by controlling urban development in sloped and high-altitude regions [79]. On the other hand, the transformation of agricultural production methods should be encouraged through the promotion of conservation tillage, agricultural water conservancy infrastructure, and ecological farming practices, which can mitigate soil structure degradation caused by farmland cultivation [63].

At the same time, in response to the uneven spatiotemporal distribution of water resources under future climate change, it is essential to strengthen the development of regional soil erosion monitoring and early warning systems. By employing remote sensing, big data, and machine learning technologies, dynamic monitoring and intelligent management of soil erosion can be achieved. This approach will facilitate timely adjustments to response strategies, thereby improving the sustainable management capacity of regional water and soil resources.

5. Conclusions

The analysis of soil erosion in Southwest China from 2000 to 2023 reveals a remarkable decline in soil erosion intensity. The average soil erosion intensity decreased from $4.23 \text{ t} \cdot \text{ha}^{-2} \cdot \text{yr}^{-1}$ in 2000 to $1.77 \text{ t} \cdot \text{ha}^{-2} \cdot \text{yr}^{-1}$ in 2020, representing a 58.16% reduction. In 2023, the spatial distribution of soil erosion indicated that 90.9% of the region experienced slight erosion, with areas of moderate and severe erosion covering only 4.56% of the total area. Notably, the northwest, particularly the upper Jinsha River and Nujiang-Lancangjiang River basins, remained areas with higher erosion intensity. The period from 2005 to 2020

witnessed significant improvement, with the most substantial reductions occurring in areas such as Anshun and Liupanshui, where average erosion intensity decreased by 7.27% and 6.10%, respectively. However, some regions, particularly in the southern parts of the Sichuan Basin and Yunnan-Guizhou Plateau, experienced localized increases in erosion intensity. Between 2020 and 2023, the area affected by severe erosion dropped to 0.72%, with the majority of the region experiencing mild to light erosion. Despite overall improvements, the study highlights persistent risks, with 671.7 hm² of area transitioning from lower to higher erosion intensity, underscoring the need for continued erosion control and monitoring in specific regions.

The study demonstrates that natural factors, particularly DEM and precipitation serve as the primary drivers of soil erosion in the southwestern region. Higher elevations and greater precipitation significantly contribute to erosion, with steep slopes and shallow soils further exacerbating the risk. Precipitation exceeding 500 mm plays a critical role, intensifying erosion in mountainous areas. Temperature and potential evapotranspiration also influence soil erosion, though their impact is more moderate. Human activities, including GDP, land use and population density, further shape erosion patterns. Higher GDP and increased built-up areas exhibit a positive correlation with elevated soil erosion, while the proportion of cropland demonstrates a clear, gradual rise in erosion risk. Population density exhibits a weaker and more variable effect. The interaction between climatic and topographic factors, particularly the precipitation-elevation relationship, amplifies erosion in high-elevation areas during intense rainfall events. Additionally, socioeconomic factors such as GDP and land use act synergistically with natural factors to modify erosion patterns, highlighting the necessity for integrated strategies to mitigate soil erosion by addressing both environmental and anthropogenic influences.

Projections of soil erosion in Southwest China for the period 2030–2050, based on the RUSLE model and three future climate scenarios (SSP119, SSP245, and SSP585), indicate a general increase in soil erosion intensity, with the SSP585 scenario exhibiting the highest projected increase. The spatial distribution of erosion intensity will largely follow current patterns, with high-erosion areas concentrated in the northwest and low-erosion areas in the southeast. Notably, regions with slight erosion will decrease, while areas with light erosion will expand over time. The average soil erosion intensity will increase steadily under all scenarios, with the SSP119 scenario demonstrating a consistent upward trend, the SSP245 scenario showing an initial increase followed by a decrease, and the SSP585 scenario exhibiting an initial decline before increasing by 2050. Western Sichuan is projected to experience the most severe erosion, particularly due to increased precipitation and mountainous terrain. Furthermore, by 2050, moderate and severe erosion will primarily occur in high-altitude regions dominated by grassland land use, where soil erosion risks are exacerbated by extreme weather events. These findings suggest growing challenges for soil conservation, with heightened erosion risks and potential for significant soil loss, particularly in high-altitude regions under changing climatic conditions.

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Abbreviations

The following abbreviations are used in this manuscript:

MDPI	Multidisciplinary Digital Publishing Institute
DOAJ	Directory of open access journals
TLA	Three letter acronym
LD	Linear dichroism

References

1. Sessay, M.F.; Blaikie, P.; Brookfield, H. *Land Degradation and Society*; Routledge: New York, NY, USA, 1987.
2. Obalum, S.E.; Buri, M.M.; Nwite, J.C.; Hermansah, Yoshinori, W.; Igwe, C.A.; Toshiyuki, W. Soil Degradation-Induced Decline in Productivity of Sub-Saharan African Soils: The Prospects of Looking Downwards the Lowlands with the Sawah Ecotechnology. *Appl. Environ. Soil Sci.* **2012**, *2012*, 673926. [[CrossRef](#)]
3. Yang, X.M.; Zhang, X.P.; Deng, W.; Fang, H.J. Black soil degradation by rainfall erosion in Jilin, China. *Land Degrad. Dev.* **2003**, *14*, 409–420. [[CrossRef](#)]
4. Xu, X.Z.; Xu, Y.; Chen, S.C.; Xu, S.G.; Zhang, H.W. Soil loss and conservation in the black soil region of Northeast China: A retrospective study. *Environ. Sci. Policy* **2010**, *13*, 793–800. [[CrossRef](#)]
5. Fan, H.; Cai, Q.; Cheng, G.; Cui, M. Comparative study of the soil erosion and control in the three major black soil regions in the world. *J. Nat. Resour.* **2005**, *20*, 387–393.
6. Wang, Y.; Yang, M.Y.; Liu, P.L. Contribution partition of water and wind erosion on cultivated slopes in northeast black soil region of China. *J. Nucl. Agric. Sci.* **2010**, *24*, 790–795.
7. Humphrey, O.S.; Osano, O.; Aura, C.M.; Marriott, A.L.; Dowell, S.M.; Blake, W.H.; Watts, M.J. Evaluating spatio-temporal soil erosion dynamics in the Winam Gulf catchment, Kenya for enhanced decision making in the land-lake interface. *Sci. Total Environ.* **2022**, *815*, 151975. [[CrossRef](#)]
8. Baiamonte, G.; Minacapilli, M.; Novara, A.; Gristina, L. Time scale effects and interactions of rainfall erosivity and cover management factors on vineyard soil loss erosion in the semi-arid area of southern Sicily. *Water* **2019**, *11*, 978. [[CrossRef](#)]
9. Williams, J.R.; Renard, K.G.; Dyke, P.T. A new method for assessing erosion's effects on soil productivity. *J. Soil Water Conserv.* **1983**, *38*, 381–383. [[CrossRef](#)]
10. Koirala, P.; Thakuri, S.; Joshi, S.; Chauhan, R. Estimation of soil erosion in Nepal using a RUSLE modeling and geospatial tool. *Geosciences* **2019**, *9*, 147. [[CrossRef](#)]
11. Panagos, P.; Borrelli, P.; Matthews, F.; Liakos, L.; Bezak, N.; Diodato, N.; Ballabio, C. Global rainfall erosivity projections for 2050 and 2070. *J. Hydrol.* **2022**, *610*, 127865. [[CrossRef](#)]
12. Le Roux, J.J.; Morgenthal, T.L.; Malherbe, J.; Pretorius, D.J.; Sumner, P.D. Water erosion prediction at a national scale for South Africa. *Water Sa* **2008**, *34*, 305–314. [[CrossRef](#)]
13. 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](#)]
14. Polykretis, C.; Alexakis, D.D.; Grillakis, M.G.; Manoudakis, S. Assessment of intra-annual and inter-annual variabilities of soil erosion in Crete Island (Greece) by incorporating the Dynamic “Nature” of R and C-Factors in RUSLE modeling. *Remote Sens.* **2020**, *12*, 2439. [[CrossRef](#)]
15. Castro, R.M.; dos Santos Alves, W.; de Oliveira Marcionilio, S.M.L.; De Moura, D.M.B.; da Silva Oliveira, D.M. Soil losses related to land use and rainfall seasonality in a watershed in the Brazilian Cerrado. *J. South Am. Earth Sci.* **2022**, *119*, 104020. [[CrossRef](#)]
16. Sun, W.; Shao, Q.; Liu, J.; Zhai, J. Assessing the effects of land use and topography on soil erosion on the Loess Plateau in China. *Catena* **2014**, *121*, 151–163. [[CrossRef](#)]
17. Dou, H.; Wang, R.; Wang, H.; Jian, W. Rainfall early warning threshold and its spatial distribution of rainfall-induced landslides in China. *Rock Mech. Bull.* **2023**, *2*, 100056. [[CrossRef](#)]
18. Johannsen, L.L.; Schmaltz, E.M.; Mitrovits, O.; Klik, A.; Smoliner, W.; Wang, S.; Strauss, P. An update of the spatial and temporal variability of rainfall erosivity (R-factor) for the main agricultural production zones of Austria. *Catena* **2022**, *215*, 106305. [[CrossRef](#)]
19. Wang, K.; Zhang, C.; Chen, H.; Yue, Y.; Zhang, W.; Zhang, M.; Qi, X.; Fu, Z. Karst landscapes of China: Patterns, ecosystem processes and services. *Landsc. Ecol.* **2019**, *34*, 2743–2763. [[CrossRef](#)]

20. García-Ruiz, J.M.; Beguería, S.; Nadal-Romero, E.; González-Hidalgo, J.C.; Lana-Renault, N.; Sanjuán, Y. A meta-analysis of soil erosion rates across the world. *Geomorphology* **2015**, *239*, 160–173. [\[CrossRef\]](#)
21. Taye, G.; Poesen, J.; Vanmaercke, M.; Van Wesemael, B.; Martens, L.; Teka, D.; Nyssen, J.; Deckers, J.; Vanacker, V.; Haregeweyn, N. Evolution of the effectiveness of stone bunds and trenches in reducing runoff and soil loss in the semi-arid Ethiopian highlands. *Z. Geomorphol.* **2015**, *59*, 477–493. [\[CrossRef\]](#)
22. Li, Y.H.; He, Y.M.; Yang, Z.S. Analysis on reduced grain yield from agricultural natural disaster in Jinsha River Basin of Yunnan province. *J. Mt. Sci.* **2002**, *20*, 43–48.
23. Li, Y.; Bai, X.; Zhou, Y.; Qin, L.; Tian, X.; Tian, Y.; Li, P. Spatial–Temporal Evolution of Soil Erosion in a Typical Mountainous Karst Basin in SW China, Based on GIS and RUSLE. *Arab. J. Sci. Eng.* **2016**, *41*, 209–221. [\[CrossRef\]](#)
24. Zhao, R.; Zhang, Q.; Tjugito, H.; Cheng, X. Granular impact cratering by liquid drops: Understanding raindrop imprints through an analogy to asteroid strikes. *Proc. Natl. Acad. Sci. USA* **2015**, *112*, 342–347. [\[CrossRef\]](#)
25. Su, B.; Huang, J.; Mondal, S.K.; Zhai, J.; Wang, Y.; Wen, S.; Gao, M.; Lv, Y.; Jiang, S.; Jiang, T. Insight from CMIP6 SSP-RCP scenarios for future drought characteristics in China. *Atmos. Res.* **2021**, *250*, 105375. [\[CrossRef\]](#)
26. Kumar, N.; Singh, S.K.; Dubey, A.K.; Ray, R.L.; Mustak, S.; Rawat, K.S. Prediction of soil erosion risk using earth observation data under recent emission scenarios of CMIP6. *Geocarto Int.* **2022**, *37*, 7041–7064. [\[CrossRef\]](#)
27. Chen, L.; Wang, G.; Miao, L.; Gnyawali, K.R.; Li, S.; Amankwah, S.O.Y.; Huang, J.; Lu, J.; Zhan, M. Future drought in CMIP6 projections and the socioeconomic impacts in China. *Int. J. Climatol.* **2021**, *41*, 4151–4170. [\[CrossRef\]](#)
28. Chen, D.; Wei, W.E.I.; Chen, L.D.; Yun, Y. Progress of the ecosystem services and management of terraces. *Mt. Res.* **2016**, *34*, 374–384.
29. Zhang, H.; Zhang, R.; Qi, F.; Liu, X.; Niu, Y.; Fan, Z.; Zhang, Q.; Li, J.; Yuan, L.; Song, Y. The CSLE model based soil erosion prediction: Comparisons of sampling density and extrapolation method at the county level. *Catena* **2018**, *165*, 465–472. [\[CrossRef\]](#)
30. Duan, X.; Gu, Z.; Li, Y.; Xu, H. The spatiotemporal patterns of rainfall erosivity in Yunnan Province, southwest China: An analysis of empirical orthogonal functions. *Glob. Planet. Change* **2016**, *144*, 82–93. [\[CrossRef\]](#)
31. Xiwen, L.; Walker, D. The plant geography of Yunnan Province, southwest China. *J. Biogeogr.* **1986**, *13*, 367–397. [\[CrossRef\]](#)
32. Hong, D.J.; Bo, C.Q.; Quan, T.Y.; Qiang, L.J. Dynamic change and spatial characteristics of soil erosion in Yunnan Province. *West. For. Sci.* **2018**, *47*, 15–21.
33. Duan, X.; Bai, Z.; Rong, L.; Li, Y.; Ding, J.; Tao, Y.; Li, J.; Li, J.; Wang, W. Investigation method for regional soil erosion based on the Chinese Soil Loss Equation and high-resolution spatial data: Case study on the mountainous Yunnan Province, China. *Catena* **2020**, *184*, 104237. [\[CrossRef\]](#)
34. Panagos, P.; Karydas, C.G.; Gitas, I.Z.; Montanarella, L. Monthly soil erosion monitoring based on remotely sensed biophysical parameters: A case study in Strymonas river basin towards a functional pan-European service. *Int. J. Digit. Earth* **2012**, *5*, 461–487. [\[CrossRef\]](#)
35. Peng, S.; Ding, Y.; Liu, W.; Li, Z. 1km monthly temperature and precipitation dataset for China from 1901 to 2017. *Earth Syst. Sci. Data* **2019**, *11*, 1931–1946. [\[CrossRef\]](#)
36. Li, X.; Che, T.; Li, X.; Wang, L.; Bao, Q. CASEarth Poles: Big Data for the Three Poles. *Bull. Am. Meteorol. Soc.* **2020**, *101*, E1475–E1491. [\[CrossRef\]](#)
37. Peng, S.; Ding, Y.; Wen, Z.; Chen, Y.; Cao, Y.; Ren, J. Spatiotemporal change and trend analysis of potential evapotranspiration over the Loess Plateau of China during 2011–2100. *Agric. For. Meteorol.* **2017**, *233*, 183–194. [\[CrossRef\]](#)
38. Ding, Y.; Peng, S. Spatiotemporal Trends and Attribution of Drought across China from 1901–2100. *Sustainability* **2020**, *12*, 477. [\[CrossRef\]](#)
39. Ding, Y.; Peng, S. Spatiotemporal change and attribution of potential evapotranspiration over China from 1901 to 2100. *Theor. Appl. Climatol.* **2021**, *145*, 79–94. [\[CrossRef\]](#)
40. Yoder, D.; Lown, J. The future of RUSLE: Inside the new revised universal soil loss equation. *J. Soil Water Conserv.* **1995**, *50*, 484–489. [\[CrossRef\]](#)
41. Swain, R.; Sahoo, N.K.; Mishra, A. Potential Soil Erosion Mapping and Priority-Based Adaption Strategies Using RUSLE and Geospatial Techniques. *J. Hydrol. Eng.* **2024**, *29*, 05024007. [\[CrossRef\]](#)
42. Tao, H.; Wang, W. Analysis of nitrogen and phosphorus losses in soil erosion process based on GIS: Taking Dingxi city Anding district as an example. *J. Green Sci. Technol.* **2018**, *24*, 15–17.
43. Wischmeier, W.H. Rainfall energy and its relationship to soil loss. *Eos Trans. Am. Geophys. Union* **1958**, *39*, 285–291.
44. Zhang, J.; Gao, G.; Li, Z.; Fu, B.; Gupta, H.V. Identification of climate variables dominating streamflow generation and quantification of streamflow decline in the Loess Plateau, China. *Sci. Total Environ.* **2020**, *722*, 137935. [\[CrossRef\]](#)
45. Williams, J.R.; Jones, C.A.; Kiniry, J.R.; Spanel, D.A. The EPIC crop growth model. *Trans. ASAE* **1989**, *32*, 497–0511. [\[CrossRef\]](#)
46. Foster, G.R.; McCool, D.K.; Renard, K.G.; Moldenhauer, W.C. Conversion of the universal soil loss equation to SI metric units. *J. Soil Water Conserv.* **1981**, *36*, 355–359. [\[CrossRef\]](#)

47. Fu, S.H.; Liu, B.Y.; Zhou, G.Y.; Sun, Z.X.; Zhu, X.L. Calculation tool of topographic factors. *Sci. Soil Water Conserv.* **2015**, *13*, 105–110.
48. Renard, K.G. *Predicting Soil Erosion by Water: A Guide to Conservation Planning with the Revised Universal Soil Loss Equation (RUSLE)*; US Department of Agriculture, Agricultural Research Service: Washington, DC, USA, 1997.
49. Mccool, D.K.; Brown, L.C.; Foster, G.R.; Mutchler, C.K.; Meyer, L.D. Revised slope steepness factor for the Universal Soil Loss Equation. *Trans. ASAE* **1987**, *30*, 1387–1396. [[CrossRef](#)]
50. Liu, B.Y.; Nearing, M.A.; Shi, P.J.; Jia, Z.W. Slope Length Effects on Soil Loss for Steep Slopes. *Soil Sci. Soc. Am. J.* **2000**, *64*, 1759–1763. [[CrossRef](#)]
51. Cai, C.; Ding, S.; Shi, Z.; Huang, L.; Zhang, G. Study of applying USLE and geographical information system IDRISI to predict soil erosion in small watershed. *J. Soil Water Conserv.* **2000**, *14*, 19–24.
52. Li, T.; Zheng, L. Soil erosion changes in the Yanhe watershed from 2001 to 2010 based on RUSLE model. *J. Nat. Resour.* **2012**, *27*, 1164–1175.
53. Li, H.; Hao, L.A.; Zhang, X.M.; Wang, C.G.; Zhang, Y.J.; Ma, B. Temporal and Spatial Variation of Soil Erosion in Yarlung Zangbo, Nyangqu and Lhasa Rivers Area of Xizang Autonomous Region. *Bull. Soil Water Conserv.* **2024**, *44*, 291–301.
54. Zhou, L.; Wang, P.; Cao, R. Soil Erosion Driving Factors and Ecological Security Evaluation for Yan'an City from 2000 to 2020. *J. Ecol. Rural Environ.* **2022**, *38*, 511–520.
55. Friedman, J.H. Greedy function approximation: A gradient boosting machine. *Ann. Stat.* **2001**, *29*, 1189–1232. [[CrossRef](#)]
56. Chen, T.; Guestrin, C. XGBoost: A Scalable Tree Boosting System. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Francisco, CA, USA, 13–17 August 2016; pp. 785–794.
57. Sundararajan, M.; Najmi, A. The many Shapley values for model explanation. In Proceedings of the International Conference on Machine Learning, PMLR, Virtual, 13–18 July 2020; pp. 9269–9278.
58. Hateffard, F.; Mohammed, S.; Alsafadi, K.; Enaruvbe, G.O.; Heidari, A.; Abdo, H.G.; Rodrigo-Comino, J. CMIP5 climate projections and RUSLE-based soil erosion assessment in the central part of Iran. *Sci. Rep.* **2021**, *11*, 7273. [[CrossRef](#)]
59. Zhao, G.; Mu, X.; Wen, Z.; Wang, F.; Gao, P. Soil Erosion, Conservation and Eco-Environment Changes in the Loess Plateau of China. *Land Degrad. Dev.* **2013**, *24*, 499–510. [[CrossRef](#)]
60. Ganasri, B.P.; Ramesh, H. Assessment of soil erosion by RUSLE model using remote sensing and GIS—A case study of Nethravathi Basin. *Geosci. Front.* **2016**, *7*, 953–961. [[CrossRef](#)]
61. Li, Z.; Fang, H. Impacts of climate change on water erosion: A review. *Earth-Sci. Rev.* **2016**, *163*, 94–117. [[CrossRef](#)]
62. Julien, Y.; Sobrino, J.A. The Yearly Land Cover Dynamics (YLCD) method: An analysis of global vegetation from NDVI and LST parameters. *Remote Sens. Environ.* **2009**, *113*, 329–334. [[CrossRef](#)]
63. Xiong, M.; Sun, R.; Chen, L. Effects of soil conservation techniques on water erosion control: A global analysis. *Sci. Total Environ.* **2018**, *645*, 753–760. [[CrossRef](#)]
64. Panagos, P.; Meusburger, K.; Alewell, C.; Montanarella, L. Soil erodibility estimation using LUCAS point survey data of Europe. *Environ. Model. Softw.* **2012**, *30*, 143–145. [[CrossRef](#)]
65. Wang, X.; Zhao, X.; Zhang, Z.; Yi, L.; Zuo, L.; Wen, Q.; Liu, F.; Xu, J.; Hu, S.; Liu, B. Assessment of soil erosion change and its relationships with land use/cover change in China from the end of the 1980s to 2010. *Catena* **2016**, *137*, 256–268. [[CrossRef](#)]
66. 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](#)]
67. Feng, X.; Fu, B.; Lu, N.; Zeng, Y.; Wu, B. How ecological restoration alters ecosystem services: An analysis of carbon sequestration in China's Loess Plateau. *Sci. Rep.* **2013**, *3*, 2846. [[CrossRef](#)]
68. Piao, S.; Wang, X.; Park, T.; Chen, C.; Lian, X.U.; He, Y.; Bjerke, J.W.; Chen, A.; Ciais, P.; Tømmervik, H. Characteristics, drivers and feedbacks of global greening. *Nat. Rev. Earth Environ.* **2020**, *1*, 14–27. [[CrossRef](#)]
69. Shi, P.; Li, P.; Li, Z.; Sun, J.; Wang, D.; Min, Z. Effects of grass vegetation coverage and position on runoff and sediment yields on the slope of Loess Plateau, China. *Agric. Water Manag.* **2022**, *259*, 107231. [[CrossRef](#)]
70. Nearing, M.A.; Jetten, V.; Baffaut, C.; Cerdan, O.; Couturier, A.; Hernandez, M.; Le Bissonnais, Y.; Nichols, M.H.; Nunes, J.P.; Renschler, C.S. Modeling response of soil erosion and runoff to changes in precipitation and cover. *Catena* **2005**, *61*, 131–154. [[CrossRef](#)]
71. Panagos, P.; Borrelli, P.; Poesen, J.; Ballabio, C.; Lugato, E.; Meusburger, K.; Montanarella, L.; Alewell, C. The new assessment of soil loss by water erosion in Europe. *Environ. Sci. Policy* **2015**, *54*, 438–447. [[CrossRef](#)]
72. Chen, Y.; Wang, X.; Huang, L.; Luo, Y. Spatial and temporal characteristics of abrupt heavy rainfall events over Southwest China during 1981–2017. *Int. J. Climatol.* **2021**, *41*, 3286–3299. [[CrossRef](#)]
73. Zhou, P.; Luukkanen, O.; Tokola, T.; Nieminen, J. Effect of vegetation cover on soil erosion in a mountainous watershed. *Catena* **2008**, *75*, 319–325. [[CrossRef](#)]
74. Ouyang, Z.; Zheng, H.; Xiao, Y.; Polasky, S.; Liu, J.; Xu, W.; Wang, Q.; Zhang, L.; Xiao, Y.; Rao, E.; et al. Improvements in ecosystem services from investments in natural capital. *Science* **2016**, *352*, 1455–1459. [[CrossRef](#)]

75. Poesen, J.; Nachtergaele, J.; Verstraeten, G.; Valentin, C. Gully erosion and environmental change: Importance and research needs. *Catena* **2003**, *50*, 91–133. [[CrossRef](#)]
76. Panagos, P.; Borrelli, P.; Meusburger, K.; Alewell, C.; Lugato, E.; Montanarella, L. Estimating the soil erosion cover-management factor at the European scale. *Land Use Policy* **2015**, *48*, 38–50. [[CrossRef](#)]
77. Yang, R.; Yang, S.; Chen, L.; Yang, Z.; Xu, L.; Zhang, X.; Liu, G.; Jiao, C.; Bai, R.; Zhang, X. Effect of vegetation restoration on soil erosion control and soil carbon and nitrogen dynamics: A meta-analysis. *Soil Tillage Res.* **2023**, *230*, 105705. [[CrossRef](#)]
78. Wen, X.; Zhen, L. Soil erosion control practices in the Chinese Loess Plateau: A systematic review. *Environ. Dev.* **2020**, *34*, 100493. [[CrossRef](#)]
79. Borrelli, P.; Robinson, D.A.; Fleischer, L.R.; Lugato, E.; Ballabio, C.; Alewell, C.; Meusburger, K.; Modugno, S.; Schütt, B.; Ferro, V. An assessment of the global impact of 21st century land use change on soil erosion. *Nat. Commun.* **2017**, *8*, 2013. [[CrossRef](#)]

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