

Article

Study on Soil Erosion Driving Forces by Using (R)USLE Framework and Machine Learning: A Case Study in Southwest China

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Abstract: Soil erosion often leads to land degradation, agricultural production reduction, and environmental deterioration, which seriously restricts the sustainable development of regions. Clarifying the driving factors of soil erosion is the premise of preventing soil erosion. Given the lack of current research on the driving factors/force changes of soil erosion in different regions or under different erosion intensity grades, this paper pioneered to use machine learning methods to address this problem. Firstly, the widely used (Revised) Universal Soil Loss Equation ((R)USLE) framework was applied to simulate the spatial distribution of soil erosion. Then, the K-fold algorithm was used to evaluate the accuracy and stability of five machine learning algorithms for fitting soil erosion. The random forest (RF) method performed best, with average accuracy reaching 86.35%. Then, the Permutation Importance (PI) and the Partial Dependence Plot (PDP) methods based on RF were introduced to quantitatively analyze the main driving factors under different geological conditions and the driving force changes of each factor under different erosion intensity grades, respectively. Results showed that the main drivers of soil erosion in Chongqing and Guizhou were cover management factors (PI: 0.4672, 0.4788), while that in Sichuan was slope length and slope factor (PI: 0.6165). Under different erosion intensity grades, the driving force of each factor shows nonlinear and complex inhibitory or promoting effects with factor value changing. These findings can provide scientific guidance for the refined management of soil erosion, which is significant for halting or reversing land degradation and achieving sustainable use of land resources.

Keywords: soil erosion; (R)USLE framework; machine learning; driving forces; southwest China



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1. Introduction

Soil erosion usually leads to the loss of soil nutrients, land degradation, agricultural production reduction, increase in runoff, and aggravation of geological disasters such as landslides and debris flows [1,2]. According to statistics, the global average soil loss is 12~15 tons per hectare per year, severely threatening the ecological environment and human life safety [3,4]. The Sustainable Development agenda put forward by the United Nations in 2015 clearly points out that halting or reversing land degradation is one of the goals that urgently need to be achieved [5]. Topography, vegetation coverage, precipitation, soil texture, and other factors jointly affect soil erosion intensity. For example, the slope affects the soil erosion rate, and the vegetation canopy can reduce the direct scour of the soil surface caused by heavy rain. Studying the driving factors of soil erosion and quantifying their influence on soil erosion plays an important role in developing appropriate measures for soil erosion control and ecological restoration [6].

In the quantitative study of soil erosion, the (Revised) Universal Soil Loss Equation ((R)USLE) families are the most widely used and effective methods [7,8]. Borrelli et al. [9] constructed a Global Applications of Soil Erosion Modeling Tracker (GASEMT) database including 435 soil-erosion models, in which the models belonging to the (R)USLE families are by far the most widely used soil erosion models worldwide, covering 41% of the total applications in the database. In addition, they also found a strong rising trend of the (R)USLE-type applications across all continents. So the (R)USLE framework is favored by scholars because of its full consideration of influence factors, simple model, and easily accessed data [10–14]. It has been applied successfully to the soil erosion study in many areas of China, including the mountainous regions in southern Yunnan, the Loess Plateau, the middle and lower reaches of the Yangtze River, and the Karst areas achieved good results [15–18].

In recent years, based on the quantitative evaluation of soil erosion, scholars have further focused on its driving factors [19]. Zhang et al. [20], Chen et al. [21], Yang et al. [22], graded or classified the soil erosion factors such as slope, elevation, and land cover type, and analyzed the soil erosion amount of each factor under different erosion intensity or classifications. However, this method does not consider the effect of multi-factor synergism on soil erosion. Wang et al. [4], Zhao et al. [23], Matomela et al. [24], and other scholars have quantitatively analyzed the driving factors of soil erosion using the geographic detector method, which can realize the identification of driving forces based on the synergistic effect of two factors. As we know, soil erosion results from multi-factor coupling, and this method is still insufficient to explain the complex multi-factor process of soil erosion. Machine learning has the ability to learn relevant rules from data automatically. It can effectively explain multivariable correlation and has been applied to research on driving forces in many fields [25], such as land cover change [26], soil moisture content [27], forest fire [28], power demand [29], and locust plague outbreak [30], and has shown good application potential. However, few scholars have applied machine learning algorithms to studies on soil erosion driving forces.

In the past decade, global land use change has increased the total amount of soil erosion by 2.5%, and the soil erosion rate is one to two orders of magnitude higher than the soil formation rate [31,32]. China has the most severe soil erosion, with broad soil erosion areas and high erosion rates. According to the Ministry of Ecology and Environment statistics, the area of soil loss in China was $271.08 \times 10^4 \text{ km}^2$ in 2019, and the soil loss in southwest China is the most serious [4]. Most of the research on soil erosion driving forces carried out by domestic scholars in southwest China is mainly in a single region, lacking comparisons among soil erosion driving factors in different geological environments. In fact, in the same area, the main driving factor of soil erosion may change under different erosion intensity grades. Still, relevant studies are rarely reported, which is significant for implementing refined soil erosion management.

In summary, the current research on soil erosion driving forces still has some problems, such as few considerations of the synergy effects of multiple factors and unclear change rules of factor driving force under different erosion intensity grades. This situation makes it difficult to carry out refined soil erosion management and restricts the sustainable use of land resources to a certain extent. Based on the estimation of soil erosion modulus with multi-source data, this paper takes the lead in applying machine learning methods to study the driving factors and force changes of soil erosion in Southwest China. The main contribution of this paper is to evaluate the fitting ability of various machine learning models to soil erosion, explore the main driving factors of soil erosion under the synergistic action of multiple factors, and quantify the complex changes of driving forces of each factor under different erosion intensity grades. Specifically, this paper aims: (1) to determine an optimal machine learning algorithm that has good performance on soil erosion fitting; (2) to quantify the complex change relationship of erosion factors on soil erosion under different erosion intensity grades; and (3) to provide suggestions for refined management of soil erosion to support the sustainable development goal of halting land degradation.

2. Materials and Methods

2.1. Study Area and Data Sources

2.1.1. Study Area

Southwest China, as the main distribution area of hydraulic erosion in China, has complex topography and geomorphology, numerous rivers, and rich natural resources (Figure 1a). Sichuan, Guizhou, and Chongqing suffer from severe soil erosion every year. Sichuan Province is located in the upper reaches of the Yangtze River, the terrain is high in the west and low in the east, and it crosses the first and second steps of China. The mountains and hills are widely distributed, the topographic gradient is large, and hydraulic erosion is severe in Sichuan. According to statistics, about 24.9% of the areas in Sichuan suffer from soil erosion [33]. Guizhou Province is a Karst plateau with the main uplift in Sichuan Basin, northern Guangxi, and western Hunan. The landform is mainly mountainous, and the terrain is broken, with an average elevation of more than 1100 m. Because of the unique geological structure and the destruction of forest vegetation, Guizhou has become one of the high-risk areas for soil loss in China. Since 1981, an area of 47,247.37 km² of soil erosion in Guizhou has been governed [34]. Due to the large number of mountains, large slopes, uneven seasonal distribution of precipitation, and spatial differences in soil types in Chongqing, regional soil erosion is relatively strong [35]. According to the statistics of the Chongqing Conservancy Bureau, soil loss occurred in 30.52% of the city in 2020. To sum up, the topography, geological environment, vegetation cover conditions, and soil erosion intensity grades in the above three regions are different (Figure 1b). Therefore, this study selects Sichuan, Chongqing, and Guizhou as the study area.

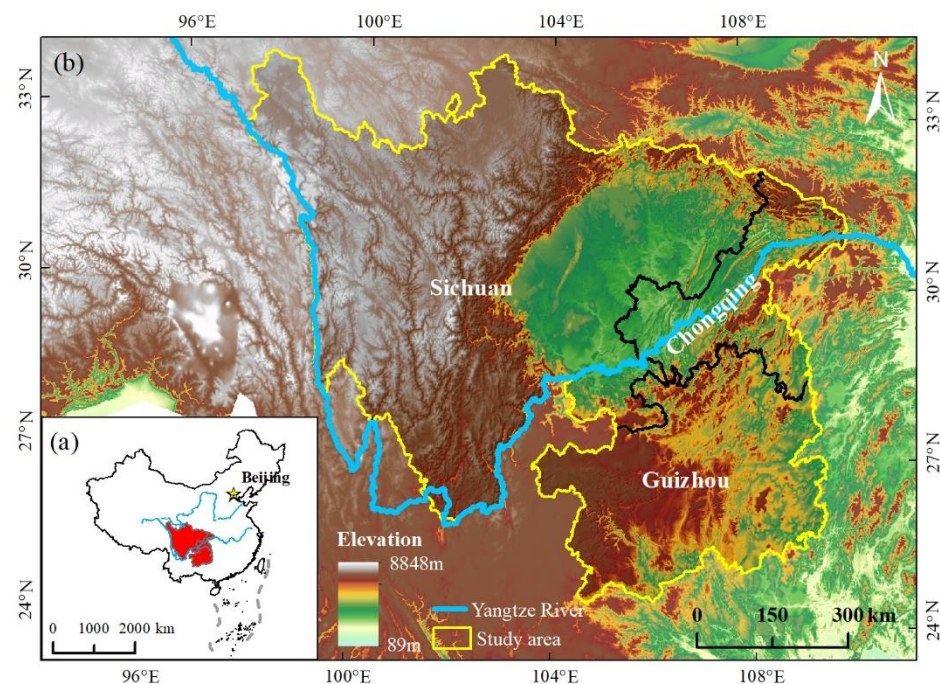


Figure 1. (a) Location of the study area in China; (b) Elevation distribution of the study area.

2.1.2. Data Sources

The data used in this study mainly include soil, climate, land use, topography, vegetation cover, and other data sources. The rainfall erosivity factor (R) is calculated from the monthly surface rainfall data set of $0.5^\circ \times 0.5^\circ$ in China obtained by the National Meteorological Center. The data set is of good quality after cross-verification and error analysis. The soil erodibility factor (K) is calculated from the Chinese soil data set based on the Harmonized World Soil Database (HSWD) provided by the National Qinghai-Tibet Plateau Data Center. The slope length and steepness factors (LS) are calculated from the DEM data supplied by NASA JPL, with a spatial resolution of 30 m. The cover-management factor

(C) is calculated from MODIS Surface Reflectance products (MYD09GA). This product has a resolution of 500 m and is used to calculate NDVI. The support practice factor (p) is assigned by the land cover product MCD12Q1 (IGBP). It is derived using supervised classifications of MODIS Terra and Aqua reflectance data. The study area includes 16 land cover types (Figure 2). Due to the unavailability of some soil erosion factor data in recent years, the relatively new year of 2020 was selected for research. Details of each data set are shown in Table 1.

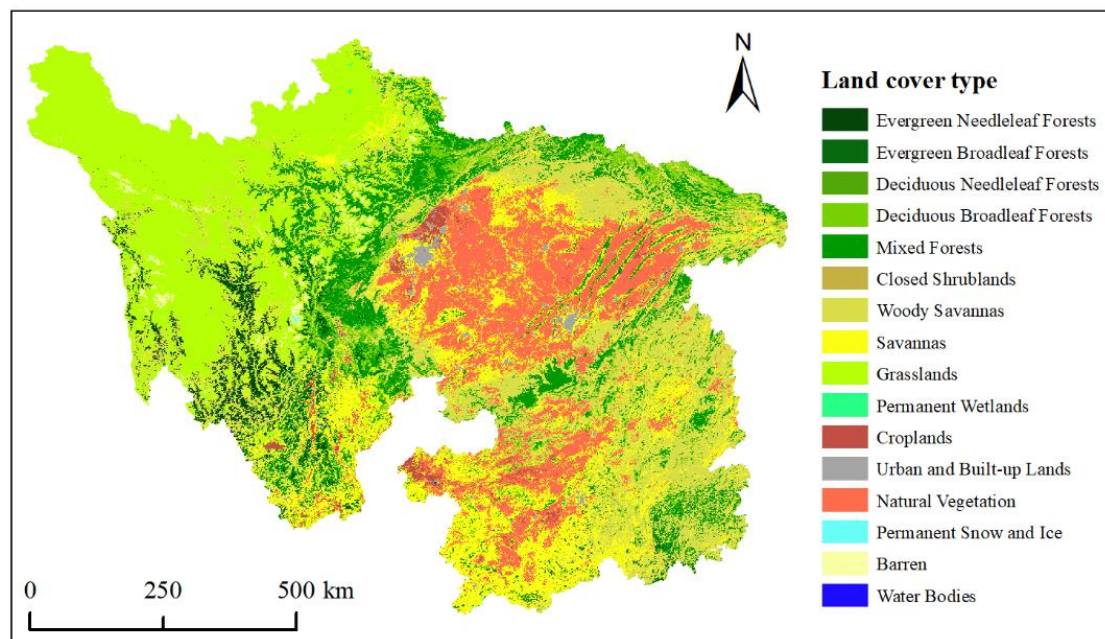


Figure 2. Land cover map of the study area.

Table 1. Data sources.

Data	Type	Spatial Resolution	Year	Data Sources
Vector boundary of the study area	shp	—	2020	http://www.resdc.cn (accessed on 4 March 2022)
Rainfall erosivity factor (R)	txt	—	2020	http://data.cma.cn (accessed on 4 March 2022)
Soil erodibility factor (K)	tif	1000 m	2009	http://data.tpdc.ac.cn (accessed on 4 March 2022)
Slope length and steepness factors (LS)	tif	30 m	2000	NASA SRTM DEM
Cover-management factor (C)	tif	500 m	2020	MOD09GA
Support practice factor (P)	tif	500 m	2020	MCD12Q1

2.2. Methods

The research method of this paper includes three parts: (1) Estimation of soil erosion based on the (R)USLE framework, including the calculation of erosion factors and the classification of soil erosion intensity grades. (2) Soil erosion simulation of five machine learning models based on the K-fold algorithm. (3) Explanation of machine learning on driving force of soil erosion based on Permutation Importance (PI) and Partial Dependence (PDP) methods. The technical flowchart is shown in Figure 3.

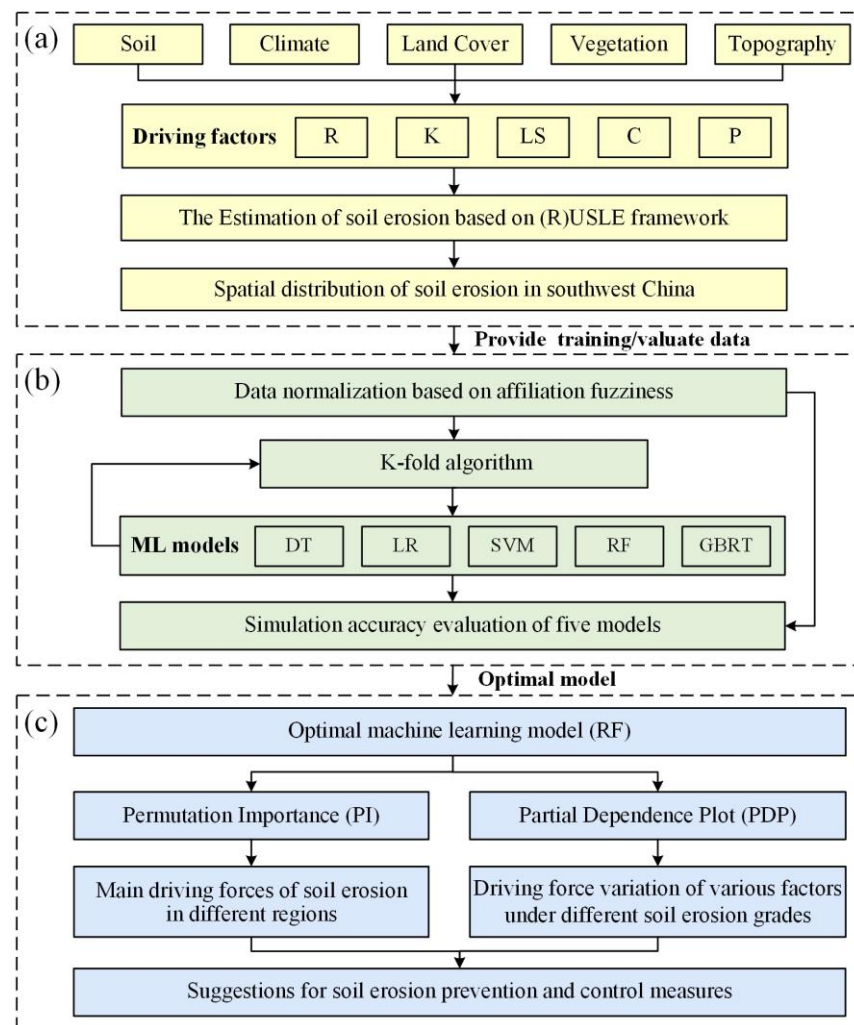


Figure 3. Technical flowchart. (a) Soil erosion estimation of southeast China based on (R)USLE framework; (b) Soil erosion simulation using ML models; (c) Driving force analysis of soil erosion by using RF model. R: Rainfall Erosivity Factor; K: Soil Erodibility Factor; LS: Slope Length and Steepness Factors; C: Cover-Management Factor; P: Support Practice Factor; ML: Machine Learning; DT: Decision Tree; LR: Logistics Regression; SVM: Support Vector Machine; RF: Random Forest; GBRT: Gradient Boosting Regression Tree.

2.2.1. Estimation of Soil Erosion Based on the (R)USLE Framework

The RUSLE framework is an improved USLE model put forward by the Agricultural Research Institute of the United States Department of Agriculture (USDA) in 1992 and implemented in 1997 [36], which is suitable for a broader range of empirical models [37]. Its mathematical formula is as follows:

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

where A is the average annual soil erosion modulus ($\text{t} \cdot \text{km}^{-2} \cdot \text{a}^{-1}$); R is the rainfall erosivity factor; K is the soil erodibility factor; LS is the slope length and steepness factors; C is the cover-management factor; and P is the support practice factor.

In order to better adapt to different landforms of China, this paper comprehensively referred to the application cases of (R)USLE framework in China and selected proper calculation methods for factors LS, C, and P to construct a new (R)USLE model suitable for the study area base on the original USLE model. The calculation methods for each factor are as follows:

(1) Calculation of rainfall erosivity factor (R)

Rainfall is the main driving factor of soil erosion, and raindrop splash and runoff erosion are the main forms of soil erosion [38]. In this study, the rainfall erosivity model based on monthly rainfall established by Wischmeier and Smith [39] is used to calculate factor R. The relationship between rainfall and erosivity is an exponential function. The annual rainfall is calculated through the accumulation of monthly rainfall, and the rainfall erosivity factor is calculated. The mathematical formula is shown in Equation (2):

$$R = \sum_{i=1}^{12} 1.735 \times 10^{[1.5 \lg(\frac{p_i^2}{p}) - 0.8188]} \quad (2)$$

where R is the rainfall erosivity factor; p_i is monthly rainfall (in mm); p is annual rainfall (in mm).

(2) Calculation of soil erodibility factor (K)

Soil erodibility factor K is calculated by the soil erosion and productivity impact estimation model (EPIC) [3]. The soil organic matter and the particle composition were used to calculate the K value. The mathematical formula is shown in Equation (3):

$$K = 0.1317 \times \left\{ 0.2 + 0.3 \exp \left(-0.0256 SAN \left(1 - \frac{SIL}{100} \right) \right) \right\} \times \left[\frac{SIL}{CAL + SIL} \right]^{0.3} \times \left\{ 1.0 - \frac{0.25C}{[C + \exp(3.72 - 2.95C)]} \right\} \times \left\{ 1.0 - \frac{0.7SN_1}{[SN_1 + \exp(-5.51 + 22.9SN_1)]} \right\} \quad (3)$$

where SAN is the subsoil sand fraction; SIL is the subsoil silt fraction; CAL is the subsoil clay fraction (in %); C is the topsoil carbon content (in %). $SN_1 = 1 - SAN/100$.

(3) Calculation of slope length and steepness factors (LS)

Topography is the basic geographical factor affecting soil erosion. Estimates of slope length and steepness over large areas are usually calculated from DEM [38]. The slope length factor L adopts the empirical formula proposed by Fu et al. [40]. Its mathematical formulas are shown in Equations (4) and (5):

$$L = \left(\frac{\lambda}{22.13} \right)^m \quad (4)$$

$$m = \begin{cases} 0.2 & \theta \leq 0.5^\circ \\ 0.3 & \theta \leq 1.5^\circ \\ 0.4 & \theta \leq 3^\circ \\ 0.5 & \theta > 3^\circ \end{cases} \quad (5)$$

where λ denotes the slope length (in m); m is the slope length index; θ is the slope angle (in $^\circ$).

The slope steepness factor S adopts the slope factor calculation formula put forward by Zhang et al. [41]. The mathematical formula is shown in Equation (6):

$$S = \begin{cases} 10.8 \sin \theta + 0.03 & \theta < 5^\circ \\ 16.8 \sin \theta - 0.5 & \theta \geq 5^\circ \\ 21.9 \sin \theta - 0.96 & \theta \geq 10^\circ \end{cases} \quad (6)$$

where θ is the slope angle.

Then the LS is calculated by L multiply S .

(4) Calculation of cover-management factor (C)

Factor C adopts the calculation method proposed by Cai et al. [42] and Li and Zhen [43]. The mathematical formula is shown in Equations (7) and (8):

$$NDVI_C = \frac{NDVI_i - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \quad (7)$$

$$C = \exp \left(-a \times \frac{NDVI_C}{b - NDVI_C} \right) \quad (8)$$

where $NDVI_C$ is the value of factor C of the calculated pixel, $NDVI_{max}$ and $NDVI_{min}$ are the maximum and minimum values of the whole study area; a and b are parameters determining the shape of the $NDVI_C$ curve, and their values are 2 and 1, respectively.

(5) Calculation of support practice factor (P)

The conservation practice factor P reflects the influence of specific conservation measures on soil erosion. It ranges from 0 to 1, with 0 indicating where soil erosion will not occur and 1 indicating the area where no soil and water conservation measures have been taken. The value of factor P was assigned based on the global vegetation classification product of the International Geosphere-Biosphere Programme (IGBP) in 2020 and the assignment rules of references You and Li [44] and Cha, Deng, and Gu [45]. It is generally considered that soil and water conservation measures are not taken in the herbaceous cover, natural vegetation, broad-leaved trees, shrubs, mosaic herbs, and grasslands, so factor P in these areas is assigned 1. Usually, soil erosion does not occur in rivers and impervious surface distribution areas. So factor P in these areas is given 0. The p value of barren land (at least 60% of area is non-vegetated barren (sand, rock, soil) areas with less than 10% vegetation) is given 0.4, and that of cropland is 0.7.

All factors were resampled to 30 m resolution and unified into the same projection coordinate system of WGS_1984_Albers. At last, the soil erosion intensity was graded into six grades according to the *Standards for classification and gradation of soil erosion* issued by the Ministry of Water Resources of the People's Republic of China [46] (Table 2).

Table 2. Soil erosion grading standard [46].

Soil Erosion Intensity Grades	Soil Erosion Modulus/($10^2 \cdot t \cdot km^{-2} \cdot a^{-1}$)
Very light	<5
Light	5–20
Moderate	20–50
Strong	50–80
Very strong	80–150
Extremely strong	>150

2.2.2. Soil Erosion Simulation Based on Machine Learning and K-Fold Algorithm

Five traditional machine learning models were selected in this study to verify the fitting accuracy of various machine learning methods for soil erosion, including the tree-based model (Decision tree, DT), the linear model (Logistics Regression, LR), the kernel function-based model (Support Vector Machine, SVM), and the integrated algorithm (Random Forest, RF, and Gradient Boosting Regression Tree, GBRT). The principles of the above machine learning algorithms can be found in references [47–51].

We obtained training data by randomly spreading points by taking the soil erosion intensity result of 2020 as labels and the factors R , K , LS , C , and P as features. The points in the three regions were obtained by randomly scattering 2,000,000 points in the whole study area and ensuring the distance of the adjacent points was no less than 100 m. We finally obtained 1,658,265 points due to the distance constraints and counted the number of points falling into the three regions, respectively. A total of 1,048,575 data points were obtained in Sichuan, 97,211 data points in Chongqing, and 512,479 data points in Guizhou. Each factor was normalized from 0 to 1 by using the membership ambiguity function. Five algorithms were applied to fit the soil erosion modulus, including DT, LR, SVM, RF, and GBRT. The K-fold algorithm was used to evaluate the accuracy and stability of the models, and then the best model was selected to study the driving forces of soil erosion.

The K-fold algorithm divides the data into K disjoint subsets called packets. For each packet, the remaining data are used to train a model, and then the data of this packet are used in the trained model to generate predictions. When the K packets are processed in a loop, the predicted values of each packet are summarized and compared with the

actual target to evaluate the model's accuracy [50,52]. The accuracy can be calculated by Equation (9):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (9)$$

where TP stands for True Positive; TN stands for True Negative; FP stands for False Positive; and FN stands for False Negative.

2.2.3. Driving Forces Explanation of Soil Erosion Based on Machine Learning

(1) PI method for exploring the main driving factor of soil erosion

The Permutation Importance (PI) is a heuristic method proposed by Altmann et al. [53] to normalize the measure of feature importance, which can correct the deviation of feature importance. It can identify potential feature interactions in the model to understand the importance of features to the results. The PI method randomly disrupts the single column of the verification data and makes the target and all other data columns stay where they are. It uses the resulting data set to predict and calculate the loss function through prediction and actual target values and judge the importance of variables by comparing the accuracy of the disrupted data. In this study, PI was used to analyze the main driving factors of soil erosion in different regions. The flow of the algorithm is shown in Algorithm 1.

Algorithm 1. PI implementation process.

Input: Fitting pre-training model (m), Dataset (D)
 Calculate the model accuracy of dataset(D) about S
 For columns j (columns D):
 Several repetitions $1, \dots, k$:
 Randomly scramble the column j , Generate corrupted data $D_{k,j}$
 Calculate ($D_{k,j}$) the accuracy $S_{k,j}$
 Importance calculation formula is shown in Equation (10):

$$i^j = s - \frac{1}{K} \sum_{k=1}^K S_{k,j} \quad (10)$$

Note: $S_{k,j}$: Accuracy; K : Number of repetitions; i^j : Importance of one factor (j : randomly scramble column).

(2) PDP method for exploring driving force changes of each factor

Although the PI method can simulate the driving effect of multi-factor coupling by disturbing the order of features, it cannot reflect the impact intensity of each factor change on soil erosion. Partial Dependence Plot [54] (PDP) can show the marginal effect of one or more features on the prediction results to explain whether the influence of features on the results is linear, monotonous, or more complex (Equation (11)). PDP assumes that the feature X^C is not related to other feature X^S , and marginalizes the resulting output to the feature distribution in set C . By marginalizing other features, a function that only depends on the features in S is obtained to explore the relationship between the features S and the predicted results. PI shows which feature impacts the results most, while PDP shows how features affect the model results. In this study, the PDP was used to analyze the driving force variation of each erosion factor under different erosion intensity grades.

$$f^S(X^S) = \frac{1}{N} \sum_{i=1}^N f(X^S, X_i^C) \quad (11)$$

where f^S is the prediction model; S is the independent variable; and C is the other independent variables set.

3. Results

3.1. Soil Erosion Intensity Distribution in the Study Area

Figure 4 shows the distribution maps of the five soil erosion driving factors. The higher the value of these factors, the easier it is to promote soil erosion. Although Figure 4 shows that these five factors have no strong relation in their spatial distribution, they jointly determine the spatial distribution of soil erosion in the study area. These maps can help us understand how the driving factors work when the soil erosion intensity changes.

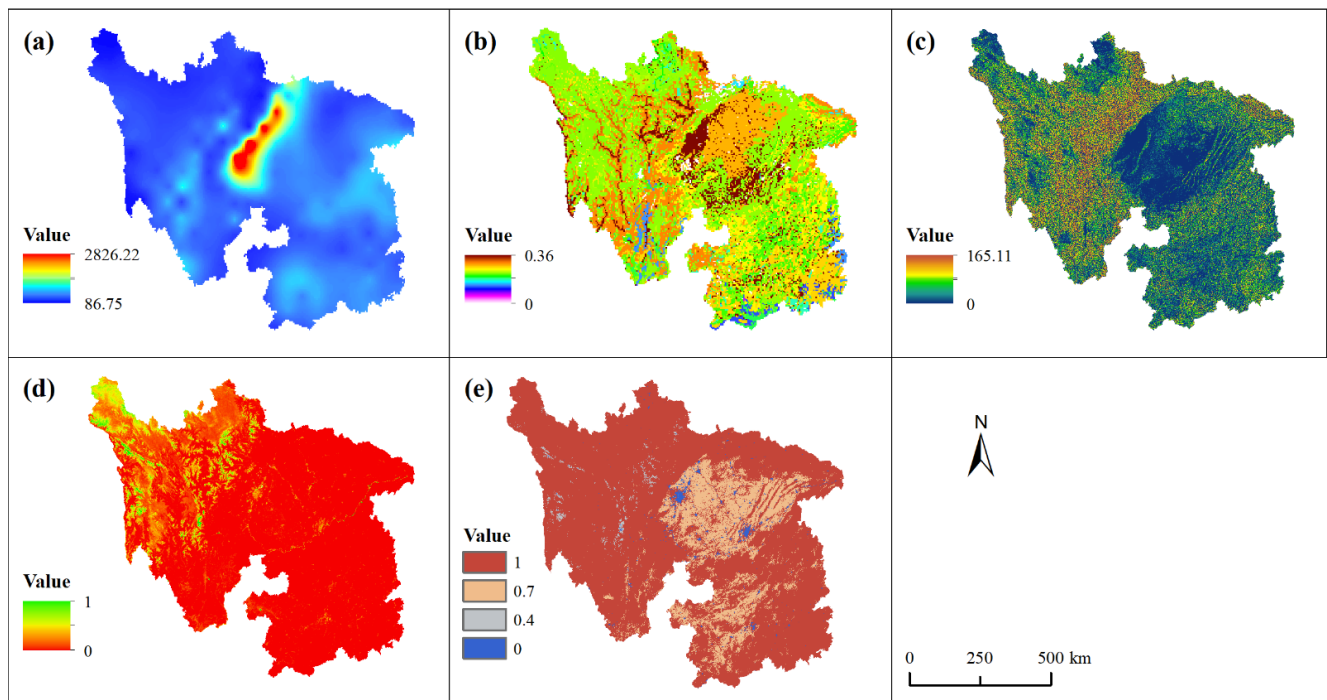


Figure 4. Spatial distribution characteristics of five soil erosion factors. (a) R: rainfall erosivity factor; (b) K: soil erodibility factor; (c) LS: slope length and steepness factors; (d) C: cover-management factor; (e) P: support practice factor.

The study area's average annual soil erosion modulus in 2020 is estimated based on (R)USLE. In order to further analyze the spatial distribution characteristics of soil erosion intensity, the soil erosion results were graded according to Algorithm 1. The spatial distribution maps of soil erosion intensity in Sichuan, Guizhou, and Chongqing are shown in Figure 5. The soil erosion intensity is graded into six grades: very light, light, moderate, strong, very strong, and extremely strong.

It can be seen from Figure 5 that the overall degree of soil erosion in Sichuan Province is relatively high, and the areas with strong, very strong, and extremely strong soil erosion intensity grades are mainly concentrated in the northwest of Sichuan. The erosion intensity grades in Chongqing and Guizhou are mostly very light or light.

The area and proportion of each soil erosion intensity grade and average annual soil erosion modulus in each region are shown in Table 3. The results showed that about 32% of the areas had apparent soil erosion in 2020, in which the strong to extremely strong grades accounted for 18.97% of the total area, and the average erosion modulus was $50.22 \text{ t} \cdot \text{km}^{-2} \cdot \text{a}^{-1}$. The overall risk of soil erosion in Sichuan is rather high. The results are relatively consistent with the 14.71% proportion of strong and more intense erosion areas in Sichuan reported in the 2020 Soil and Water Conservation Bulletin. The soil erosion intensity in Guizhou and Chongqing is generally in very light and light grades, and the risk of soil erosion is relatively low. However, there are still areas above moderate erosion intensity grade in these two regions, which is consistent with the results of Wang et al. [4] of southwest China.

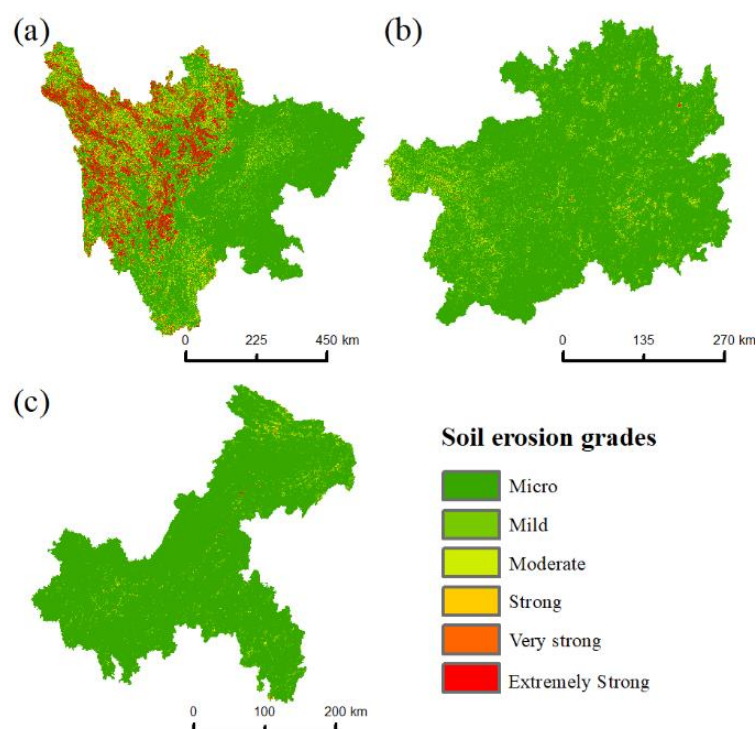


Figure 5. Distribution of soil erosion intensity in the study area. (a) Sichuan; (b) Guizhou; (c) Chongqing.

Table 3. Area and proportion of each erosion intensity grade and erosion modulus in three regions.

Erosion Intensity Grade	Sichuan		Guizhou		Chongqing	
	Area (10 ⁴ km ²)	Proportion (%)	Area (10 ⁴ km ²)	Proportion (%)	Area (10 ⁴ km ²)	Proportion (%)
Very light	32.696	67.68	15.381	88.06	7.815	95.44
Light	4.299	8.90	1.740	9.96	0.319	3.89
Moderate	2.152	4.45	0.249	1.42	0.035	0.42
Strong	1.750	3.62	0.063	0.36	0.011	0.13
Very strong	2.521	5.22	0.027	0.16	0.006	0.08
Extremely strong	4.889	10.13	0.006	0.04	0.003	0.04
Average annual soil erosion modulus (t·km ^{−2} ·a ^{−1})	50.22		1.99		0.67	

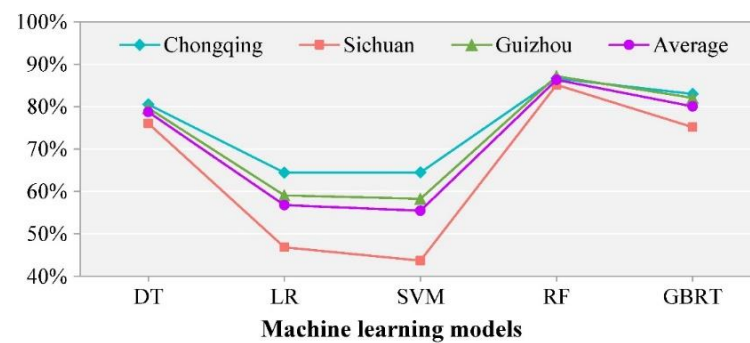
Figure 5a shows that the spatial distribution of soil erosion in Sichuan has apparent erosion-graded performance, which is more severe than that in Chongqing and Guizhou. The topography and land cover in Sichuan are more complex than those in Chongqing and Guizhou. Therefore, Sichuan Province will be taken as an example in the subsequent analysis of the driving forces of various factors under different erosion intensity grades.

3.2. Soil Erosion Simulation Based on Machine Learning

Five machine learning models, including DT, LR, SVM, RF, and GBRT, were used to fit the soil erosion in the three regions, and the accuracy of each model was evaluated based on the K-fold algorithm. Each model has been cross-validated ten times, and the accuracy evaluation results are shown in Table 4 and Figure 6. The results show that the fitting accuracy of RF is the highest in the three regions with an average accuracy of 86.35%. At the same time, from the fluctuation degree of fitting accuracy in the three regions, it can be seen that RF has the highest stability.

Table 4. Accuracy evaluation of five machine learning models in the three regions.

Region	DT	LR	SVM	RF	GBRT
Chongqing	80.55%	64.46%	64.48%	86.69%	82.98%
Sichuan	76.04%	46.86%	43.71%	85.16%	75.19%
Guizhou	79.65%	59.09%	58.29%	87.19%	82.11%
Average	78.75%	56.80%	55.49%	86.35%	80.09%

**Figure 6.** Accuracy evaluation of five machine learning models. DT, Decision Tree; LR, Logistic Regression; SVM, Support vector machine; RF, Random Forest; GBRT, Gradient Boosting Regression Tree.

It can be found from Figure 6 that the accuracies of SVM and LR are always at a low level in 10 cross-validations, which is because the idea of SVM and LR is to make the best partition through a line (or a higher-dimensional equivalence class) [48,49]. The dividing line of this kind of algorithm is linear, so these two algorithms do not perform very well in multi-classification scenarios. RF is an integrated algorithm based on DT. Evaluating the importance of input features is an important function of RF. A random process is introduced into the model to calculate the accuracy of the model by disturbing the out-of-bag data that does not participate in DT training. Hence, RF has higher accuracy than DT. Although GBRT is also an integrated algorithm based on DT, the prediction accuracy of the model is not stable without recalibration, and the time complexity of GBRT is much higher than that of RF [55,56]. Therefore, RF was selected to quantitatively attribute the driving force of soil erosion in this study.

3.3. Driving Factors and Driving Force Variation of Soil Erosion

3.3.1. Main Driving Factors of Soil Erosion in Different Regions

Based on RF and PI methods, the importance of soil erosion factors in the three regions in 2020 was ranked (Table 5 and Figure 7). It can be seen that the main driving factors of soil erosion are different in the three regions. The most important driving factor in Chongqing and Guizhou is factor C, while that in Sichuan is factor LS.

Table 5. Ranking of factor importance.

Sichuan		Guizhou		Chongqing	
Factor	PI	Factor	PI	Factor	PI
LS	0.6165 ± 0.0029	C	0.4788 ± 0.0012	C	0.4672 ± 0.0042
C	0.5757 ± 0.0013	LS	0.4455 ± 0.0023	LS	0.4259 ± 0.0075
R	0.2422 ± 0.0016	R	0.1533 ± 0.0017	R	0.0876 ± 0.0023
K	0.0404 ± 0.0005	P	0.0589 ± 0.0016	K	0.0268 ± 0.0010
P	0.0028 ± 0.0001	K	0.0434 ± 0.0013	P	0.0183 ± 0.0012

Note: R: Rainfall Erosivity Factor; K: Soil Erodibility Factor; LS: slope Length and Steepness Factors; C: Cover-Management Factor; P: Support Practice Factor.

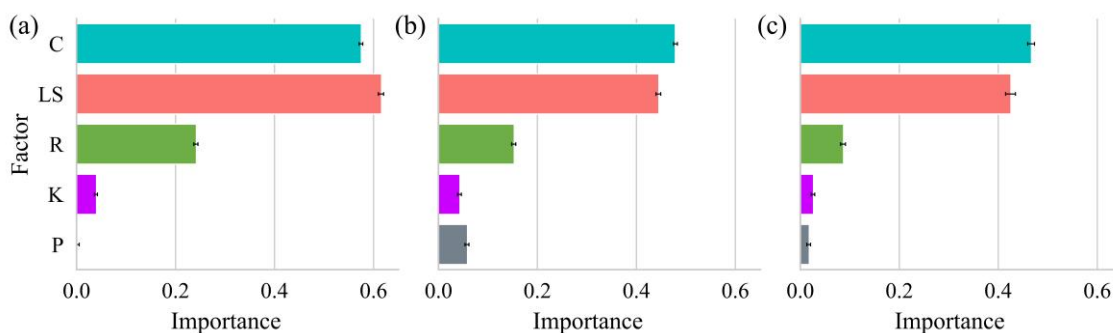


Figure 7. The importance of different factors in three regions. (a) Sichuan; (b) Guizhou; (c) Chongqing.

The landforms of Sichuan vary significantly from east to west, with a complex topography and great height difference. The eastern part of Sichuan is one of the largest basins in China, the northwest region is the northwest plateau, and the southwest is the northern section of the Hengduan Mountains. Therefore, the LS factor ($PI = 0.6165 \pm 0.0029$) is the main driving factor of soil erosion in Sichuan. On the other hand, the overall vegetation coverage in Sichuan is 69%, which is lower than that in Chongqing and Guizhou, making it another reason why the LS factor becomes the main driving factor. Despite the LS factor, the C factor also shows its second important position in Sichuan, which means that the C factor is a significant factor in soil erosion.

The land use in Guizhou is characterized by prominent mountain features, various land-use types, a high land reclamation rate, a large proportion of sloping farmland, and large forest and grassland areas. Building land and unused land in Guizhou only account for 13.87%, making the C factor ($PI = 0.4788 \pm 0.0012$) the main driver of soil erosion in Guizhou. At the same time, due to the diversity of land use types in Guizhou, the importance of the P factor for soil erosion is higher than that of the K factor compared with Sichuan and Chongqing.

Chongqing is located in the upper reaches of the Yangtze River and belongs to the subtropical monsoon humid climate, making evergreen broad-leaved forest the typical vegetation. The vegetation coverage density is high in Chongqing, with a vegetation cover area of 75,989.2 km², accounting for about 92.25% of the total area of the city. Under the dual influence of climate and vegetation, the C factor has become the main driving factor of the whole region ($PI = 0.4672 \pm 0.0042$). At the same time, the landforms of Chongqing are mainly hills and mountains, of which mountains account for 76%, making the LS factor the second important factor of soil erosion ($PI = 0.4259 \pm 0.0075$).

As we all know, heavy rainfall will cause soil loss, and a certain amount of water current scour is necessary for soil loss [57]. The rainfall in the three regions is mainly light rain, and the number of light rain days accounts for about 75% of the total precipitation days [58]. Therefore, the importance of factor R in all three regions shows the ranking third, indicating that although factor R is not ranked high, it also has a certain importance.

3.3.2. Variation of the Driving Forces under Different Erosion Intensity Grades

The above research shows that the soil erosion intensity grades in Guizhou and Chongqing are mainly very light and light. The soil erosion intensity in Sichuan is relatively high, and about 32% of the areas have apparent soil erosion. Therefore, this study takes Sichuan as an example to analyze the driving force changes of factors under different erosion intensity grades to put forward scientific and reasonable soil and water control measures for soil erosion. Figure 8 shows the PDP diagram of each driving factor for soil erosion in Sichuan, which can characterize the changing trend of driving forces of various factors under different erosion intensity grades.

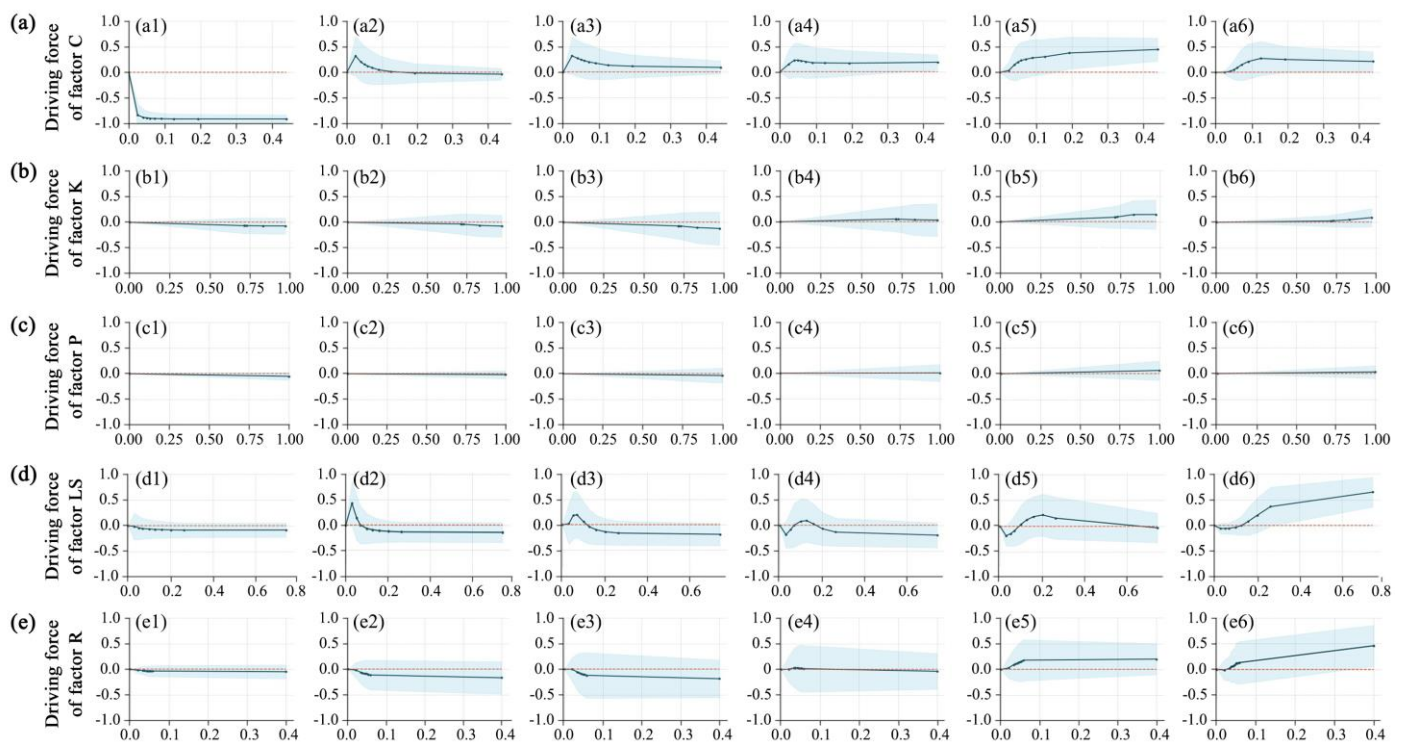


Figure 8. The PDP diagrams of each factor under different erosion intensity grades; (a) Cover-Management Factor; (b) Soil Erodibility Factor; (c) Support Practice Factor; (d) Slope Length and Steepness Factors; (e) Rainfall Erosivity Factor; 1 to 6 represents the soil erosion intensity grade is very light, light, moderate, strong, very strong, and extremely strong, respectively. The y-axis represents the influence of different factors on soil erosion; positive values represent promotion, and negative values represent inhibition). The X-axis represents the range of factors. The blue shaded area indicates the level of confidence. The points on the lines represent the concentrated range of different factors.

Vegetation can reduce the erosion of precipitation on the ground and use roots to stabilize the soil. It can be found from Figure 8a that there is a negative correlation between the cover-management factor (C) and soil erosion under the grade of very light. Under the erosion intensity grades of light, moderate, and strong, the driving force of the C factor on soil erosion first increases and then weakens. However, under the very strong erosion intensity grade, the C factor changed from a negative correlation (very light) to a strong positive correlation to soil erosion. Under the extremely strong grade, the increase of the C factor shows the phenomenon of restraining soil erosion. So, we could know that maintaining greening can effectively prevent and control soil erosion under low erosion intensity grades, while strengthening greening can reduce the impact of soil erosion under very light, moderate, and strong erosion intensity grades. Under the very strong and extremely strong grades, the inhibitory effect of the C factor on soil erosion gradually weakened along with the increase of the C factor. It is because soil erosion is the result of multi-factor coupling. Most of the very strong and extremely strong grades are distributed in areas with great height differences and complex topography, and the enhancement of vegetation coverage cannot restrain the growth rate of soil erosion.

Different soil types have different textures, and the abilities of soil erosion resistance are also different. The soil erodibility factor (K) reflects the reducing effect after implementing soil and water conservation measures, and the value is between 0 and 1. Figure 8b show that the K factor will inhibit soil erosion at the moderate erosion intensity grade. At the erosion intensity grades of strong and above, the K factor positively correlates with soil erosion in general.

It is found that there is an obvious linear relationship between the Support Practice Factor (P) and soil erosion, which is because when we assign values to land cover types, most of the values are concentrated in 0 and 1. It is difficult to capture the influence of small amount of data on the results in the process of calculation, so selecting higher resolution land cover data to explain the changes of soil erosion under different grades is the content that needs further discussion.

The slope length and steepness factors (LS) affect the soil erosion intensity by acting on the discharge and velocity of the slope runoff. Figure 8d shows that the LS factor's effect on soil erosion is very complex and related to Sichuan's physical geography. The LS factor is negatively correlated with soil erosion at the strong grade and below. At the extremely strong grade, soil erosion will increase dramatically with the increase of slope length and steepness. Therefore, at the extremely strong erosion intensity grade, proper construction of a gentle slope and reduction of height difference can effectively prevent and control soil erosion.

The rainfall factor (R) is the unit rainfall acting on the surface, producing the energy of soil and water flow. Figure 8e shows a significant positive correlation between R factors and soil erosion under extremely strong and very strong grades. Therefore, strengthening waterproofing under high erosion intensity grades can effectively prevent and control soil erosion.

Based on the above analysis, PDP shows that different measures can be taken to prevent and control soil erosion under different grades. For example, strengthening greening can effectively prevent and control soil erosion at the middle and low erosion intensity grades. In contrast, building gentle slopes, reducing height differences, and enhancing waterproofing can effectively prevent soil erosion at a high erosion intensity grade.

4. Discussion

4.1. (R)USLE Validation

Due to the significant terrain undulation of the study area and the higher time consumption for field measurement of soil loss, it is hard to obtain actual field data. So, we used previous studies and widely approved soil loss products to verify the reliability of the (R)USLE results from both qualitative and quantitative aspects. Qualitatively, compared with the results of Chen, Xiong, and Lan [34] and Wang et al. [4] in southwest China, the spatial distribution results of soil erosion intensity in this study are basically consistent with the previous results. Quantitatively, we used the soil erosion monitoring system, considered could be used in scientific research, proposed by Ouellette [59] in 2021 to calculate the soil erosion modulus of Chongqing in 2020 to compare with the result of this study. Products provided by this system are created using sentinel-2 data to monitor the NDVI of the whole year and the change of time series of bare soil to calculate soil erosion modulus. The results show that the average annual soil erosion modulus calculated by sentinel-2 in Chongqing is $0.63 \text{ t} \cdot \text{km}^{-2} \cdot \text{a}^{-1}$ (Figure 9), which is only lower 5.97% than the result of $0.67 \text{ t} \cdot \text{km}^{-2} \cdot \text{a}^{-1}$ of this study. Although, due to the limitation of the computing power of the system platform, the annual soil erosion modulus of Sichuan and Guizhou were not obtained, it also proved that our results estimated by the (R)USLE framework are reliable to some extent.

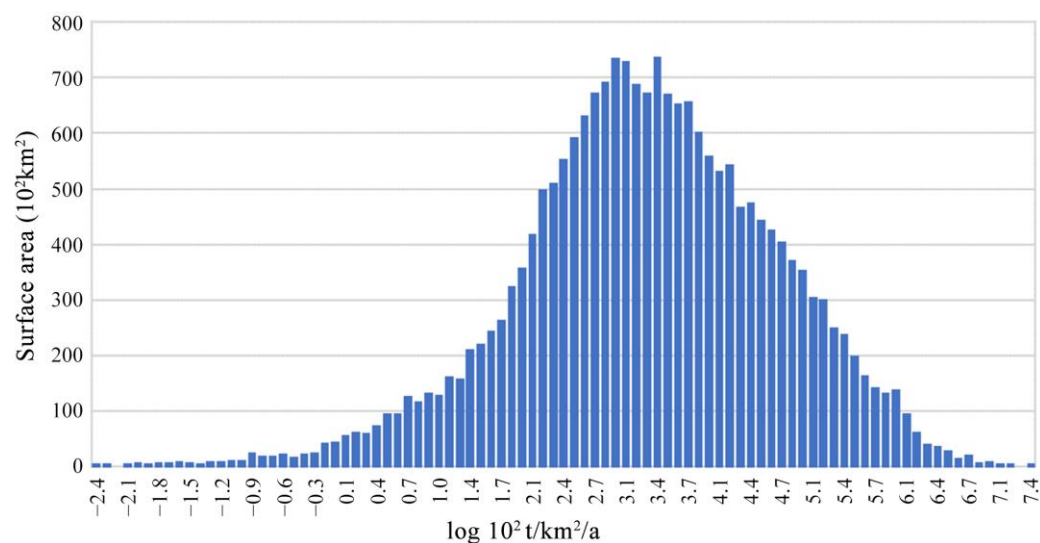


Figure 9. Soil Erosion Hazard (Log A) Distribution of Chongqing City in 2020.

4.2. Capability of Machine Learning to Explain the Driving Force of Soil Erosion

When the parameters are not re-calibrated, the RF is the most accurate and stable model in fitting soil erosion, with an average accuracy of 86.35%, which means that the machine learning method can be used to estimate soil erosion precisely. Compared with the traditional single-factor driving force analysis, and two-factor interaction based on the geographic detector, the PI method adopted in this paper can realize the importance rank of all driving factors by fully considering the synergistic effect of multiple factors and then identifying the main soil erosion factors in different regions. The PI results proved differences in the main driving factor in different regions. Furthermore, the PDP results can provide more information than the PI method by showing whether the influence of factors on soil erosion is linear, positive, negative, or more complex. It shows that the main driving factors may change when the soil erosion intensity grades vary. In addition, the PDP can also explain the changing trend of driving forces of various factors under different erosion intensity grades by analyzing continuous variables other than discrete variables as the two-factor interaction method does.

In conclusion, the machine learning method can not only simulate soil erosion with high precision and obtain the main driving factors of different regions, but also provide more information about the complex changing process of the driving forces along with factors changing at different erosion intensity grades. So, we conclude that the machine learning method has an excellent capability to explain the driving forces of soil erosion.

4.3. Analysis of Driving Force of Soil Erosion

Clarifying the driving factors and their driving force changing low over complex geographical conditions is the key to preventing soil erosion effectively. Our result shows that the main driving factor of soil erosion in Sichuan is the LS factor, which is consistent with the study that carried out in the Tuojiang River Basin in Sichuan [60]. Liu et al. [61] analyzed the driving factor of soil erosion in the Sancha River Basin in Guizhou, and concluded that vegetation factors dominated soil erosion, which was also consistent with C being the main driving factor of soil erosion in Guizhou in this work. As for the main driving factor of soil erosion in Chongqing, though many research have studied the influencing factors of soil erosion, no one had pointed out which factor was dominated the soil erosion (which study that analyze only some areas of Chongqing) [62,63]. This paper finds that the cover-management factor is the main driving factor of soil erosion in Chongqing. All these findings can provide guidance for making general governance measures of soil erosion.

As we know, under different environmental conditions, the main driving factor of soil erosion may be different, especially in large areas with significant terrain undulation like

Sichuan. So, more specific information for how driving force changing when conditions are different is need to make refined and adapted-to-local management measures. From the PDP diagram, we found that each factor's driving force generally shows a trend from inhibition to promotion along with the soil erosion intensity changing from very light to extremely strong. The variation trend of each factor has its own characteristics. Taking the LS factor as an example, in the very light grade, it always showed an inhibitory effect; in the light and moderate grades, it presented a trend of promoting first and then inhibiting; while in the strong and very strong grades, it presented an opposite trend, and finally tended to a gentle trend. In the extremely strong grade, the LS factor showed a nonlinear trend of increased promoting influence. The above information indicates that the driving force of each factor on soil erosion is constantly changing under different erosion intensity grades. By comparing the changing trend of each factor under the same erosion intensity grade, we found that the C and LS factors were the two main driving factors of soil erosion. With the erosion intensity getting strong, the influence of the LS factor was gradually stronger than that of the C factor. These findings are different from previous studies, and they can provide more detailed information for refined management of soil erosion. Therefore, compared with identifying the main driving factor, digging the relationship between factors' driving force change trend and different erosion rates is more important.

4.4. Suggestions for Soil Erosion Prevention and Control Measures

Soil erosion is considered a major environmental threat in terrestrial ecosystems, which seriously impacts the ecological environment and productivity [64]. The formation of soil erosion patterns is caused by many factors, such as K, LS, P, R, and C. Therefore, it is necessary to analyze the factors affecting erosion intensity patterns from many aspects. In this paper, the erosion intensity grades of strong, very strong, and extremely strong in Sichuan account for 18.91% of the total area, and the erosion intensity is high in the west and low in the southeast. The causes of soil erosion are complex and changeable. So, the quantitative description of the driving force changes can effectively explain the action form of factors under different erosion intensity grades and then provide scientific guidance for the formulation of corresponding soil erosion prevention and control measures in different erosion areas.

Combined with the soil erosion intensity and driving force analysis results in Sichuan, erosion hot areas could be located. Then corresponding protective measures in different areas could be taken, which could provide scientific decision making for regional sustainable development and effectively reduce the investment of funds. Most areas with strong and extremely strong erosion intensity grades in Sichuan have steep topography and low vegetation cover. In addition, due to limited cultivated land resources, Sichuan has a lot of unreasonable land use, especially in western Sichuan, where the natural conditions are bad. The main geomorphological types are high mountains and extremely high mountains with a significant disparity in topography, making soil erosion especially severe. The main land-use patterns in the areas with moderate erosion intensity grade and below are shrubland, sparse forest, and cultivated land. The regional vegetation coverage is relatively high, and soil erosion is relatively slight. Based on the above understanding, this paper puts forward the following suggestions for the prevention and control of soil erosion in Sichuan: (1) to strengthen greening and returning farmland to the areas of very light, light, moderate, and strong erosion intensity grades; and (2) to build gentle slope, reduce height difference and improve the erosion resistibility in the areas of extremely strong and very strong erosion intensity grades.

4.5. Research Limitations and Prospects

- (1) Due to the significant terrain undulation of the study area and the continuous long-term time requirement of field soil loss data obtaining, which may take a whole year, we did not use the actual field data to validate the results of (R)USLE. Instead, we verified the reliability of (R)USLE results qualitatively and quantitatively by

comparing the distribution of soil erosion and the erosion rate of this paper with previous studies or existing widely approved soil loss products, which is a limitation of this study. In the future, with the accumulation of field monitoring data on soil erosion by local supervision departments of water and soil conservation, this issue may be addressed.

- (2) According to the main driving factor and the driving force change trend, this paper provided several targeted suggestions for soil erosion management of Sichuan Province. Although each driving factor was finally sampled to a unified spatial resolution of 30 m, the original resolution of the factor R is 0.5° (~55 km), making the spatial information not detailed enough. When the driving factor data obtained are fine enough, we can extend the application of machine learning on soil erosion driving force to a smaller scale, such as river watersheds that are prone to soil erosion, to support the managers to carry out more targeted and accurate prevention and control measures.
- (3) In this study, we conducted a detailed analysis of soil erosion and its driving force in Sichuan Province in 2020. In the future, we can develop long-term monitoring of soil erosion and its driving force changes on this basis. Then, combined with the governance measures taken during the study period and the driving factors changes, evaluate the effectiveness of different governance measures, and explore better treatment schemes for different erosion intensity grades.

5. Conclusions

Based on the (R)USLE framework, this paper reveals the distribution pattern of soil erosion in Sichuan, Guizhou, and Chongqing. Based on machine learning algorithms, the soil erosion of southwest China was simulated, the main driving factors of soil erosion in different regions were analyzed, and the driving force changes of soil erosion factors under different erosion intensity grades were explained. The results show that the machine learning method has an excellent capability for fitting the soil erosion and exploring the driving force of soil erosion. The RF model performed better than models DT, LR, SVM and GBRT in fitting soil erosion with an average accuracy of 86.35%. PI method can be used to rank the importance of all driving factors. The PDP method can explain well whether the influence of factors on soil erosion is linear, positive, negative, or more complex. These results can provide scientific guidance for the refined management of soil erosion, then contribute to halting or reversing land degradation and achieving sustainable use of land resources.

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Data Availability Statement: The data that support the findings of this study are openly available in Google Earth Engine at <https://developers.google.com/earth-engine/datasets/> (accessed on 4 March 2022), in the National Meteorological Center of China at <http://data.cma.cn> (accessed on 4 March 2022) and in the National Qinghai-Tibet Plateau Data Center at <http://data.tpdc.ac.cn> (accessed on 4 March 2022).

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