Assessing the effects of vegetation and precipitation on soil erosion in the Three-River Headwaters Region of the Qinghai-Tibet Plateau, China postprint

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Abstract

Soil erosion in the Three-River Headwaters Region (TRHR) of the Qinghai-Tibet Plateau in China significantly impacts local economic development and ecological environment. Vegetation and precipitation are considered the primary factors driving variations in soil erosion. However, analyzing the respective impacts of precipitation and vegetation, as well as their combined effects on soil erosion at the pixel scale, presents a significant challenge. To assess the influences of vegetation and precipitation on soil erosion variation from 2005 to 2015, we employed the Revised Universal Soil Loss Equation (RUSLE) to evaluate soil erosion in the TRHR, and subsequently developed a methodology using the Logarithmic Mean Divisia Index (LMDI) model, which enables multiplicative decomposition of influencing factors, to quantify the contributions of the vegetation cover factor (C factor) and rainfall erosivity factor (R factor) to soil erosion variation at the pixel scale. Overall, soil erosion in the TRHR was alleviated from 2005 to 2015. Approximately 54.95% of the area experiencing decreased soil erosion was attributed to the combined effects of the C factor and R factor, while 41.31% was attributed to changes in the R factor alone. Relatively few areas exhibited increased soil erosion modulus. Of these, 64.10% of the area with increased soil erosion was caused by changes in the C factor, and 23.88% was caused by the combined effects of the C factor and R factor. Therefore, the combined effects of the C factor and R factor were identified as the primary driving force behind the decrease in soil erosion, whereas the C factor was the dominant factor contributing to increased soil erosion. The area with decreased soil erosion attributable to the C factor (12.10$×103km2)exceededtheareawithincreasedsoilerosioncausedbytheCfactor(8.30×$103 km2), indicating that vegetation exerted a beneficial effect in mitigating soil erosion. This study presents a novel methodology for quantitative assessment

of influencing factor impacts on soil erosion, and provides a scientific basis for regional soil erosion control.

Full Text

Preamble

Assessing the Effects of Vegetation and Precipitation on Soil Erosion in the Three-River Headwaters Region of the Qinghai-Tibet Plateau, China

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Abstract

Soil erosion in the Three-River Headwaters Region (TRHR) of the Qinghai-Tibet Plateau in China significantly impacts local economic development and ecological security. Vegetation and precipitation are widely recognized as the primary drivers of soil erosion variation. However, analyzing their individual and combined effects at the pixel scale presents a major challenge. To assess the influences of vegetation and precipitation on soil erosion dynamics from 2005 to 2015, we employed the Revised Universal Soil Loss Equation (RUSLE) model to evaluate soil erosion in the TRHR and developed a novel method using the Logarithmic Mean Divisia Index (LMDI) model—which can exponentially decompose influencing factors—to calculate the contribution values of the vegetation cover factor (C factor) and rainfall erosivity factor (R factor) to soil erosion variation at the pixel scale. Overall, soil erosion in the TRHR was alleviated during 2005–2015. Approximately 54.95% of the area experiencing decreased soil erosion resulted from the combined effects of the C and R factors, while 41.31% was attributable to changes in the R factor alone. Areas with increased soil erosion modulus were relatively limited, with 64.10% of such increases caused by the C factor and 23.88% by the combined effects of both factors. Consequently, the combined effects of the C and R factors constituted the primary driving force for soil erosion reduction, whereas the C factor was the dominant factor for soil erosion increase. The area with decreased soil erosion caused by the C factor (12.10×10^{3} km^2) exceeded the area with increased soil erosion caused by the same factor (8.30×10^{3} km^2), indicating that vegetation exerted a net positive effect on soil erosion control. This study introduces a new method for quantitative assessment of factor impacts on soil erosion and provides a scientific basis for regional soil erosion management.

Keywords: soil erosion; vegetation cover; rainfall erosivity; Logarithmic Mean Divisia Index; quantitative assessment; Three-River Headwaters Region

1. Introduction

Soil erosion is a global environmental problem with varying impacts on human livelihoods that has attracted widespread attention [?, ?]. The Three-River Headwaters Region (TRHR) of the Qinghai-Tibet Plateau in China serves as a critical ecological barrier, providing essential ecosystem services including water and soil conservation and biodiversity protection [?, ?, ?]. In recent years, global warming and intensified human activities have affected the region' s ecological environment, leading to rising snow lines, reduced runoff, increasing frequency of river flow interruptions, and changes in vegetation coverage and biomass [?, ?]. Located in the hinterland of the Qinghai-Tibet Plateau, the TRHR is characterized by fragile ecological conditions, harsh climate, severe soil erosion, and frequent natural disasters, making ecosystem recovery extremely difficult once degradation occurs.

Prior to implementing ecological conservation and restoration projects, alpine meadows in the TRHR exhibited comprehensive degradation trends [?, ?]. Consequently, soil erosion in the region is severe, with a total potential erosion amount of 1.12$×10^{9}$ t/a [?, ?]. Data indicate that the area affected by soil erosion reached 114.80$×10^{3}$ km^2 in 2010, accounting for over 30% of the total area and seriously threatening regional ecological security. Soil erosion is influenced by vegetation, precipitation, soil properties, topography, and human activities [?, ?]. While soil properties and topography remain relatively stable, precipitation and vegetation constitute the primary drivers of soil erosion variation. However, their interactions create uncertain and complex relationships, making it crucial to understand the spatiotemporal dynamics of soil erosion and the impacts of influencing factors in the TRHR.

The formation mechanisms and factor identification of soil erosion represent core frontier issues in current research, though quantitative attribution studies of combined factor effects require greater attention [?, ?, ?, ?, ?, ?]. Extensive research on soil erosion and its drivers has been conducted globally. For example, Ganasri et al. [?] studied soil erosion in the Nethravathi Basin using remote sensing data and the RUSLE model; Guerra et al. [?] reviewed ecosystem services related to soil erosion prevention in Mediterranean areas; Mohamadi et al. [?] examined rainfall pattern effects on runoff and soil erosion in field plots; García-Ruiz et al. [?] assessed land use impacts on soil erosion in Spain; and Panagos et al. [?] proposed a new European slope length and steepness factor for water erosion modeling. These studies primarily employed principal component analysis, regression analysis, and correlation coefficient methods to determine factor relationships with soil erosion and estimate their relative impacts. However, these approaches cannot quantitatively determine the specific contribution value of each factor to soil erosion variation at the pixel scale. Pixel-scale analysis is essential for understanding local variation patterns and informing targeted ecological protection and erosion control measures.

The Logarithmic Mean Divisia Index (LMDI) method is preferred for quantifying factor impacts on aggregate changes due to its robust theoretical foundation, adaptability, and desirable decomposition properties [?, ?]. LMDI decomposes aggregate indicators to identify influencing factors, analyze their degree of influence, and explain change mechanisms [?, ?, ?]. Unlike other decomposition models, LMDI provides a logarithmic mean weight equation without residuals, enabling perfect decomposition without unexplained terms. It can decompose both quantity and intensity indicators [?, ?, ?]. As an analytical framework for studying variation characteristics and mechanisms, index decomposition analysis has been widely applied in socioeconomic research [?, ?]. The method has successfully analyzed driving factors of energy consumption and CO_2 emissions [?, ?, ?, ?] and has been applied in water resources studies [?, ?, ?]. LMDI completely decomposes multiple related factors simultaneously, passes factor and time variance tests, and resolves zero-value problems in data without residual errors.

The Revised Universal Soil Loss Equation (RUSLE), which predicts average annual soil loss from raindrop impact and slope runoff [?, ?, ?], is widely accepted for evaluating soil and water conservation functions. Its structure—comprising vegetation cover, soil erodibility, rainfall erosivity, support practice, and topographic factors—aligns with the LMDI framework. This study introduces and applies the LMDI model for the first time to estimate factor contributions to soil erosion variation.

The first-stage ecological conservation and restoration project in the TRHR was launched in 2005 and completed in 2013, involving large-scale vegetation construction and restoration that significantly altered the regional ecological environment. Understanding how soil erosion spatially differentiated in response to climate change and increased human activities, and how it responded to the ecological project, holds significant research value for policymaking and environmental governance in the TRHR. Therefore, based on RUSLE and LMDI models, this study quantitatively evaluates soil erosion dynamics and factor effects in the TRHR, aiming to provide a new analytical method for soil erosion factor analysis and inform policy recommendations for erosion control.

2.1 Study Area

The study area (TRHR) is located in the hinterland of the Qinghai-Tibet Plateau (31°32 -36°17 N, 89°24 -102°15 E; Fig. 1 [Figure 1: see original paper]), China. As the birthplace of the Yangtze River, Yellow River, and Lancang River, the TRHR serves as a crucial ecological functional zone for water conservation and represents one of China' s most sensitive and vulnerable ecosystems [?, ?]. The region covers approximately 350.60$×10^{3}$ km^2 with complex terrain dominated by mountainous landforms, averaging 4,592.87 m in elevation.

The region experiences a typical plateau continental climate with alternating hot and cold seasons, distinct wet and dry seasons, long sunshine duration, and strong radiation. Annual mean temperature ranges from -5.6°C to 7.8°C, while mean annual precipitation varies between 262.2 and 772.8 mm, decreasing gradually from southeast to northwest with significant regional differentiation. Soils are generally barren, with alpine meadow soil as the dominant type, and permafrost is extensively developed [?, ?]. Natural vegetation types including coniferous forests, shrubs, alpine meadows, alpine grasslands, and alpine sparse vegetation are distributed sequentially from southeast to northwest.

2.2 Data Sources

2.2.1 Normalized Difference Vegetation Index (NDVI) Data

NDVI data were obtained from the Resource and Environment Data Cloud Platform (http://www.resdc.cn/), including SPOT/VEGETATION NDVI datasets for 2005 and 2015. The data have a spatial resolution of 1 km and temporal resolution of 10 days. Digital images were processed using the Maximum Value Composite (MVC) method to extract annual maximum NDVI values. The MVC algorithm is the most common compositing criterion for generating NDVI composite data [?, ?], effectively eliminating noise from NDVI time series and sensor-related artifacts to produce more reliable values [?, ?]. After mosaicking and clipping, we obtained NDVI composite data for the study area for both years.

2.2.2 Meteorological Observation Data

Meteorological data for 2005 and 2015 were provided by the National Meteorological Center of China (http://data.cma.cn/) from 174 stations, some within and others adjacent to the study area (Fig. 1a). Data outliers were removed before calculating rainfall erosivity. Traditional interpolation methods such as Inverse Distance Weighting (IDW) and Kriging perform poorly for meteorological data in highly heterogeneous areas like the Qinghai-Tibet Plateau [?, ?, ?]. Therefore, we employed the Australian Smooth Spline Function Interpolation Tool (ANUSPLIN), a recognized professional interpolation method [?, ?]. ANUSPLIN is a multivariate climate interpolation tool using smoothing spline functions with elevation as a covariate [?, ?, ?], demonstrating higher accuracy for meteorological data interpolation. In this study, rainfall interpolation was performed using ANUSPLIN, and results from 18 stations within the TRHR were validated against observed values (Fig. 2 [Figure 2: see original paper]). Correlation coefficients (R^2) for both years were $ $0.90, indicating satisfactory interpolation accuracy. Spatial distributions of total annual rainfall for 2005 and 2015 are shown in Figure S1 (Supplementary material).

2.2.3 Soil and Digital Elevation Model (DEM) Data

Soil attribute data were obtained from the 1:1,000,000-scale soil database of China [?, ?], which includes spatial soil type distribution, physical properties, soil structure, and percentages of sand, silt, clay, and organic matter. Soil types in the study area were screened and matched with corresponding properties to calculate the erodibility factor. DEM data were derived from Shuttle Radar Topography Mission images in Geo-TIFF format (90 m resolution) provided by the Geospatial Data Cloud (http://www.gscloud.cn/) and resampled to 1 km resolution. DEM outliers were removed using ArcGIS, and topographic factor spatial distribution data were extracted from the processed DEM.

2.2.4 Land Use Data

Land use data for 2005 and 2015 were obtained from the Resource and Environment Data Cloud Platform (http://www.resdc.cn/). Classification follows the second-level standard of the Chinese Academy of Sciences, comprising 25 land use types including paddy fields, drylands, and lakes based on natural resource attributes. The land use map was used to assign support practice (P) factor values.

2.2.5 Statistical Data

Soil and water conservation statistics for 2015 were obtained from the Qinghai Provincial Water Resources Department (http://slt.qinghai.gov.cn/), documenting soil erosion amounts in the TRHR for model validation.

All data were uniformly projected using the Krasovsky_{{{1940}}_{{Albers}}} coordinate system to ensure spatial consistency. Considering the 1 km resolution of remote sensing and land use data, all datasets were resampled to a common 1 km$×$1 km spatial resolution.

2.3 Methods

A database for soil erosion assessment and factor analysis was constructed using vegetation, meteorological, and topographic data. The workflow and methods are presented in Figure 3 [Figure 3: see original paper]. First, soil erosion in 2005 and 2015 was evaluated using the RUSLE model, with results validated against Qinghai Provincial Water Resources Department statistics and previous research findings. Second, spatial distribution and variation characteristics of soil erosion were analyzed. Third, based on assessment results, an LMDI-based method was designed to quantitatively analyze the contribution values of vegetation cover (C factor) and rainfall erosivity (R factor) to soil erosion variation at the pixel scale. Finally, spatial distribution characteristics of relative factor impacts were examined.

2.3.1 Revised Universal Soil Loss Equation (RUSLE) Model

Wischmeier and Smith [?] developed the Universal Soil Loss Equation (USLE) based on extensive regional observations and simulated rainfall experiments. The USDA Agricultural Research Service subsequently advanced this into the

Revised Universal Soil Loss Equation (RUSLE) model. RUSLE is among the most widely used soil erosion models, estimating erosion through five factors representing vegetation, precipitation, soil properties, topography, and land use effects. Average annual soil loss is calculated by multiplying these factors:

$$A = R \times K \times LS \times C \times P$$

where A is soil erosion amount ($\mathrm{t}/(\mathrm{hm}^2 \cdot \mathrm{a})$); C is the vegetation cover factor (dimensionless) indicating vegetation coverage influence, calculated using the method of Cai et al. [?]; R is the rainfall erosivity factor ($\mathrm{MJ} \cdot \mathrm{mm}/(\mathrm{hm}^2 \cdot \mathrm{h} \cdot \mathrm{a})$) indicating precipitation effects, computed using Wischmeier and Smith' s [?] equation; LS is the topographic factor (dimensionless) representing slope steepness and length effects, obtained using Fu et al.' s [?] method suitable for China; K is the soil erodibility factor ($\mathrm{t} \cdot \mathrm{hm}^2 \cdot \mathrm{h}/(\mathrm{hm}^2 \cdot \mathrm{MJ} \cdot \mathrm{mm})$) representing soil type effects, calculated using the EPIC model [?, ?]; and P is the support practice factor (dimensionless), defined as the ratio of soil loss with specific support practices to that with upslope-downslope cultivation [?, ?]. The P factor ranges from 0 (high-quality conservation practices) to 1 (poor practices). Based on previous Qinghai-Tibet Plateau studies [?, ?], agricultural lands were assigned $P = 0.15$; water bodies, wetlands, bare rock, snow, and ice received $P = 0$ (no erosion); and remaining land use types received $P = 1$ (no conservation measures). Spatial distribution maps of each factor are shown in Figure 4 [Figure 4: see original paper], with detailed calculation methods provided in Supplementary material Section 2.

2.3.2 LMDI Model

As previously described, LMDI is the preferred decomposition analysis method due to its theoretical robustness and desirable properties [?, ?]. The general decomposition structure is as follows [?, ?]:

The target variable V changes over time in relation to n index factors, each linked to index variables $(x_1, x_2, x_3, ..., x_n)$. The general index decomposition is:

$$V = \sum_i V_i = \sum_i x_{1,i} \times x_{2,i} \times x_{3,i} \times \cdots \times x_{n,i}$$

where subscript i represents sub-categories of the target variable.

In additive decomposition, the target variable difference is attributed to respective factors $(\Delta V_{x1}, \Delta V_{x2}, ..., \Delta V_{xn})$:

$$\Delta V_{tot} = V_T - V_0 = \Delta V_{x1} + \Delta V_{x2} + \cdots + \Delta V_{xn}$$

where ΔV_{tot} is total change; V_0 and V_T are target variables in base period 0 and planned period T; and ΔV_{xk} $(k = 1, 2, 3, ..., n)$ represents differences associated with respective factors.

In multiplicative decomposition, the ratio change is decomposed as:

$$D_{tot} = \frac{V_T}{V_0} = D_{x1} \times D_{x2} \times \cdots \times D_{xn}$$

where D_{tot} is the target variable ratio between periods T and 0, and D_{xk} represents ratio changes associated with respective factors.

Using Ang et al.' s [?] LMDI approach, factor contribution values are calculated as:

$$\Delta V_{xk} = \sum_i \frac{V_i^T - V_i^0}{\ln V_i^T - \ln V_i^0} \times \ln\left(\frac{x_{k,i}^T}{x_{k,i}^0}\right)$$

$$D_{xk} = \exp\left(\sum_i \frac{V_i^T - V_i^0}{\ln V_i^T - \ln V_i^0} \times \ln\left(\frac{x_{k,i}^T}{x_{k,i}^0}\right) / V_{tot}^0\right)$$

Comparing LMDI with RUSLE reveals structural compatibility: soil erosion amount is the target variable, with index factors C, R, LS, K, and P ($n = 5$ corresponding to variables x_1 through x_5). Since each RUSLE factor is a spatially distributed raster dataset, LMDI can calculate per-pixel contribution values. Additive and multiplicative decompositions are equally valid [?, ?, ?], but additive decomposition yields results in physical units rather than indices, making interpretation easier [?, ?].

2.3.3 Contributions of Influencing Factors to Soil Erosion Variation

The RUSLE equation identifies topography, soil, vegetation, precipitation, and support practices as main influencing factors. However, we did not evaluate contributions of the LS, K, and P factors for the following reasons: (1) the LS factor remained essentially unchanged during the study period; (2) the K factor showed minimal change, and the soil dataset from the Second National Soil Survey was the only available source, limiting temporal analysis; and (3) the P factor is primarily determined by land use types, which varied negligibly from 2005 to 2015 (cropland increased by 0.0009%; water, wetland, bare land, snow, and ice increased by 0.0083%; other types decreased by 0.0092%).

We applied the LMDI model to quantitatively analyze C and R factor contributions to soil erosion variation during the ecological conservation and restoration project period.

Based on LMDI additive decomposition and RUSLE, the C factor contribution was calculated at the pixel scale:

$$\Delta A_C = \frac{A_{2015} - A_{2005}}{\ln A_{2015} - \ln A_{2005}} \times \ln\left(\frac{C_{2015}}{C_{2005}}\right)$$

where ΔA_C is the C factor contribution value (t/(hm$^2 \cdot$ a)); A_{2015} and A_{2005} are soil erosion moduli in 2015 and 2005 (t/(hm$^2 \cdot$ a)); and C_{2015} and C_{2005} are vegetation cover factors for respective years. Positive ΔA_C indicates aggravated soil erosion, while negative values indicate alleviation.

The R factor contribution was determined by:

$$\Delta A_R = \frac{A_{2015} - A_{2005}}{\ln A_{2015} - \ln A_{2005}} \times \ln\left(\frac{R_{2015}}{R_{2005}}\right)$$

where ΔA_R is the R factor contribution value (t/(hm$^2 \cdot$ a)); R_{2015} and R_{2005} are rainfall erosivity factors. Positive ΔA_R indicates increased soil erosion, while negative values indicate decreased erosion.

Spatial distribution maps of C and R factor contributions were generated through pixel-scale calculations. To further understand relative effects, we combined ΔA, ΔA_C, and ΔA_R values into six categories (Table 1).

3.1 Validation of RUSLE Model Results

Model accuracy was validated against Qinghai Provincial Water Resources Department statistics for 2015. The RUSLE model estimated a soil erosion area of 12.13$×10^{4}$ km^2, compared to the statistical value of 13.07$×10^{4}$ km^2, yielding a simulation-to-measured ratio of 0.93. Additionally, we compared our 2015 spatial distribution map with that from the Ministry of Water Resources of China, showing good consistency. Minor differences between simulated and measured results can be attributed to varying data sources and processing methods, particularly meteorological data interpolation approaches. Overall, RUSLE model estimates demonstrated high accuracy.

3.2 Spatial Distribution and Variation of Soil Erosion

Spatial distribution maps for 2005 and 2015 were generated using RUSLE (Fig. 5 [Figure 5: see original paper]). Soil erosion modulus was classified into five classes: <100, 100–200, 200–300, 300–400, and >400 t/(hm$^2 \cdot$ a). The average soil erosion modulus decreased from 54.19 t/(hm$^2 \cdot$ a) in 2005 to 37.96 t/(hm$^2 \cdot$ a) in 2015, a 29.95% reduction. Distribution patterns were consistent between years, with severe erosion concentrated in south-central and northeastern areas where modulus exceeded 300 t/(hm$^2 \cdot$ a), reaching >400 t/(hm$^2 \cdot$ a) on steep slopes. These areas correspond to deep canyons with broken terrain in the lower reaches of the Yangtze and Yellow Rivers. Western and eastern regions showed relatively slight erosion (<100 t/(hm$^2 \cdot$ a)) due to flat terrain and higher vegetation coverage. Areas with modulus <100 t/(hm$^2 \cdot$ a) accounted for over

80% of the total area in both years, followed by 100-200 t/(hm^2 · a) areas, indicating moderate to high erosion severity overall.

Despite total erosion area increasing from 12.01×10^{4} km^2 in 2005 to 12.13×10^{4} km^2 in 2015, the average modulus decreased. Reductions were concentrated in the 0-100 t/(hm^2 · a) range (308.16 km^2), followed by 100-200 t/(hm^2 · a) reductions (10.63 km^2) in south-central and northeastern areas. Increased modulus occurred primarily in the 0-100 t/(hm^2 · a) range (8.48 km^2) and >200 t/(hm^2 · a) range, mainly in southeastern areas with centralized distribution. These results demonstrate that while total erosion area increased, overall severity was mitigated, showing gradual improvement.

3.3 Decomposition Analysis of C and R Factor Influences

3.3.1 Impact of the C Factor on Soil Erosion

Vegetation is the most important environmental factor controlling soil erosion, particularly on slopes [?, ?]. Its influence is primarily manifested in surface runoff prevention and soil conservation. In this study, the C factor was determined using NDVI, the most frequently used parameter for vegetation-erosion relationship analysis. Average NDVI values were 0.48 in 2005 and 0.44 in 2015, indicating slight vegetation degradation overall, though some areas showed increasing coverage due to ecological conservation efforts [?, ?]. Theoretically, increased vegetation coverage should decrease soil erosion modulus.

The spatial distribution map of C factor-induced soil erosion variation (2005-2015) was generated using LMDI additive decomposition (Fig. 6 [Figure 6: see original paper]). Positive and negative contributions were categorized into three classes (0-100, 100-200, >200 t/(hm^2 · a)). Without considering other factors, C factor-induced variation was mainly distributed in central areas. Increased erosion modulus concentrated in the 0-100 t/(hm^2 · a) range (143.27×10^{3} km^2), with limited areas showing >100 t/(hm^2 · a) increases. Decreased erosion modulus occurred primarily in western and eastern areas, with reductions of 0-100 t/(hm^2 · a). The decrease in soil erosion caused by C factor changes exceeded the increase during 2005-2015, suggesting vegetation' s positive effect on erosion control in the TRHR.

To understand vegetation impacts across different NDVI change ranges, we overlaid NDVI change maps with C factor-induced soil erosion variation maps using ArcGIS spatial analysis tools. Cumulative C factor contribution values across different NDVI intervals (Fig. 7a [Figure 7: see original paper]) showed similar variation characteristics in both increased and decreased NDVI ranges. In NDVI increase ranges, cumulative contributions were negative. With increasing NDVI, cumulative values first increased then decreased, peaking when NDVI increase was 0.05-0.10, followed by 0.10-0.15. Similarly, the highest cumulative contribution to increased soil erosion occurred when NDVI decreased by 0.10-0.05.

3.3.2 Impacts of the R Factor on Soil Erosion

Average annual precipitation in the TRHR was 476.70 mm in 2005 and 369.05 mm in 2015, with corresponding rainfall erosivity values of 562.86 $MJ \cdot mm/(hm^2 \cdot h \cdot a)$ and 381.86 $MJ \cdot mm/(hm^2 \cdot h \cdot a)$ (Figs. 2 and 4). The overall precipitation and rainfall erosivity decline in 2015 mitigated soil erosion when the C factor was not considered. LMDI results (Fig. 6b and d) showed that some areas experienced increased erosion due to R factor changes, though overall contributions declined. Reduced erosion modulus concentrated in the 0-100 $t/(hm^2 \cdot a)$ range (307.64 km^2), with 100-200 $t/(hm^2 \cdot a)$ reductions in central areas. Increased erosion modulus occurred mainly in southeastern TRHR, with much smaller affected area than decreased regions (Fig. 6d). Precipitation is concentrated in summer and autumn, and its uneven spatiotemporal distribution is a primary cause of soil erosion variation misdistribution.

Overlaying R factor change maps with R factor-induced erosion variation maps revealed cumulative R factor contributions across different R intervals (Fig. 7b [Figure 7: see original paper]). Cumulative contributions in decreased R intervals far exceeded those in increased intervals, showing an initial increase then decrease with expanding ranges. This indicates gradient-like properties in R factor influence on soil erosion variation.

3.3.3 Assessment of Dominant Factors Influencing Soil Erosion

Soil erosion in the TRHR decreased substantially from 2005 to 2015 (Fig. 8 [Figure 8: see original paper]). Decreased erosion caused by combined C and R factor effects (DECR) occupied the largest proportion (54.95% of decreased erosion area), mainly distributed in western and eastern areas. The R factor alone was the second greatest contributor (41.31% of decreased area), primarily in central TRHR. C factor alone caused decreased erosion over a smaller area (12.10×10^{3} km^2), mainly in southeastern areas. The area with increased soil erosion (12.95×10^{3} km^2) was smaller than the decreased area (325.01×10^{3} km^2) (Figs. 8 and 9 [Figure 9: see original paper]). Among increased erosion factors, C factor, R factor, and combined effects accounted for 64.10%, 12.02%, and 23.88%, respectively. The C factor was the dominant cause of increased erosion, with affected areas mainly in central and eastern regions (Fig. 9 [Figure 9: see original paper]). Areas with increased erosion from combined C and R factor effects were primarily in southern areas.

4.1 Advantages of the LMDI Method in Analyzing Soil Erosion Factors

This study demonstrates several advantages of using LMDI over traditional statistical or regression approaches [?, ?, ?, ?, ?]. First, factor impact analyses are independent, with no direct dependence between C and R factors in Equations 8 and 9. Each factor is analyzed through independent formulas without affecting others. Second, no factor decomposition order is required in calculations. Third, LMDI quantifies factor impacts and calculates contribution values pixel-by-pixel, generating spatial distribution maps. Traditional regression methods describe regional vegetation and precipitation influences but cannot quantitatively identify specific pixel-scale contributions, neglecting spatial heterogeneity. Additionally, traditional methods rely on difficult-to-obtain experimental or statistical data, particularly in undeveloped areas. LMDI performs residual-free decomposition using freely available remote sensing (e.g., MODIS, Landsat) and meteorological data instead of hard-to-obtain experimental data. This study obtained quantitative C and R factor contribution values (Fig. 6 [Figure 6: see original paper]), clearly revealing vegetation and precipitation influences through contribution maps.

4.2 Factors Influencing Soil Erosion in the TRHR

Numerous studies demonstrate that soil erosion variation results from combined vegetation and precipitation actions [?, ?, ?, ?, ?, ?, ?]. These factors have interactive coupling relationships, though the mechanism remains unclear. Understanding factor influence mechanisms is fundamental for formulating reasonable ecological protection policies. The TRHR' s alpine ecosystem is extremely vulnerable [?, ?]. In 2005, the government invested 7.5$\times10^{9}$ CNY to launch the first-stage ecological conservation and restoration project [?, ?, ?], which positively impacted vegetation recovery from 2005 to 2015 [?, ?]. Soil erosion alleviation during this period (Fig. 5 [Figure 5: see original paper]) and the dominant role of combined C and R factor effects (Fig. 8 [Figure 8: see original paper]) demonstrate project effectiveness, consistent with previous studies [?, ?, ?].

Decreased precipitation reduced the R factor from 2005 to 2015, contributing to erosion reduction [?, ?, ?]. However, this impaired precipitation's positive effects on vegetation growth [?, ?], suggesting the need for scientifically deployed artificial rain enhancement projects [?, ?, ?, ?]. Precipitation uncertainty increases erosion control difficulty [?, ?], and IPCC reports indicate potential future precipitation increases [?, ?], which may cause more severe erosion events in the TRHR, necessitating proactive measures.

Vegetation significantly affects erosion variation, particularly in the southeastern corner (Figs. 8 and 9 [Figure 9: see original paper]). Improving vegetation coverage effectively reduces erosion [?, ?, ?]. However, the TRHR' s harsh environment slows root layer recovery crucial for soil and water conservation, as well as soil physical-chemical property restoration [?, ?, ?], indicating that ecological restoration is a long-term, arduous task requiring continuous effort. Climate conditions and human activities drive vegetation changes [?, ?, ?]. Overgrazing can degrade vegetation and increase erosion, while ecological projects like returning farmland to forests and grasslands reduce erosion by altering land surface coverage. We recommend continuing and strengthening the ecological conservation and restoration project to mitigate erosion damage.

In the TRHR, soil erosion and grassland degradation interact in a vicious cycle of alpine ecosystem degradation [?, ?]. Rampant rodent infestation reduces soil organic carbon content and degrades soil quality [?, ?], while grazing significantly influences soil properties [?, ?, ?, ?]. Soil-grass-animal interactions complicate erosion mechanisms [?, ?, ?]. Future measures should strengthen scientific grassland grazing planning and rodent pest management to prevent erosion aggravation from overgrazing and rodents, maintaining balanced alpine ecosystem development.

4.3 Uncertainty Analysis

Soil erosion mechanisms in the TRHR are complex, involving freeze-thaw, wind, and water erosion [?, ?, ?]. However, RUSLE primarily considers water erosion, representing a technical limitation for application in dynamic environments with multiple erosion types [?, ?].

Various precipitation interpolation methods exist, and LMDI relies on spatial precipitation distribution from interpolated meteorological data. Interpolation accuracy significantly influences results. We used ANUSPLIN, extensively applied for global hydrometeorological surface interpolation [?, ?, ?, ?, ?, ?], achieving high accuracy (R^2=0.90 in 2005, R^2=0.95 in 2015) (Fig. 2 [Figure 2: see original paper]). However, the limited number of meteorological stations on the Qinghai-Tibet Plateau affects interpolation accuracy, and different methods may yield different results, warranting future investigation.

Land use types remained virtually unchanged during 2005–2015, though topography and soil properties may have varied. Changes in soil physical-chemical properties, texture, and structure would alter the K factor [?, ?, ?], affecting erosion variation. However, lack of multi-year DEM and soil data prevented analysis of LS and K factor influences.

More experimental or statistical data are needed for precise results. Due to limitations, we did not conduct field experiments for validation (e.g., ^{13}Cs nuclear tracer techniques). We validated spatial distributions by comparing RUSLE results with measured data and previous studies [?, ?, ?, ?], showing consistency. Despite lacking 2005 statistics, comparison with literature values [?, ?] also showed consistency. Government statistics and previous literature confirm satisfactory estimation accuracy.

The ecological conservation and restoration project was implemented in 2005 [?, ?]. By 2015, the first stage was complete and the second stage underway, aiming to improve vegetation coverage and ecological quality through grassland, forest, and wetland protection. Large-scale conversion of sloping farmland to grassland and forest significantly increased local vegetation coverage [?, ?], reducing erosion severity and demonstrating project effectiveness. However, some areas still show vegetation deterioration, indicating the need for continuous project strengthening.

5 Conclusions

This study evaluated soil erosion in the TRHR during the first-stage ecological restoration project (2005–2015) using the RUSLE model and designed an LMDI-based method to quantitatively assess C and R factor contributions. Soil erosion showed an overall downward trend, with average modulus decreasing from 54.19 $t/(hm^2 \cdot a)$ in 2005 to 37.96 $t/(hm^2 \cdot a)$ in 2015. The area with increased erosion was smaller than that with decreased erosion. Cumulative C factor contributions to erosion decrease exceeded those to increase, benefiting from improved vegetation coverage and demonstrating project effectiveness. The combined C and R factor effects dominated erosion decrease, followed by the R factor alone, while the C factor was the primary cause of erosion increase.

This method provides a new approach for large-scale soil erosion factor studies worldwide with broad application prospects. Future research should comprehensively assess LS and K factor influences.

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References

Ang B W, Zhang F Q, Choi K. 1998. Factorizing changes in energy and environmental indicators through decomposition. Energy, 23(6): 489–495.

Ang B W. 2004. Decomposition analysis for policymaking in energy: Which is the preferred method? Energy Policy, 2(9): [page numbers not provided in original].

Ang B W. 2005. The LMDI approach to decomposition analysis: A practical guide. Energy Policy, 33(7): 867–871.

Ang B W. 2015. LMDI decomposition approach: A guide for implementation. Energy Policy, 86: 233–238.

Beck P S A, Jönsson P, Høgda K A, et al. 2007. A ground-validated NDVI dataset for monitoring vegetation dynamics and mapping phenology in Fennoscandia and the Kola Peninsula. International Journal of Remote Sensing, 28(19): 4311–4330.

Cai C F, Ding S W, Shi Z H, et al. 2000. Study of applying USLE and geographical information system IDRISI to predict soil erosion in small watershed. Bulletin of Soil and Water Conservation, 14(2): 19–24. (in Chinese)

Cao W, Liu L L, Dan W U. 2018. Soil erosion changes and driving factors in the Three-River Headwaters region. Acta Prataculturae Sinica, 27(6): 10–22.

(in Chinese)

Cazcarro I, Martín-Retortillo M, Serrano A. 2019. Reallocating regional water apparent productivity in the long term: Methodological contributions and application for Spain. Regional Environmental Change, 19(5): 1455–1468.

Cook J, Oreskes N, Doran P T, et al. 2016. Consensus on consensus: A synthesis of consensus estimates on human-caused global warming. Environmental Research Letters, 11(4): 48002, doi: 10.1088/1748-9326/11/4/048002.

Dissanayake D, Morimoto T, Ranagalage M. 2019. Accessing the soil erosion rate based on RUSLE model for sustainable land use management: A case study of the Kotmale watershed, Sri Lanka. Modeling Earth Systems and Environment, 5(1): 291–306.

Fan J W, Shao Q Q, Liu J Y, et al. 2010. Assessment of effects of climate change and grazing activity on grassland yield in the Three Rivers Headwaters Region of Qinghai–Tibet Plateau, China. Environmental Monitoring and Assessment, 170(1–4): [page numbers not provided].

Fick S E, Hijmans R J. 2017. WorldClim 2: New 1-km spatial resolution climate surfaces for global land areas. International Journal of Climatology, 37(12): 4302–4315.

Fu S H, Liu B Y, Zhou G Y, et al. 2015. Calculation tool of topographic factors. Science of Soil and Water Conservation, 13(5): 105–110. (in Chinese)

Ganasri B P, Ramesh H. 2016. Assessment of soil erosion by RUSLE model using remote sensing and GIS: A case study of Nethravathi Basin. Geoscience Frontiers, 7(6): 953–961.

García-Ruiz J M. 2010. The effects of land uses on soil erosion in Spain: A review. CATENA, 81(1): 1–11.

Goh T, Ang B W. 2019. Tracking economy-wide energy efficiency using LMDI: Approach and practices. Energy Efficiency, 12(4): 829–847.

Gu J, Li X, Huang C, et al. 2009. A simplified data assimilation method for reconstructing time-series MODIS NDVI data. Advances in Space Research, 44(4): 501–509.

Guerra A J T, Fullen M A, Jorge M C O, et al. 2017. Slope processes, mass movement and soil erosion: A review. Pedosphere, 27(1): 27–41.

Guerra C A, Maes J, Geijzendorffer I, et al. 2016. An assessment of soil erosion prevention by vegetation in Mediterranean Europe: Current trends of ecosystem service provision. Ecological Indicators, 60: 213–222.

Guo B, Zhou Y, Zhu J, et al. 2016. Spatial patterns of ecosystem vulnerability changes during 2001–2011 in the Three-River Source Region of the Qinghai-Tibetan Plateau, China. Journal of Arid Land, 8(1): 23–35.

Guo B, Zhang F F, Yang G, et al. 2017. Improved method of freeze–thaw erosion for the Three-River Source Region in the Qinghai–Tibetan Plateau, China. Geomatics, Natural Hazards and Risk, 8(2): 1678–1694.

Han Z, Song W, Deng X, et al. 2018. Grassland ecosystem responses to climate change and human activities within the Three-River Headwaters region of China. Scientific Reports, 8(1): 9079, doi: 10.1038/s41598-018-27150-5.

He G H, Zhao Y, Wang J H, et al. 2018. Impact of large-scale vegetation restoration project on summer land surface temperature on the Loess Plateau, China. Journal of Arid Land, 10(6): 892–904.

Hijmans R J, Cameron S E, Parra J L, et al. 2005. Very high resolution interpolated climate surfaces for global land areas. International Journal of Climatology, 25(15): 1965–1978.

Huang L, Shao Q Q, Liu J Y. 2011. Spatial-temporal analysis of soil erosion in grassland over the past three decades in Sanjiangyuan region, Qinghai Province, China. Journal of Geo-Information Science, 13(1): 12–21. (in Chinese)

Huang L, Cao W, Xu X, et al. 2018. Linking the benefits of ecosystem services to sustainable spatial planning of ecological conservation strategies. Journal of Environmental Management, 222: 385–395.

Hutchinson M F, Xu T B. 2004. Anusplin Version 4.2 User Guide. Canberra: Fenner School of Environment and Society, Australian National University.

IPCC (Intergovernmental Panel on Climate Change). 2018. Global Warming of 1.5°C. [2020-03-23]. https://www.ipcc.ch/sr15/.

Jiang C, Li D Q, Wang D, et al. 2016. Quantification and assessment of changes in ecosystem service in the Three-River Headwaters Region, China as a result of climate variability and land cover change. Ecological Indicators, 66: 199–211.

Jiang C, Zhang L B. 2016. Ecosystem change assessment in the Three-river Headwater Region, China: Patterns, causes, and implications. Ecological Engineering, 93: 24–33.

Kang L, Zhou T, Gan Y, et al. 2018. Spatial and temporal patterns of soil erosion in the Tibetan Plateau from 1984 to 2013. Chinese Journal of Applied and Environmental Biology, 24(2): 245–253. (in Chinese)

Li X L, Perry G L W, Brierley G, et al. 2014. Quantitative assessment of degradation classifications for degraded alpine meadows (Heitutan), Sanjiangyuan, western China. Land Degradation & Development, 25(5): 417–427.

Lieskovský J, Kenderessy P. 2014. Modelling the effect of vegetation cover and different tillage practices on soil erosion in vineyards: A case study in Vráble (Slovakia) using WATEM/SEDEM. Land Degradation & Development, 25(3): 288–296.

Lin H L, Zheng S T, Wang X L. 2017. Soil erosion assessment based on the RUSLE model in the Three-Rivers Headwaters area, Qinghai-Tibetan Plateau, China. Acta Prataculturae Sinica, 26(7): 11-22. (in Chinese)

Liu M, Li D Q, Wen Y M, et al. 2005. The spatial analysis of soil retention function in Sanjiangyuan region and its value evaluation. China Environmental Science, 25(5): 627-631. (in Chinese)

Liu X F, Zhang J S, Zhu X F, et al. 2014. Spatiotemporal changes in vegetation coverage and its driving factors in the Three-River Headwaters Region during 2000-2011. Journal of Geographical Sciences, 24(2): 288-302.

Liu Z H, Li L T, McVicar T R, et al. 2008. Introduction of the professional interpolation software for meteorology data-ANUSPLIN. Mettorological Monthly, 10(1): 14-19.

Llop M. 2019. Decomposing the changes in water intensity in a Mediterranean region. Water Resources Management, 33(9): [page numbers not provided].

McVicar T R, van Niel T G, Li L T, et al. 2007. Spatially distributing monthly reference evapotranspiration and pan evaporation considering topographic influences. Journal of Hydrology, 338(3-4): 196-220.

Meng Z J, Dang X H, Gao Y, et al. 2018. Interactive effects of wind speed, vegetation coverage and soil moisture in controlling wind erosion in a temperate desert steppe, Inner Mongolia of China. Journal of Arid Land, 10(4): 534-547.

Mishra N B, Mainali K P. 2017. Greening and browning of the Himalaya: Spatial patterns and the role of climatic change and human drivers. Science of The Total Environment, 587-588: 326-339.

Mohamadi M A, Kavian A. 2015. Effects of rainfall patterns on runoff and soil erosion in field plots. International Soil and Water Conservation Research, 3(4): 273-281.

Mousavi B, Lopez N S A, Biona J B M, et al. 2017. Driving forces of Iran' s CO_2 emissions from energy consumption: An LMDI decomposition approach. Applied Energy, 206: 804-814.

Moutinho V, Madaleno M, Inglesi-Lotz R, et al. 2018. Factors affecting CO_2 emissions in top countries on renewable energies: A LMDI decomposition application. Renewable and Sustainable Energy Reviews, 90: 605-622.

Nearing M A, Pruski F F, O' neal M R. 2004. Expected climate change impacts on soil erosion rates: A review. Bulletin of Soil and Water Conservation, 59(1): 43-50.

Nearing M A, Jetten V, Baffaut C, et al. 2005. Modeling response of soil erosion and runoff to changes in precipitation and cover. Catena, 61(2-3): 131-154.

Nie X Q, Yang L C, Xiong F, et al. 2018. Aboveground biomass of the alpine shrub ecosystems in Three-River Source Region of the Tibetan Plateau. Journal of Mountain Science, 15(2): 357–363.

Ochoa P A, Fries A, Mejía D, et al. 2016. Effects of climate, land cover and topography on soil erosion risk in a semiarid basin of the Andes. Catena, 140: 31–42.

Panagos P, Borrelli P, Meusburger K. 2015a. A new European slope length and steepness factor (LS-Factor) for modeling soil erosion by water. Geosciences, 5(2): 117–126.

Panagos P, Borrelli P, Meusburger K, et al. 2015b. Estimating the soil erosion cover-management factor at the European scale. Land Use Policy, 48: 38–50.

Plouffe C C, Robertson C, Chandrapala L. 2015. Comparing interpolation techniques for monthly rainfall mapping using multiple evaluation criteria and auxiliary data sources: A case study of Sri Lanka. Environmental Modelling & Software, 67: [page numbers not provided].

Pourebadollahan C M, Fallahi F, Alizadeh E, et al. 2018. Decomposing the influencing factors of CO_2 emissions in East Azarbayjan Province manufacturing industries using the LMDI approach. Quarterly Journal of Applied Theories of Economics, 5(2): 199–222.

Renard K G, Foster G R, Weesies G A, et al. 1997. Predicting Soil Erosion by Water: A Guide to Conservation Planning with the Revised Universal Soil Loss Equation (RUSLE). Tucson: USDA-ARS, Southwest Watershed Research Center, 16–18.

Sha Z Y, Xie Y C, Tan X C, et al. 2017. Assessing the impacts of human activities and climate variations on grassland productivity by partial least squares structural equation modeling (PLS-SEM). Journal of Arid Land, 9(4): 473–488.

Shao Q, Fan J, Liu J, et al. 2017. Target-based assessment on effects of first-stage ecological conservation and restoration project in Three-River Source region, China and policy recommendations. Bulletin of Chinese Academy of Sciences, 32(1): 35–44. (in Chinese)

Shao Q Q, Xiao T, Liu J Y, et al. 2011. Soil erosion rates and characteristics of typical alpine meadow using ^{137}Cs technique in Qinghai-Tibet Plateau. Chinese Science Bulletin, 56(16): 1708–1713.

Shao Q Q, Cao W, Fan J W, et al. 2017. Effects of an ecological conservation and restoration project in the Three-River Source Region, China. Journal of Geographical Sciences, 27(2): 183–204.

Sharpley A N, Williams J R. 1990. EPIC-erosion/productivity impact calculator: I. Model documentation. II. User manual. Technical Bulletin–United States Department of Agriculture, 4(4): 206–207.

Shen X, An R, Feng L, et al. 2018. Vegetation changes in the Three-river headwaters region of the Tibetan Plateau of China. Ecological Indicators, 93: 804–812.

Shi X Z, Yu D S, Warner E D, et al. 2004. Soil database of 1:1,000,000 digital soil survey and reference system of the Chinese genetic soil classification system. Soil Survey Horizons, 45(4): 129-136.

Sun W Y, Shao Q Q, Liu J Y. 2013. Soil erosion and its response to the changes of precipitation and vegetation cover on the Loess Plateau. Journal of Geographical Sciences, 23(6): 1091-1106.

Tan J B, Li A N, Lei G B. 2016. Contrast on Anusplin and Cokriging meteorological spatial interpolation in southeastern margin of Qinghai-Xizang Plateau. Plateau Meteorology, 35(4): 875-886. (in Chinese)

Teng H F, Liang Z Z, Chen S C, et al. 2018. Current and future assessments of soil erosion by water on the Tibetan Plateau based on RUSLE and CMIP5 climate models. Science of The Total Environment, 635: 673-686.

Thomas J, Joseph S, Thrivikramji K P. 2018. Assessment of soil erosion in a tropical mountain river basin of the southern Western Ghats, India using RUSLE and GIS. Geoscience Frontiers, 9(3): 893-906.

Wang H, Ang B W. 2018. Assessing the role of international trade in global CO_2 emissions: An index decomposition analysis approach. Applied Energy, 218: 146-158.

Wang L H, Wang Y F, Saskia K, et al. 2018. Effect of soil management on soil erosion on sloping farmland during crop growth stages under a large-scale rainfall simulation experiment. Journal of Arid Land, 10(6): 921-931.

Wischmeier W H, Smith D D. 1978. Predicting Rainfall Erosion Losses: A Guide to Conservation Planning. Hyattsville: USDA, Science and Education Administration, 57.

Xiong Q L, Xiao Y, Halmy M W A, et al. 2019. Monitoring the impact of climate change and human activities on grassland vegetation dynamics in the northeastern Qinghai-Tibet Plateau of China during 2000-2015. Journal of Arid Land, 11(5): [page numbers not provided].

Yao H F, Shi C X, Shao W W, et al. 2016. Changes and influencing factors of the sediment load in the Xiliugou basin of the upper Yellow River, China. Catena, 142: 1-10.

Yin F, Deng X Z, Jin Q, et al. 2014. The impacts of climate change and human activities on grassland productivity in Qinghai Province, China. Frontiers of Earth Science, 8(1): 93-103.

Zhao B H, Li Z B, Li P, et al. 2017. Spatial distribution of soil organic carbon and its influencing factors under the condition of ecological construction in a hilly-gully watershed of the Loess Plateau, China. Geoderma, 296: 10-17.

Zhang G L, Dong J W, Zhou C P, et al. 2013. Increasing cropping intensity in response to climate warming in Tibetan Plateau, China. Field Crops Research, 142: 36-46.

Zhang H Y, Fan J W, Cao W, et al. 2018. Changes in multiple ecosystem services between 2000 and 2013 and their driving factors in the grazing withdrawal program, China. Ecological Engineering, 116: 67-79.

Zhang L X, Fan J W, Zhou D C, et al. 2017. Ecological protection and restoration program reduced grazing pressure in the Three-River Headwaters region, China. Rangeland Ecology and Management, 70(5): 540-548.

Zhang S L, Su X L, Singh V P, et al. 2018. Logarithmic Mean Divisia Index (LMDI) decomposition analysis of changes in agricultural water use: A case study of the middle reaches of the Heihe River basin, China. Agricultural Water Management, 208: 422-430.

Zhang X, Li Z B, Li P, et al. 2018. Influences of sand cover on erosion processes of loess slopes based on rainfall simulation experiments. Journal of Arid Land, 10(1): 39-52.

Zhang Y, Zhang C B, Wang Z Q, et al. 2016. Vegetation dynamics and its driving forces from climate change and human activities in the Three-River Source Region, China from 1982 to 2012. Science of The Total Environment, 563-564: 210-220.

Zheng K, Wei J Z, Pei J Y, et al. 2019. Impacts of climate change and human activities on grassland vegetation variation in the Chinese Loess Plateau. Science of The Total Environment, 660: 236-244.

Zuazo V H D, Pleguezuelo C R R. 2009. Soil-erosion and runoff prevention by plant covers: A review. Agronomy for Sustainable Development, 28(1): 65-86.

Supplementary Material

1. Spatial Distribution of Total Annual Rainfall

Fig. S1 Spatial distribution of total annual rainfall in 2005 (a) and 2015 (b)

2.1 Vegetation Cover Factor (C Factor)

The C factor is closely related to vegetation coverage, significantly influencing soil erosion [**?**, **?**]. We used Cai et al.’ s [**?**] method:

$$C = \begin{cases} 1 & \text{if } f_c \leq 78.3\% \\ 0.6508 - 0.3436\ln(f_c) & \text{if } f_c > 78.3\% \end{cases}$$

where C is the vegetation cover factor (dimensionless); f_c is vegetation coverage determined from SPOT-VGT NDVI-derived NDVI; $\mathrm{NDVI}_{\mathrm{min}}$ is bare soil NDVI; and $\mathrm{NDVI}_{\mathrm{max}}$ is regional maximum NDVI.

2.2 Rainfall Erosivity Factor (R Factor)

The R factor reflects raindrop splash erosion potential [?, ?]. We used Wischmeier and Smith' s [?] equation:

$$R = \sum_{i=1}^{12} 1.735 \times 10^{\left(1.5 \log_{10}\left(\frac{P_i^2}{P}\right) - 0.08188\right)}$$

where R is rainfall erosivity ($\mathrm{MJ \cdot mm/(hm^2 \cdot h \cdot a)}$); P_i is monthly rainfall (mm); and P is annual rainfall (mm).

2.3 Topographic Factor (LS Factor)

The LS factor comprises slope length and steepness [?, ?]. DEM was used to estimate LS factor using Fu et al.' s [?] calculation tool suitable for China:

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

$$S = \begin{cases} 10.8 \sin\theta + 0.03 & \text{if } \theta < 9^\circ \\ 16.8 \sin\theta - 0.50 & \text{if } 9^\circ \leq \theta < 18^\circ \\ 21.91 \sin\theta - 0.96 & \text{if } \theta \geq 18^\circ \end{cases}$$

where L is slope length factor (dimensionless); S is slope steepness factor (dimensionless); θ is slope angle (°); m is a dimensionless constant; and λ is slope length (m), dependent on percent slope steepness.

2.4 Soil Erodibility Factor (K Factor)

The K factor depends on soil texture and organic matter content [?, ?]. We used the EPIC equation [?, ?]:

$$K = (0.2 + 0.3 \exp(-0.0256 \times \mathrm{SAN})) \times \left(\frac{\mathrm{SIL}}{\mathrm{CLA} + \mathrm{SIL}}\right)^{0.3} \times \left(1 - \frac{0.25 \times \mathrm{OM}}{\mathrm{OM} + \exp(3.72 - 2.95 \times \mathrm{OM})}\right) \times \left(1 - \frac{}{\mathrm{SN} + \mathrm{ex}}\right.$$

where SAN, SIL, CLA, and OM are percentage contents of sand, silt, clay, and organic matter (%), respectively; and SN = 1 - SAN/100.

2.5 Support Practice Factor (P Factor)

The P factor is the ratio of soil loss with specific support practices to upslope-downslope cultivation loss [?, ?], ranging from 0 (high-quality conservation) to 1 (poor practices) [?, ?]. Based on land use types and previous literature, agricultural lands received P=0.15 [?, ?]; water bodies, wetlands, bare rock, snow, and ice received P=0 (no erosion) [?, ?]; and remaining land use types received P=1 (no conservation measures) [?, ?, ?].

References (Supplementary Material)

Cai C F, Ding S W, Shi Z H, et al. 2000. Study of applying USLE and geographical information system IDRISI to predict soil erosion in small watershed. Bulletin of Soil and Water Conservation, 14(2): 19-24. (in Chinese)

Dissanayake D, Morimoto T, Ranagalage M. 2019. Accessing the soil erosion rate based on RUSLE model for sustainable land use management: A case study of the Kotmale watershed, Sri Lanka. Modeling Earth Systems and Environment, 5(1): 291-306.

Fayas C M, Abeysingha N S, Nirmanee K G S, et al. 2019. Soil loss estimation using RUSLE model to prioritize erosion control in KELANI river basin in Sri Lanka. International Soil and Water Conservation Research, 7(2): 130-137.

Fu B J, Liu Y, Lü Y H, et al. 2011. Assessing the soil erosion control service of ecosystems change in the Loess Plateau of China. Ecological Complexity, 8(4): 284-293.

Fu S, Zha X. 2008. Study on predicting soil erosion in Dongzhen watershed based on GIS and USLE. Geo-information Science, 10(3): 390-395. (in Chinese)

Fu S H, Liu B Y, Zhou G Y, et al. 2015. Calculation tool of topographic factors. Science of Soil and Water Conservation, 13(5): 105-110. (in Chinese)

Ganasri B P, Ramesh H. 2016. Assessment of soil erosion by RUSLE model using remote sensing and GIS: A case study of Nethravathi Basin. Geoscience Frontiers, 7(6): 953-961.

Kang L, Zhou T, Gan Y, et al. 2018. Spatial and temporal patterns of soil erosion in the Tibetan Plateau from 1984 to 2013. Chinese Journal of Applied and Environmental Biology, 24(2): 245-253. (in Chinese)

Li T H, Zheng L N. 2012. Soil erosion changes in the Yanhe watershed from 2001 to 2010 based on RUSLE model. Journal of Natural Resources, 27(7): 1164-1175.

Sharpley A N, Williams J R. 1990. EPIC-erosion/productivity impact calculator: I. Model documentation. II. User manual. Technical Bulletin-United States Department of Agriculture, 4(4): 206-207.

Wischmeier W H, Smith D D. 1978. Predicting Rainfall Erosion Losses: A Guide to Conservation Planning. Hyattsville: USDA, Science and Education Administration, 57.

Zhao L, Yuan G L, Zhang Y, et al. 2007. The amount of soil erosion in Baoxiang Watershed of Dianchi Lake based on GIS and USLE. Bulletin of Soil and Water Conservation, 27(3): 42-46. (in Chinese)