

Soil Erosion Assessment Dataset Development of the Qinghai-Xizang Plateau Based on the Ensemble RUSLE Model (1981–2018)

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Abstract: The Qinghai-Xizang Plateau is characterized by ecological fragility and high sensitivity to climate change, with soil erosion posing a major threat to the ecological security of the Pan-Third Pole region. To reduce discrepancies in current assessments of soil erosion on the Qinghai-Xizang Plateau and to provide a more reliable representation of the spatial distribution and temporal dynamics in soil erosion, the authors applied an ensemble RUSLE model. This model integrates multiple datasets, including the China Meteorological Forcing Dataset (CMFD), Climate Hazards group Infrared Precipitation with Stations (CHIRPS) and ERA-Interim, SoilGrids soil data, and a 90-m DEM, combined with diverse erosion factor schemes (9 *R* factors × 3 *K* factors × 3 *LS* factors × 3 *C* factors). The model was used to evaluate soil erosion on the Qinghai-Xizang Plateau from 1981 to 2018. The "RUSLE-IC-SDR" method was compared with measured sediment yield data to develop a soil erosion dataset for the Qinghai-Xizang Plateau. The dataset includes: (1) multi-year average water erosion data for the periods 1981–2018, 1981–1998, and 1999–2018, corresponding to the median values from the ensemble model; and (2) rates of change in water erosion for 1981–2018, 1981–1998, and 1999–2018. The spatial resolution of the data is 100 m. The dataset is archived in .tif format and consists of 26 data files, with a total size of 12.3 GB (compressed into 6 files, 5.38 GB).

Keywords: soil erosion; Qinghai-Xizang Plateau; ensemble RUSLE model; change; soil erosion by water

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Dataset Availability Statement:

The dataset supporting this paper was published and is accessible through the *Digital Journal of Global Change Data Repository* at: <https://doi.org/10.3974/geodb.2025.06.05.V1>.

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1 Introduction

The Qinghai-Xizang Plateau is characterized by active tectonic deformation, complex topography, diverse surface material properties, and high sensitivity to climate change^[1–3]. These unique natural conditions coupled with intensified climate change, have exacerbated soil erosion across the region^[3–7]. As a result, vast areas of fragile surface cover have developed, posing serious challenges to ecological restoration and environmental management. Severe soil erosion also threatens pastoral management, transportation infrastructure, and the safety of residents' lives and property on the Qinghai-Xizang Plateau. Studies using the RUSLE model to assess soil erosion on the plateau have attracted broad attention. However, discrepancies in data sources and the parameterization of erosion factors have produced large variations in reported erosion magnitudes, spatial patterns, and temporal dynamics^[6,8–11]. Such inconsistencies hinder the establishment of a unified and reliable understanding of regional erosion processes, limiting the design of effective soil and water conservation practices and constraining ecological management strategies. Therefore, a refined, robust, and reliable assessment of water erosion on the Qinghai-Xizang Plateau is urgently needed.

The RUSLE model is widely applied because it integrates diverse measured data, including geographic and climatic parameters, and directly utilizes remote sensing data, making it the most widely used soil erosion model to date^[12–14]. On the Qinghai-Xizang Plateau, however, most RUSLE-based studies have relied on a single data source and algorithmic implementations for estimating erosion factors, leading to uncertainties and limitations. To overcome this shortcoming, this study developed an ensemble modeling framework that integrated multi-source data and multiple algorithmic schemes, yielding 243 soil erosion assessment scenarios (9 *R*-factor $\times$ 3 *K*-factor $\times$ 3 *LS*-factor $\times$ 3 *C*-factor implementations). By exploiting the complementary strengths of different data sources and algorithmic, this framework significantly enhances the robustness and reliability of soil erosion estimates while minimizing biases associated with single-source data or methodologies. This integrated strategy allows for more precise identification of spatial distribution and temporal dynamics of water erosion across the Qinghai-Xizang Plateau, producing a soil erosion dataset spanning 1981–2018. The dataset provides a more reliable scientific basis for detecting regional erosion hotspots, supporting policy formulation, and informing future scenario projections^[15].

2 Metadata of the Dataset

The metadata of the Soil erosion assessment dataset of the Qinghai-Xizang Plateau based on the RUSLE model analysis (1981–2018)^[16] is summarized in Table 1. It includes the dataset full name, short name, authors, year of the dataset, spatial resolution, data format, data size, data files, data publisher, and data sharing policy, etc.

3 Methods

3.1 Data Sources and Processing

According to the input factors of the RUSLE model, the study utilized precipitation, soil, digital elevation model (DEM), and vegetation datasets. Precipitation data used were obtained from 3 sources: the China Meteorological Forcing Dataset (CMFD), the Climate Hazards group Infrared Precipitation with Stations dataset (CHIRPS), and the ERA-Interim dataset^[18–20], all at a daily temporal resolution. Soil data were obtained from the SoilGrids

Table 1 Metadata summary of Soil erosion assessment dataset of the Qinghai-Xizang Plateau based on the RUSLE model analysis (1981–2018)

Items	Description
Dataset full name	Soil erosion assessment dataset of the Qinghai-Xizang Plateau based on the RUSLE model analysis (1981–2018)
Dataset short name	SoilerosionERUSLE_1981–2018
Authors	Huang, Y. Z., Research Center for Eco-Environmental Science, CAS, yzhuang_st@rcees.ac.cn Xin, Z. B., Beijing Forestry University, xinzhongbao@126.com Gao, G. Y., Research Center for Eco-Environmental Science, CAS, gygao@rcees.ac.cn Ma, Y., Institute of Geographic Science and Natural Resources Research, CAS, maying@igsnrr.ac.cn Yang, L. H., Institute of Geographic Science and Natural Resources Research, CAS, yanglihu@igsnrr.ac.cn Song, X. F., Institute of Geographic Science and Natural Resources Research, CAS, songxf@igsnrr.ac.cn
Geographical region	Qinghai-Xizang Plateau
Year	1981–2018
Spatial resolution	100 m
Data format	.tif
Data size	5.38 GB (after compression)
Data files	The multi-year average hydraulic erosion data corresponding to the median of the integrated model 1981–2018, 1981–1998, and 1999–2018; The rate of change of hydraulic erosion 1981–2018, 1981–1998, and 1999–2018
Foundation	Ministry of Science and Technology of P. R. China (2019QZKK0403)
Data publisher	Global Change Research Data Publishing & Repository, http://www.geodoi.ac.cn
Address	No. 11A, Datun Road, Chaoyang District, Beijing 100101, China
Data sharing policy	(1) <i>Data</i> are openly available and can be free downloaded via the Internet; (2) End users are encouraged to use <i>Data</i> subject to citation; (3) Users, who are by definition also value-added service providers, are welcome to redistribute <i>Data</i> subject to written permission from the GCdataPR Editorial Office and the issuance of a <i>Data</i> redistribution license; and (4) If <i>Data</i> are used to compile new datasets, the “ten percent principal” should be followed such that <i>Data</i> records utilized should not surpass 10% of the new dataset contents, while sources should be clearly noted in suitable places in the new dataset ^[17]
Communication and searchable system	DOI, CSTR, Crossref, DCI, CSCD, CNKI, SciEngine, WDS, GEOSS, PubScholar, CKRSC

dataset^[21], which provides soil organic carbon, USDA-based soil texture, soil sand, clay, silt content, and WRB classification. The 90-m spatial resolution DEM data were sourced from the NASA Shuttle Radar Topography Mission (SRTM-90 m)^[22]. Normalized Difference Vegetation Index (NDVI) data were derived from 2 sources: GIMMS-NDVI-3g and MOD13Q1.V6^[23,24]. To extend the temporal availability of vegetation data and ensure comparability, spatiotemporal stability analysis and statistical downscaling techniques were applied to correct the 2 NDVI datasets based on their overlapping period (February 2000 to December 2015)^[25]. Vegetation type data were downloaded from the “1:1,000,000 Spatial distribution data of vegetation types in China” available on the Resource and Environmental Science Data Platform, originally sourced from the “Vegetation atlas of China”^[26]. All data were resampled to a spatial resolution of 100 m.

3.2 Technical Workflow

The study applied the widely used RUSLE model for large-scale soil erosion assessment. An ensemble modeling framework was developed by integrating multi-source data and multiple calculation methods for erosion factors, resulting in 243 assessment scenarios. These scenarios encompassed all possible combinations of 9 rainfall erosivity (*R*) factor schemes, 3

soil erodibility (K) factor schemes, 3 slope length and steepness (LS) factor schemes, and 3 cover-management (C) factor schemes. The close relationship between sediment connectivity (IC) and sediment delivery ratio (SDR) was further utilized to output the erosion assessment. This approach enabled the determination of soil erosion conditions on the Qinghai-Xizang Plateau based on the ensemble model. The median value from the assessment results were used to analyze the spatial patterns and temporal dynamics of soil erosion over the past 40 years (1981–2018) on the plateau (Figure 1).

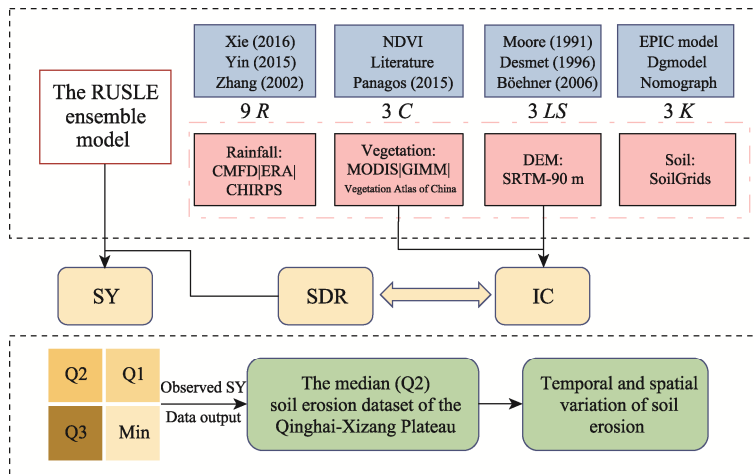


Figure 1 Flowchart of the dataset development

3.3 Realization of the RUSLE Ensemble Model

The RUSLE was established by Wischmeier and Smith based on 30 years of runoff plot data and artificial rainfall experiments from 30 states in the United States^[27]:

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

where A is the potential water soil erosion rate ($t \text{ ha}^{-1} \text{ yr}^{-1}$), R is the rainfall erosivity factor ($\text{MJ mm ha}^{-1} \text{ h}^{-1} \text{ yr}^{-1}$), K is the soil erodibility factor ($\text{Mg ha h MJ}^{-1} \text{ ha}^{-1} \text{ mm}^{-1}$), LS is the slope length and steepness factor (dimensionless), C is the cover-management factor (dimensionless), and P is the support practice factor (dimensionless). Due to the harsh living environment on the Qinghai-Xizang Plateau, there are relatively few human land development and management measures^[28]. Therefore, in this study, the P factor is ignored (that is, P is set to 1).

3.3.1 R Factor

The calculation of the R factor was based on 3 daily rainfall datasets: CMFD, CHIRPS, and ERA-Interim. To derive the R factor, the methods of Zhang, *et al.* (Equation 2–4), Xie, *et al.* (Equation 5), and Yin, *et al.* (Equation 6) were applied^[29–31].

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

$$\beta = 0.8363 + \frac{18.177}{P_{d12}} + \frac{24.455}{P_{y12}} \quad (3)$$

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

where R_j ($\text{MJ mm ha}^{-1} \text{ h}^{-1} \text{ yr}^{-1}$) is the rainfall erosivity of the j half-month; k is the number

of days in the j half-month; P_d (mm) is the daily effective rainfall (≥ 12 mm); P_{d12} (mm) is the average daily rainfall (≥ 12 mm); P_{y12} (mm) is the yearly average rainfall for days with rainfall ≥ 12 mm.

$$R_{day} = 0.2686 \left[1 + 0.5412 \cos \left(\frac{\pi}{6} j - \frac{7\pi}{6} \right) \right] P_d^{1.7265} \quad (5)$$

where R_{day} ($\text{MJ mm ha}^{-1} \text{ h}^{-1} \text{ yr}^{-1}$) is daily rainfall erosivity; j presents the j_{th} month; P_d (mm) is the daily effective rainfall (≥ 9.7 mm)^[31].

$$R_{month} = 0.077 P_{month} (P_{day})_{month} \quad (6)$$

where R_{month} ($\text{MJ mm ha}^{-1} \text{ h}^{-1} \text{ yr}^{-1}$) is monthly rainfall erosivity; P_{month} (mm) is the sum of daily effective rainfall (≥ 9.7 mm) in this month. $(P_{day})_{month}$ (mm) is the maximum daily rainfall for the month.

3.3.2 K Factor

The K factors in this study were implemented by the common algorithms: EPIC (Equation 7), Dg (Equation 8–10), and Nomograph (Equation 11–12)^[27,32,33]. According to the availability of SoilGrids, the data of soil layer 0–15 cm are used to calculate the K factor^[10].

$$K = 0.1317 \times \left(0.2 + 0.3 \times e^{\left[-0.0256 \times San \left(-1 - \frac{Sil}{100} \right) \right]} \right) \times \left(\frac{Sil}{Cla + Sil} \right)^{0.3} \times \left[1 - \frac{0.25 \times TOC}{TOC + e^{(3.72 - 2.95 \times TOC)}} \right] \times \left[1 - \frac{0.7 \times SN_1}{SN_1 + e^{(22.9 \times SN_1 - 5.51)}} \right] \quad (7)$$

where K ($\text{Mg ha h MJ}^{-1} \text{ ha}^{-1} \text{ mm}^{-1}$) is the soil erodibility; San (%) is the sand content (0.05–2 mm); Sil (%) is the silt content (0.002–0.05 mm); Cla (%) is the clay content (< 0.002 mm); TOC (%) is the soil total organic carbon content; and $SN_1 = 1 - San/100$. After multiplying by 0.1317, the K value is expressed in an SI metric ($\text{Mg ha h MJ}^{-1} \text{ ha}^{-1} \text{ mm}^{-1}$). For soil samples with organic matter content ($TOC = SOM \times 0.58$) above 4%, the upper limit of 4% has been applied, to prohibit an underestimation of soil erodibility for soils that are rich in organic matter^[27,34].

$$K = 0.1317 \times 0.0293 \left(0.65 - Dg + 0.24 Dg^2 \right) f_{TOC, Cla} \quad (8)$$

$$Dg = \sum (f_i / 100) \lg \sqrt{d_i d_{i-1}} \quad (9)$$

$$f_{TOC, Cla} = e^{-0.0021 \frac{TOC}{Cla/100} - 0.00037 \left(\frac{TOC}{Cla/100} \right)^2 - 4.02 \frac{Cla}{100} + 1.71 \left(\frac{Cla}{100} \right)^2} \quad (10)$$

where Dg is the Napierian logarithm of the geometric mean of the particle size distribution, d_i (mm) is the maximum diameter of the i -th class, d_{i-1} (mm) is the minimum diameter; f_i is the mass fraction in the corresponding particle size class (For example, if the lower limit of clay was set as 0.000,05 mm, the Dg of soil containing 15% clay, 40% silt and 45% sand was equal to -3.569).

$$K = 0.1317 \left[0.00021 M^{1.14} (12 - TOC) + 3.25 (s - 2) + 2.5 (p - 3) \right] / 100 \quad (11)$$

$$M = N_1 (100 - N_2) \quad (12)$$

where M is a factor related to soil texture. N_1 (%) is the silt and very fine sand content (0.002–0.1 mm), which is commonly approximated as 20% of the sand content^[34]; N_2 (%) is the clay content (< 0.002 mm). The soil structure parameter (s) is determined according to the WRB soil classification. Soil permeability (p) is obtained from the USDA soil texture

classification.

3.3.3 *LS* Factor

3 algorithms, Böhner, Desmet, and Moore, in the System for Automated Geoscientific Analysis (SAGA) software were used to calculate the *LS* factor in this study^[15,35–37]. Firstly, DEM should be filled with sinks in ArcGIS using the Fill tool. Then Flow Accumulation tool was used to calculate Total Catchment Area (TCA) in SAGA, and Flow Width and Specific Catchment Area tool were used to calculate Specific Catchment Area (SCA). Finally, SAGA’s *LS* factor was used to calculate the *LS* factor.

3.3.4 *C* Factor

C factor is considered the most important factor for policy and land-use decisions because it is the factor most directly influenced by human activities to reduce erosion^[38]. In this study, 3 *C* factor schemes were realized through satellite remote sensing data (e.g., NDVI) (Equation 13), literature values (Table 2), and the combination of the two methods (Equation 14).

$$C=\exp\left[\alpha\left(\frac{NDVI}{\beta-NDVI}\right)\right]$$

(13)

where *C* is the cover-management factor, $\alpha=-2$, and $\beta=1$.

The *C*-factor for each land-cover type was calculated as the weighted average of soil erosion ratio, with values ranging from 0 to 1. However, the same land-cover class may exhibit different *C* factors due to variations in vegetation density (Table 2). In this study, following previous studies and summaries, the median of empirical values was used to represent the *C* factor of a certain vegetation class^[15].

Table 2 Vegetation types and their corresponding literature values of *C* factor

No.	Class	Vegetation types	Ranges of <i>C</i>	<i>C</i>
1	Cultivated	Croplands	0.15–0.2	0.175
2	Forestlands	Needleleaf forest	0.000,1–0.003	0.001,55
3		Mixed forest	0.000,1–0.003	0.001,55
4		Broadleaf forest	0.000,1–0.003	0.001,55
5		Shrub forestland	0.01–0.15	0.08
6	Shrublands	Sparse shrub	0.1–0.45	0.275
7		Steppe	0.05–0.15	0.1
8		Tussock	0.05–0.1	0.075
9		Meadow	0.01–0.08	0.045
10	Grasslands	Alpine vegetation	0.01–0.15	0.08
11		Water	0	0
12		Glacier	0	0
13		Bare soil	0.1–0.55	0.325
14		Marsh	0	0

The third calculation method of the *C* factor adopts the method of Panagos, *et al.*^[30], and combines the assignment method and land coverage for calculation.

$$C=\min(C_{landuse})+\text{Range}(C_{landuse})(1-F_{cover})$$

(14)

where $\min(C_{landuse})$ is the minimum value in literature values for this vegetation type; $\text{Range}(C_{landuse})$ represents the range for vegetation type of literature values; F_{cover} is vegetation coverage. The assignments *C* factor of various vegetation types was obtained

according to Panagos and Majhi^[38,39], and combined with the C values of relevant studies on the Qinghai-Xizang Plateau (Table 2).

3.4 Data Analysis

3.4.1 Change-Point Analysis

The study utilized the “cpm” package in R, applying the Kolmogorov-Smirnov test to identify change points in the soil erosion time series. The termination year with a rapid increase in the cumulative number of change points was designated as the change point, dividing year between the earlier and later periods. Notably, this statistical change coincides with the launch of China’s large-scale ecological restoration initiatives in 1999—the Grain-for-Green Program and the Returning Grazing Land to Grassland Program—which further supports the validity of the identified change point^[40].

3.4.2 Soil Erosion Trend

A pixel-based linear least squares regression was employed to calculate the trend of annual soil erosion changes^[40]. The Equation is as follows:

$$Slope = \frac{n \sum_{i=1}^n x_i i - \sum_{i=1}^n x_i \sum_{i=1}^n i}{n \sum_{i=1}^n i^2 - \left(\sum_{i=1}^n i \right)^2} \quad (15)$$

where *Slope* represents the rate of change in the variable x over the time series; x_i denotes the value of variable x in the i -th year; i is an integer ranging from 1 to n (number of years).

3.5 Data Output

The “RUSLE-IC-SDR” method was employed to calculate sediment yields corresponding to the minimum, first quartile (Q1), second quartile (Q2/median), and third quartile (Q3) erosion results from the ensemble model. The computed sediment yields were compared with observed sediment yield data collected from 24 hydrological monitoring stations, including 13 from water resources departments and 11 from literature records, to determine the optimal output. Results demonstrated that the Q2 output of the ensemble model showed closer agreement with observed measurements from hydrological stations ($R^2=0.81$, RMSE = 7.04, NSE=0.81) (Figure 2). Therefore, the median values from the ensemble model were selected as the final dataset output.

4 Data Results

4.1 Dataset Composition

The Soil erosion assessment dataset of the Qinghai-Xizang Plateau based on the RUSLE model analysis (1981–2018) provides: (1) The multi-year average water erosion data (unit: $t\ ha^{-1}\ yr^{-1}$) corresponding to the median of the integrated model from 1981 to 2018, from 1981 to 1998, and from 1999 to 2018; (2) The rate of change of water erosion (unit: $t\ ha^{-1}\ yr^{-1}\ yr^{-1}$) from 1981 to 2018, from 1981 to 1998 and from 1999 to 2018. The spatial resolution of the data is 100 m. The dataset is archived in .tif format.

4.2 Spatial Distribution and Changes in Erosion

The multi-year average soil erosion rate on the Qinghai-Xizang Plateau from 1981 to 2018

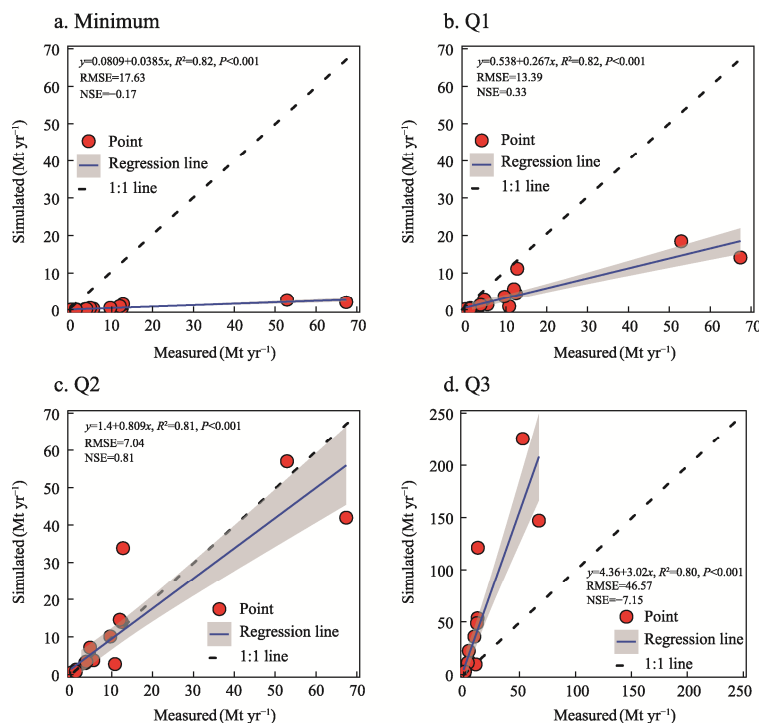


Figure 2 Performance of the ensemble model in simulating mean annual sediment yield

was $5.91\pm2.29\text{ t ha}^{-1}\text{ yr}^{-1}$, corresponding to an annual soil loss of $1,526\pm591\text{ Tg}$ caused by water erosion. Higher erosion rates were observed in the middle and upper reaches of Yarlung Tsangpo River in Shigatse, the lower reaches of Yarlung Tsangpo River in Nyingchi, the Western Sichuan region, the eastern Qinghai-Xizang Plateau, and the Pamir Plateau (Figure 3). In contrast, the soil erosion rates in the Qaidam Basin and Changtang Plateau were the lowest.

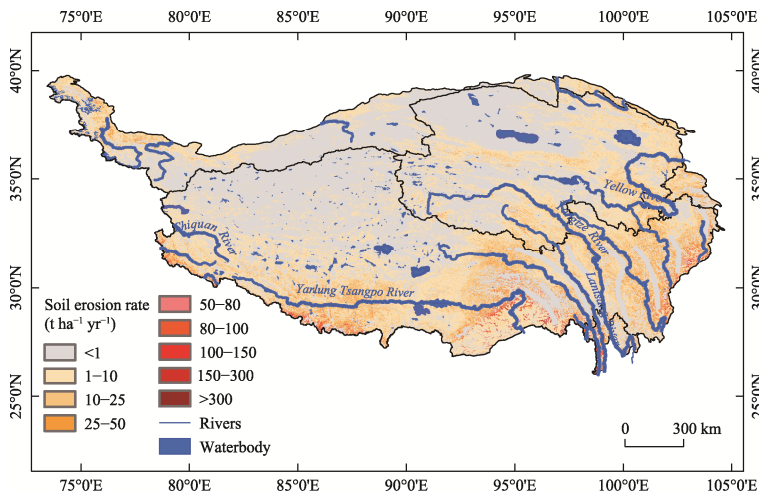


Figure 3 Distribution map of the average soil erosion rate in Qinghai-Xizang Plateau (1981–2018)

Based on change-point analysis and the timeline of the “Grain-for-Green Program”, the year 1999 was identified as a turning point in soil erosion dynamics (Figure 4), dividing the

study period into an earlier phase (1981–1998) and a later phase (1999–2018). The Qinghai-Xizang Plateau showed an increasing trend in soil erosion (Figures 4a and 5a), with erosion rates significantly higher in the later phase than in the earlier one ($P=9.5\text{e-}5$). However, the sharp acceleration observed before 1999 was substantially reduced afterward (earlier trend: $0.075\text{ t ha}^{-1}\text{ yr}^{-1}\text{ yr}^{-1}$; later trend: $0.013\text{ t ha}^{-1}\text{ yr}^{-1}\text{ yr}^{-1}$) (Figure 4a). During the earlier period, increased soil erosion trends were primarily observed in the middle reaches of the Yarlung Tsangpo River and southeastern Qinghai-Xizang Plateau (Figure 5b). In contrast, these regions experienced declining erosion rates in the later period (Figure 5c). intensified soil erosion became concentrated mainly in the western and eastern Plateau during the later phase. Notably, the area showing mitigated soil erosion expanded by 65.6% across the entire Qinghai-Xizang Plateau during this later period (Figure 5c).

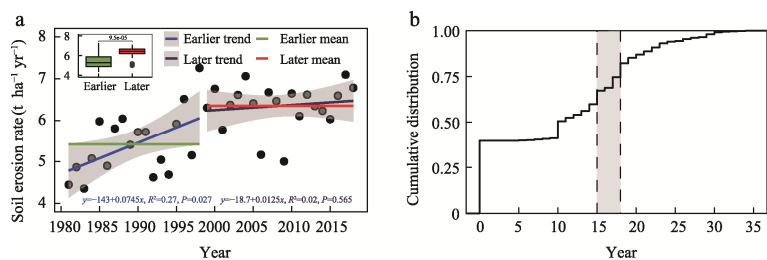


Figure 4 Annual trends of soil erosion on the Qinghai-Xizang Plateau

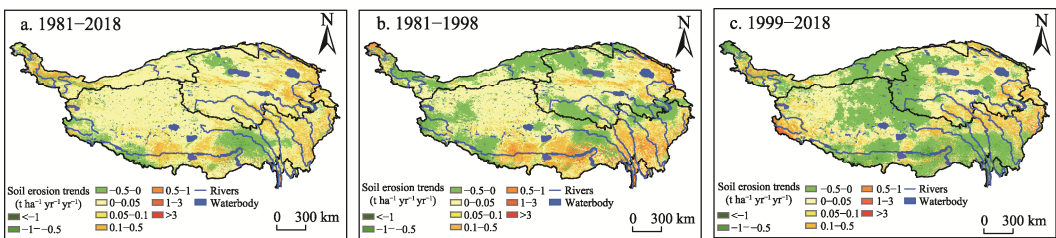


Figure 5 Distribution maps of soil erosion changes and SOC erosion changes in Qinghai-Xizang Plateau

5 Discussion and Conclusion

The Qinghai-Xizang Plateau serves as a critical ecological security barrier for China, characterized by extremely fragile ecosystems and shallow soil formation. Unsustainable human activities and climate change have intensified water erosion across the plateau. Understanding these processes is essential for environmental protection, biodiversity conservation, and sustainable resource management. This study employed an ensemble RUSLE model, integrating multi-source data and multiple erosion factor calculation methods, to develop a more reliable soil erosion dataset. The results identified erosion hotspot, with the highest rates concentrated in the Yarlung Tsangpo River basin and eastern Qinghai-Xizang Plateau. Analysis of erosion dynamics from 1981 to 2018 further indicated that future soil erosion intensification requires particular attention in western and eastern parts of the plateau. The water erosion dataset developed provides scientific support and guidance for targeted soil and water conservation initiatives.

Author Contributions

Song, X. F., Gao, G. Y., Xin, Z. B., and Huang, Y. Z. contributed to the overall design of the dataset development; Huang, Y. Z. and Ma, Y. designed the models and algorithms; Song, X. F. and Yang, L. H. provided optimization suggestions for the paper and data; Huang, Y. Z.

wrote the paper.

Conflicts of Interest

The authors declare no conflicts of interest.

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