Spatiotemporal Variation and Influencing Factors of Water Erosion in the Central Northern Slope of the Tianshan Mountains Based on the CSLE Model: A Postprint

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Abstract

Understanding the spatial differentiation patterns of soil water erosion and their driving forces on the northern slope of the Tianshan Mountains is crucial for ecological early warning and soil erosion prevention and control, and provides theoretical basis and data support for comprehensive management of the regional ecological environment. Taking the middle section of the northern slope of the Tianshan Mountains as an example, and based on the Chinese Soil Loss Equation (CSLE), this study employs methods including field investigation, Geographic Information Systems (GIS), mathematical statistics, and the Geographical Detector to quantitatively analyze the spatiotemporal pattern characteristics (area, intensity, and geographic distribution) of soil hydraulic erosion in the study area from 2000 to 2018, and uses the Geographical Detector to explore the intrinsic driving forces of rainfall, topography, soil, and vegetation on soil hydraulic erosion intensity. The results indicate: (1) From 2000 to 2018, soil hydraulic erosion intensity in the middle section of the northern slope of the Tianshan Mountains was dominated by slight and mild erosion, accounting for 32.34%~40.87% and 33.36%~43.01% of the total area, respectively. The areas of slight and mild erosion both showed decreasing trends over the past 20 years (-26.70 $km^2 \cdot a^{-1}$, -77.47 $km^2 \cdot a^{-1}$), while the areas of other erosion intensities showed increasing trends (22.10~30.96 $km^2 \cdot a^{-1}$), with the overall soil hydraulic erosion intensity exhibiting an increasing trend. (2) The overall soil erosion modulus follows the pattern: Urumqi City > Changji City > Fukang City > Hutubi County > Manas County > Shawan County > Shihezi City. The spatial distribution of erosion intensity in the middle section of the northern slope of the Tianshan Mountains is closely related to rainfall, topography, soil, and vegetation; areas with soil types of brown calcic soil, felty soil, and chestnut soil, vegetation coverage less than 15%, slope gradient greater than 15°, and rainfall

within the range of 400~450 mm are high-risk erosion zones. (3) The degree of differentiation is measured by the q-value in the factor detector; the larger the q-value, the stronger the explanatory power of the influencing factor on the spatial distribution of soil erosion, showing the pattern: rainfall (0.49) > soil type (0.17) > slope gradient (0.11) > vegetation coverage (0.10). Different influencing factors significantly enhance the spatial heterogeneity of soil erosion through interactions, particularly the coupling effect between vegetation coverage and rainfall factors, which shows an extremely large increase in q-value; identifying key areas for soil erosion control is of great importance for comprehensive soil erosion prevention and control.

Full Text

Study on Temporal and Spatial Variation Characteristics and Influencing Factors of Hydraulic Erosion in the Middle Section of the Northern Slope of Tianshan Mountains Based on the CSLE Model

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Abstract

Understanding the spatial patterns and driving forces of soil water erosion differentiation on the northern slope of the Tianshan Mountains is of great significance for ecological early warning and soil erosion prevention, providing theoretical basis and data support for comprehensive management of the regional ecological environment. Taking the mountainous area in the middle section of the northern slope of the Tianshan Mountains as an example, based on the Chinese Soil Loss Equation (CSLE), this study quantitatively analyzed the spatiotemporal pattern characteristics (area, intensity, and geographic distribution) of soil hydraulic erosion in the study area from 2000 to 2018 using field investigation, geographic information systems, mathematical statistics, and geographic detector methods, and explored the internal driving forces of rainfall, topography, soil, and vegetation on soil hydraulic erosion intensity. The results showed that: (1) From 2000 to 2018, the intensity of soil hydraulic erosion in the middle section of the northern slope of the Tianshan Mountains was mainly slight and light erosion, accounting for 32.34%-40.87% and 33.36%-43.01% of the total area, respectively. In recent years, the areas of slight and light erosion showed a decreasing trend (-26.70 $km^2 \cdot a^{-1}$, -77.47 $km^2 \cdot a^{-1}$), while the areas of other erosion intensities showed an increasing trend (22.10-30.96 $km^2 \cdot a^{-1}$), with the overall soil hydraulic erosion intensity showing an increasing trend. (2) The overall soil erosion modulus was Urumqi > Changji City > Fukang City > Hutubi County > Manas County > Shawan County > Shihezi City. The spatial distribution of erosion intensity was closely related to rainfall, topography, soil, and vegetation. Areas with soil types of brown calcic soil, grass felt soil, and chestnut soil, vegetation coverage less than 15%, slope greater than 15°, and rainfall in the range of 400-450 mm were high-risk erosion areas. (3) The magnitude of differentiation was measured by the q value in the factor detector. The larger the q value, the stronger the explanatory power of the influencing factor on the spatial distribution of soil erosion, showing rainfall (0.49) > soil type (0.17) > slope (0.11) > vegetation coverage (0.10). Different influencing factors significantly enhanced the spatial heterogeneity of soil erosion through interaction, and the coupling effect of vegetation coverage and rainfall factors caused a substantial increase in the q value. Determining key soil erosion control areas is of great significance for comprehensive soil erosion prevention and control.

Keywords: northern slope of Tianshan Mountains; hydraulic erosion; CSLE model; temporal and spatial pattern; geographic detector; influencing factors

Introduction

Soil erosion refers to the process of soil and its parent material being eroded, destroyed, transported, and deposited under natural and anthropogenic factors. Studying soil erosion has positive impacts on improving land productivity, ameliorating the environment, and reducing natural disasters such as wind erosion, sandstorms, and debris flows. Faced with increasingly serious ecological and environmental problems like soil erosion, there is an urgent need to carry out soil erosion monitoring work and explore the driving impact factors to provide data support for comprehensive soil erosion management on the northern slope of the Tianshan Mountains in Xinjiang, while also offering scientific references for soil and water conservation and sustainable economic development in the region.

For quantitative research on soil erosion, soil erosion modeling is the most extensive and effective method. The Universal Soil Loss Equation (USLE) and Revised Universal Soil Loss Equation (RUSLE) are typical representatives of foreign empirical models. Liu Baoyuan improved the RUSLE model and proposed the Chinese Soil Loss Equation (CSLE), which is suitable for China. The CSLE model fully considers the characteristics of steep slope soil erosion in China and soil and water conservation measures, with a simple structure and easily obtainable parameters. The CSLE model has been widely applied in arid and semi-arid regions to explore the temporal and spatial dynamics of soil erosion and influencing factors. Although previous studies have focused on the impacts of geographic environmental factors and human activities on soil erosion, they could not quantify the degree of influence of these factors on soil erosion. Geographic detectors can not only analyze the explanatory power of a single independent variable on a dependent variable but also determine the impact of interactions between independent variables on the dependent variable. In recent years, geographic detectors have been widely applied across various scales from national to township levels, and in fields including social sciences, human health, natural sciences, and environmental science. Some scholars have used geographic detectors for quantitative attribution research on soil erosion. Applying the CSLE model to quantitatively evaluate soil erosion and using geographic detectors to explore the spatial differentiation and internal driving forces of soil erosion has become a basic trend in regional soil erosion research.

Most soil erosion research in Xinjiang has focused on the Ili Valley region with relatively high precipitation, while studies on the northern and southern slopes of the Tianshan Mountains are scarce. Moreover, existing research has concentrated on soil erosion conditions in small watersheds for single years, lacking studies on temporal and spatial dynamic changes and quantitative attribution of soil erosion. Rainfall in the Tianshan Mountains shows obvious spatial heterogeneity, with the northern slope (windward slope) receiving more precipitation than the southern slope (leeward slope). The northern slope of the Tianshan Mountains is a national key soil erosion prevention area. According to data from the first national water conservancy census bulletin, areas with relatively severe water erosion on the northern slope of the Tianshan Mountains are mainly concentrated in the middle section, including the mountainous and hilly regions of seven administrative districts: Fukang City, Urumqi City, Changji City, Hutubi County, Manas County, Shihezi City, and Shawan County. Therefore, this study takes the mountainous area in the middle section of the northern slope of the Tianshan Mountains as an example, uses the CSLE model to quantitatively analyze the temporal and spatial variation characteristics of soil hydraulic erosion in the study area from 2000 to 2018, fully grasp the status of soil erosion, and applies the geographic detector method to quantitatively explore the multiple factors causing soil erosion, providing scientific support and theoretical basis for subsequent soil and water conservation construction.

1 Study Area and Methods

1.1 Study Area Overview

The study area is located in the middle section of the northern slope of the Tianshan Mountains, encompassing the mountainous regions of seven administrative districts from Fukang to Shawan [Figure 1: see original paper]. The geographic location is 84°50 -88°58 E, 42°55 -44°22 N, with a total area of approximately 33,400 km^2. The terrain is higher in the south and lower in the north, with elevations ranging from 400 to 5,251 m. The northern slope of the Tianshan Mountains is windward and shady, receiving abundant rainfall with less solar radiation and relatively humid conditions. The multi-year average rainfall is 472-525 mm, with rainfall concentrated in May-September, accounting for 66.59% of annual precipitation. The multi-year average temperature is 7.2°C, with summer average temperature of 23.9°C and winter average temperature of -12.5°C. Soil types are mainly brown calcic soil, chestnut soil, black calcic soil, gray-cinnamon soil, black felt soil, and grass felt soil. Vegetation types are diverse with large temporal and spatial distribution differences, primarily composed of herbaceous vegetation (72.13%) and shrubs (7.10%), with other types accounting for 0.68%. Vegetation coverage is higher in mountainous areas and lower in plain areas, and higher on shady slopes and lower on sunny slopes.

1.2 Data Sources and Processing

Based on Xinjiang' s seasonal climate and vegetation growth conditions, the study period was selected as May-September. Landsat series remote sensing image data were selected, with temporal resolution of 16 days and spatial resolution of 30 m, obtained from the United States Geological Survey (https://www.usgs.gov/) and NASA Earth Data (https://earthdata.nasa.gov/). MOD13Q1 NDVI data were obtained from the National Aeronautics and Space Administration with a temporal resolution of 16 days and spatial resolution of 250 m. Daily precipitation data from 2000-2018 were collected from seven meteorological stations (Urumqi Pastoral Experiment Station, Urumqi, Changji, Hutubi, Manas, Shihezi, and Shawan) and surrounding areas from the China Meteorological Data Network (http://data.cma.cn/). DEM data with 30 m spatial resolution were obtained from the Geospatial Data Cloud (http://www.gscloud.cn/). Land use data were interpreted from Landsat series remote sensing images and high-resolution images through human-computer interaction. According to the "Current Land Use Classification Standard" (GB/T 21010-2017) and combined with the actual situation of the study area, land use was classified into nine types: natural grassland, artificial grassland, other grassland, arbor forest land, shrub forest land, other forest land, dry land, irrigated land, mining land, scenic facilities land, inland beach land, and rural residential land. Stratified random sampling was used to extract 450 sample points from each period' s land use classification map based on the spatial distribution characteristics of regional land use types. After field investigation and verification with Google Earth historical high-resolution images, the overall classification accuracy exceeded 85%, meeting research requirements. Soil type data for the study area were obtained from the Resource and Environmental Science Data Center of the Chinese Academy of Sciences (https://www.resdc.cn/).

Landsat remote sensing images were preprocessed using ENVI 5.3 software. After radiometric calibration, the FLAASH (Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes) module was used for atmospheric correction. Using corrected Landsat TM images as standard base maps, quadratic polynomial fitting was employed for geometric correction of images, followed by extraction and clipping processes.

MODIS MOD13Q1 data were converted to NDVI data through format conversion, projection transformation, clipping, and maximum value composition using MODIS Reprojection Tool software. Based on the main vegetation types in the study area, when calculating vegetation coverage for different land use types, the relationship between NDVI values and corresponding measured vegetation coverage at sample points was substituted into the pixel dichotomy model to obtain a binary linear equation system, thereby calculating NDVIveg (pure vegetation endmember NDVI value) and NDVIsoil (pure soil endmember NDVI value) for different vegetation coverage types, achieving vegetation coverage estimation.

Field surveys employed stratified random sampling methods. Based on soil types and grassland types, combined with watershed integrity, terrain slope position, land use type, grazing prohibition and grazing status, sample points were designed according to uniformity and accessibility. Field sampling was conducted at 450 sample points in July-August 2018. Sample plots were set as 30 m $\times$ 30 m, with 1 m $\times$ 1 m quadrats at both ends and the center of the diagonal. Actual land use types were verified and soil samples from the 0-20 cm layer were collected. Soil organic matter content was determined using the potassium dichromate volumetric method, and soil particle size was measured using a Microtrac Bluewave S350 laser particle size analyzer. Forest canopy density was obtained using the vertical upward photography method, while vegetation coverage of grassland and shrubland was obtained using the vertical downward photography method.

1.3 Methods

1.3.1 Soil Hydraulic Erosion Model The Chinese Soil Loss Equation (CSLE) was used for model construction, with the calculation formula as follows:

$$A = R \cdot K \cdot L \cdot S \cdot B \cdot E \cdot T$$

where:
- A is the average annual soil loss per unit area ($\mathrm{t \cdot hm^{-2} \cdot a^{-1}}$)
- R is the rainfall erosivity factor ($\mathrm{MJ \cdot mm \cdot hm^{-2} \cdot h^{-1} \cdot a^{-1}}$)
- K is the soil erodibility factor ($\mathrm{t \cdot hm^{2} \cdot h \cdot hm^{-2} \cdot MJ^{-1} \cdot mm^{-1}}$)
- L and S are the slope length factor and slope steepness factor, respectively
- B, E, and T are the biological practice factor, engineering practice factor, and tillage practice factor, respectively

The raster data of the R, K, L, S, B, E, and T factors were multiplied spatially. When the land use type was cultivated land, the tillage practice factor was selected to multiply with the other five factor rasters; when the land use type was non-cultivated land, the biological practice factor was selected to multiply with the other five factor rasters to obtain the soil erosion modulus data for the middle section of the northern slope of the Tianshan Mountains. According to the "Standards for Classification and Gradation of Soil Erosion" (SL190-2007) issued by the Ministry of Water Resources, soil erosion intensity was classified into six levels: slight (0-200 $t \cdot km^{-2} \cdot a^{-1}$), light (200-2500 $t \cdot km^{-2} \cdot a^{-1}$), moderate (2500-5000 $t \cdot km^{-2} \cdot a^{-1}$), strong (5000-8000 $t \cdot km^{-2} \cdot a^{-1}$), very strong (8000-15000 $t \cdot km^{-2} \cdot a^{-1}$), and severe (>15000 $t \cdot km^{-2} \cdot a^{-1}$).

Rainfall Erosivity Factor (R): Based on algorithm comparison and data availability, the algorithm model by Zhang Wenbo et al. was adopted to calculate half-month rainfall erosivity from daily rainfall data. To maintain temporal consistency with the biological practice factor, the half-month rainfall erosivity model was improved to a monthly rainfall erosivity model. The rainfall erosivity for each month (at 5-day intervals) was calculated for seven meteorological stations, and the annual rainfall erosivity was obtained by accumulating the monthly values. Inverse Distance Weighting (IDW) interpolation was used to calculate the rainfall erosivity for the study area from 2000 to 2018.

Soil Erodibility Factor (K): Compared with direct measurement and formula methods, the Nomograph Model proposed by Wischmeier for calculating K values, although cumbersome, provides higher accuracy and more stable K values. The CSLE model uses a Modified Nomograph Model to calculate the Mnomo value for each soil sample, obtaining the average K value for each soil type, which was then assigned to the soil type spatial distribution map to generate the soil erodibility factor for the study area.

Slope Length and Slope Steepness Factors (L, S): The slope length factor was calculated using Foster' s formula for segmented slopes. The slope steepness factor was calculated using McCool' s formula for slopes <10° and Liu Binyuan' s formula for slopes $ $10°.

Biological Practice Factor (B): Landsat data are affected by cloud and rain, making it impossible to obtain continuous high-quality time series data, while MODIS data have good timeliness but low spatial resolution. Therefore, the Enhanced Spatial and Temporal Adaptive Reflectance Fusion Model (ESTARFM) was used to fuse Landsat NDVI spatial data (30 m resolution) with MODIS NDVI temporal data (250 m resolution). The fused data had the same spatial resolution as Landsat NDVI and the same temporal resolution as MODIS data, using day of year to represent acquisition dates (days 65-337) with a temporal resolution of 16 days.

Vegetation coverage was estimated using the pixel dichotomy model. The key to estimating vegetation coverage lies in determining NDVIveg (pure vegetation endmember NDVI value) and NDVIsoil (pure soil endmember NDVI value). Previous studies used NDVImax from the image as NDVIveg and NDVImin as NDVIsoil. However, image noise can make NDVIveg too high or NDVIsoil too low. To avoid this error, when calculating vegetation coverage for different vegetation types, the relationship between NDVI values and corresponding measured vegetation coverage at sample points was substituted into the pixel dichotomy model to obtain a binary linear equation system, thereby calculating NDVIveg and NDVIsoil for different vegetation coverage types. Using the fused NDVI data and land use data as masks, vegetation coverage was estimated and annual vegetation coverage data were obtained (at 16-day intervals).

The biological practice factor B was calculated using the relationship between the biological practice factor and vegetation coverage established by Cai Chongfa et al. to estimate B values at 16-day intervals. Based on the original RUSLE model, the weighted average biological practice factor within the year was calculated by combining the 16-day biological practice factor with the proportion of rainfall erosivity factor for each period.

Engineering Practice Factor (E): Based on remote sensing interpretation and field survey results, no engineering practice types listed in the "Technical Regulations for Dynamic Monitoring of Regional Soil Erosion (Trial)" were found in the study area. Therefore, the engineering practice factor was uniformly assigned a value of 1.

Tillage Practice Factor (T): According to the tillage practice rotation assignment table in the "Technical Regulations for Dynamic Monitoring of Regional Soil Erosion (Trial)", the middle section of the northern slope of the Tianshan Mountains belongs to the northwest arid irrigation single-crop and double-crop region, and the northern Xinjiang irrigation single-crop fallow region. Values were assigned according to each plot, with cultivated land assigned a value of 1 and other land types assigned a value of 0.

1.3.2 Geodetector Geodetector is a statistical method comprising four components: factor detector, interaction detector, ecological detector, and risk detector. It reveals the driving forces behind certain phenomena by detecting the spatial stratified heterogeneity of elements. The factor detector can analyze whether a driving force is the main cause of soil erosion spatial pattern characteristics. The magnitude of differentiation is measured by the q value, which identifies the dominant factors influencing soil erosion. The interaction detector can identify whether the interaction between influencing factors enhances or weakens the explanatory power on soil erosion spatial distribution. The ecological detector can compare whether there are significant differences in the impact of two influencing factors on soil erosion spatial distribution. The risk detector can determine whether there are significant differences in soil erosion amount among various layers of a single influencing factor and identify high-risk soil erosion areas.

Soil erosion is affected by multiple factors including rainfall, topography, soil, and vegetation. This study selected multi-year average rainfall, multi-year average vegetation coverage, slope, and soil type as soil erosion influencing factors. Multi-year average rainfall, multi-year average vegetation coverage, and slope are continuous variables that were discretized using the quantile method.

2 Results

2.1 Vegetation Coverage Estimation Model Construction and Accuracy Analysis

Using measured vegetation coverage from 200 grassland sample points, 150 shrubland sample points, and 50 arbor forest land sample points, linear regression equations were constructed [Figure 2: see original paper]. The results showed that NDVI was extremely significantly positively correlated with vegetation coverage for both grassland and shrubland (r = 0.90, r = 0.96). For arbor forest land, NDVI was extremely significantly positively correlated with canopy density (r = 0.70). A linear relationship was established between measured and estimated vegetation coverage values, yielding a scatter plot [Figure 3: see original paper] with a coefficient of determination R^2 of 0.84 and root mean square error (RMSE) of 0.09. The scatter points were relatively concentrated, mainly distributed near the 1:1 line (y = x) with a slope K of 0.96, indicating high overall prediction accuracy.

2.2 Temporal Pattern Characteristics of Soil Hydraulic Erosion

From 2000 to 2018, soil hydraulic erosion intensity in the middle section of the northern slope of the Tianshan Mountains was dominated by slight and light erosion, accounting for 32.34%-40.87% and 33.36%-43.01% of the total area, respectively . The areas of slight and light erosion showed decreasing trends, reducing at rates of -26.70 $km^2 \cdot a^{-1}$ and -77.47 $km^2 \cdot a^{-1}$, respectively, while areas of other erosion intensities showed increasing trends (22.10-30.96 $km^2 \cdot a^{-1}$). Overall, soil hydraulic erosion intensity was increasing. The multi-year average soil erosion modulus showed an upward trend, increasing by 576.93 $t \cdot km^{-2} \cdot a^{-1}$ annually [Figure 4: see original paper]. The soil erosion modulus was lowest in 2000 at 1673.49 $t \cdot km^{-2} \cdot a^{-1}$ and highest in 2018 at 4496.08 $t \cdot km^{-2} \cdot a^{-1}$. The multi-year average soil erosion modulus was 2817.63 ± 940.76 $t \cdot km^{-2} \cdot a^{-1}$.

2.3 Spatial Pattern Characteristics of Soil Hydraulic Erosion

The proportion of moderate, strong, very strong, and severe erosion increased by 7.37%, 3.08%, 2.97%, and 3.02%, respectively . The total soil erosion area showed an increasing trend, with soil erosion area increasing by 13.84% compared to 2000. This was mainly due to the gradual increase in moderate, strong, very strong, and severe erosion areas. In 2000, soil erosion area decreased and soil erosion conditions improved slightly, with the proportion of soil erosion decreasing by 5.30%. This was mainly because moderate and higher erosion areas decreased, with the proportion of soil erosion decreasing from 34.30%, while slight and light erosion areas increased by 26.21%.

The multi-year average soil erosion modulus for each administrative region in the middle section of the northern slope of the Tianshan Mountains showed the following order: Urumqi (3595.54 ± 1383.32 $t \cdot km^{-2} \cdot a^{-1}$) > Changji City (3321.55

$\pm$ 1182.19 $t \cdot km^{-2} \cdot a^{-1}$) > Fukang City (3256.73 $\pm$ 1170.54 $t \cdot km^{-2} \cdot a^{-1}$) > Hutubi County > Manas County > Shawan County > Shihezi City (1752.93 $\pm$ 767.79 $t \cdot km^{-2} \cdot a^{-1}$) . In recent years, the development of tourism in Urumqi has brought economic growth but also impacted the ecological environment of tourist areas. Tourism activities disturb soil and vegetation, causing changes in soil erodibility and biological practice factors that can easily induce soil erosion. Changji City ranked second, with relatively developed animal husbandry, followed by Fukang City, which is a concentrated area of mineral resources. With the development of tourism, animal husbandry, and mining, factors that hinder soil erosion occurrence such as vegetation coverage have decreased, leading to increased soil erosion in some areas.

The spatial distribution of soil hydraulic erosion intensity showed that areas with relatively severe erosion were mainly concentrated in the Dabancheng District and southern high mountain areas of Urumqi [Figure 5: see original paper].

2.4 Analysis of Soil Erosion Influencing Factors

2.4.1 Climate Factors The northern slope of the Tianshan Mountains is a windward slope with relatively large rainfall, and the main climate factor affecting soil erosion is rainfall. Analysis of soil erosion modulus under different rainfall grades showed that when rainfall was 200-250 mm, the soil erosion modulus was smallest and relatively stable at 2193.76 $\pm$ 740.47 $t \cdot km^{-2} \cdot a^{-1}$; when rainfall was 400-450 mm, the soil erosion modulus was largest and highly variable at 5881.15 $\pm$ 5159.30 $t \cdot km^{-2} \cdot a^{-1}$. Rainfall showed a positive correlation with soil erosion modulus.

2.4.2 Terrain Factors Slope is a key factor of topography and an important factor affecting soil erosion. Analysis of soil erosion modulus under different slope grades showed that when slope <5°, the soil erosion modulus was smallest and relatively stable at 491.33 $\pm$ 169.21 $t \cdot km^{-2} \cdot a^{-1}$; when slope >35°, the soil erosion modulus was largest and highly variable at 4362.28 $\pm$ 1680.50 $t \cdot km^{-2} \cdot a^{-1}$. Slope had a positive effect on soil erosion modulus, with soil erosion modulus increasing as slope increased. The total soil erosion modulus for slopes >35° was 62.12 $\times$ 10^4 $t \cdot km^{-2} \cdot a^{-1}$, accounting for 78.68% of the total soil erosion. This indicates that soil erosion mainly occurred in areas with slopes >35°, primarily because these steep slopes had sparse vegetation and high soil erodibility, resulting in severe soil erosion.

2.4.3 Soil Factors Different soil types have varying capacities to resist soil erosion. The soil erosion modulus showed the following pattern: grass felt soil > gray-brown desert soil > brown calcic soil > chestnut soil > cold calcic soil > black felt soil > gray desert soil > black calcic soil > gray-cinnamon soil . The total soil erosion modulus for brown calcic soil, grass felt soil, and chestnut soil was 42.02 $\times$ 10^4 $t \cdot km^{-2} \cdot a^{-1}$, accounting for 71.65% of the total soil erosion. This indicates that soil erosion mainly occurred in areas with these three soil types, primarily because brown calcic soil and chestnut soil are located in the northern alluvial fans and inclined plains at elevations of 1600-3000 m, with poor vegetation coverage, high soil erodibility, and large land area. Grass felt soil is located above 3000 m and has the highest soil erosion modulus.

2.4.4 Vegetation Factors Analysis of soil erosion modulus under different vegetation coverage grades showed that as vegetation coverage increased, soil erosion modulus decreased . When vegetation coverage <15%, soil erosion modulus was largest and highly variable at 4362.28 ± 1680.50 t · km^{-2} · a^{-1}, easily inducing soil erosion; when vegetation coverage >75%, soil erosion modulus was smallest and relatively stable at 561.44 ± 290.90 t · km^{-2} · a^{-1}, indicating that higher vegetation coverage can protect soil and prevent soil erosion. The total soil erosion modulus for vegetation coverage <15% was 61.72×10^4 t · km^{-2} · a^{-1}, accounting for 77.65% of the total soil erosion. This indicates that soil erosion mainly occurred in areas with vegetation coverage <15%, primarily because the land area with vegetation coverage <15% was large (14,147.50 km^2) and had high soil erosion modulus.

2.5 Quantitative Analysis of Soil Erosion Influencing Factors

The geographic detector results for soil erosion influencing factors in the middle section of the northern slope of the Tianshan Mountains showed that different influencing factors had significantly different explanatory powers on soil erosion intensity, with q values decreasing in the order: rainfall (0.49) > soil type (0.17) > slope (0.11) > vegetation coverage (0.10) . Rainfall had the strongest explanatory power on soil erosion intensity and was the main factor affecting the spatial pattern distribution of soil erosion, followed by soil type, whose physical and chemical properties are closely related to soil erosion.

Interaction detector results showed that the impact of different influencing factors on soil erosion spatial distribution through interaction was much greater than that of single factors. Among them, slope soil type showed nonlinear enhancement, while other pairwise interactions showed dual-factor enhancement. The interactions between rainfall and other factors were significantly greater than those among remaining factors. Ecological detector results indicated that there were significant differences in the impact of slope and soil type on soil erosion spatial distribution.

Using the risk detector combined with the above influencing factor analysis, high-risk areas were identified as regions with soil types of brown calcic soil, grass felt soil, and chestnut soil, vegetation coverage <15%, slope >15°, and rainfall in the range of 400-450 mm.

3 Discussion

According to the first national water conservancy census bulletin for soil and water conservation in 2013, the total water erosion area in Xinjiang was 8.76×10^4

km^2, with light erosion accounting for the largest proportion (74.06%), followed by moderate erosion (21.40%), while strong, very strong, and severe erosion accounted for relatively small proportions (2.92%, 1.51%, and 0.11%, respectively). In the middle section of the northern slope of the Tianshan Mountains, the proportions of slight, light, moderate, strong, very strong, and severe erosion were 36.99%, 38.37%, 10.40%, 5.32%, 4.63%, and 4.30%, respectively. Comparatively, the erosion intensity in the middle section of the northern slope of the Tianshan Mountains is slightly higher than the Xinjiang average.

Most previous studies on the northern slope of the Tianshan Mountains have been limited to small watersheds and single-year soil erosion conditions, while reasonable estimation of soil erosion modulus and spatial distribution characteristics at the regional scale with long time series is particularly important for accurate soil erosion prediction. This study fully considered the seasonal dynamics of rainfall and vegetation coverage, calculating both the rainfall erosivity factor and biological practice factor at half-month time steps. Since the magnitude of the biological practice factor is very sensitive to rainfall-induced soil erosion, it is necessary to determine the impact of plants at different growth stages on rainfall erosion. Schmidt et al. concluded that compared with using a single annual biological practice factor, focusing on seasonal or 12-month biological practice factor dynamics helps reduce errors in annual soil erosion calculations, and the combination of spatiotemporally variable rainfall erosivity factors and biological practice factors enables more dynamic and accurate assessment of soil erosion risk.

Using geographic detectors for quantitative analysis of rainfall, topography, soil, and vegetation factors, the results showed that rainfall is the main driving factor causing soil erosion. The northern slope of the Tianshan Mountains is affected by seasonal heavy precipitation, resulting in relatively severe water erosion. This study also showed that slope has a positive effect on soil erosion modulus, which is consistent with existing research. Black calcic soil and gray-cinnamon soil had the lowest soil erosion modulus. Black calcic soil and gray-cinnamon soil are soils under grassland vegetation and forest-shrub vegetation, respectively, with relatively fertile soil and good vegetation coverage, and lush understory grasses and shrubs. Forest and grassland cover can block rainfall splash erosion, prevent soil erosion, and thus forest and grassland soils are less prone to erosion. Better quality soils have stronger water retention capacity, promote vegetation growth, and thereby reduce soil erodibility, which is basically consistent with this study' s results. As vegetation coverage increases, soil erosion modulus decreases, mainly because good surface vegetation can prevent raindrop splash erosion, slow surface runoff, and well-developed underground root systems can fix soil and improve soil conditions, preventing runoff erosion.

4 Conclusions

Based on the CSLE model, this study applied sample surveys, geographic information systems, mathematical statistics, and geographic detector methods to quantitatively analyze the temporal and spatial pattern characteristics of soil hydraulic erosion and clarify the impacts of rainfall, topography, soil, and vegetation factors on soil hydraulic erosion in the middle section of the northern slope of the Tianshan Mountains from 2000 to 2018. The main conclusions are as follows:

1) Temporally, from 2000 to 2018, soil hydraulic erosion intensity in the middle section of the northern slope of the Tianshan Mountains was dominated by slight and light erosion, accounting for 32.34%-40.87% and 33.36%-43.01% of the total area, respectively. In recent years, the areas of slight and light erosion showed decreasing trends (-26.70 $km^2 \cdot a^{-1}$, -77.47 $km^2 \cdot a^{-1}$), while areas of other erosion intensities showed increasing trends (22.10-30.96 $km^2 \cdot a^{-1}$), indicating increasingly severe soil erosion. Spatially, the multi-year average soil erosion modulus was highest in Urumqi (3595.54 $\pm$ 1383.32 $t \cdot km^{-2} \cdot a^{-1}$), followed by Changji City (3321.55 $\pm$ 1182.19 $t \cdot km^{-2} \cdot a^{-1}$) and Fukang City (3256.73 $\pm$ 1170.54 $t \cdot km^{-2} \cdot a^{-1}$), while Shawan County and Shihezi City were lowest (1752.93 $\pm$ 767.79 $t \cdot km^{-2} \cdot a^{-1}$ and 1651.66 $\pm$ 491.33 $t \cdot km^{-2} \cdot a^{-1}$, respectively).
2) Different influencing factors showed varying responses in soil erosion. Rainfall amount had different impacts on soil erosion intensity, with the smallest soil erosion modulus at 250-300 mm and the largest at 400-450 mm. Slope had a significant positive effect on soil erosion intensity, with soil erosion modulus increasing as slope increased. Different soil types had different capacities to resist soil erosion, showing the pattern: grass felt soil > gray-brown desert soil > brown calcic soil > chestnut soil > cold calcic soil > black felt soil > gray desert soil > black calcic soil > gray-cinnamon soil. Higher vegetation coverage could protect soil and prevent soil erosion, with soil erosion modulus decreasing as vegetation coverage increased.

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Note: Figure translations are in progress. See original paper for figures.