Change pathway and intersection of rainfall, soil, and land use influencing water-related soil erosion

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A R T I C L E   I N F O

Keywords:
Soil erosion
Multiple indicators
Contribution importance
Interacted impact
Rainfall change
Human activity

A B S T R A C T

Soil erosion causes fertility loss and land degradation, threatening food security and environmental quality. Understanding the spatial relationship and joint impact of factors on the water-related soil erosion can help combat erosion. Change pathway and intersection of trigger factors, key metrics for determining the soil erosion aggravation or improvement, remain unclear and limited in the quantification in previous researches. To solve this problem, this study performed a spatially statistical exploration by using multiple models. Taking the Yili region as the case-study area, the field soil survey, remote sensing inversion and modified Revised Universal Soil Loss Equation were used to estimate the soil erosion in 1990 and 2015. Then, a spatial analysis model was used to quantify the relative importance of multiple indicators and mutual interactions in the soil erosion. The spatial distribution of soil erosion was shown to be basically related to topography with the largest importance in Yili region. Importance of land use, rainfall, and soil changes along with the rugged topography influencing the soil erosion evolution decreased successively. The largest interacted impact was found in the topography with a non-linear enhancement with vegetation factor. The decrease in soil erosion cannot be explained by the increase in rainfall erosivity, but it is likely to the result of land-use changes, reflected in the improvement of the vegetation cover and management factor and erosion control practice factor within the sloping areas. Examining the spatial consistency and intersection of triggering factors, it implied that reasonably reclaiming the desert grassland with the soil improvement and biomass accumulation would mitigate the soil erosion in the Yili region. Our study demonstrated that quantifying the importance for the different pathways of changing factors and their intersection would provide a better understanding and new insight into the soil erosion process.

1. Introduction

Accelerated water-related soil erosion has become a major threat to society’s well-being, raising numerous environmental problems (FAO, 2015). Soil erosion removes the most fertile soil layer (Pan and Wen, 2014), which not only leads to the land degradation and fertility loss (Lal, 2001), but also influences the associated biogeochemical cycles, such as the siltation and eutrophication of water, enhancement of flooding, and increase or decrease in CO₂ emissions (Boardman and Poosen, 2007; Quinton et al., 2010). Moreover, soil erosion seriously imperils the future food security and environmental quality (Pimentel, 2006; Hu et al., 2019). Thus, there is a need to better understand the soil erosion process to effectuate soil erosion control and sustainable soil utilization and management.

Soil erosion is a complicated process, responding to multiple physical and anthropogenic factors, such as rainfall regimes, topographic factors, soil characteristics, vegetation characteristics, and land utilization and management (Quinton et al., 2010; Zhao et al., 2014). The runoff and erosion material is generally driven by the rainfall (Hu et al., 2019; Molina et al., 2012), and thus, the spatio-temporal heterogeneity of rainfall significantly influences soil erosion (Li et al., 2000; Wei et al., 2007). Topographic factors determine the kinetic energy of runoff transport and sediment washout processes (Sun et al., 2014). Steep slopes increase the erosion volume but flat slopes produce less (Xu and Zhang, 2018). Soil properties and related hydraulic parameters, such as water interception, soil hydraulic conductivity, and soil infiltration (Ouyang et al., 2018), can affect a soil’s capability to resist runoff scouring, transport soil materials, and temporal soil erosion amounts (Durner and Iden, 2011). The planet’s land surface responses to land use change would easily enhance the surface vulnerability to erosions (Ouyang et al., 2018; Pelacani et al., 2008). Reclamation or afforestation can greatly affect the land surface and further lead to water and
soil losses (Zheng, 2006). Land use activities, including deforestation, overgrazing, tillage, and unsuitable agricultural practices, are the primary causes of intensified soil erosion (Mancino et al., 2016; Pan and Wen, 2014). With considerable factors related to the soil erosion (Zhao et al., 2014), a diagnosis of potential soil erosion and its causes are necessary to support for soil conservation.

Changes generally occur in multiple indicators, with the exception of the topographic factor, which seems to be relatively stable (Sun et al., 2014), leading to synergic or tradeoff effects on soil erosion. With an increase in the rainfall erosivity, increasing the soil erosion potential and vegetation cover, particularly in forests, and significantly reducing the sloping cropland can mitigate the soil erosion risk (Mancino et al., 2016). Significant differences in the response of soil erosion to slope gradients from different land uses were found (Sun et al., 2014). Thus, Ochoa et al. (2016) found a very low soil erosion risk within areas of high precipitations and steep slopes but high vegetation covers. Combining the effects of land use and soil property, reclassifying paddy fields was found to be mitigate soil erosion, but changes in the saturated hydraulic conductivity could accelerate the soil erosion potential (Ouyang et al., 2018). These results show the synergic effects of factors that would accelerate the deterioration or improvement of the erosion process, but the tradeoff effect would potentially mitigate the influence of different factors.

Until now, few studies quantified the contribution importance of factors to soil erosion (Mancino et al., 2016; Ochoa et al., 2016; Ouyang et al., 2018; Sun et al., 2014). Their combined impacts have been commonly analyzed by changing one variable and holding the other variables constant, which means the analysis has been qualitatively or semi-quantitatively evaluated. The multiple linear regression equation (Yao et al., 2016) and partial least-squares regression (Shi et al., 2013) were used to analyze the correlation between multiple factors and soil erosion amount in limited studies but did not quantify the interacted effects between the factors. For example, the conversion from natural vegetation to cropland is primarily the result of changes in plant types (Hobbie et al., 2006), while reclaiming the soil and plowing croplands destroyed the soil structure and aggregate structure (Gelaw et al., 2014) and also reduced watershed capacities to regulate runoff occurred in areas (Turner et al., 2018), which are jointly related to the soil erosion process. Thus, the spatial relationship of multiple factors and their interacted effect with soil erosion remains unclear despite many investigations (Yao et al., 2016). The geographical detector model provides an effectively spatial tool to detect the spatial relationship between factors and relevant resultant outcomes (Wang et al., 2010), which would help explore the complex impacts of factors on soil erosion.

The objective of this paper was to (1) detect the historical change in soil erosion and its trigger factors; (2) examine the complex effects of multiple indicators and their contributions to soil erosion. To examine the roles of different change pathway and interaction of trigger factors in the variations in soil erosion, the Yili region, one of the important land-resource development regions in China, with rapid farmland expansion over the past few decades (Zhu Lei et al., 2010), was taken as a case-study area. The field survey for soil sampling and remote sensing techniques were applied to map spatiotemporal variations of land use, soil, vegetation, and rainfall. Revised Universal Soil Loss Equation (RUSLE) was applied to calculate the soil erosion. Finally, the contribution degree of triggering factors and their interaction to the soil erosion process was examined by the spatial detection tool.

2. Materials and methods

2.1. Study region

The Yili region is located in western Xinjiang Province, China, roughly between 42° 15’ N–44° 55’ N latitude and 80° 5’ E–84° 5’ E longitude with the altitude range of 477–6325 m (Fig. 1). Its geographic types consist of alpine areas, plains, and valleys, exhibiting two basins surrounding three mountains. Yili region covers an area of 55,300 km², belonging to the mid-temperate continental climate and alpine climate zones. The sierozem, chestnut soil, chernozem, and meadow soil are the major soil types in the study area. The natural vegetation mainly belongs to the semi-desert sagebrush steppe. Compared to the Xinjiang Province with an average annual precipitation of ca. 130 mm (Li et al., 2011), the Yili region is the most humid region with an average annual precipitation of 200–800 mm by the China Meteorological Forcing Dataset (Chen et al., 2011). Multiple risk factors, with the highest rain erodibility in the extremely dry region, the rugged terrain and large-scale cultivation, easily cause the water-related soil erosion. This calls for a better understanding of relationship between them to combat erosion.

2.2. Data collection and source

Two time nodes representing 1990 and 2015 were selected to calculate the erosion triggering factors and soil erosion amounts in this study. Data of sources and processing used are shown in Table 1. The rainfall from 1986 to 2015 were provided by the China Meteorological Forcing Dataset (Chen et al., 2011) (http://westdc.westgis.ac.cn/). This data was produced by combining three precipitation datasets with the temporal resolution of three hours and spatial resolution of 0.1 × 0.1 degree, respectively. Data of soil mechanical composition and organic matter in 1990 were obtained from the Dataset of 1 × 1 km² rasterized China Soil Characteristics (Shangguan et al., 2012) and Dataset of 30 × 30 arc-second rasterized China Soil Characteristics (Congalton, 1991). Both of datasets were generated from the data from National Soil Survey in the 1980s, and mapped the spatial distribution of soil properties within the soil types. The soil texture dataset was constructed by using the USDA (United States Department of Agriculture) system from soils at depths of 0–30 cm. The H₂SO₄-K₂Cr₂O₇ oxidation method was used to measure soil organic matter (Nelson and Sommers, 1996). Since the soil dataset consists of data regarding soils at different depths, the soil organic matter at the topsoil of 0–30 cm depth was estimated via the weighted depth method provided by Yan et al. (2011).

Referencing to the temporal comparison method of soil properties (Ouyang et al., 2018), this study performed a soil survey sampling according to the spatial distribution within soil classification and land use types (Fig. 2). The soil types in the Yili region under the Chinese Genetic Soil Classification of China (GSCC) and international FAO-UNESCO classification systems are shown in Table 2. 170 soil plots were sampled from depths of 0–30 cm by using a soil auger of 5-cm diameter. At each sampling plot of 10 m × 10 m, five sites, four at the corners and one in the center of the plot, were selected. The soil samples from the five sites were mixed into one sealed plastic bag to represent the soil properties at each plot, with spatial coordinates of the plot center recorded in the GPS. Soil samples were transported to a laboratory and preprocessing was conducted. The soil texture was determined using the Malvern Mastersizer 2000 particle size analyzer, which measured clay (< 0.002 mm), silt (0.002–0.05 mm), sand (0.05–2.00 mm), and gravel (> 2.00 mm) ratios using USDA system. The soil organic matter was measured via the H₂SO₄-K₂Cr₂O₇ oxidation method, the same as that used in the 1980 s. Similar to the soil properties in the 1980 s, spatial distribution of soil texture and organic matter dataset in 2015 used the polygon linkage method with a combination of soil classification and land use types. In addition, soil sampling was not performed in the alpine frost soils, located in the high elevation. Thus, the soil properties in 2015 were assumed to be stable without human disturbance and assigned the same value as those in 1990. Normalized difference vegetation index (NDVI) were calculated by images from Landsat 4–5 TM for 1990 and Landsat8 OLI for 2015. The cloud-free images were selected and downloaded from the US Geological Survey website (http://glovis.usgs.gov/). The paths and rows of images are shown in Table S1. A seamless mosaic tool was used
for fusing multispectral images by the Environment for Visualizing Images (ENVI) software. The near infrared and red bands of the Landsat images were used to calculate the NDVI (Pettorelli et al., 2005). Then the monthly NDVI value used calculated by the maximum value composite method at two periods.

The land use maps were visually interpreted by using the images from Landsat 4–5 TM for 1990 and Landsat 8 OLI for 2015 (Fig. 3). If there were no effective cloud-free or cloudless images, images within a time node of ±2 y would be selected as proxy. Land use was mapped into nine categories—the built-up land, water, forest, paddy field, dry land, grassland, desert, alpine desert, and glacier. A hundred and seventy field investigations were conducted during soil sampling to test land use classification accuracy. A thousand sites from Google Earth were collected for the accuracy assessment of land use map. A total of 1170 ground reference points were used to calculate the overall accuracy and kappa coefficient (Congalton, 1991), which were 95.4% and 0.932 for the land use map in 2015 and indicated a high classification accuracy. According to the same series of Landsat images and land use interpreter, the land use mapping accuracy at 1990 was assumed to be close to that at 2015. Then both of them can be used in the subsequent analysis.

### 2.3. Soil erosion estimation

The RUSLE was widely applied in multiple previous researches (Fu et al., 2005; Hu et al., 2019; Pan and Wen, 2014; Sun et al., 2014; Zeng et al., 2017) and was selected in this study as follows:

\[
A = R \times K \times LS \times C \times P
\]

(1)

where \(A\) indicates the annual mean soil erosion modulus (t ha\(^{-1}\)a\(^{-1}\)), \(R\) means the rainfall erosivity factor (MJ mm ha\(^{-1}\)h\(^{-1}\)a\(^{-1}\)), \(K\) is the soil erodibility factor (t ha\(^{-1}\)MJ \(^{-1}\)mm\(^{-1}\)), \(L\) and \(S\) are the slope length factor and slope gradient factor, respectively, \(C\) indicates the vegetation cover and management factor, and \(P\) is the erosion control practice factor. According to the national professional standards SL190-2007 for classification and gradation of erosion risk (Ministry of Water Resources of PR China, 2008), the \(A\) was categorized into six erosion degree classes: micro, mild, moderate, strong, very strong, and violent classes, with soil erosion modulus ranges of <5, 5–25, 25–50, 50–80, 80–150, and >150 t ha\(^{-1}\)a\(^{-1}\), respectively (Table 3).

R characterizes the source power of the rain to cause erosion, meaning the potential of soil erosion caused by rainfall (Wen et al., 2015). Corresponding to a transformation method provided by Zhang et al. (2002), calculation equations are as follows:

### Table 1

Data source and description.

<table>
<thead>
<tr>
<th>Factor</th>
<th>Time</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rainfall</td>
<td>1986–2000</td>
<td>China Meteorological Forcing Dataset (Chen et al., 2011), Cold and Arid Regions Science Data Center at Lanzhou (<a href="http://westdc.westgis.ac.cn/">http://westdc.westgis.ac.cn/</a>)</td>
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<tr>
<td></td>
<td>2001–2015</td>
<td></td>
</tr>
<tr>
<td>Soil properties</td>
<td>1990</td>
<td>Soil texture Dataset (Shangguan et al., 2012), Soil organic matter Dataset (Congalton, 1991), Cold and Arid Regions Science Data Center at Lanzhou (<a href="http://westdc.westgis.ac.cn/">http://westdc.westgis.ac.cn/</a>)</td>
</tr>
<tr>
<td></td>
<td>2015</td>
<td>Field soil samples: soil texture which was determined by Malvern Mastersizer 2000 particle size analyzer, soil organic matter was measured by the H(_2)SO(_4)-K(_2)Cr(_2)O(_7) oxidation method; spatial distribution of soil properties were drawn by the polygon linkage method</td>
</tr>
<tr>
<td>NDVI</td>
<td>1990 (±2 y)</td>
<td>Images of Landsat 4–5 TM, visually interpreted land use map</td>
</tr>
<tr>
<td></td>
<td>2015 (±2 y)</td>
<td>Images of Landsat 8 OLI, visually interpreted land use map</td>
</tr>
</tbody>
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![Fig. 1. Location and topography of Yili Region.](image-url)
∑ = \sum_{i,j,k} R^i_j \beta^k

\beta = 0.8363 + \frac{17.177}{P_{912}} + \frac{24.455}{P_{912}}

\alpha = 21.586 \times \beta^{0.7951}

where \( R^i_j \) means the annual rainfall erosivity factor (MJ·mm ha\(^{-1}\)·h\(^{-1}\)·a\(^{-1}\)); \( k \) denotes the number of raining days causing potential erosion (d); \( D^i_j \) is the effective precipitation in \( P_{912} \) day (mm), which is the actual precipitation if the daily actual precipitation is higher than twelve mm, otherwise, \( D^i_j = 0 \); \( \alpha, \beta \) are model parameters; \( \bar{P}_{912} \) is the daily precipitation that is higher than 12 mm (mm), and \( \bar{P}_{912} \) is the annual average rainfall with rainfall more than 12 mm (mm). Daily rainfall data were calculated by using the sum of the gridded precipitation data with a 3-hour retrieval period.

\( K \) expresses the soil vulnerability of erosion, which represents the soil sensitivity to denudation separated under raindrop splash, fluviaration, and transportation by runoff. Using the soil organic matter and proportions of sand, silt and clay, \( K \) was calculated by the following equation (Williams and Arnold, 1997):

\[ K = \left\{ 0.2 + 0.3 \exp \left[ -0.0256 SAN \left( 1 - \frac{SIL}{100} \right) \right] \right\} \times \left\{ \frac{SAN}{(CL + SIL)^{1.5}} \times \left( 1 - \left( 1 + \exp(0.75 - 2.69C) \right) \right) \times \left( 1 - \frac{SAN}{100} \right) \right\} \]

where \( K \) indicates the soil erodibility factor (t·h·MJ\(^{-1}\)·mm\(^{-1}\)·a\(^{-1}\)), \( SAN, SIL, \) and \( CL \) mean the sand proportion (0.05–2.00 mm, %), silt proportion (0.002–0.05 mm, %), and clay proportion (< 0.002 mm, %), respectively; \( C \) denotes the soil organic matter content (%). Soil proportions of sand, silt and clay and organic matter content (Table 1) were used to obtained \( K \) values for two periods, respectively.

Topographical factors, slope length and slope gradient, directly influence the soil erosion process. \( LS \) quantifies their impact via empirical formulas. The equation recommended by McCool et al. (1989) and Liu et al. (2000) was used to calculate the slope length \( L \), and the equation provided by McCool et al. (1987) and developed by Liu et al. (1994) was used to calculate the slope gradient factor \( S \). The equations are as follows:

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

\[ S = \left\{ \begin{array}{ll}
10.8 \sin \theta + 0.3 & \theta > 5' \\
16.8 \sin \theta - 0.05 & 5' \leq \theta < 10'
\end{array} \right. \]

\[ 21.91 \sin \theta - 0.96 & \theta \geq 10' \]

where \( L \) denotes the slope length factor; \( S \) is the slope gradient factor; \( \lambda \) and \( \theta \) mean the slope length (m) and the slope angle (°), respectively. The topographical factors \( LS \) were calculated by using the
C. The geographical detector model is a new spatially statistical tool for determining causes of endemic disease (Wang et al., 2010) and is applied to analyze the relationship between independent variables and dependent variable in different research domains (Ren et al., 2014; Xu and Zhang, 2014). The basic hypothesis of geographical detector model is that if a variable X significantly influences the outcome A, there is a similar spatial consistency between X and A (Wang et al., 2010). The contribution of X to A is quantified as the explanatory power of spatial variation of X on that of A. Based on the spatial variance analysis, it detects the spatial relationship of A (e.g., the soil erosion modulus in our study) to the geographical strata of X (e.g., the soil erosion triggering factors in our study). It overlays the spatial pattern of A over the strata of X. Then, the research area is separated as several sub-stratifications (X1, X2, ... Xn) (Wang et al., 2010). Then the Power of Determinant (PD) is the metric to quantify the contribution degree of X to A according to the spatial consistency between them, which is calculated in the following equation:

\[
PD(X) = 1 - \frac{\sum_{i=1}^{n} N_{A,i} \times Var_{A,i}(X)}{N \times VarA}
\]  

(10)

where \(PD(X)\) is the PD for the soil erosion triggering factor of X, including the R, K, LS, C, and P; \(N_{A,i}\) denotes the area of the sub-strata of i category of X; \(Var_{A,i}\) means variations of A in the whole area; \(Var_{A,i}(X)\) means variations of A within the sub-stratifications of \(X_i\). \(PD(X)\) ranges from 0 to 1. When A was totally caused by the variable X, \(PD(X) = 1\); when A was not totally influenced by X, \(PD(X) = 0\). Thus, a larger value of \(PD(X)\) means that a higher effect of X on A. \(PD(X)\) is calculated for each erosion triggering factor.

All the data were resampled as a pixel size of 1 km × 1 km to execute the geographical detector model. To quantify the interacted impact of two variables, the geographical detector model overlays the two variables to generate the new strata. The attribute of this new layer is determined by combination of two strata. Like the single-factor PD, the model quantifies the contribution degree of new strata to outcome A according to the spatial consistency between them and calculates the interacted PD to evaluate the interacted effect of two factors by the Eq. (10). With the single-factor PD and interacted PD, the geographical detector model consists of four detectors. a) Risk detector, comparing the significance of differences between the \(X_i\) on the A, based on the t-value test; b) Factor detector, calculating the relative importance of each factor; c) Ecological detector, comparing the significance of differences between different factors; and d) Interaction detector, quantifying the interacted effect of two factors based on the F-value test. To meet the data format demand for the independent variables in the tool,
Fig. 4. Erosion triggering actors of in 1990 and 2015. R: rainfall erosivity factor, K: soil erodibility factor, L and S: slope length factor and slope gradient factor, C: vegetation cover and management factor, P: erosion control practice factor. Topographic factor of L and S are relatively stable without time node and calculated.
every soil erosion triggering factor were discretized into six discrete levels by the natural breaks method in Arcgis 10.0. A version of Excel-GeoDetector was selected in this paper.

3. Result

3.1. Variation of soil erosion factors from 1990 to 2015

The spatial patterns of calculated soil erosion triggering factors in 2015 were shown in Fig. 4. The rainfall erosivity factor R was 1035.81 MJ·mm ha\(^{-1}\)·h\(^{-1}\)·a\(^{-1}\) in 1990 and significantly increased to 1507.23 MJ·mm ha\(^{-1}\)·h\(^{-1}\)·a\(^{-1}\) in 2015. R presented a large variation range between the two periods, where R was high in the Zhaosu Xian within the southwestern regions and relatively low in other regions in 1990, but R was relatively high in the northern, central, and southeastern mountainous regions in 2015. The average annual erosive rainfall increased from 226.4 mm to 309.7 mm between the two periods. As the source power driving the erosion, the soil erosion risk increased with increasing rainfall erosivity from 1990 to 2015.

The change in soil properties occurs over a long-time process; as such, the soil erodibility factor K was 0.043 MJ·mm ha\(^{-1}\)·h\(^{-1}\)·a\(^{-1}\) in 1990 and slightly increased to 0.046 MJ·mm ha\(^{-1}\)·h\(^{-1}\)·a\(^{-1}\) in 2015, presenting a similar variation range between the two periods. A similar spatial distribution was evident for K between 1990 and 2015, showing high K values in the central hill regions. The soil erodibility factor in the Fluvo-aquic soil, Solonchak, Chernozem, and Sierozem soils within the farmland and grassland were relatively high, with mean values of 0.0549, 0.0512, 0.507, and 0.0506 MJ·mm ha\(^{-1}\)·h\(^{-1}\)·a\(^{-1}\), respectively. The soil erodibility factor was relatively low in boggy soil (0.0335 MJ·mm ha\(^{-1}\)·h\(^{-1}\)·a\(^{-1}\)) from farmlands, and in grey cinnamon soil and alpine meadow soil (0.0326 and 0.0374 MJ·mm ha\(^{-1}\)·h\(^{-1}\)·a\(^{-1}\)) from grasslands and forests within high elevations. Relatively large changes in K occurred in parts of newly reclaimed regions. Due to cultivation activities converting natural vegetation to farmlands, the disturbance of soils would alter in a manner leading to the susceptibility of soils to erosion.

The topographic factor L and S presented a similar spatial distribution. They showed a larger variation and more scattered distribution of topographical factors than those of other soil erosion factors. The average, minimum, and maximum values of L were 2.14, 1.02, and 17.52; and average, minimum, and maximum values of S were 1.23, 0.03, and 17.32. The high values of L and S were mainly pertaining to the local areas of the southern, central, and northern mountainous regions, as parts of the Tianshan Mountains in Xinjiang Province. In contrast, areas of low values of L and S were mainly located in the flat areas of basins and valleys, surrounded by the mountains.

The average C significantly decreased from 0.098 to 0.069 from 1990 to 2015. The significant changes in C were found mainly in newly reclaimed regions that were converted from grasslands with a high C to farmlands with a relatively low C. Also, the areas without land use changes experienced an increase in vegetation cover, which helped decrease the factor C. The factor C presented a relatively similar spatial distribution between the two periods, where areas of high C values mainly corresponded to the desert, alpine desert, desert grassland and glaciers, while grasslands with high vegetation covers and other areas had a relatively low C.

The erosion control practice factor P slightly decreased from 0.75 to 0.71 from 1990 to 2015; this was mainly due to land use change (Table 4). With a small proportion for paddy field, the areas of paddy field and dry land were summed as cultivated region. This region exhibited a huge expansion from 6.96 thousand km\(^2\) to 9.04 thousand km\(^2\) at the expense of grasslands (major source) and forests. Areas of significantly decreased P values from 1990 to 2015 were mainly located in newly reclaimed regions. Desert would mainly experience the wind erosion and alpine deserts and glaciers would mainly experience freeze–thaw erosion. Thus, the soil erosion driven by runoff hardly occurs in the desert, alpine deserts and glaciers. In these cases, as well, the values of P were set to zero. Thus, the soil erosion was mainly focused on farmlands, grasslands, and forests in the Yili region, exhibiting an almost opposite spatial distribution to that of C, where the values of P were low in farmlands but high in grasslands and forests.

3.2. Spatio-temporal soil erosion modulus change

The soil erosion modulus in the two periods was estimated by using the RUSLE (Fig. 5) and reclassed by the grading standard is according to the national professional standards (Table 3). The soil erosion in 2015 is slight in the whole study region, mainly consisting of micro and mild classes, however, severe soil erosion classes were also found in several areas. Areas of very strong and violent erosion classes only covered 0.85% and 0.26% of the total study area, respectively, which were mainly disturbed in local areas of southern, middle, and northern regions with high elevations and mountainous regions in the adjacent hill regions between Nilik Xian and Yining Xian. This spatial distribution of severe soil erosion was consistent with that of high values of trigger factors, especially the LS, C and R (Figs. 4 and 5). Areas of severe soil erosion class are mainly located in grasslands with the low vegetation cover and high rainfall in steep areas. Conversely, the area proportions of the micro and mild erosion classes were 73.40% and 19.62%, respectively. Areas of these soil erosion classes were distributed in the relatively flat areas, which were cultivated or sylvicultural. Thus, the spatial distribution of slight soil erosion was similar with that of low values of LS, C, and P (Figs. 4 and 5).

Comparing soil erosion modulus in the two periods, it presented a trend of total improvement but partial deterioration. The average erosion modulus decreased from 6.36 in 1990 tha\(^{-1}\)·a\(^{-1}\) to 5.83 tha\(^{-1}\)·a\(^{-1}\)in 2015. The area proportion of the micro erosion classes in 1990 was lower than that in 2015 (66.67% vs. 73.40%) but the area proportions of the other erosion classes were larger than those in 2015. In particular, the area proportions of moderate and strong erosion classes decreased from 6.39% and 3.01% in 1990 to 4.38% and 1.50% in 2015, respectively. The overall spatial patterns of soil erosion were similar in the two periods, where soil erosion modulus did not change significantly to be another erosion class but with relative variations in the majority of Yili region. A significant improvement of erosion was found in the central and northern Yili region, where the erosion factors of C and P decreased in these areas. In contrast, a slight aggravation of erosion was shown in the northeastern mountainous areas, which is consistent with the increase in the rainfall erosivity factor R.

3.3. Contributions of triggering factors to soil erosion

Using the geographical detector model, the spatial consistency between the soil erosion modulus and triggering factors were analyzed at the two periods. The PEs of five factors were calculated as shown in Table 5. The five factors in 1990 were ordered as follows: LS (0.497) > P (0.120) > K (0.106) > R (0.084) > C (0.077) and the

<table>
<thead>
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<th>Table 4</th>
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<tbody>
<tr>
<td>Area of land use structure of Yili region in 1990 and 2015.</td>
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<td></td>
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<tr>
<td>Paddy field</td>
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<tr>
<td>Dry land</td>
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<td>Forest</td>
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<td>Grassland</td>
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<td>Water</td>
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<td>Built-up land</td>
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<td>Desert</td>
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<td>Alpine desert</td>
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<td>Glacier</td>
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factors in 2015 were ordered as follows: \( \text{LS} (0.382) > \text{P} (0.146) > \text{R} (0.137) > \text{C} (0.121) > \text{K} (0.112) \). The PD of \( \text{LS} \) decreased from 1990 to 2015 but the PDs of other factors increased. The topographical factor had the highest importance with a much higher PD than the other factors at the two periods. A near 50% increase in the PDs of \( \text{R} \) and \( \text{C} \) indicated an increase in importance for rainfall and land use. The PD of \( \text{R} \) ranked fourth in 1990 and third in 2015. The land use determined \( \text{P} \) and significantly influenced \( \text{C} \), associated with climate change and the topographic pattern. The PD of \( \text{P} \) ranked second but was slightly higher than the PDs of other factors at the two periods, implying the important effect of human activities on the soil loss. Also, the importance of \( \text{C} \)
erosion in the areas of long slope length and steep slope would accelerate soil erosion, which means that pairs of variables enhance one another when the newly reclaimed regions would have a lower soil erosion with the highest interacted PD (Table 6 and 7). In contrast, a slight decrease in K was evident with an increase in LS, which did not enhance each other on the aggravation of soil erosion. For the factors R and P, their values in level 1 of LS were low but presented a variation within other levels. Thus, this led to a relatively non-significant enhanced effect for R and P.

To assess the complex effects of land use with other factors on soil erosion, the soil erosion modulus and factor values within different land use and cover categories were calculated (Fig. 7). The erosion modulus of farmlands, forests, and grasslands were 0.38, 5.44, and 10.27 t ha\(^{-1}\)a\(^{-1}\), with changes of −0.09, 1.54, and −0.28 t ha\(^{-1}\)a\(^{-1}\). The differences for LS and C from different land uses were correlated with the soil erosion modulus, confirming the high impact of LS and the interacted impact of LS and C (Tables 5–7). Except for the specified erosion control practice factor for farmlands, the much lower values of LS and R can explain the low soil erosion modulus for farmlands. Thus, the newly reclaimed regions would have a lower soil erosion with reasonable management. With the close R between the forest and grassland but the higher LS in the forest, a much lower value of C and K resulted in a lower erosion modulus in forests than that in grasslands.

With the different change trends and magnitudes of factors, a decrease in the soil erosion was evident in farmlands and grasslands, with an increase in forests from 1990 to 2015. The R and K slightly increased but the LS and C in farmlands was relatively stable, resulting in a slight decrease in soil erosion. The significantly increased R and the relatively stable values of other factors lead to an increase in the erosion modulus in forests. Changes in soil erosion did not result from the significant increase in R in grasslands. With the relatively stable LS and K, the significant decrease in C mitigated the soil erosion within the grasslands at the two periods. The significant increase in R in the steep areas easily accelerated soil erosion without effective vegetation cover; thus, a slight aggravation was evident in the northeastern mountainous areas. In contrast, a significant improvement in the central and northern regions was due to the significant improvement in vegetation cover and relatively stable change in rain erosivity.

### 4. Discussion

Using the field survey, remote sensing techniques, and RUSLE, soil erosion and the associated factors in the Yili region from 1990 to 2015 were assessed and mapped. Based on the geographical detector model, this study explored the complex impacts of variables on soil losses. In particular, the relative importance of soil erosion factors and their interacted effects were quantified, which provided more available information than previous studies to serve as reference to soil erosion management and control (Mancino et al., 2016; Ochoa et al., 2016; Ouyang et al., 2018; Sun et al., 2014). The PDs, relating the spatial consistency of factors with the soil erosion modulus, were calculated and their orders were indicative of their relative importance for soil erosion in the two periods. Spatial analysis can help identify the key indicators but also reveal the interacted factors influencing the soil erosion.

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**Table 6**  
Comparison of interacted and individual PDs for soil erosion in 1990.

<table>
<thead>
<tr>
<th>C ∩ A ∩ B</th>
<th>A</th>
<th>B</th>
<th>A + B</th>
<th>Conclusion</th>
<th>Interpretation</th>
</tr>
</thead>
<tbody>
<tr>
<td>LS ∩ C</td>
<td>0.737</td>
<td>0.497</td>
<td>0.077</td>
<td>0.574</td>
<td>C &gt; A + B</td>
</tr>
<tr>
<td>LS ∩ R</td>
<td>0.573</td>
<td>0.497</td>
<td>0.084</td>
<td>0.581</td>
<td>C &lt; A + B;</td>
</tr>
<tr>
<td>LS ∩ P</td>
<td>0.522</td>
<td>0.497</td>
<td>0.120</td>
<td>0.617</td>
<td>C &gt; A + B;</td>
</tr>
<tr>
<td>LS ∩ K</td>
<td>0.518</td>
<td>0.497</td>
<td>0.106</td>
<td>0.603</td>
<td>C &lt; A + B;</td>
</tr>
<tr>
<td>R ∩ C</td>
<td>0.300</td>
<td>0.084</td>
<td>0.077</td>
<td>0.161</td>
<td>C &gt; A + B</td>
</tr>
<tr>
<td>R ∩ P</td>
<td>0.238</td>
<td>0.120</td>
<td>0.106</td>
<td>0.227</td>
<td>C &gt; A + B</td>
</tr>
<tr>
<td>P ∩ C</td>
<td>0.205</td>
<td>0.120</td>
<td>0.077</td>
<td>0.198</td>
<td>C &gt; A + B</td>
</tr>
<tr>
<td>P ∩ R</td>
<td>0.201</td>
<td>0.120</td>
<td>0.084</td>
<td>0.204</td>
<td>C &lt; A + B;</td>
</tr>
<tr>
<td>R ∩ K</td>
<td>0.197</td>
<td>0.084</td>
<td>0.106</td>
<td>0.190</td>
<td>C &gt; A + B;</td>
</tr>
</tbody>
</table>

**Note:** “↑↑” denotes A and B enhance each other; “↑↑” denotes a non-linear enhanced combination of A and B.

---

**Table 7**  
Interaction between pairs of factors influencing soil erosion in 2015.

<table>
<thead>
<tr>
<th>C ∩ A ∩ B</th>
<th>A</th>
<th>B</th>
<th>A + B</th>
<th>Conclusion</th>
<th>Interpretation</th>
</tr>
</thead>
<tbody>
<tr>
<td>LS ∩ C</td>
<td>0.744</td>
<td>0.382</td>
<td>0.121</td>
<td>0.503</td>
<td>C &gt; A + B</td>
</tr>
<tr>
<td>LS ∩ R</td>
<td>0.439</td>
<td>0.382</td>
<td>0.137</td>
<td>0.519</td>
<td>C &lt; A + B;</td>
</tr>
<tr>
<td>LS ∩ P</td>
<td>0.444</td>
<td>0.382</td>
<td>0.146</td>
<td>0.527</td>
<td>C &gt; A + B;</td>
</tr>
<tr>
<td>R ∩ C</td>
<td>0.434</td>
<td>0.137</td>
<td>0.121</td>
<td>0.258</td>
<td>C &gt; A + B</td>
</tr>
<tr>
<td>R ∩ K</td>
<td>0.427</td>
<td>0.382</td>
<td>0.112</td>
<td>0.494</td>
<td>C &lt; A + B;</td>
</tr>
<tr>
<td>P ∩ C</td>
<td>0.327</td>
<td>0.146</td>
<td>0.121</td>
<td>0.267</td>
<td>C &gt; A + B</td>
</tr>
<tr>
<td>K ∩ C</td>
<td>0.319</td>
<td>0.112</td>
<td>0.121</td>
<td>0.233</td>
<td>C &gt; A + B</td>
</tr>
<tr>
<td>P ∩ K</td>
<td>0.292</td>
<td>0.146</td>
<td>0.112</td>
<td>0.257</td>
<td>C &gt; A + B</td>
</tr>
<tr>
<td>P ∩ R</td>
<td>0.220</td>
<td>0.146</td>
<td>0.137</td>
<td>0.283</td>
<td>C &lt; A + B;</td>
</tr>
<tr>
<td>R ∩ K</td>
<td>0.215</td>
<td>0.137</td>
<td>0.112</td>
<td>0.249</td>
<td>C &gt; A + B;</td>
</tr>
</tbody>
</table>

**Note:** “↑↑” denotes A and B enhance each other; “↑↑” denotes a non-linear enhanced combination of A and B.
erosion process. The complex changes of erosion triggering factors accelerates or mitigates soil erosion (Ochoa et al., 2016; Ouyang et al., 2018; Yao et al., 2016), which calls for the spatial analysis for a deep understanding of soil erosion process (Molina et al., 2012). Our study suggested that the spatio-temporal variations of soil erosion in Yili region could only be revealed when different change ways of triggering factors and their relative importance were spatially quantified. With the highest importance for the spatial distribution of soil erosion being that of topographic factors (Table 5), the distribution of other factors along with the rugged topography would help explain the change in soil erosion (Tables 6 and 7, Fig. 6). With the complex effects of soil erosion factors, the change in soil erosion did not result from the significant increase in $R$ and slight increase in $K$, as the direction of change is

Fig. 6. Comparison of erosion triggering factors with different topography levels in 1990 and 2015. $LS$: multiplier of slope length factor and slope gradient factor. A higher level means a high value of $LS$ with the following classification interval: level 1 (< 0.54), level 2 (0.54–1.31), level 3 (1.31–3.24), level 4 (3.24–6.87), and level 5 (> 6.87).
opposite from 1990 to 2015. The decrease in soil erosion was correlated with the decrease in C and P and the interacted impact of the change in LS. The highest soil erosion modulus is primarily related to large erosion potential of LS and R coupled with poor erosion control factors of C and P. However, a significant improvement in vegetation cover could decrease the soil erosion potential within large values of LS and R, in accordance with other studies (Ochoa et al., 2016). The overlay of two factors presented different spatial distributions and provided new information, which would explain the detailed spatial variation of soil erosion. A non-linear enhanced effect of LS and C, with the highest interacted PD in both periods was evident. With a higher importance of LS ∩ C than LS ∩ R, the overall change trend of soil loss was consistent with C but opposite to R. With the low LS associated with low C, the overlay of them presented a spatial consistency and non-linear enhanced effect on soil erosion. The topographic gradient, characterized by their topographic and climatic varieties, presented shifts in land use types (Tovar et al., 2013). They showed that farmlands with the relatively low C were mainly distributed in the flat regions of low LS, but grasslands with relatively high C were mainly located in areas of high LS in the Yili region (Fig. 6). An increase in rainfall would

Fig. 7. Comparison of soil erosion equation factors with different land use types in 1990 and 2015.
be beneficial for vegetation growth in the semi-arid region (Rietkerk et al., 2002), and the ecological protection and conservation projects will also help restore the vegetation and decrease the C (Zhang et al., 2015). Low C, indicating high vegetation cover, increased the interception range and effect of vegetation stems and leaves on rainfall, and also increased the consolidation effect of vegetation roots on soils (Syrbe et al., 2018; Zhou et al., 2008). A significant decrease in C from 1990 to 2015 helped control the soil erosion.

Reclamation was considered to easily cause soil erosion compared to the native vegetation (Montgomery, 2007; Ochoa et al., 2016; Sun et al., 2014). However, examining different spatial pathways of changing factors and their intersection on soil erosion, soil erosion of farmlands was even lower than those of forests and grasslands in Yili region, according to this study. Reasonably reclaiming the desert grassland can help soil erosion control in Yili region (Fig. 8). Unlike other study areas, there are adequate flat land resources for agricultural production in Yili region (Jia et al., 2004); thus, farmlands were widely distributed in the flat areas with a much lower LS than that in grasslands and forests. Also, rainfall is lower in cultivated regions than that in grasslands and forests (Fig. 7), which decreases the soil erosion risk in farmlands. Moreover, reasonable agricultural practices would maintain adequate soil organic matter and aggregate structures and help control soil erosion (Pimentel, 2006). The values of the soil erosion factor K for farmlands were found to be close to those for desert grasslands (Fig. 7). According to our soil samples, the sum of the average proportions of silt and clay in farmlands was 66.81%, higher than the 53.03% found in desert grasslands. Also, the soil organic matter and silt proportion of farmlands are nearly 10% higher than the low vegetation cover of desert grasslands, according to our field samples. The uncultivated grasslands were limited by water resources and a lower rate of bioaccumulation (Zhao et al., 2014), and vegetation and soil degradation easily occurred due to overgrazing. Under the cultivation in the study area, the native vegetation witnessed a number of changes, including the nutrient input from fertilizer application and desalinization from farmland water conservancy (Xu et al., 2011). Therefore, the improved conditions of soil moisture and biomass growth after reclamation decreased value of vegetation cover and management factor C. Also, the protecting and maintaining agricultural production from farmland shelterbelts and soil conversation engineer decreased value of erosion control practice factor P to help control soil erosion.

Temporal and spatial soil loss maps can be a basis for the reasonable planning to avoid potential water and soil losses. There is a high soil erosion risk on sloping grasslands of the Yili region, which calls for the implementation of management and control measures. Based on the spatial analysis, the key indicators influencing the soil erosion and their interacted impacts were quantified and identified. The topographic factor LS is the dominance of regional soil erosion, which calls for a better spatial optimal allocation of land use to avoid the steep areas prone to erosion (Sadeghi et al., 2009). The consideration of the combined impact of topographic factors with other factors in water and soil conservation planning was designed as follows. Closing the land for the vegetation restoration measures was suggested for erosion control in the rugged regions in the northern, central and southern mountainous areas, especially the low cover of grasslands in the Huocheng Xian and Qapqal Xibe Zizhixian. The protection and restoration of grasslands and plantation of cash trees were suggested in the low hilly regions. A reasonable reclamation from the low cover grasslands within the relative flat valley regions was suggested help improve local soil erosion. Also, the construction and maintain of farmland shelterbelt network would be widely implemented to erosion control in the cultivated areas.

The interacted impact of trigger factors quantified in this study can be further explored and tested for the soil conservation. Unlike grasslands and forests, the stability of precipitation in farmlands in the past decades has decreased the risk of erosion. Thus, future risk to erosion from spatial and temporal changes in precipitation should be noted and evaluated by using the climate change prediction model (Doblas-Reyes et al., 2013). The future R can be calculated and areas of increased rainfall erosivity risk coupled with high risks of other factor would be called for attention in the soil conversation planning. In addition, how change in one trigger factor may cause changes in other factors with the plot observation and model simulation can be quantified and tested to better predict the soil erosion. The erosion conversation measure, jointly taking the K, C, and P into consideration, can be designed in the plot experiment and used to examine their impact on the soil erosion control.

5. Conclusion

Quantifying and exploring the spatial relationship of topography, rainfall, soil, and land use, and their interacted effects, with soil erosion can provide the information needed to effectively combat soil erosion. Taking the Yili region as a case-study area and using field surveys, remote sensing techniques, RUSLE, and the geographical detector model,
this study provided new insights into the complex responses of soil erosion to changes of multiple triggering indicators. Results showed a trend of overall improvement but local worsening, with a decreased average erosion modulus from 6.36 in 1990 to 5.83 t ha\(^{-1}\) a\(^{-1}\) in 2015. The rainfall erosivity factor \(R\), significantly increased and soil erodibility factor \(K\), significantly increased from 1990 to 2015. In contrast, the vegetation cover and management factor \(C\) significantly decreased and erosion control practice factor \(P\), slightly decreased. Our study demonstrated that soil erosion process can be understood by analyzing the different pathway and intersection of changing factors and their relative importance. The topographic factor is of the highest importance for soil erosion and the interacted impacts of topographic with other factors were still high. The interacted effects of rainfall, soil, and land use along with rugged topography would help better explain and understand the changes in soil erosion. The interacted effect of \(LS\) and \(C\) had a higher importance than that of \(LS\) and \(R\), showing that change in soil erosion did not result from an increase in \(R\) but was correlated with a decrease in \(C\). Moreover, the spatial consistency of lower soil erosion factor values in farmlands, especially a much lower \(LS\) and \(R\), resulted in a lower soil erosion modulus in farmlands (0.38 t ha\(^{-1}\) a\(^{-1}\)) than that in forests and grasslands (5.44, and 10.27 t ha\(^{-1}\) a\(^{-1}\)). It was suggested that the complex impacts of topographic and other factors be taken into consideration to serve as the basis for soil erosion control in the Yili region. Our study demonstrated that spatial exploration can help identify key indicators but also reveal interacted indicators influencing the soil erosion process.

**CRediT authorship contribution statement**

Erqi Xu: Conceptualization, Methodology, Software, Writing - original draft. Hongqi Zhang: Conceptualization, Methodology, Writing - review & editing.

**Declaration of Competing Interest**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

**Acknowledgements**

This work was financially by Strategic Priority Research Program of the Chinese Academy of Sciences (XDA19040305) and National Natural Science Foundation of China (Grant No. 41601095).

**Appendix A. Supplementary data**

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2020.106281.

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