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Spatial and temporal evolution characteristics and driving factors of soil conservation services on the Qinghai-Tibet Plateau

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ABSTRACT

As an important ecosystem regulating service, soil conservation services play an important role in preventing soil erosion and maintaining regional ecological security. The Revised Universal Soil Loss Equation (RUSLE) model and trend analysis were used to quantitatively assess the soil conservation services on the Qinghai-Tibet Plateau (QTP) from 2000 to 2015. Then, we explore the driving factors of the spatial variation in soil conservation with the help of the geographical detector. The results showed that (1) the soil conservation on the QTP decreased and then increased over time, and the spatial pattern had an overall distribution characteristic of being high in the southeast and low in the northwest; (2) soil conservation on the QTP overall was elevated, with 61.39 % and 38.59 % of the area having increasing and decreasing soil conservation trends, respectively, and the spatial fluctuations had the characteristics of "high in the northwest and low in the southeast, with low fluctuations dominating"; and (3) precipitation was the most important factor influencing the spatial variation in soil conservation services, followed by slope, and the influence of landform type was the lowest. The explanatory power of the interaction among factors was higher than that of a single factor, and the explanatory power of the interaction between the slope factor and other influencing factors was highest overall, among which the interaction between slope and annual precipitation had the greatest influence. (4) The study revealed the suitable range of each factor to promote the function of soil conservation, and the mean value of soil conservation reached its maximum when the annual precipitation was 1656.44 ~ 2794.65 mm, the mean annual temperature was 10.41 ~ 22.32 °C, the slope was 35.00 ~ 65.79°. The results of the study provide a scientific basis for regional soil and water conservation measures and ecological protection and construction on the QTP.

1. Introduction

Ecosystem services are the goods and services that humans obtain directly or indirectly from ecosystems (Costanza et al., 1997). Soil conservation, as an important regulating service, refers to the erosion control capacity of an ecosystem to prevent soil loss and improve sediment storage and retention capacity (Liu et al., 2019; Costanza et al., 1997) and plays important roles in preventing the environmental problems caused by soil erosion and in maintaining regional ecological security (Jia et al., 2021; Rao et al., 2013). Related studies have shown that soil erosion may increase globally under the combined influence of human activities and climate change (Yang et al., 2020; Wall and Six, 2015). Regional soil erosion has been reported as one of the serious ecological problems, which may lead to soil degradation, reduced soil productivity, agricultural production and food security crisis (An and Zhao, 2022; Rong et al., 2022; Xue and Luo, 2015). Soil erosion can increase the risk of natural disasters and seriously affect progress towards the Sustainable Development Goals established by the United Nations (United Nations, 2015; An and Zhao, 2022).

China is one of the countries with the most serious soil erosion in the world (Wang et al., 2019), and the total area of soil erosion (including water erosion, wind erosion and freeze–thaw erosion) accounts for 51.1 % of the total national land area (Li et al., 2008). The Qinghai-Tibet Plateau (QTP) is a vast area with significant differences in topography, climate, and vegetation in different regions, and the QTP contains almost all terrestrial soil erosion camp types (Chen et al., 2020; Liu et al., 2006). With the warming and humidification-dominated climatic period and the influence of human activities, the distribution of precipitation is

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uneven in space and time, and these challenges are coupled with serious land degradation and more bare land. As a result, the QTP is prone to water erosion and has become one of the most serious soil erosion areas in China, and this level of erosion seriously affects its ecological barrier function. Therefore, a comprehensive scientific assessment of the current status of soil conservation services and an analysis of its spatial and temporal evolutionary trends and drivers are crucial for maintaining ecological security and regional sustainable development on the QTP.

In recent years, many scholars have studied the spatial distribution characteristics of soil conservation services in different regions and ecosystems using multisource data and different methods. Model simulations are often used to assess soil conservation services. Usually, two types of models are commonly used: physically based models and empirical models (Guo et al., 2019; Li et al., 2017). Physics-based models include Water Erosion Prediction Project (WEPP), the Soil and Water Assessment Tool (SWAT)) and so on. Most of them are theoretically more transferable than empirical models and are more likely to achieve reasonable estimates (Merritt et al., 2003). However, a large number of parameters based on physical models are difficult to measure and calibrate directly, leading to the uncertainty of simulation results (Xia et al., 2021). Therefore, empirical models are widely used in soil erosion and soil conservation worldwide. The most commonly used empirical model is the Revised Universal Soil Loss Equation (RUSLE), which has long been recognized as one of the most useful empirical models due to its simple structure and low requirement of input data and parameters. (Fernandez and Vega, 2018; Renard et al., 1997). The combination of Geographic Information system (GIS) and RUSLE model is suitable for large-scale study can provide a reasonable assessment of soil erosion and spatial distribution in region (Rao et al., 2014; Yan et al., 2020). In recent years, RUSLE model has also been applied to soil erosion assessment in the QTP of China (Fan et al., 2021; Hou et al., 2021), and achieved relatively good results.

The driving factors of soil erosion and soil conservation have received extensive attention. A large number of studies have shown that soil erosion and soil conservation are mainly caused by climate and land use change (Zhou et al., 2021; Daryanto et al., 2020; Guo et al., 2019), but related studies have shown that there are also differences due to different regions. For example, climate change was the main driving factor for soil erosion variation in the Yanwachuan watershed on the Loess Plateau (Xia et al., 2021). A study on the driving factors of ecosystem services in the Pearl River Delta showed that NDVI and DEM were the main influencing factors of soil conservation services (Liu et al., 2022). In addition, Fang et al. (2021) showed that slope was the most important factor affecting soil conservation services in the Yellow River Basin and the Yangtze River Basin. Therefore, it can be seen that the dominant factors of soil conservation in different regions are diverse. Until now, the response of soil conservation services to climate change and land use on the QTP has been rarely studied. The driving mechanism of soil conservation variations on the QTP remain inadequately understood. Therefore, it is necessary to evaluate the changes and driving factors of soil conservation services in the QTP, so as to provide a basis for soil and water conservation planning.

There are two categories of methods commonly used to identify explanatory factors for soil conservation services: non-spatial models and spatial models (Liu et al., 2022). Non-spatial models mainly include multiple regression analysis (Lorilla et al., 2020; Hao et al., 2017), redundancy analysis (Feng et al., 2017; Sun et al., 2020), ordinary least squares (OLS) and so on. Spatial models mainly include the geographical detector method, geographically weighted regression (GWR), spatial error model and so on. Compared with the non-spatial model, the spatial model is more accurate by considering the spatial heterogeneity of driving factors (Pribadi and Pauleit, 2016). Among the spatial models, geographical detector method can consider the interaction between multiple drivers and determine the contribution of all drivers (Wang et al., 2016). Compared with the traditional statistical analysis methods, the geographical detector method has unique advantages in analyzing the driving force of geographic factors and the coupling of driving factors (Sannigrahi et al., 2020).

A number of studies have been carried out on the quantitative assessment of soil conservation services on the QTP (Hou et al., 2021; Lin et al., 2021; Wang et al., 2021b). However, few studies have focused on the spatial and temporal characteristics of soil conservation services and the interaction of multiple influencing factors in the QTP, which is of great significance for ecological protection of the QTP. Therefore, this study aims to: (1) evaluate the spatial and temporal variation of soil conservation services on the QTP from 2000 to 2015; (2) analyze the spatial–temporal evolution trend and fluctuation of soil conservation services on the QTP; (3) explore the key driving factors of soil conservation services and analyze the interaction of driving factors. A better understanding of the spatial and temporal characteristics of soil conservation services and their driving factors will help the government make informed decisions on soil and water conservation management.

2. Materials and methodology

2.1. Study area

The Qinghai-Tibet Plateau (QTP, 26°00′N ~ 39°47′N, 73°19′E ~ 104°47′E) is located in the western region of China, and it is known as the "roof of the world" and the "third pole of the earth", with an average elevation greater than 4,000 m, and it is the highest plateau in the world and the largest in China. The QTP plays an important role as a barrier to ecological security in China and Asia. The total area of the QTP is approximately 2.5 million km^2, and its spatial scope involves six provinces and regions, namely, Tibet, Xinjiang, Qinghai, Gansu, Sichuan and Yunnan. The QTP has a special geographical location and significant climate differences (see Fig. 1). The regional climate is simultaneously influenced by the westerlies, Indian monsoon and East Asian monsoon, with a large diurnal temperature difference. The annual average temperature ranges from −16 °C to 20 °C, and the annual precipitation decreases from 2000 mm to less than 50 mm from the southeast to northwest. The QTP has a large grassland area, with unused land in the north and forestland in the southeast. The main ecosystem types of the QTP include alpine meadow ecosystems, alpine grassland ecosystems and forest ecosystems, and the main soil types include alpine soil, leached soil, primary soil and hydromorphic soil.

2.2. Data sources and processing

The data required for the soil conservation service calculation based on the RUSLE model and the spatial dispersion driver analysis based on the geographical detector included the study area boundary data, meteorological data, land use data, digital elevation model (DEM), normalized vegetation index (NDVI), soil data, and topographic and geomorphological data.

The data on the spatial extent of the geographic boundaries of the QTP were obtained from the Global Change Research Data Publishing and Repository (https://www.geodoi.ac.cn). Based on the research achievements in related fields and many years of field practice, Zhang et al. (2002) demonstrated the principles for determining the extent and boundary of the QTP, and combined with information technology methods, made accurate positioning and quantitative analysis of the extent and boundary of the QTP. It is concluded that the QTP in part of China from the Pamir Plateau in the west, to the Hengduan Mountains in the east, from the southern edge of the Himalayan mountains in the south, to the north of the Kunlun Mountains-Qilian Mountains.

The meteorological data were obtained from the National Meteorological Information Center (NMIC) (https://data.cma.cn/), the National Tibeten Plateau Data Center (NTPDC) (https://data.tpdc.ac.cn/), and the Resource and Environmental Science Data Center of the Chinese Academy of Sciences (RESDCCAS) (https://www.resdc.cn/). The 1 km resolution monthly precipitation dataset in China was derived from

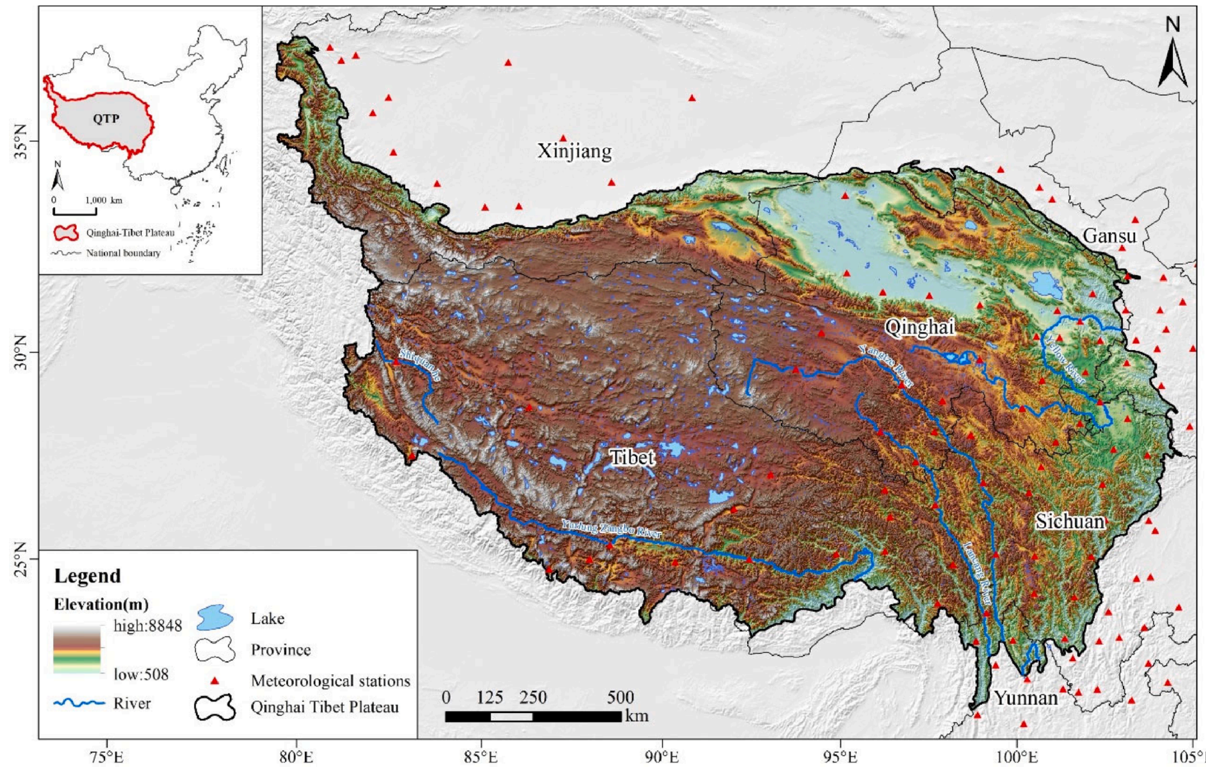

Fig. 1. Location of the study area.

NTPDC and used to calculate the rainfall erosivity factor (R) in the RUSLE model. This dataset was generated by downscaling the Delta spatial downscaling scheme in China based on the global 0.5° climate dataset published by Climatic Research Unit (CRU) and the global high-resolution climate dataset published by WorldClim. Moreover, the data of 496 independent meteorological observation points (derived from NMIC) are used for verification, and the verification results are credible. The spatial interpolation dataset of annual mean temperature and annual precipitation with 1 km spatial resolution in China is derived from RESDCCAS. It is based on the daily observation data of more than 2400 meteorological stations in China, and generated by sorting, calculation and spatial interpolation processing with ANUSPLIN software. This dataset is taken into the geographical detector as influencing factors.

The land use data were obtained from the National Tibeten Plateau Data Center (https://data.tpdc.ac.cn/) and included the multiyear remote sensing monitoring dataset of land use status in six provinces (including Xinjiang, Tibet, Qinghai, Yunnan, Sichuan and Gansu) in western China with a spatial resolution of 1 km. The datasets were based on Landsatt TM/ETM remote sensing images in 2000, 2005, 2010 and 2015, and were generated by manual visual interpretation using professional software. Land use types were divided into six categories: cultivated land, forest land, grassland, wetland, construction land, unused land. The datasets are currently the highest precision land use remote sensing monitoring data products, and have played an important role in the land resources survey, hydrology and ecological research.

DEM data with a resolution of 90 m derived from the Shuttle Radar Topography Mission (SRTM) dataset, which was provided by the Resource and Environmental Science Data Center of the Chinese Academy of Sciences (https://www.resdc.cn/). SRTM data has the advantages of being realistic and free to obtain. Many applications around the world use SRTM data for environmental analysis. DEM data were used to calculate the slope length and steepness factor (LS) in RUSLE model.

The soil texture data came from the Chinese soil dataset (V1.1) based on the Harmonized World Soil Database (HWSD) (https://data.tpdc.ac.cn/). The dataset includes soil texture (sand, silt and clay content) and soil organic carbon data from the second Soil Survey of China. These data were used to calculate the soil erodibility factor (K). The soil type data came from the Resource and Environmental Science Data Center of the Chinese Academy of Sciences (https://www.resdc.cn/).

The NDVI data were obtained from MOD12Q1 data in the MODIS product of NASA (https://ladsweb.modaps.eosdis.nasa.gov/), with a spatial resolution of 250 m and a temporal resolution of 16 d. We converted MOD13Q1 data into Geo-Tiff format and Albers map projection using MODIS Reprojection Tool (MRT). The maximum synthesis method was used to better reflect the vegetation cover condition.

Since different data sources have different spatial resolutions, the data were unified to a 1 km × 1 km spatial resolution, and the projection coordinates were unified to the Albers equal area projection. In addition, We clip the all the data using the vector QTP boundary for further analyses.

2.3. RUSLE model

Soil conservation was represented by soil retention. The RUSLE model (Renard et al., 1997) was used to estimate the soil conservation amount of different ecosystems in the study area, that is, the difference between potential soil erosion and actual soil erosion. The potential soil erosion is the soil erosion that occurs without vegetation cover and any soil and water conservation measures; the actual soil erosion is the soil erosion under the consideration of vegetation cover and soil and water conservation measures. The calculation formula of soil conservation is as follows:

$$SC = R \times K \times LS \times (1 - C \times P)\# \quad (1)$$

where SC is the soil conservation, R is the rainfall erosion factor (MJ mm $ha^{-1}h^{-1}$), K is the soil erodibility factor (t ha h $mj^{-1}mm^{-1}ha^{-1}$), L is the slope length factor, S is the steepness factor, C is the vegetation cover factor, and P is the support practice factor.

Rainfall erosion factor R: It reflects the average annual precipitation and the response degree of soil erosion to precipitation. Using the method based on monthly values of precipitation data proposed by Wischmeier, which was modified by Arnoldus (Arnoldus et al., 1980), the calculation formula is as follows:

$$R = \sum_{i=1}^{12} 1.735 \times 10^{\left(1.5log_{10}\left(\frac{p_i^2}{p}\right) - 0.8188\right)} \# \tag{2}$$

where p_i is the monthly rainfall (mm), and p is the annual rainfall (mm).

Soil erodibility factor K: It reflects the sensitivity of soil to erosion. The Erosion/Productivity Impact Calculator (EPIC), an erosion productivity evaluation model proposed by Williams et al. (1989), was used and calculated as follows:

$$K = \left(0.2 + 0.3exp\left(-0.0256Sand\left(1.0 - \frac{Silt}{100}\right)\right)\right) \times \left(\frac{Silt}{Clay + Silt}\right)^{0.3} \times \left(1.0 - \frac{0.25C}{C + exp(3.72 - 2.95C)}\right) \times \left(1.0 - \frac{0.7SN1}{SN1 + \exp(-5.51 + 22.9SN1)}\right) \times 0.1317\# \tag{3}$$

where *Sand*, *Silt* and *Clay* are the contents of *Sand*, *Silt* and *Clay*, respectively (%), C is the soil organic carbon content (%), and$SN1 = 1\text{-}Sand/100$.

Slope length and steepness factor LS: Calculated based on DEM data. Slope is the most direct kinetic energy source of soil and water loss, and slope length determines the degree of erosion. The slope length factor (L) andslope steepness (S) were calculated according to the core algorithm of McCool et al. (1987) and Liu et al. (1994), which were verified to be suitable for plateau areas (Fu et al., 2015). The formula is as follows:

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

$$m = \frac{\beta}{1 + \beta} \# \tag{5}$$

$$\beta = \frac{sin\theta/0.0896}{3.0 \times (sin\theta)^{0.8} + 0.56} \tag{6}$$

$$S = \begin{cases} 10.8 \times sin\theta + 0.03\theta < 5^\circ \\ 16.8 \times sin\theta - 0.55^\circ \leq \theta < 10^\circ \# \\ 21.91 \times sin\theta - 0.96\theta \geq 10^\circ \end{cases} \tag{7}$$

where L is the slope length factor, S is the steepness factor, λ is the horizontal projection length of the raster cell (m), m is the slope length index, β is the ratio of rill erosion to interrill erosion, and θ is the slope extracted using the DEM.

Vegetation cover factor C: The ground cover factor is a factor that reflects the influence of vegetation on soil erosion according to the different statuses of ground vegetation cover and is closely related to the land use type and cover degree. The calculation method refers to the study of Cai et al. (2000), and the formula is as follows:

$$C = \begin{cases} 1(f = 0) \\ 0.6508 - 0.3436 \times lgf(0 < f \leq 78.3\%) \\ 0(f > 78.3\%) \end{cases} \tag{8}$$

$$f = \frac{NDVI - NDVI_{soil}}{NDVI_{veg} - NDVI_{soil}} \times 100\% \# \tag{9}$$

where f is the vegetation cover (%), *NDVI* is the normalized difference vegetation index, and $NDVI_{soil}$ and $NDVI_{veg}$ are the are the NDVI values of a pure pixel for bare soil and a pure pixel with 100 % vegetation coverage, respectively (Carlson and Ripley, 1997). In this study, $NDVI_{soil}$ and $NDVI_{veg}$ are defined as 0.5 % and 99.5 % quantile of all the *NDVI* values, respectively (Ge et al., 2018; An and Zhao, 2022).

The support practice factor P reflects the difference in soil loss caused by the difference in management measures of vegetation, and the value was obtained by referring to relevant literature (Fu et al., 2011; Wang and Dai, 2020; Xiao et al., 2015).

2.4. Trend analysis and coefficient of variation (CV)

Unary linear regression analysis (Liu et al., 2015; Wang et al., 2021a; Deng et al., 2013) was used to analyze the trend on the grid scale of the QTP. The temporal and spatial evolution trends of the soil conservation services in the study area were reflected by simulating the change characteristics of soil conservation in each grid during the study period. Its calculation formula is as follows:

$$Slope = \frac{n \times \sum_{i=1}^{n} i \times SC_i - \sum_{i=1}^{n} i \sum_{i=1}^{n} SC_i}{n \times \sum_{i=1}^{n} i^2 - \left(\sum_{i=1}^{n} i\right)^2} \# \tag{10}$$

where *Slope* is the slope of the soil conservation change trend, n is the cumulative number of years, i is the year's serial number, and SC_i is the soil conservation value in year i. If *Slope* is greater than 0, it indicates that the variation trend of soil conservation in this region increases over time, and the larger the *Slope* value is, the more obvious the increase trend is. The opposite indicates soil conservation shows a decreasing trend with time. If *Slope* equals 0, it indicates that the soil conservation in this region has not changed. The confidence of the significance test was 95 %.

The CV refers to the ratio of the standard deviation of data to the mean and is often used to measure the volatility of geographic data (Liu et al., 2018; Sharma et al., 2017). This method was adopted to reflect the spatial fluctuation characteristics of soil conservation, and the calculation formula is as follows:

$$C_v = \frac{1}{\overline{SC}} \times \sqrt{\frac{\sum_{i=1}^{n} (SC_i - \overline{SC})^2}{n - 1}} \# \tag{11}$$

where C_v is the coefficient of variation of soil conservation, n is the cumulative number of years, i is the year number, SC_i is the value of soil conservation in year i, and $\overline{SC}$ is the average value of soil conservation in the study period. The smaller the C_v value is, the smaller the degree of fluctuation is, indicating that the interannual variation in soil conservation is smaller; in contrast, the greater the degree of fluctuation is, the greater the interannual variation is.

2.5. Geographical detector

A geographic detector is a statistical method used to detect the heterogeneity of the spatial stratification of elements and reveal their driving forces (Wang and Xu, 2017; Wang et al., 2016; Wang et al., 2010). The core idea is that if an independent variable has a significant influence on a dependent variable, then the spatial distribution of the independent and dependent variables should be similar. The magnitude of spatial heterogeneity can be measured by the q value of the geographic detector. By calculating and comparing the q value of each single factor and the q value of two factors after superposition, the geographic detector can judge whether there is interaction between the two factors and whether the interaction is strong, weak, directional, linear or nonlinear. The geographic detector consists of four modules: factor detector, interaction detector, risk detector and ecological detector. This paper used three parts, which are factor detection, interaction detection and ecological detection.

The factor detector is used to detect the spatial heterogeneity of the dependent variable and to detect the extent to which the influence factor (X) explains the spatial heterogeneity of the dependent variable (Y), which is measured by the q value, and the formulas are as follows:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} = 1 - \frac{SSW}{SST}\# \tag{12}$$

$$SSW = \sum_{h=1}^{L} N_h \sigma_h^2 \# \tag{13}$$

$$SST = N\sigma^2 \# \tag{14}$$

where $h = 1, 2\cdots, L$ is the stratification of the dependent variable or independent variable, and N_h and N are the number of cells within stratum h and the whole region, respectively. σ_h^2 and σ^2 are the variances of the values of the dependent variable in stratum h and the whole region, respectively. SSW is the sum of the variances within the stratum, and SST is the total variance of the whole region. The value of q can indicate the spatial differentiation of the dependent variable and the explanatory ability of the independent variable to the dependent variable. The range of q is [0,1], and the larger the value is, the more obvious the spatial differentiation of the dependent variable is. If stratification is generated by independent variable X, the q value indicates that X explains $100\times q$% Y. The closer the q value is to 1, the stronger the explanatory ability independent variable X has in relation to the dependent variable Y, and vice versa.

The interaction detectors are the greatest advantage of geographic detectors over other statistical methods. Thus, this method can be used to detect interactions between two variables, that is, to assess whether the interaction of two factors increases or decreases the explanatory power of the dependent variable. By comparing the q values of a single factor and a double factor, we can judge the direction and mode of interaction between the two factors. The types of interaction include the following: if $q(X1 \cap X2) < Min(q(X1), q(X2))$, the interaction shows nonlinear weakening; if $Min(q(X1), q(X2)) < q(X1 \cap X2) < Max(q(X1), q(X2))$, the interaction shows single-factor nonlinear weakening; if $q(X1 \cap X2) > Max(q(X1), q(X2))$, the interaction shows double-factor enhancement; if $q(X1 \cap X2) = q(X1) + q(X2)$, the interaction shows double-factor independence; and if $q(X1 \cap X2) > q(X1) + q(X2)$, the interaction shows nonlinear enhancement.

The risk detector can be used to detect the appropriate range or type of influence of different influencing factors on the dependent variable with t-statistics.

In this research, the geographic detector was used to identify the spatial heterogeneity of soil conservation, to measure the extent to which the influencing factors explained the spatial heterogeneity of soil conservation with the help of q values, and to analyze the interactions between the factors. According to previous studies, natural factors (including climatic factors, vegetation factors, topographic and geomorphic factors and soil factors) and land use factors are the main driving factors of soil conservation services in most regions (Matomela et al., 2022; Pan et al., 2022; Liu et al., 2022; Fang et al., 2021; Shen et al., 2020; Su and Fu, 2013b). However, it is not clear whether natural and land use factors contribute to soil conservation services in the QTP. The influencing factors selected in this study included meteorological factors (annual mean precipitation, annual mean temperature), topographic and geomorphic factors (slope, DEM, geomorphic type), vegetation factors (NDVI), soil factors (soil type), and land use factors (land use type). The input variables of the geographic detector are required to be categorical data and need to be discretized for continuous type variables. Referring to the data discretization method proposed by (Wang and Xu, 2017) and related experiences, we classified slope into 9 categories (<2°, 2° ~5°, 5°~10°, 10°~15°, 15°~20°, 20°~25°, 25°~30°, 30°~35°, > 35°) and land use type into 6 categories (cultivated land, forestland, grassland, wetland, construction land, unused land). The geomorphic type was divided into 7 categories (plain, terrace, hill, small rolling mountain, medium rolling mountain, large rolling mountain, great rolling mountain), and the soil type was divided into 17 categories (luvic soils, semi-luvic soils, calcic soils, arid soils, desert soils, primordic soils, semi-hydrogenic soils, hydrogenic soils, saline alkaline soils, anthropogenic soils, alpine soils, ferrite soils, rocks, glacier and snow covers, northwest salt crust, water bodies, others). DEM were classified into 8 categories according to the natural breakpoint method. The mean annual temperature, annual mean precipitation, and NDVI were classified into 9 categories.

3. Results

3.1. Interannual variation in soil conservation

The total multiyear average soil conservation on the QTP was 1.47×10^{10} t. From 2000 to 2015, soil conservation showed a trend of first decreasing and then increasing, and there was a significant difference between the changes in soil conservation before and after 2006 (Fig. 2). The total amount of soil conservation had an obvious decreasing trend from 2000 to 2006, with a decreasing rate of 7.105×10^8 t/a. It reached a minimum value of 1.25×10^{10} t in 2006 and decreased by 39 % in 2006 compared with that in 2000; additionally, the total soil conservation from 2006 to 2015 showed a fluctuating increasing trend, and the total soil conservation in 2015 increased by 57 % compared with that in 2006.

3.2. Spatial and temporal distributions of soil conservation

The spatial distribution of rainfall erosion factor (R), soil erodibility factor (K), slope length and steepness factor (LS), vegetation cover factor (C), and support practice factor (P) displayed obvious spatial differences (see supplementary information Fig. S1–5). From the spatial distribution of soil conservation services on the QTP from 2000 to 2015 (Fig. 3), the soil conservation had obvious spatial heterogeneity, and the spatial pattern as a whole had distribution characteristics of being high in the southeast and low in the northwest. The high values were mainly concentrated in the southeastern part of the QTP in the deep valleys of the high mountains of western Sichuan and eastern Tibet, especially in the Minshan, Qionglai and Daxue Mountain areas, while the low values were mainly located in the western part of the Kunlun Mountains and the lake basin area of the Qiangtang Plateau in the northwestern QTP. In terms of the spatial and temporal distribution characteristics, the regional distribution of high soil conservation in Xinjiang became wider from 2000 to 2008, and the distribution of high values tended to contract again from 2008 to 2015. Soil conservation in Qinghai Province was mainly located in its eastern and southern regions, and the distribution of high-value areas of soil conservation first increased and then decreased from 2000 to 2015. The distribution of soil conservation in Sichuan Province and Yunnan Province was uniform, and the amount was generally high. The area with high soil conservation decreased gradually in Tibet, and there were more low values in central and northern Tibet.

3.3. Trend analysis and fluctuation characteristics

Based on the results of the trend analysis and significance test, the

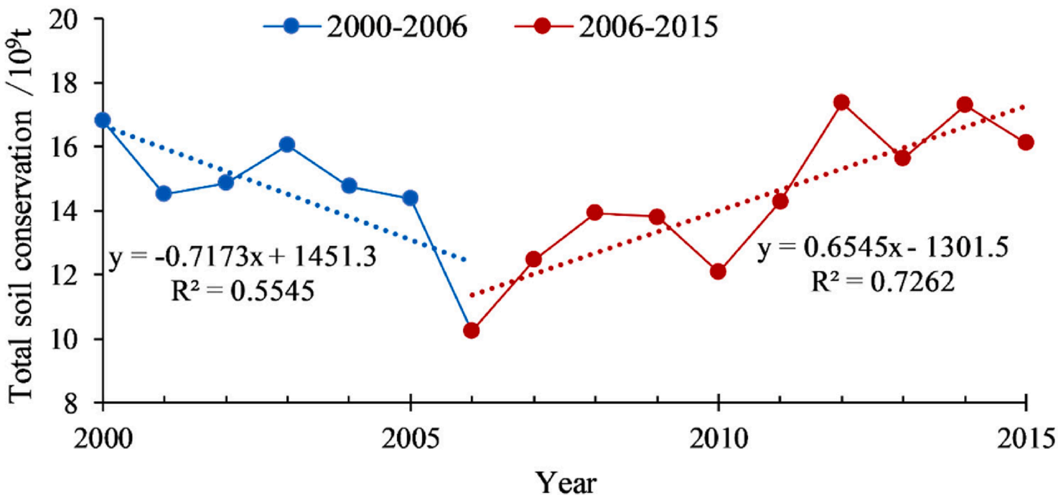

Fig. 2. Temporal variation in soil conservation on the QTP from 2000 to 2015.

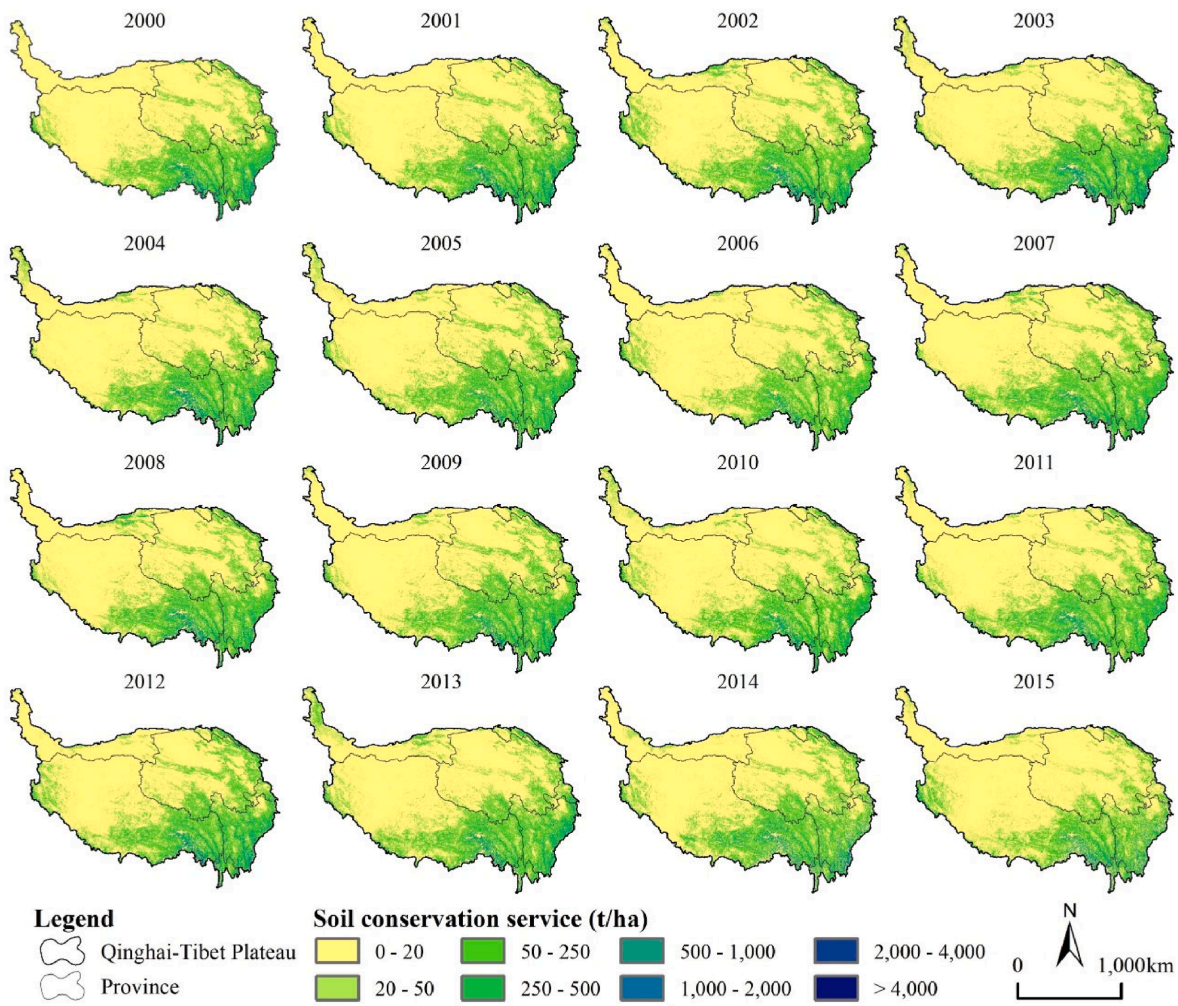

Fig. 3. Spatial pattern of soil conservation services on the QTP from 2000 to 2015.

Fig. 3. Spatial pattern of soil conservation services on the QTP from 2000 to 2015.

trends of soil conservation on the QTP were classified into five categories, namely, significant increase (slope > 0, $p < 0.05$), insignificant increase (slope > 0, $p > 0.05$), insignificant decrease (slope < 0, $p > 0.05$), significant decrease (slope < 0, $p < 0.05$), and no significant change (slope = 0). From the spatial distribution of trends (Fig. 4a), the soil conservation on the QTP showed an overall increasing trend, with 61.39 %, 38.59 % and 0.02 % of the area showing increasing (slope > 0), decreasing (slope < 0) and no significant change (slope = 0) trends,

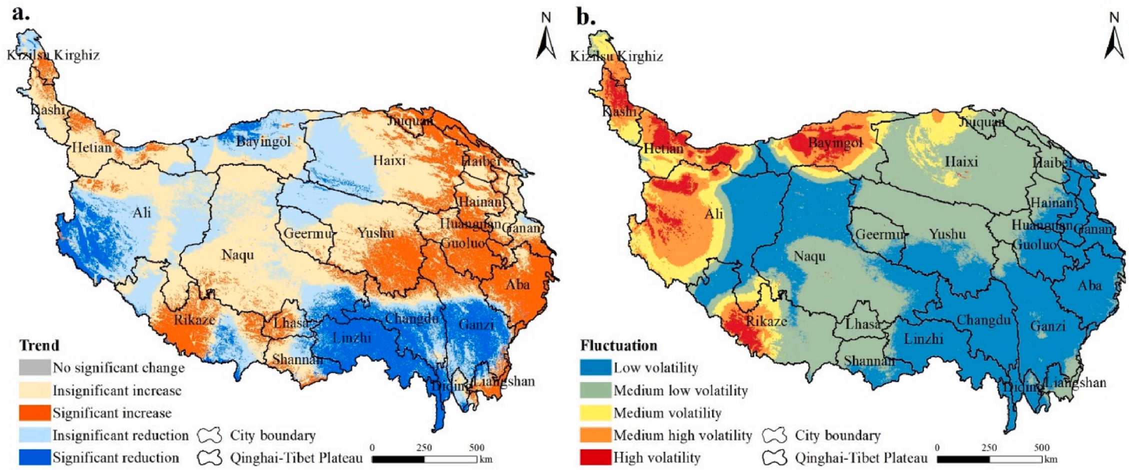

Fig. 4. Spatial variation trend (a) and fluctuation characteristics (b) of soil conservation services on the QTP.

respectively. In terms of the increasing trend, 40.91 % of the area showed no significant increase, and 20.48 % of the area showed a significant increase. The areas with significant increases were mainly located in eastern Qinghai Province, northern Sichuan Province, central Shigatse and central and western Lhasa in Tibet, and there were also some areas with significant increases in Kashgar and Hotan areas in Xinjiang. Soil conservation on the QTP showed a decreasing trend in 38.61 % of the area, of which 13.96 % and 24.63 % were significantly and insignificantly decreasing areas, respectively. The significantly decreasing areas were mainly distributed in the southwestern part of the Ali region, the southern part of Qamdo city, the counties of Nyingchi city in Tibet, the southern part of Garz Prefecture in Sichuan and the northern part of Bayingolin in Xinjiang.

From the spatial distribution of volatility (Fig. 4b), the CV of the study area ranged from 0 to 3.86, indicating that there were significant spatial variation characteristics of soil conservation capacity changes on the QTP. The fluctuation was classified into five categories according to the natural break method, namely, low volatility (0 ~ 0.24), medium low volatility (0.24 ~ 0.44), medium volatility (0.44 ~ 0.70), medium high volatility (0.70 ~ 0.93), and high volatility (0.93 ~ 3.86). In general, the distribution pattern was "high in the northwest and low in the southeast, with low volatility and relatively low volatility dominating". The areas with high and medium high volatility were mainly located in the western part of the Kunlun Mountains (Kashgar and Hotan areas in Xinjiang), Ali area, Bayingolin Mongol Autonomous Prefecture and central part of Shigatse city in the northwestern part of the plateau. Regions with medium to low volatility were mostly concentrated in the Qaidam Basin, Lhasa, southern Nagchu and eastern Shigatse. Soils in the eastern and southeastern QTP maintained relatively stable services with relatively weak volatility. The soil conservation was relatively stable, and the fluctuation was relatively weak in the eastern and southeastern QTP.

3.4. Factors identification of spatial heterogeneity of soil conservation services

3.4.1. Single factor analysis

The mean value of soil conservation from 2000 to 2015 was taken as the dependent variable; the mean values of the NDVI, annual average precipitation and annual average temperature from 2000 to 2015 were taken as the independent variables; and the values of the land use type, DEM, slope, geomorphic type and soil type in 2015 were taken as the independent variables due to the small interannual change. Each factor was discretized according to the corresponding method and analyzed by a geographical detector to obtain the explanatory power q value (see Table 1). Table 1 shows that the q-values of each influencing factor on soil conservation services were, in descending order, mean annual precipitation (0.546) > slope (0.458) > soil type (0.319) > mean annual temperature (0.288) > NDVI (0.195) > DEM (0.177) > land use type (0.174) > landform type (0.141), and all the factors passed the significance test ($p < 0.01$). The mean annual precipitation was the most important factor influencing the spatial heterogeneity of soil conservation, with an explanatory power of more than 50 %, which was significantly higher than that of the other factors. Second, the slope, soil type and annual mean temperature had moderate explanatory power, while the NDVI, DEM and land use type had weak explanatory power for soil conservatsion. Geomorphic types accounted for only 13.3 % and had the weakest impact on the spatial heterogeneity of soil conservation.

3.4.2. Double-factor interaction analysis

The interaction detector can identify the interaction of two factors and analyze whether the explanatory power of soil conservation increases or decreases. The results show that the interaction of two factors was stronger than the power of a single factor in explaining the spatial differentiation of soil conservation (Fig. 5). The interaction between DEM and geomorphic type and between DEM and Slope had nonlinear enhancement trend, and the other factors had a double-factor enhancement trend, which indicated that the spatial variation in the soil conservation services on the QTP was not controlled by a single factor but was the result of the interaction of multiple factors. The q value of the interaction between slope and annual precipitation was 0.852, which was significantly higher than the interaction between other influencing factors, indicating that the interaction between the slope and annual precipitation had the greatest explanatory power and strongest influence on the spatial distribution of soil conservation. In addition, the explanatory power of the interaction between the slope factor and other influencing factors was higher, and the explanatory powers of the slope and soil type, slope and mean annual temperature

Table 1
The q values of influencing factors of the soil conservation service in the QTP.

Influencing factor	Mean annual precipitation	Mean annual temperature	NDVI	Land use type	DEM	Slope	Geomorphic type	Soil type
q value	0.546**	0.288**	0.195**	0.174**	0.177**	0.458**	0.141**	0.319**

Note: ** represents significance level $p < 0.001$.

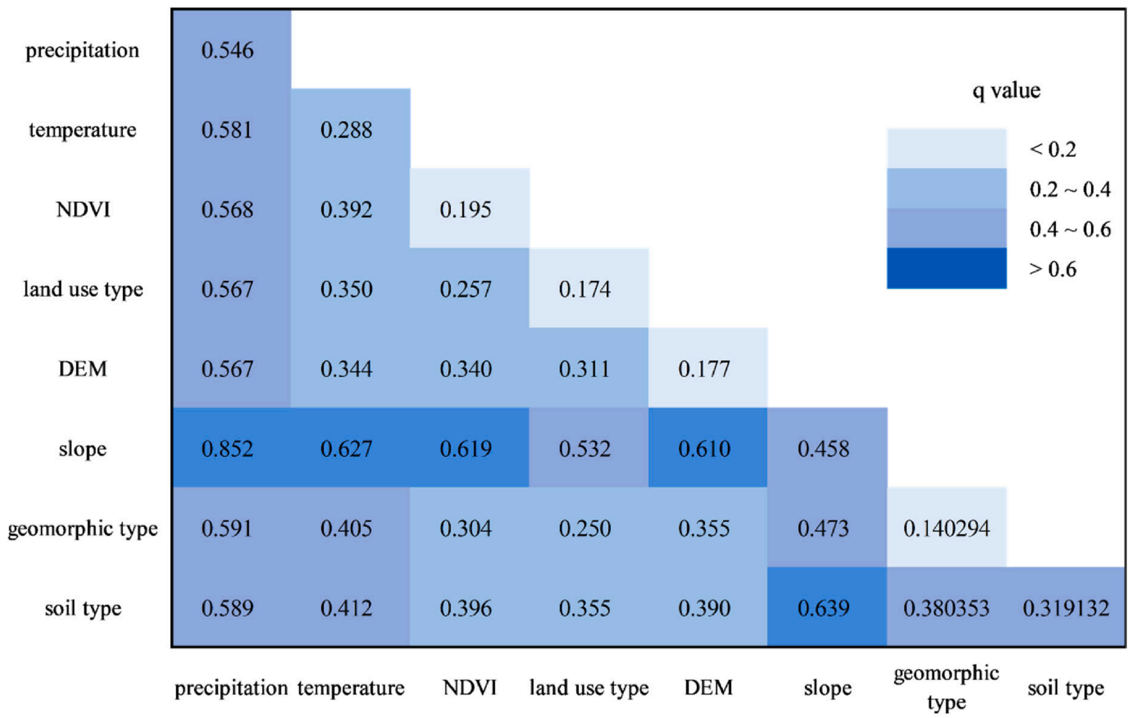

Fig. 5. The interactive influencing factor explanatory power and ecological detection of soil conservation services in the QTP.

Table 2
Suitable ranges or types of different influencing factors.

Influencing factor	Suitable range/type	Mean value of soil conservation (t/ha)
Mean annual precipitation (mm)	1656.44–2794.65	2195.35
Mean annual temperature (°C)	10.41–22.32	611.05
NDVI	0.76–0.91	247.21
Land use type	Forestland	280.52
DEM (m)	397–2453	607.30
Slope (°)	35.00–65.79	1185.66
Geomorphic type	Greatly rolling mountain	220.26
Soil type	Ferralsol (laterite, latosolic red soil, red earth, yellow earth)	1015.67

were all higher than 62 %. The interaction between annual precipitation and other influencing factors also had a high explanatory power for the spatial variation in soil conservation services, and the explanatory power of all of them was greater than 55 %.

3.4.3. Suitability zone analysis

The risk detector was used to detect the suitable range or type of soil conservation promoted by each factor to determine the region with the highest soil conservation service in each factor partition, which passed the significance test at the 95 % confidence level. The risk detection results are shown in Table 2. The mean values of soil conservation differed significantly for different impact factors. With the increase in annual precipitation, annual mean temperature, NDVI, and slope, the mean value of soil conservation on the QTP gradually increased. The mean value of soil conservation services reached the maximum when the annual precipitation was 1656.44 ~ 2794.65 mm, the annual temperature was 10.41 ~ 22.32 °C, the NDVI was 0.76 ~ 0.91, and the slope was 35.00 ~ 65.79°. The maximum values were 2195.35 t/ha, 611.05 t/ha, 247.21 t/ha and 1185.66 t/ha, respectively. This result indicates that climatic factors, vegetation factors and slope factors contributed to the increase in soil conservation in the above areas.

The increase in annual precipitation on the mean value of soil conservation was significantly higher than the effect of other factors, indicating that the increase in annual precipitation had a greater impact on the improvement of the soil conservation service function. For elevation factors, the lower the elevation range was, the higher the mean value of soil conservation was. The mean value of soil conservation was 607.30 t/ha when the DEM was 397 ~ 2453 m, and the mean value of soil conservation decreased with increasing elevation. However, the difference in land use, geomorphology and soil type caused the mean value of soil conservation to fluctuate. Among land use types, forestland had the highest amount of soil conservation, which was consistent with the research results of Sun et al. (2019). Among the geomorphic types, the highest soil conservation amount was found in the extremely hilly mountains (including extremely hilly mountains, mountains and extreme mountains), with an average value of 220.26 t/ha. Regarding the soil type factors, the ability of different soil types to withstand soil erosion was quite different, and ferrite was more conducive to the utilization of the soil conservation service function on the QTP.

4. Discussion

This research used the soil conservation services of the QTP from 2000 to 2015 as the research object and revealed the spatial heterogeneity pattern of soil conservation and its evolution trend in the region. Soil conservation showed a decreasing trend from the southeast to the northwest of the QTP and was consistent with the spatial pattern of vegetation types (from southeast to northwest in the order of forest, meadow, grassland, and bare soil), vegetation cover, slope, temperature, precipitation, and other natural conditions (gradually decreasing from the southeast to northwest), which was consistent with the results of existing studies (Hou et al., 2021; Li et al., 2020). The area with an increasing trend of soil conservation services was much higher than the area with a decreasing trend on the QTP, indicating that the soil conservation function has improved overall.

Table 3
Comparison of the results of this study with those of previous studies.

Study area	Method	Time of study	Annual mean Soil conservation amount (t)	Annual mean soil conservation per unit area(t/hm^2)	This study	Reference
Qinghai-Tibet Plateau	In VEST model	2010	11.592 × 10^9	—	12.072 × 10^9 t	Fan et al. (2021)
Qinghai-Tibet Plateau	RUSLE model	2000–2015	—	38.15	39.08 t/hm^2	Wang et al. (2021a,b)
Tibet	RUSLE model	2000–2015	2000–2008: 4.164 × 10^9 2008–2015: 3.923 × 10^9	—	2000–2008: 4.205 × 10^9 t 2008–2015: 4.026 × 10^9 t	Huang et al. (2018)
Nagqu	In VEST model	2000–2018	—	39.62	38.94 t/hm^2	Jing et al. (2022)

4.1. Validation of model results

Some scholars have calculated soil conservation services in relevant areas of the QTP. In this study, previous research results on soil conservation service functions in the QTP study area were used for cross-validation (Table 3). Fan et al. (2021) estimated that the soil conservation of the QTP in 2010 was 11.592 × 10^{9}t by using In VEST model, and the value of this study was 12.072 × 10^{9}t, with a difference of less than 5 %. Wang et al. (2021b) quantified that the annual mean soil conservation per unit area of the QTP from 2000 to 2015 was 38.15 t/hm^2, which was similar to the results of this study. In addition, the results of this study were consistent with those of soil conservation services in Tibet and Nagqu (Huang et al., 2018; Jing et al., 2022). Through comparison, it could be seen that the evaluation results of this study are reasonable and relatively reliable.

4.2. Single factor influencing mechanism for soil conservation

Compared with the mean annual temperature and NDVI, the mean annual precipitation was the most important factor affecting soil conservation services, and with an increase in annual average precipitation, the soil conservation services became stronger. This pattern is because precipitation can promote the growth of vegetation on the QTP, especially in the alpine region, thus reducing soil loss and improving the soil conservation capacity of the region. The effect of temperature on soil conservation was much lower than that of precipitation. The increase in temperature is beneficial to plant development, but it also increases the evaporation of surface water and decreases soil water, thus limiting vegetation growth (Ma et al., 2021). Therefore, precipitation was a direct climate factor affecting soil conservation services, and temperature was an indirect climate factor. Slope also had a relatively high impact on the spatial differentiation of soil conservation services, and with an increase in slope, the soil conservation services become stronger. However, some studies have shown that soil erosion increases with increasing slope (Wang et al., 2013; Wang et al., 2019). The reason for this difference may be that areas with a high slope are susceptible to soil erosion by gravity and other external forces, which in turn affects the soil conservation function; most of the areas with the highest slope category (>35°) in this study area are located in the deep valleys of the high mountains of the southeastern QTP, and 55.73 % of the area is forestland with high precipitation and good vegetation growth. Under the combined influence of these factors, the areas with high slopes showed a strong soil conservation service status.

4.3. Multiple factors influencing the mechanism for soil conservation

The complexity of geographical processes often leads to the joint action of influencing factors rather than a single factor (Dai and Wang, 2020; Yang et al., 2018). Many studies have shown that the generation, state and evolution of ecosystem services are caused by a variety of factors (Matson et al., 2002; Su and Fu, 2013a), and similar conclusions were reached in this study. Based on the single factor detection of soil conservation, the interaction analysis of each factor was further carried out in this paper. The effect of factor interaction on soil conservation services was stronger than that of a single factor, indicating that the spatial differentiation of soil conservation services on the QTP was not controlled by a single factor or a single type of factor but was rather simultaneously affected by the climatic conditions, slope and soil types. This result reflects the complexity of the determinants and influencing mechanisms of soil conservation services. The results of the interaction showed that the interaction between precipitation and slope was significantly higher than that of other factors, which was the main mechanism affecting soil conservation function. The interaction between precipitation and slope is mainly reflected in the dual effects of precipitation and slope on soil conservation function. Runoff is formed on the ground under the influence of precipitation, and the greater the ground slope is, the faster the flow rate of runoff is, the more sediment is carried away by rainwater, and the greater the potential of surface cover for soil conservation. In addition, the superposition of slope and other factors, such as soil type, temperature and vegetation cover, can enhance the explanatory power of soil conservation. It is worth mentioning that the explanatory power of the interaction between DEM and geomorphic type was much higher than the sum of the explanatory power of the two single factors, and the influence of the two factors on soil conservation reached the effect of "1 + 1 > 2". Moreover, the risk detector indicated that lower elevations were more suitable for the soil conservation service function, indicating that the lower elevation in the highly undulating mountains of the QTP had a stronger soil conservation ability.

4.4. Spatial distribution of suitable areas for soil conservation

The suitable range or types of each factor of soil conservation were spatialized and overlapped, and the spatial distribution of the number of suitable areas is shown in Fig. 6. Overall, the suitable areas of different influencing factors were mainly located in the eastern, southeastern and northwestern regions of the QTP. The suitable areas of annual mean precipitation, annual mean temperature, DEM, slope and soil type were mainly distributed in a small part of the southeastern margin of the QTP, while the suitable areas of the NDVI and land use type were distributed in the eastern and southeastern parts of the QTP. The suitable area of geomorphic types was distributed in the great rolling mountains in the southeast and northwest of the QTP. The number of suitable areas showed an increasing spatial distribution trend from northwest to southeast. The proportion of suitable area was 10.87 % in category 1, 3.69 % in category 2, 0.65 % in category 3, 0.35 % in category 4, 0.12 % in category 5, 0.04 % in category 6, and 0.01 % in category 7. Most of the suitable regions that satisfied the requirements of multiple influencing factors to promote soil conservation were located in the Yarlung Zangbo River Valley and Hengduan Mountain region on the southeastern edge of the QTP, mainly because of the rich vegetation types and high rainfall in this region, which contributed to the suitable soil conservation function

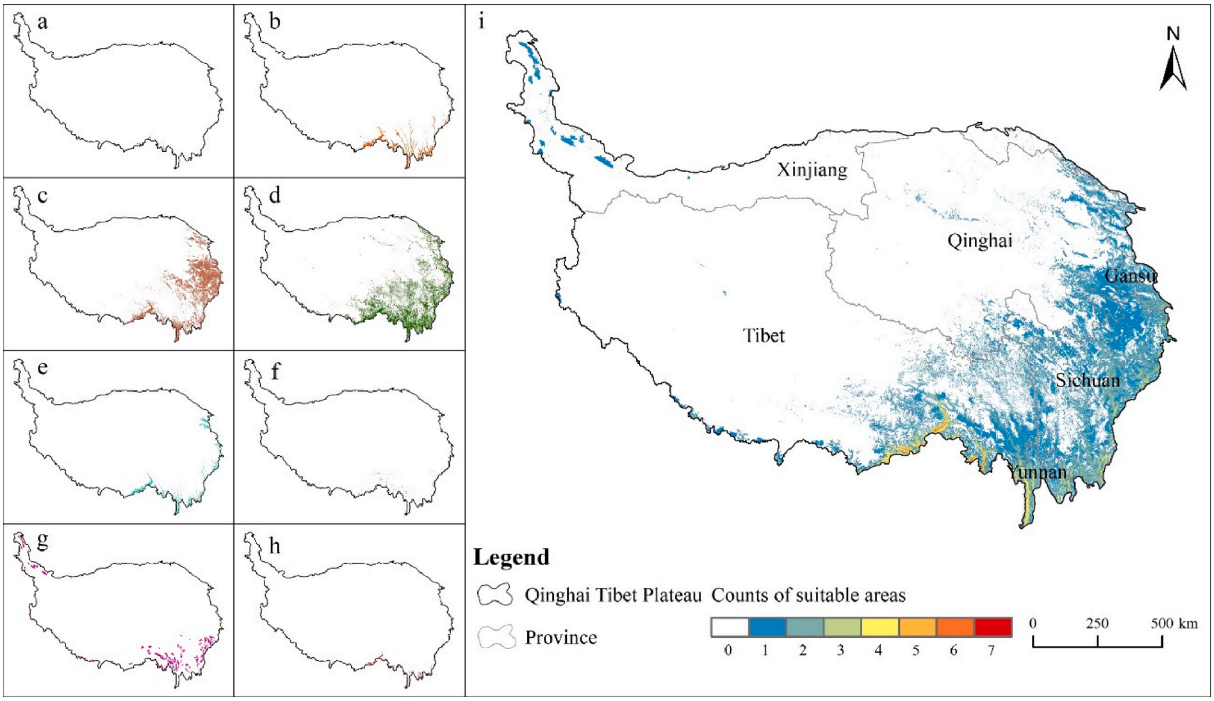

Fig. 6. The suitable regional spatial distribution of influencing factors of soil conservation on the QTP: a) mean annual precipitation; b) mean annual temperature; c) NDVI; d) land use type; e) DEM; f) slope; g) geomorphic type; h) soil type; i) numbers of suitable areas.

in this region. However, 84.27 % of the area was not suitable for soil conservation service influencing factors, and these areas were mainly distributed in the central and northwestern parts of the QTP. More attention should be given to these areas, and adequate soil and water conservation measures should be put into improving the soil conservation capacity to avoid more serious soil erosion in the future.

4.5. Limitations and caveats

The RUSLE model is a universally recognized empirical model used to assess regional large-scale soil conservation services. The limitation of the model is that it considers only slope erosion and does not consider gully erosion, gravity erosion or other erosion sources (Liu et al., 2019). The climate, soil, topography, vegetation and other data required by the model will affect the accuracy of the model results, as the data have different resolutions and accuracies. For example, precipitation data will vary with the distribution of meteorological stations and interpolation methods. The DEM, NDVI, land use and other data were all unified to a 1 km spatial resolution. With low resolution, it is difficult to distinguish local differences in soil conservation, which weakens the accuracy of the spatial differentiation results of soil conservation services. In addition, this paper studied only the spatial and temporal evolution characteristics and influencing factors of the entire QTP and did not consider the complex geographical characteristics of the QTP. In different geomorphic types and ecological geographical regions, the dominant factors affecting the spatial differentiation of soil conservation may be different, and the main measures used to improve soil conservation function may also be different. Most of the influencing factors detected in this paper were natural factors, while the only selected human factor was land use type and social factors such as regional economic development and population status were not considered. Although the evaluation results of this study are consistent with previous similar studies and have relative credibility, more measured data are still needed to verify. Therefore, it is important to improve the accuracy of the soil conservation service assessment model and carry out multiscale spatial differentiation and attribution difference analysis in the future.

5. Conclusion

This study evaluated the distribution characteristics of the soil conservation services on the QTP from 2000 to 2015. The spatial and temporal evolution trends of the soil conservation service were analyzed by using trend analysis, the influencing factors and interactions among factors were explored by using a geographic detector. The main conclusions are as follows:

(1) The soil conservation services on the QTP from 2000 to 2015 showed a decreasing trend followed by an increasing trend and had obvious spatial heterogeneity, with the spatial pattern showing the distribution characteristics of being high in the southeast and low in the northwest. The overall soil conservation service of the QTP was elevated, with 61.39 % and 38.59 % of the area showing an increasing and decreasing trend, respectively.
(2) Annual precipitation was the most important factor influencing the spatial variation in soil conservation services, followed by slope, and was the least influenced by geomorphic type. The explanatory power of the interaction between all factors was higher than that of a single factor, and the explanatory power of the interaction between the slope factor and other influencing factors was highest, among which the interaction between the slope and annual precipitation had the strongest influence on the spatial variation in soil conservation.
(3) The mean value of soil conservation services reached the maximum when the annual precipitation was 1656.44–2794.65 mm, the annual mean temperature was 10.41 ~ 22.32 °C, the NDVI was 0.76 ~ 0.91, the slope was 35.00 ~ 65.79°, the DEM was 397 ~ 2453 m, the land use type was forest, the geomorphic type was greatly rolling mountainous and the soil type was ferralsol. The higher the altitude was, the smaller the mean value of soil conservation was, which was less conducive to the soil conservation function. The higher the annual precipitation, mean annual temperature, NDVI and slope were, the greater the mean value of soil conservation was, which contributed to the soil conservation function in this region.

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.

Data availability

Data will be made available on request.

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Appendix A. Supplementary material

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