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Integrating multi-source data to improve water erosion mapping in Tibet, China

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ABSTRACT

Quantitative estimation for soil erosion is necessary for protection of the environment, and to improve agricultural productivity. However, due to the large area, sparse and limited data in Tibet, soil erosion there is still poorly quantified. Here, we improved the factors of the Revised Universal Soil Loss Equation (RUSLE) and calculated water erosion in Tibet. Rainfall erosivity (*R*) was calculated with the 0.25°CPC Morphing technique (CMORPH) data and subsequently downscaled to 1-km spatial resolution using artificial neural network (ANN) based on environmental covariates; slope length and steepness (*LS*) was estimated using the 3 arc sec Shuttle Rader Topography Mission (SRTM) digital elevation model (DEM); cover management (*C*) and control practice (*P*) were assigned based on land cover and protection measurements; and soil erodibility (*K*) was calculated using the Environmental Policy Integrated Climate model (EPIC) with inputs of the contents of sand, silt, clay and organic carbon in soil samples from Tibet. We used the data-mining algorithm to model the *K* factor and the spatially referenced variables to generate a *K* factor map. The obtained factors were then used to calculate soil loss in Tibet at1-km resolution. Our study estimated the annual water erosion at5.43 t ha^{-1} y^{-1}in Tibet, about5.44 × 10^8 t of soil lost yearly. The erosion rate increased from northwest to southeast, with most serious erosion occurring in the humid rain forest area in the southeast of Tibet. Our estimates of erosion area were generally consistent with previous national estimates. The largest differences were in the humid zone, Hengduan Mountain, and Yarlung Zangbo River basin, which are characterized by complex terrain and climate. Because of the applications of the best available data, we supply better, quantitative, finer spatial resolution estimates than previous studies. Our study is valuable for assessment of soil erosion in other data-scarce area suffering from soil loss by water erosion.

1. Introduction

Soil erosion seriously threatens our environment (Lal, 2001). It severely affects soil structure, soil productivity, hydrological systems, habitats and thereby the ecosystem services, particularly in the areas of the extremely fragile environment of Tibet. According to the second national soil erosion survey, Tibet suffers severe soil erosion. Further, soil erosion in Tibet seems to be significantly exacerbated due to the continuously rising temperature and increased precipitation induced by global warming. Although it is important, there are few studies on soil erosion in Tibet. Thus, accurate evaluation of soil loss is urgent to protect the environment and interpret climate change scenarios on this unique region.

Traditionally, soil erosion has been evaluated using process-based models, for example the Water Erosion Prediction Project (WEPP) (Coen et al., 2004), and the Revised Wind Erosion Equation (RWEQ) (Fryrear et al., 2000), combining various geomorphological methods including field experiments (Cerdan et al., 2010), fallout of the radionuclides of ^{137}Cs (Y. Wang et al., 2008), remote sensing surveys (Kinsey-Henderson and Wilkinson, 2013), and reservoir sedimentation studies (Sharda and Ojasvi, 2016). However, these approaches require a lot of input information, which is usually not available in large regions, especially in Tibet, which is limited by meteorological observation and field measurements due to its harsh climate, remoteness, and diverse topography. Recently, many researchers have modeled soil loss using remote sensing (RS) and geographic information systems (GIS) technologies (Benzer, 2010; Biswas, 2014; Dabral et al., 2008; Pandey et al., 2007; Teng et al., 2018). These studies have demonstrated that RS was

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able to acquire latest ground data and GIS could process large amounts of spatial data to rapidly assess the soil loss in an area. Earth observation data obtained from RS can get over the lack of exhaustive datasets of spatially referenced data necessary for modeling including rainfall, vegetation cover, topography, land use.

The Revised Universal Soil Loss Equation (RUSLE) is being used for the evaluation of water erosion globally (Mhangara et al., 2012; Wischmeier and Smith, 1978). It is most commonly applied in estimation of water erosion at large scale, especially at national scale, e.g. China (Wang et al., 2016), Australia (Teng et al., 2016), Europe (Panagos et al., 2014), Canada (Wall et al., 2002). RUSLE is an empirical model derived from original Universal Soil Loss Equation (USLE) to be used in estimating the annual soil loss through a linear equation with rainfall erosivity, soil erodibility, slope length and steepness, cover management and conservation practices as input factors (Kinnell, 2010; Park et al., 2011; Yang et al., 2003).

Among the RUSLE factors, rainfall erosivity (R) and soil erodibility (K) are particularly difficult to predict and control. Accurate mapping of the R factor and its variation spatially and temporally is essential for modeling soil erosion (Meusburger et al., 2012). At present, the R factor can be determined using data from rain gauge stations and satellites. However, there are limited rain gauges located in Tibet. The sparse rain gauge networks that exist do not have the capability to capture small-scale variability and just coarsely reflect the spatio-temporal variability in the R factor. Therefore, there is a need to analyse the R factor of fine spatio-temporal resolution precipitation data of individual rainfall events in Tibet. Satellite-derived products provide continuous rainfall at much finer spatio-temporal resolution than rain gauge measurements. However, their spatial resolutions (e.g. 0.25–0.5°) are still too coarse to capture the detailed variability of R at local scales. Thus, It is necessary to downscale the satellites' coarse resolution. The downscaled R factor can then characterise rainfall erosivity in a more detail manner and enhance the accuracy of RUSLE.

The K factor indicates the soil susceptibility to erosion, which was determined under the standard unit plot condition (Bryan, 2000). The K factor is usually derived using look-up tables that assign K-values to respective soil types (Le Bissonnais et al., 2002; Irvem et al., 2007). However, K is not constant within a soil type, it is affected by environmental variables such as climate, terrain, soil condition, vegetation. A K factor derived through establishing a relationship between K value and environmental variables may better represent its spatial heterogeneity and improve modeling of RUSLE.

The goal of our study is to improve estimates of the R and K factors and thereby the estimates of soil erosion in Tibet. We then compared our estimates of the whole of Tibet and part of region with that reported in the other related literatures.

2. Materials and methods

2.1. Study area

Tibet is located in west of China, from 78°25′ to 99°06′ E and from 26°50′ to 30°53′ N, covering about 1.2 million km^2 (Fig. 1). The elevation ranges from 84 to 8233 m. Mean annual temperature ranges from −3.0 °C to 11.8 °C, depending on location and terrain. Annual precipitation increases from the northwest to the southeast. The southeast part of Tibet has annual precipitation of 600–800 mm, while the western region is affected by drought with below 200 mm precipitation annually. Due to its complex terrain and climate, Tibet is vulnerable to soil erosion, and desertification.

2.2. Calculating soil loss potential using RUSLE

The RUSLE is applied to calculate water erosion on the hillslope landscape through a linear equs with six input environmental factors:

$$A = R \times K \times L \times S \times C \times P \tag{1}$$

where, A is the estimation of mean annual soil erosion by water (t ha^{-1} y^{-1}); R is rainfall-runoff erosivity factor (MJ mm ha^{-1} h^{-1} y^{-1}); K is soil erodibility factor (t ha h ha^{-1} MJ^{-1} mm^{-1}); L and S factors are slope length factor and slope steepness factor, respectively; C is the cover management factor; and P is the support practice factor.

2.2.1. Rainfall erosivity factor (R)

The R factor measures the water force of specific rainfall to detach and transport soil particles. Rainfall kinetic energy determines the erosivity and is in turn greatly was affected by the rainfall amount, intensity and duration. Here, the R factor was firstly estimated with the precipitation product acquired from the CPC Morphing technique (CMORPH). This technique uses precipitation products estimated from low orbiter satellite microwave observations exclusively, whose features are transported via spatial propagation information that is entirely derived from geostationary infrared satellite data (Joyce et al., 2004). This global precipitation product covers the belt between 50°S and 50°N, at a 0.25° × 0.25°spatial resolution and 3-h temporal resolution. Studies show that CMORPH provides a better approach for capturing the spatial distribution and temporal variations over most of the global regions (Sapiano and Arkin, 2009; Xie et al., 2007). The R factor was estimated as described in previous studies (Vrieling et al., 2010, 2014), following the standard equations to calculate the R factor (Renard and Freimund, 1994). First, we calculated the rainfall kinetic energy (e_K) based on rainfall intensity (I) as follows:

$$e_K = 0.283[1 - 0.52exp^{0.042I}] \tag{2}$$

where e_K expressed in MJ ha^{-1} mm^{-1} and I is in mm h^{-1}. The 3-h CMORPH data contain the value for I. The detailed coefficients description for e_K can be found in van Dijk et al. (2002). Then, we calculated the total kinetic energy per 3 h (E_{3h}) following the approach used by Vrieling et al. (2014):

$$E_{3h} = e_k * p_{3h} = e_k \times 3I \tag{3}$$

where E_{3h} is in MJ ha^{-1} and p_{3h} is the precipitation (mm) derived from CMORPH each 3 h. Due to lacking the accurate beginning and termination time of each storm case from 3-h resolution product, storm of > 3-h periods are not considered. The annual R factor was then calculated as follows:

$$R = \sum_{k=1}^{N} (E_{3\,h})_k {}^*(I_{30})_k \tag{4}$$

where, R is in MJ mm ha^{-1} h^{-1} y^{-1}; N is the counts of 3-h periods per year; I_{30} is the max 30-minute rainfall strength (mm h^{-1}).

2.2.1.1. Downscaling of the R factor using ANN model. The R factor calculated above, is too coarse at 0.25° × 0.25° spatial resolutions for the whole of Tibet (Ma et al., 2017). In a comparison of many linear and nonlinear statistical downscaling methods, Ramírez et al. (2005) and Abdellatif et al. (2013) found that artificial neural network (ANN) showed a better performance in most situations. Thus, we applied an ANN model to downscale the R factor to 1-km resolution based on the relationship between R factor and fine resolution environmental variables, shown as below (Table 1).

A complete description of the implementation of ANN to downscale factor can be found in Tolika et al. (2007). In this study, the coarse resolution data calculated above based on CMORPH which had 1827 grid nodes were split into a modeling dataset (1218) and a validation dataset (609) randomly. The latter subset was used to evaluate the downscaling model accuracy, based on the coefficient of determination (R^2) and the root mean squared error (RMSE). The ANN was programmed using the Matlab software (MathSoft Inc., Cambridge, MA, USA).

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