Geomorphology 226 (2014) 193–201

Contents lists available at ScienceDirect

Geomorphology

journal homepage: www.elsevier.com/locate/geomorph

Quantitative analysis of factors controlling sediment yield in mountainous watersheds

Z.H. Shi [a,b,*], X.D. Huang [b], L. Ai [a], N.F. Fang [a], G.L. Wu [a]

[a] State Key Laboratory of Soil Erosion and Dryland Farming on the Loess Plateau, Institute of Soil and Water Conservation, Chinese Academy of Sciences, Yangling, Shaanxi 712100, China
[b] College of Resources and Environment, Huazhong Agricultural University, Wuhan 430070, China

ARTICLE INFO

Article history:
Received 19 March 2014
Received in revised form 8 August 2014
Accepted 10 August 2014
Available online 15 August 2014

Keywords:
Sediment yield
Watershed characteristics
Codependence
Partial least-squares regression

ABSTRACT

Sediment and turbidity are primary causes of impaired river ecosystems; remedial action for these impairments requires the identification of their sources and controlling factors. This paper examines the combined effects of watershed complexity in terms of land use and physiography on the specific sediment yield of the upper Du River watershed (8973 km^2) in China. The land use composition, land use pattern, morphometric variables, and soil properties of the watershed were calculated at the subwatershed scale and considered to be potentially influential factors. Because these watershed characteristics are highly codependent, a partial least-squares regression (PLSR) was used to elucidate the linkages between the specific sediment yield and metrics composed of 19 selected watershed characteristics. The first-order factors were identified by calculating the variable importance for the projection (VIP). The results revealed that the land use composition and land use pattern exerted the largest effects on the specific sediment yield and explained 65.2% of the variation in the specific sediment yield. A set of physiographic indices was also found to have a large effect on the specific sediment yield and explained 17.7% of the observed variation in the specific sediment yield. The following are the dominant first-order factors of the specific sediment yield at the subwatershed scale: the areal percentages of agriculture and forest, patch density, value of the Shannon's diversity index, contagion, value of the hypsometric integral, and saturated soil hydraulic conductivity. The watershed size exerted a substantial effect on the sediment delivery ratio (SDR). The VIP values also suggested that the Shannon's diversity index, contagion, and hypsometric integral are important factors in the SDR. With a readily available digital spatial database and rapid developments in geographic information system (GIS) technology, this practical and simple PLSR approach could be applied to a variety of watersheds.

1. Introduction

Sediment is a natural constituent of rivers; however, excess sediment loading in rivers is a leading cause of degraded water quality and impaired aquatic ecosystems. Remedial actions require the identification of the sediment loading sources and the factors that control this loading (Belmont et al., 2011). Despite extraordinary efforts, sediment resulting from soil erosion remains one of the most difficult nonpoint source pollutants to quantify (Wu and Chen, 2012). Soil erosion is contingent on multiple factors, including climate, soil, topography, and land use (Wei et al., 2012); thus, soil erosion is typically episodic and highly localized (Trimble and Crosson, 2000). Moreover, eroded sediment may rapidly exit the watershed or be stored for long periods of time (Bracken et al., 2013). In recent decades, numerous process-based erosion models have been developed (de Vente et al., 2013). However, the application of these models suffers from a need for extensive parameterization and calibration, which is often problematic because of the low quality of available input data (Jetten et al., 2003). Not surprising, many studies on the estimation of sediment yield are based on empirical models of soil erosion and require a scalar reduction factor to estimate the sediment yield as a fraction of erosion, e.g., the sediment delivery ratio (SDR) (Lu et al., 2005). The concept of the sediment delivery problem was introduced by Walling (1983). According to this concept, only a fraction of the gross soil erosion within a catchment will reach the outlet and be represented as the sediment yield. However, few studies have provided information on how to quantify this reduction factor, and the available observations have indicated diverse and highly nonlinear scaling with respect to watershed characteristics (de Vente et al., 2007; Belmont et al., 2011; Baartman et al., 2013).

Our ability to manage landscape sediment routing and their response to anthropogenic influences depends on our ability to accurately estimate sediment yield and identify the controlling factors (Fu et al., 2009; Ali and De Boer, 2010). With readily available digital data sets, such as digital elevation models (DEMs), remote sensing images, and soil databases, investigators have relied on watershed characteristics

* Corresponding author at: College of Resources and Environment, Huazhong Agricultural University, Wuhan 430070, China. Tel.: +86 27 87288249; fax: +86 27 87671035.
E-mail address: shizhihua70@gmail.com (Z.H. Shi).

http://dx.doi.org/10.1016/j.geomorph.2014.08.012
0169-555X/

(e.g., topography, land uses, and soil types) as sediment yield predictors (Hassan et al., 2008; Ouyang et al., 2010; Tramblay et al., 2010; Xin et al., 2011; Kuhnert et al., 2012). The reliability of sediment source estimates can be improved using multiple overlapping measurement methods within geographic information systems (GIS). The relationships between watershed characteristics and the sediment yield dynamics have a large potential as an inexpensive complementation to ground-based monitoring. This approach is strengthened by a suite of new research tools that allow for the rapid and precise dating of land surfaces and high-resolution topography measurements.

Despite the substantial potential of analyzing watershed characteristics and indicator approaches, these techniques also present particular analytical challenges. Multivariate approaches commonly have been used to relate various watershed characteristics to the sediment yield at different scales, such as at the micro- and meso-watershed and river basin scales (Ouyang et al., 2010; Xin et al., 2011). However, watershed characteristics (including topography, land use, geology, and soil) are highly collinear or codependent and are not independent predictors. This lack of independence can confound correlative analyses and yield potentially misleading results. Moreover, land-use types within a watershed also tend to be patchy and spatially autocorrelated. Spatial autocorrelation may be particularly problematic in watershed studies because the locations of these land-use types often correspond to an underlying pattern in the landscape (King et al., 2005). Consequently, the apparent relationships between land use and sediment yields within watersheds could easily be explained by physiographic factors that necessarily co-vary with land-use patterns. Thus, many apparent relationships between land use and sediment yields in watersheds may be spatially confounded.

The inherent limitations of traditional multivariate approaches in handling multicollinear and noisy data can be overcome by applying multivariate statistical projection techniques. For example, principal component analysis is one of the most widely used techniques for reducing the redundancy and dimensionality of input data. Partial least-squares regression (PLSR) is a new technique that combines features of principal component analysis and multiple linear regression and generalizes these two analytical approaches (Wold et al., 2001; Abdi, 2010). The PLSR can handle highly correlated noise-corrupted data sets by explicitly assuming dependency among the variables and estimating the underlying structures, which are essentially linear combinations of the original variables (Carrascal et al., 2009). Another striking feature of PLSR is that it is particularly suitable for multivariate problems when the number of observations is less than the number of possible predictors (Onderka et al., 2012; Shi et al., 2013).

Previously, we developed quantitative relationships between sediment yield and land cover changes and land cover patterns within the upper Du River watershed in China (Shi et al., 2013; Yan et al., 2013). However, soil erosion and the resulting sediment export are caused by stochastic rainfall events and the combined effects of soil, topography, and land use (Wei et al., 2009). Quantifying the effects of watershed characteristics on sediment yield is essential for effective watershed management. Therefore, in this study the upper Du River watershed was chosen as the case study area. The PLSR was used to explore the relationships between watershed characteristics and both the specific sediment yield and SDR. The objectives of this study are the following: (i) to determine how the specific sediment yield is related to catchment size, topography, land-use composition, and land use patterns at the subwatershed scale; (ii) identify the characteristics that exert major and minor effects on the specific sediment export; and (iii) develop an empirical model for SDR as a function of the watershed characteristics.

2. Study area

The Danjiangkou Reservoir area (DRA), which is located in central China, is a useful and important setting for assessing the effects of watershed characteristics on sediment yield. The distribution of water resources is spatially uneven in China. The northern regions of China, which are similar in land area and population to the southern regions, contain only 18% of the total water supply despite comprising 65% of the total arable land. To mitigate the existing water crisis, China implemented the Middle Route Project under the South-to-North Water Transfer Project. The Danjiangkou Reservoir on the Han River, which is a tributary of the Yangtze River, is the water source for the Middle Route Project and supplies 13.8 billion m^3 of water annually to the northern regions of China (Fig. 1). Guaranteeing the quality of the transferred water has become an important concern for local and national policy makers.

The upper Du River watershed (31°30–32°27′ N., 109°11–110°25′ E.) is located in the DRA and covers 8973 km^2 (Fig. 1). This watershed is representative of the DRA in terms of its natural resources, land-use patterns, and population. Gauge records of the watershed's discharge and sediment yield have been collected since 1965. The topography of the watershed is characterized by mountain ranges, steep slopes, and deep valleys; and the elevation ranges from 220 to 2833 m. This area has a typical subtropical monsoon climate. The average yearly temperature is ~14.3 °C, and the average annual precipitation is approximately 973 mm, most of which falls during the monsoon season (June to October). According to the Chinese soil classification system, the major soil types include yellow-brown soil, brown soil, Chao soil, and purple soil (National Soil Survey Office, 1998), which correspond to Alfisols (yellow-brown and brown soils), Entisols (Chao soil), and Inceptisols (purple soil) according to the American soil taxonomy (Soil Survey Staff, 1999). The principal land cover type in this watershed is forest. The villages, small towns, and agricultural land in the watershed are concentrated along the river. Moreover, the major crops are corn (*Zea mays* L.) and wheat (*Triticum aestivum* L.).

3. Methods

3.1. Data collection

The data sources for this study included observational data from government agencies (e.g., the Soil Survey Office of Hubei Province and the Changjiang River Water Resources Commission) and data extracted from our previously published studies (Shi et al., 2013; Yan et al., 2013). Specifically, land cover data for the years 1978, 1987, 1999, and 2007 were obtained from the Changjiang River Water Resources Commission. The land cover maps were generated from Landsat images, which were obtained from the Landsat archive (http://glovis.usgs.gov/). The accuracy of the land-cover types in the area was assessed before the data were released. The topographical information was produced from a digital elevation model (DEM) with a resolution of 25 m by 25 m that was purchased from the National Geomatics Center of China. The soil data, including a soil type map (on a scale of 1:100,000) and information on the related soil properties, were obtained from the Soil Survey Office of Hubei Province. Climate data (which included daily data on precipitation, maximum and minimum temperature, solar radiation, humidity, wind speed and direction, and sunshine duration) were available from nine weather stations located within or close to the watershed (Fig. 1). Daily average discharge and sediment yield data from the Zhushan gauging station were available for the period 1965–2010.

3.2. Ungauged sub-watershed sediment yield

Only one gauge station (Zhushan) is located at the outlet of the upper Du River watershed (Fig. 1); thus, hydrologic modeling was required to estimate the discharge and sediment yield for the ungauged sub-watersheds. The Soil and Water Assessment Tool (SWAT) is one of the most suitable models for simulating runoff and sediment yield in large complex watersheds with varying soils and varying land-use and management conditions (Gassman et al., 2007). The SWAT is a

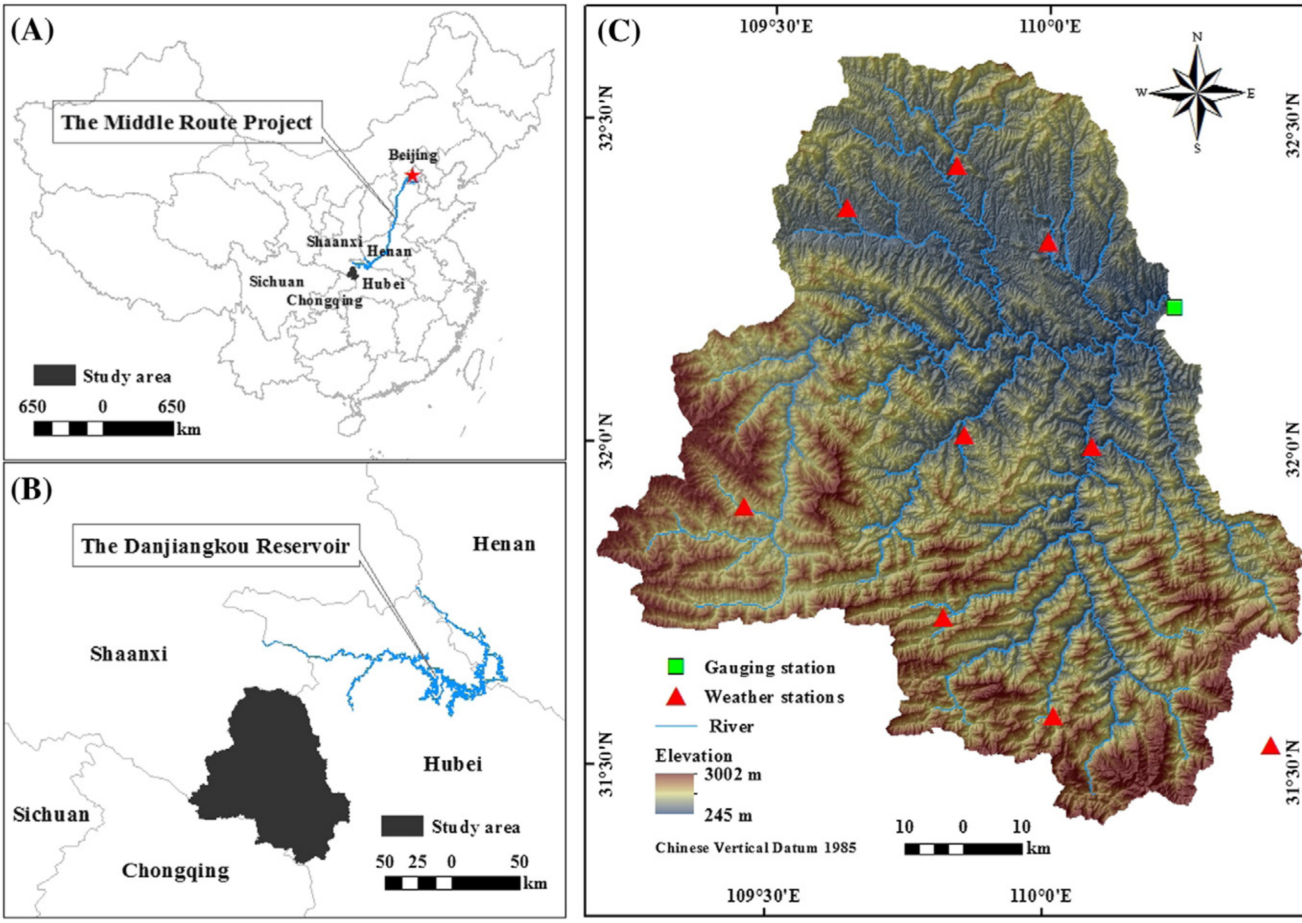

Fig. 1. Locations of the study watershed, digital elevation model (DEM), drainage system, gauge station, and weather stations.

physically based watershed-scale model that can be used to analyze small or large catchments by discretizing them into subbasins, which are then further subdivided into hydrological response units (HRU), each of which is homogeneous in terms of land use, soil type, and slope. Runoff is predicted separately for each hydrologic response unit and routed to obtain the total runoff for the whole watershed in the SWAT model. In each HRU, runoff is modeled with various aspects considered, e.g., canopy storage, infiltration, redistribution, evapotranspiration, interflow, ponds, tributary channels, and return flow. Using a variable storage coefficient method provided by Williams (1969), runoff is routed through the channel. Erosion and sediment yield are estimated for each HRU with the Modified Universal Soil Loss Equation (MUSLE) with rainfall energy in the Universal Soil Loss Equation (USLE) model replaced by a runoff factor (Williams, 1975). This increases the sediment yield prediction accuracy and eliminates the need for delivery ratios. Using a function of the peak channel velocity, sediment routing to a total sediment yield of the watershed is modeled with deposition and degradation considered. Numerous SWAT applications have been used to study hydrology and sediment yield in small and large catchments in various regions of the world (see the SWAT literature database: https://www.card.iastate.edu/swat_articles/index.aspx).

A SWAT project was built for the upper Du River watershed after preparing the necessary maps (land cover, soil, and DEM) and database files (e.g., climate and soil properties) using the collected data. The upper Du River watershed was divided into 107 sub-watersheds using the SWAT model. The daily discharge and sediment data measured at the Zhushan gauge station were used to calibrate and validate the model. The model was run to simulate daily results for a period of 20 years. The subperiod from 1971 to 1980 was used for the calibration; the subperiod from 1981 to 1990 was used for the validation. After a sensitivity analysis was performed, 10 principal factors that are associated with stream flow were determined. The five indices related to sediment yield were subsequently calibrated and validated. Three model evaluation parameters were used in accordance with the model evaluation guidelines proposed by Moriasi et al. (2007): (i) the Nash–Sutcliffe efficiency index (E_{NS}), (ii) the percent bias (*PBIAS*), and (iii) the coefficient of determination (R^2). According to Moriasi et al. (2007), a model simulation is judged to be satisfactory if $E_{NS} > 0.5$, $R^2 > 0.5$, and $PBIAS = \pm 25\%$ for flow and if $E_{NS} > 0.5$, $R^2 > 0.5$, and $PBIAS = \pm 55\%$ for sediment.

The calibrated model performed well, yielding E_{NS} and R^2 values of 0.88 and 0.94, respectively, for the discharge and E_{NS} and R^2 values of 0.67 and 0.84, respectively, for the sediment yield. The *PBIAS* values were 6.4% and 19.8% for the discharge and sediment yield, respectively. The statistical analysis of the data demonstrated a reasonable agreement between the observed and simulated values during the validation period. The observed R^2 and E_{NS} values were 0.92 and 0.87, respectively, for the discharge; and the observed R^2 and E_{NS} values were 0.81 and 0.64, respectively, for the sediment yield. The *PBIAS* values were 5.1% and 32.1% for the discharge and sediment yield, respectively. A detailed procedure for calibrating and validating the model has been previously published (Yan et al., 2013). The calibrated model was used to estimate the soil erosion and sediment yield for the 107 ungauged sub-watersheds (Fig. 2).

3.3. Potential factors that control the specific sediment yield

Data on the potential controlling factors considered in the statistical analysis were extracted for each sub-watershed to describe the sub-watershed characteristics. A total of 19 watershed descriptors were

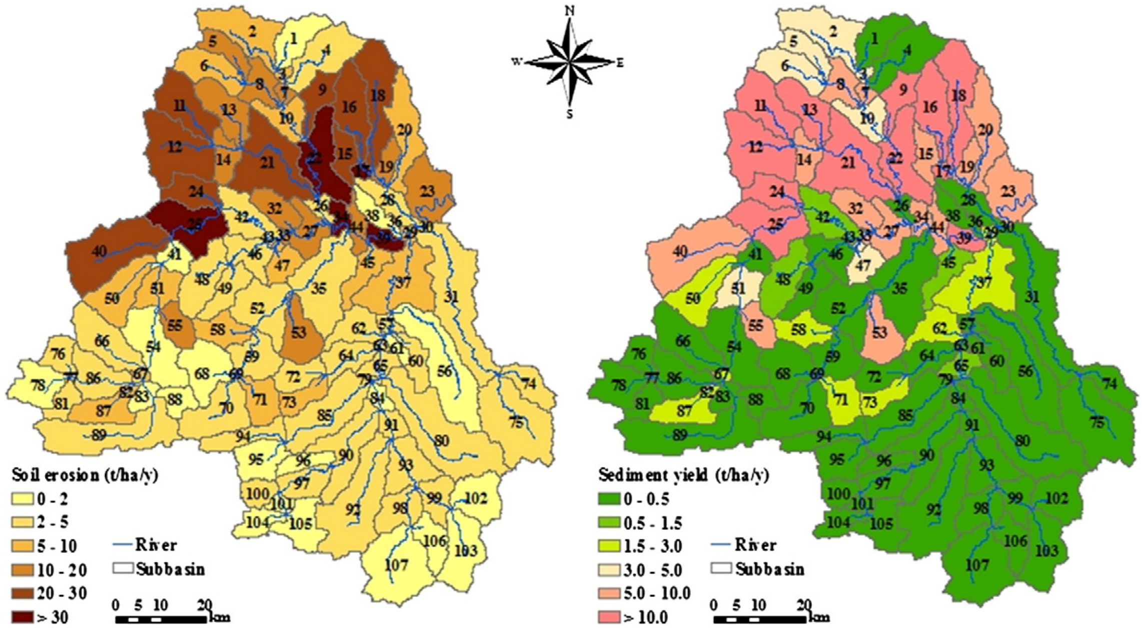

Fig. 2. Soil erosion and specific sediment yield distribution of each sub-watershed.

considered to be potential factors affecting the sediment yield. These selected descriptors have been commonly used in previous studies concerning the role of watershed characteristics in sediment yield (Verstraeten and Poesen, 2001; Restrepo et al., 2006; Tamene et al., 2006; Ali and de Boer, 2008; Haregeweyn et al., 2008; de Vente et al., 2011; Xin et al., 2011; Shi et al., 2013). These watershed characteristics were divided into four classes: morphometric, soil property, land-use composition, and land-use pattern. Within each class, several indices were calculated (Table 1). Land-use patterns were analyzed with the program FRAGSTATS 4.0 (McGarigal et al., 2012), which is a widely accepted tool for quantifying landscape metrics. A preliminary analysis demonstrated that many of the watershed characteristics were collinear (Table 2). The Agostino–Pearson K^2 test was used to determine if the sample came from a normally distributed population. The Agostino–Pearson K^2 test determines the skewness to quantify the asymmetry of a distribution and the kurtosis to quantify the shape of the distribution (D'Agostino et al., 1990). When necessary, the predictors were Napierian logarithm-transformed (ln) to achieve a normal distribution.

3.4. Partial least-squares regression

A partial least-squares regression (PLSR) revealed that the specific sediment yields of the 107 sub-watersheds within the upper Du River watershed were related to the watershed characteristics. We used SIMCA-P + 13.0 (Umetrics AB, Sweden) to perform the PLSR. The basic PLSR algorithm is not described in this paper; however, further information on PLSR can be obtained from Umetrics (Umetrics, 2012). A PLSR model was constructed to identify the primary watershed

Table 1
Abbreviations and descriptions of the selected variables for watershed characteristics.

Predictors	Abbr.	Description
Morphometric variables		
Watershed area	AREA	Area of the sub-watershed
Slope gradient	SLOPE	Average percent slope gradient of the sub-watershed
Basin relief	HD	Height difference between the outlet (H_{min}) and the highest point (H_{max}) in the sub-watershed
Basin length	HL	Horizontal length between the outlet and the most remote point in the sub-watershed
Relief ratio	RR	Ratio between the basin relief (HD) and the basin length (HL)
Hypsometric integral	HI	$HI = (H_{mean} - H_{min}) / (H_{max} - H_{min})$, where H_{mean} is the mean elevation of the watershed
Topographic wetness index	TWI	$TWI = \ln(\alpha/\tan(\beta))$, where α is the upslope area per unit contour length and $\tan(\beta)$ is the local slope
Soil variables		
Soil erodibility	RUSLE-K	K is calculated using the formula described by Renard et al. (1997)
Hydraulic conductivity	Ksat	Saturated soil hydraulic conductivity
Soil organic matter	SOM	Organic matter content of the soil
Land-use composition		
Agricultural land use	AGRI	Percentage of the watershed devoted to agricultural land use
Forest land use	FOREST	Percentage of the watershed with forest coverage
Grass land use	GRASS	Percentage of the watershed with grass coverage
Urban area	URBAN	Percentage of the watershed corresponding to urban areas
Land-use pattern		
Patch density	PD	Number of patches per unit area (number per 100 ha)
Edge density	ED	Total length of all edge segments per hectare for the considered landscape
Patch cohesion index	COHE	An index of the physical connectedness of the corresponding patch type
Contagion	CONTAG	Tendency of the patch types to be aggregated
Shannon's diversity index	SHDI	An index based on information theory that indicates the patch diversity in a landscape

Table 2
Correlation matrix of the selected watershed characteristics.

	AREA	SLOPE	HD	HL	RR	HI	TWI	RUSLE-K	Ksat	SOC	URBAN	FOREST	GRASS	AGRI	PD	ED	COHE	CONTAG	SHDI
AREA	1																		
SLOPE	0.14	1																	
HD	0.54**	0.51**	1																
HL	0.43**	−0.05	0.22*	1															
RR	−0.24*	0.36**	0.26**	−0.65**	1														
HI	0.05	0.31**	0.52**	0.07	0.21*	1													
TWI	0.06	−0.18	−0.03	0.02	0.04	−0.18	1												
RUSLE-K	−0.19*	−0.36**	−0.62**	−0.17	−0.12	−0.64**	0.08	1											
Ksat	0.16	0.27**	0.53**	0.22*	0.08	0.49**	−0.01	−0.78**	1										
SOC	0.15	0.24*	0.53**	0.15	0.14	0.50**	0	−0.75**	0.96**	1									
URBAN	−0.22*	−0.29**	−0.56**	−0.13	−0.23*	−0.51**	0.08	0.27**	−0.29**	−0.30**	1								
FOREST	0.24*	0.49**	0.82**	0.22*	0.28**	0.64**	−0.06	−0.58**	0.55**	0.53**	−0.72**	1							
GRASS	−0.19	−0.50**	−0.72**	−0.23*	−0.19	−0.59**	0.18	0.56**	−0.50**	−0.46**	0.56**	−0.89**	1						
AGRI	−0.18	−0.40**	−0.70**	−0.18	−0.26**	−0.53**	0.03	0.39**	−0.38**	−0.40**	0.74**	−0.87**	0.64**	1					
PD	−0.23*	−0.51**	−0.80**	−0.19	−0.32**	−0.64**	0.05	0.55**	−0.54**	−0.53**	0.74**	−0.96**	0.84**	0.85**	1				
ED	−0.20*	−0.52**	−0.81**	−0.21*	−0.31**	−0.64**	0.02	0.65**	−0.63**	−0.60**	0.59**	−0.95**	0.86**	0.75**	0.95**	1			
COHE	0.41**	0.37**	0.75**	0.20*	0.10	0.56**	−0.04	−0.50**	0.42**	0.38**	−0.64**	0.83**	−0.78**	−0.69**	−0.80**	−0.75**	1		
CONTAG	0.21*	0.53**	0.83**	0.21*	0.30**	0.69**	−0.07	−0.67**	0.63**	0.60**	−0.62**	0.96**	−0.87**	−0.76**	−0.93**	−0.98**	0.79**	1	
SHDI	−0.27*	−0.53**	−0.83**	−0.20*	−0.30**	−0.70**	0.07	0.67**	−0.63**	−0.59**	0.63**	−0.96**	0.87**	0.76**	0.94**	0.98**	−0.79**	−0.99**	1

* Correlation is significant at 5%.
** Correlation is significant at 1%.

characteristics that control the specific sediment yield. In this model, the independent variables were the selected watershed descriptors and the dependent variable was the specific sediment yield for the 107 subwatersheds. To avoid overfitting, the appropriate number of PLSR model components was determined using cross-validation to achieve an optimal balance between the explained variation in the response (R^2) and the predictive ability of the model (goodness of prediction, Q^2). In PLSR modeling, the importance of a predictor for the independent and dependent variables is indicated by the variable importance in the projection (VIP). The terms with high VIP values are the most relevant in explaining the dependent variable. The cross-validated goodness of prediction (Q^2), percentage of variation explained by the independent variables, and cross-validated root mean squared error (RMSECV) between the predicted and observed values of each individual pass were determined for each model. The regression coefficients of the PLSR model were used to show the direction of the relationship between each of the individual watershed characteristics and specific sediment yield.

Because the PLSR weights are linear combinations of the original variables that define the scores, they can be used to describe the quantitative relations between the predictors and the response. An empirical model for the SDR was developed using PLSR. All watershed characteristics do not have to be included in this model; redundant variables can lead to PLSR models with low statistical significance. Therefore, the following PLSR analysis process was followed to obtain an optimal model. First, a simulation was conducted using the PLSR model with all of the predictors. Next, a series of simulations using new PLSR models was performed in which each new PLSR analysis was conducted by eliminating a variable. The new PLSR model with the largest Q^2_{cum} was selected. This procedure was repeated until two predictor variables remained. Finally, the model with the largest Q^2_{cum} was selected as the optimal SDR model.

4. Results

4.1. Descriptive statistics of measures

Table 3 shows that the specific sediment yield of the 107 sub-watersheds varied substantially, i.e., from 0.48 to 21.43 t ha^{-1} y^{-1}, and the SDR also varied substantially, i.e., from 0.12 to 0.69. The SDR was less variable than the specific sediment yield according to the coefficient of variation (49.3% vs. 136.6%, respectively). The characteristics of the 107 sub-watersheds used in the analysis exhibited a broad variation. The sub-watersheds ranged in size from 376 to 29,029 ha. The mean forest use was 71.7%, and the mean agricultural and urban land usages were only 7.2% and 1.9%, respectively. The forest area varied from 9.6% to 98.8%. Moreover, the percentage of agricultural land usage varied from 0% to 48.2%. The patch density (PD), which is a measure of land-use patterns, varied from 0.61 to 24.59 per 100 ha, and the edge density (ED) varied from 12.0 to 145.0 m ha^{-1}. Interestingly, the coefficients of variation (CV) for urban land use, agricultural land use, sediment yield, patch density (PD), edge density (ED), basin length (HL), watershed size (AREA), and Shannon's diversity index (SHDI) were >70%, which demonstrates that these variables exhibited a larger variation than the other factors. The CVs of the topographic wetness index (TWI), hypsometric integral (HI), and patch cohesion index (COHE) were relatively small, i.e., <10%.

4.2. Relating watershed characteristics to specific sediment yield

A summary of the PLSR model that was constructed for determining the specific sediment yield is presented in Table 4. The prediction error decreased as the number of components increased; the minimum RMSECV occurred when three components were used. A further increase in the number of components resulted in higher prediction errors, suggesting that the subsequent components were not strongly

Table 3
Summary statistics for the sediment yield and selected watershed characteristics in this study.[a]

Category	Variables	Units	Minimum	Maximum	Mean	Standard deviation
Sediment	Sediment yield	t ha^{-1} y^{-1}	0.48	21.43	3.79	5.18
	SDR	None	0.12	0.69	0.36	0.17
Morphometric variables	AREA	ha	376	29,029	8476	6341
	SLOPE	degree (°)	4.8	36.4	26.9	5.7
	HD	m	466	2332	1325	479
	HL	m	12,698	105,967	24,314	19,488
	RR	m m^{-1}	0.014	0.286	0.081	0.05
	HI	none	0.20	0.61	0.38	0.08
	TWI	none	3.94	7.24	6.1	0.46
Soil variables	RUSLE-K	t ha h ha^{-1} MJ^{-1} mm^{-1}	0.028	0.043	0.032	0.003
	Ksat	mm h^{-1}	5.35	14.38	7.48	2.20
	SOM	%	1.017	2.354	1.403	0.265
Land-use composition	URBAN	%	0	20.3	1.9	3.6
	FOREST	%	9.6	98.8	71.1	28.9
	GRASS	%	1.3	37.4	7.4	8.5
	AGRI	%	0	48.2	7.2	10.4
Land-use pattern	PD	Number per 100 ha	0.61	24.59	5.67	4.25
	ED	m/ha	12.0	145.0	66.3	30.8
	COHESION	None	90.8	99.7	98.3	1.6
	CONTAG	%	27.0	92.7	61.6	15.8
	SHDI	None	0.08	1.57	0.87	0.41

[a] Abbreviations for the watershed characteristics are listed in Table 1.

correlated with the residuals of the predicted variable (Carrascal et al., 2009). The first component explained 65.2% of the sediment yield variation in the data set. The addition of the second component increased the model-explained variance to 82.9%. Adding more components to the PLS models did not substantially improve explained variance (Table 4). Fig. 3 (weight plot) shows that the first dimension consisted primarily of land use composition and pattern variables, such as the agricultural and forest land use (AGRI and FOREST); and the patch density (PD), Shannon's diversity index (SHDI), and contagion (CONTAG). AGRI, PD, and SHDI were positively correlated with the specific sediment yield, whereas FOREST and CONTAG were negatively correlated with the specific sediment yield (Fig. 3). The second component was dominated by soil erodibility (USLE-K) and basin relief (HD) on the positive side and the hypsometric integral (HI) and saturated hydraulic conductivity (Ksat) on the negative side.

Although the weight plot (Fig. 3) indicates the importance of the individual catchment characteristics to the specific sediment yield, a more convenient and comprehensive expression of the relative importance of the predictors can be obtained by examining their VIP values. Fig. 4 illustrates the VIP values for specific sediment yield; the regression coefficients are plotted against the watershed characteristics that were grouped into four main categories (morphometric variables, soil properties, land-use composition, and land-use pattern); the watershed characteristics are shown in descending order within each category. The highest VIP values were obtained for AGRI (VIP = 1.64; $b = 0.44$) and FOREST (VIP = 1.47; $b = -0.14$), followed by PD (VIP = 1.25; $b = 0.15$), SHDI (VIP = 1.19; $b = 0.11$), RUSLE-K (VIP = 1.19; $b = 0.05$), CONTAG (VIP = 1.17; $b = -0.08$), HI (VIP = 1.09; $b = -0.11$), Ksat (VIP = 1.09; $b = -0.07$), URBAN (VIP = 1.03; $b = 0.16$), and HD (VIP = 1.00; $b = 0.07$). The specific sediment yield appears to be lower for higher CONTAG, HI, and Ksat values (as indicated by the negative regression coefficients). As expected, a higher percentage of agricultural land use was correlated with a higher sediment yield (as indicated by the positive regression coefficient), whereas a higher percentage of forest cover was associated with a lower sediment yield (as indicated by the negative regression coefficient). We should note that all of the considered variables were to some extent related to the specific sediment yield; however, only certain variables had VIP values > 1. Predictors with VIP values < 1 were considered to be of minor importance for prediction purposes (Umetrics, 2012); therefore, the subsequent discussion is restricted to variables with VIP values > 1.

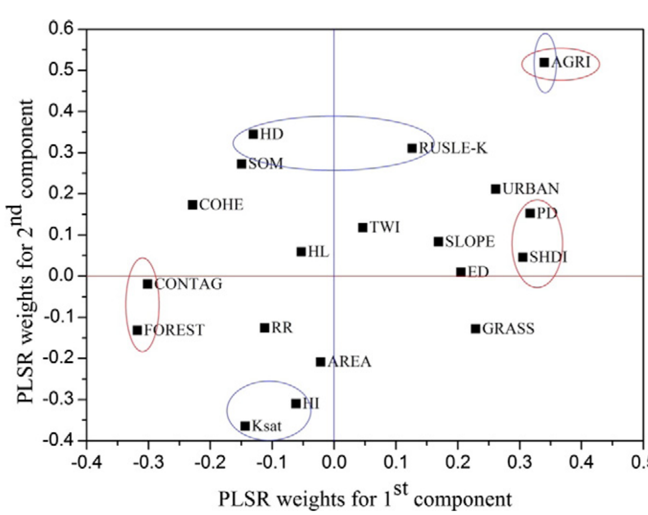

Fig. 3. Weight plot of the first and second PLSR components for the specific sediment yield. Predictors with the highest weights on the individual components are highlighted with circles. The abbreviations for the watershed variables are listed in Table 1.

Table 4
Summary of the PLSR model for specific sediment yield.

R^2	Q^2	Component	% of explained variability in Y	Cumulative explained variability in Y (%)	RMSECV (t/ha/y)	Q^2_{cum}
0.88	0.82	1	65.2	65.2	2.85	0.695
		2	17.7	82.9	2.29	0.803
		3	4.8	87.7	2.04	0.824
		4	1.7	89.4	2.18	0.815
		5	0.6	90.0	2.26	0.798

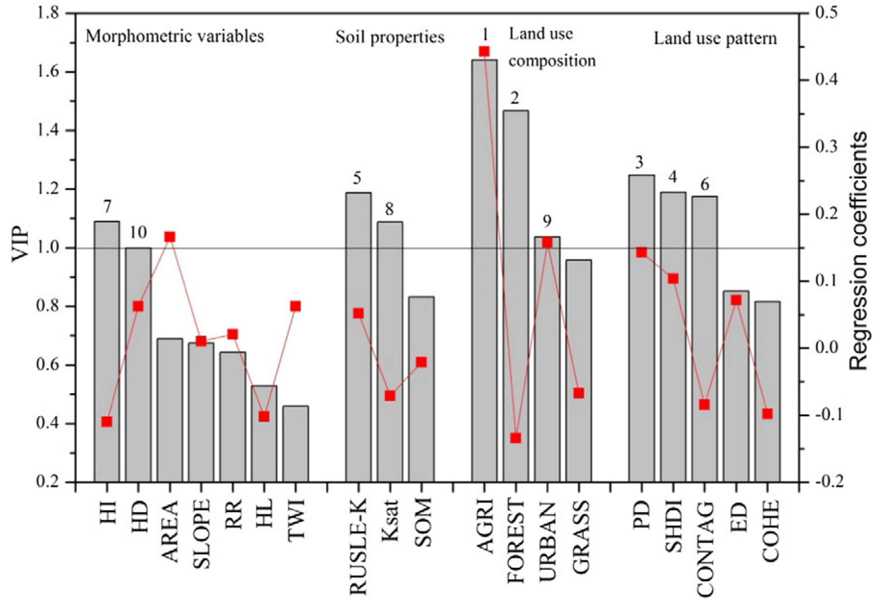

Fig. 4. Variable importance for the projection (bars) and regression coefficients (lines) of each predictor (watershed variable). The predictors were ranked within each group (morphometric variables, soil properties, land-use composition, and land-use pattern) in descending order based on their VIP values. The important predictors with VIP > 1 are consecutively numbered to show their relative importance. Regression coefficients show the direction in which the predicted response (sediment yield) depends on the predictors. The straight solid line indicates a threshold above which the predictors are considered to be important for predictive purposes. The abbreviations for the watershed variables are listed in Table 1.

4.3. Modeling the sediment delivery ratio (SDR)

The application of the PLSR regression process to the data for the 107 sub-watersheds resulted in the following optimal SDR model:

$$SDR = 0.46 + 4.74(\ln AREA)^{-1} - 0.49(HI) - 0.13\ln(CONTAG) + 0.12(SHDI)$$
$$\left(Q^2_{cum} = 0.66, R^2 = 0.76,\ RMSECV = 0.09\right). \quad (1)$$

The Q^2_{cum} value of the optimal SDR model was 0.66, which indicates the good predictive ability and robustness of the model. The validation of the best PLSR prediction model is illustrated using plots that compare the actual and predicted SDR values (Fig. 5). The predictive equation was found to be reasonable for SDR values in the range of 0.093 to 0.682. The optimal SDR model extracted two PLSR components that were relevant to four predictor variables (Table 5). The factors that governed SDR can be interpreted using the VIP and PLSR variable weights that were included in the optimal SDR model. The sub-watershed area dominated the first component of the PLSR model for SDR and had the highest VIP value (1.426). As expected, increases in HI and CONTAG were associated with lower SDRs (as indicated by the negative regression coefficients), whereas an increase in SHDI was associated with a higher SDR. To validate the SDR model, ~70% of the 107 sub-watersheds were randomly selected and used to develop a new PLSR model using the same descriptors. The new model was then used to predict the SDRs of the remaining 30% of the sub-watersheds. The procedure was repeated 10 times. The average Q^2_{cum} was 0.61, and the average coefficient of determination (R^2) for the SDRs excluded from the models was 0.69. These results indicate the good predictive ability and robustness of the optimal SDR model.

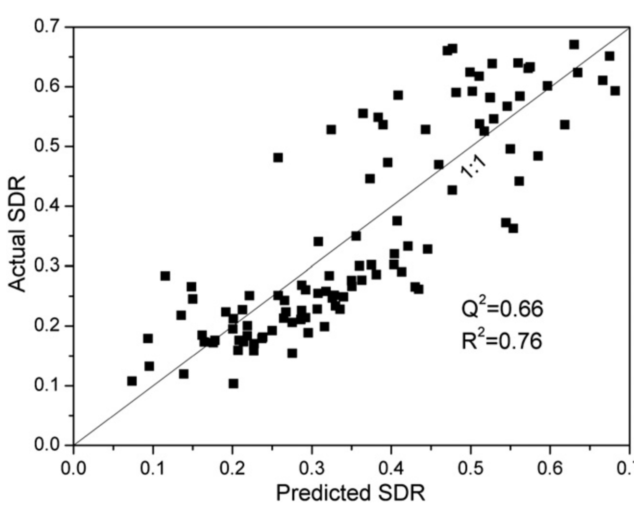

Fig. 5. Plots of the actual and predicted sediment delivery ratios (SDRs).

5. Discussion

We addressed the relative importance of watershed characteristics on the specific sediment yield in 107 sub-watersheds with diverse physiographic features and land uses. We extracted two PLSR components that are relevant to nine watershed characteristics (Fig. 3). The first and second components represent land use (including composition and pattern) and physiographic characteristics (including morphometric variables and soil properties), respectively. Therefore, the land-use composition and patterns exert the largest effect on sediment yield; the physiographic watershed characteristics are second-order effects. Focusing only on variables with VIP values > 1 (Fig. 4), the most important variable for the specific sediment yield was agricultural land use (AGRI), which exhibited a positive regression coefficient, indicating that agricultural land use is a primary sediment source. The second

Table 5
VIP values and PLSR weights for the sediment delivery ratio model.[a]

Predictor[b]	VIP	W*[1]	W*[2]
AREA	1.456	**−0.876**	−0.122
SHDI	1.209	0.083	**0.476**
CONTAG	1.155	−0.128	**−0.611**
HI	0.997	0.083	**−0.476**

[a] The bold-faced numerical values indicate that the PLSR components are primarily loaded on the corresponding variables.
[b] Abbreviations for the landscape variables are listed in Table 1.

most important variable was the areal percentage of forest (FOREST), followed by PD, SHDI, RUSLE-K, CONTAG, HI, Ksat, URBAN, and HD. Previous work has shown that the amount of eroded sediment is largely determined by the absence of protective land cover, whereas sediment delivery to rivers is determined by on-site eroded sediment and the relationships between sediment sources and rivers (Bakker et al., 2008). The latter factor is also a function of land use because runoff processes, which carry eroded sediments to rivers, vary for different land cover types (Van Oost et al., 2000; Bracken et al., 2013). Thus, land use patterns define the characteristics of the eroded sediment and its transport processes by accelerating or reducing the runoff rate (Shi et al., 2013).

The matrix, patches, and corridors are considered to be three landscape components (McGarigal et al., 2012). Within the study area's sub-watersheds, forest constituted an average of 71.1% of the total area (Table 3), which indicated that forest was the matrix for these sub-watersheds. High PD and SHDI values indicate the presence of many small patches of various land-use types in the watersheds and reflect the degree of forest fragmentation. Highly fragmented forests may not function effectively at decreasing surface runoff and eroded sediment from human-dominated land uses, e.g., agricultural and rural residential land. Thus, the specific sediment yield was positively associated with PD and SHDI (Fig. 3). This positive correlation indicates a higher sediment export when watersheds are characterized by many different land-use types that are small and interspersed (e.g., Ouyang et al., 2010; Memarian et al., 2012). Especially, Ziegler et al. (2007) quantified the effects of patchiness and the optimized patch arrangement of different land cover types to reduce runoff in two catchments in Vietnam. The CONTAG variable is associated with the dispersion and interspersion of land-use types; its value approaches 0 when land-use types are maximally disaggregated and interspersed and approaches 100 when all land-use types are maximally aggregated (McGarigal et al., 2012). In the present study, the CONTAG variable was consistently and negatively related to the specific sediment yield. The negative effects of the interspersion and diversity of land-use types within the watersheds are primarily associated with human-dominated land uses, e.g., urban and agricultural land. These results are consistent with previously reported negative relationships of CONTAG with nonpoint sources of pollution in watersheds (Xiao and Ji, 2007; Lee et al., 2009).

According to Milliman and Syvitski (1992), the topography and basin area are the major factors in the sediment yield of most rivers, with climate, geology, and land use exhibiting second-order effects. However, our results suggest that the physiographic features of watersheds are second-order effects; the negative relationship between the specific sediment yield and drainage area for the study area's sub-watersheds was weak (Fig. 3). We could conclude that although the specific sediment yield was a result of the normalization of sediment yield by watershed area, it was negatively influenced by basin area slightly, which indicated a tender scale effect on sediment yield. It might be because the sub-watershed area being small and spanning less than one order of magnitude (Table 3) that the scale effect was not significant. The inverse relationship between SDR and the watershed area in Eq. (1) is strong. The SDR is the ratio of the sediment yield at the watershed outlet to the gross soil erosion within the watershed. The sediment yield at the river outlet reflects the sum of all erosional and depositional processes that occur within the watershed (Restrepo et al., 2006). For larger watersheds, depositional processes are relatively more important (de Vente et al., 2007; Ayadi et al., 2010). Furthermore, HI and HD represent the elevation distribution and erosive power within a watershed (Tamene et al., 2006). Indeed, the VIP values (Fig. 4) demonstrate that HI and HD can be regarded as important factors in the specific sediment yield (VIP > 1). The negative regression coefficient of HI indicates that the specific sediment yield decreases with increasing HI, whereas the specific sediment yield increases with HD, as shown by the positive regression coefficient for HD. These results are consistent with the findings of Restrepo et al. (2006) and Tamene et al. (2006). The VIP values and regression coefficients of RUSLE-K and Ksat also suggest interesting patterns. These patterns are thought to be related to the inherent sensitivity of erosional processes and substantial effects of these factors on specific sediment yield. The results are consistent with our initial hypotheses that higher soil erodibility produces more eroded sediments and lower saturated hydraulic conductivity produces more surface runoff, which results in more sediment export.

This study reveals a strong influence of land use composition and patterns on the specific sediment yield of a watershed. Therefore, sediment export primarily results from multiple land use activities; however, separating the individual effects of sediment yield is difficult. Understanding the consequences of multiple land uses on sediment yield is best achieved on a watershed scale in which the watershed is divided into subwatersheds that are characterized by different human activities (Lu et al., 2005; Bakker et al., 2008; Baartman et al., 2013). Although our goal was to identify the primary factors that affect watershed-scale specific sediment yield, we also suggest that incorporating watershed characteristics, such as morphometric variables, soil properties, land-use composition, and land-use patterns, which can be easily computed from a digital land-use map, DEM, and a soil map, can substantially improve the assessment of sediment delivery and export in watersheds with no sufficient data monitored (Tramblay et al., 2010). To accommodate the highly correlated nature of the variables that are related to watershed characteristics, we used the PLSR approach in conjunction with the variable influence of the projection approach. The PLSR methodology is beneficial because it enables the elimination of confounding relationships among variables and encourages a more unbiased view of the contribution of watershed characteristics to sediment yield (Wang et al., 2014). Therefore, some credible conclusions in this study could be interpreted with multicollinear and noisy data eliminated in the PLSR approach. In the SDR model, four independent factors (AREA, HI, CONTAG, and SHDI) (Table 4) were picked out from these 19 variables in four categories (Table 3), with AREA and HI belonging to morphometric variables and CONTAG and SHDI belonging to land use pattern. To specific sediment yield, land use composition factors (AGRI and FOREST) and soil properties (RUSLE-K and Ksat) had vital impact with VIP > 1 (Fig. 4). This indicated that soil variables and land use composition had less effect on SDR than on specific sediment yield. In addition, HI was considered as an incredibly important factor to increase the accuracy and robustness of SDR predicting, for the values of R^2 (0.76) and Q^2_{cum} (0.66) in this SDR model with HI were higher than those ($R^2 = 0.58$, $Q^2_{cum} = 0.55$) in our former study (Shi et al., 2013).

6. Conclusions

In this study, we investigated the effect of watershed characteristics on the specific sediment yield at the sub-watershed scale using PLSR, which is a technique that is relatively insensitive to confounding relationships among predictor variables. The major factors that affect specific sediment yield were found to be the land-use composition (agricultural land use vs. forest) and land-use patterns (the diversity and dispersion of land-use types), which together explained 65.2% of the variation observed in the sediment yield. A set of physiographic indices (including the soil erodibility, hypsometric integral, saturated hydraulic conductivity, and basin relief) was also found to have substantial effects on the specific sediment yield. In addition, our study found that the dominant first-order factors in the specific sediment yield at the subwatershed scale were the areal percentages of agriculture and forest, which were followed by PD, SHDI, RUSLE-K, CONTAG, HI, Ksat, URBAN, and HD. The watershed size was found to have a substantial effect on the sediment delivery ratio (SDR). Our results also indicated that physiography determines the complexity and organization of the studied watersheds and has a substantial effect on sediment delivery and export.

Measurements of sediment yield are sparse in large-scale watersheds; the majority of subwatersheds in the case study watershed are not gauged. Thus, the modeling method used in this study appears to be a practical approach for providing sediment yield information. With the availability of digital spatial databases (such as DEM, remote sensing images, and soil data) decision makers are able to quantify watershed characteristics over wide areas using GIS. The PLSR approach provides a simple method for determining the relationship between predictors and the specific sediment yield in watersheds and provides quantitative information that enables decision makers to make more informed decisions regarding watershed management.

Acknowledgements

Financial support for this research was provided by the National Natural Science Foundation of China (41271296) and the National Science and Technology Supporting Program (2012BAC06B03). The authors also gratefully acknowledge Prof. Richard A. Marston and three anonymous reviewers for thoughtful and highly appreciated comments.

References

Abdi, H., 2010. Partial least squares regression and projection on latent structure regression (PLS regression). Wiley Interdiscip. Rev. Comput. Stat. 2 (1), 97–106.
Ali, K.F., de Boer, D.H., 2008. Factors controlling specific sediment yield in the upper Indus River basin, northern Pakistan. Hydrol. Process. 22 (16), 3102–3114.
Ali, K.F., de Boer, D.H., 2010. Spatially distributed erosion and sediment yield modeling in the upper Indus River basin. Water Resour. Res. 46, W08504. http://dx.doi.org/10.1029/2009WR008762.
Ayadi, I., Abida, H., Djebbar, Y., Mahjoub, M.R., 2010. Sediment yield variability in central Tunisia: a quantitative analysis of its controlling factors. Hydrol. Sci. J. 55 (3), 446–458.
Baartman, J.E., Masselink, R., Keesstra, S.D., Temme, A.J., 2013. Linking landscape morphological complexity and sediment connectivity. Earth Surf. Process. Landf. 38, 1457–1471.
Bakker, M.M., Govers, G., van Doom, A., Quetier, F., Chouvardas, D., Rounsevell, M., 2008. The response of soil erosion and sediment export to land-use change in four areas of Europe: the importance of landscape pattern. Geomorphology 98 (3–4), 213–226.
Belmont, P., Gran, K.B., Schottler, S.P., Wilcock, P.R., Day, S.S., Jennings, C., Lauer, J.W., Viparelli, E., Willenbring, J.K., Engstrom, D.R., Parker, G., 2011. Large shift in source of fine sediment in the upper Mississippi river. Environ. Sci. Technol. 45 (20), 8804–8810.
Bracken, L.J., Wainwright, J., Ali, G.A., Tetzlaff, D., Smith, M.W., Reaney, S.M., Roy, A.G., 2013. Concepts of hydrological connectivity: research approaches, pathways and future agendas. Earth-Sci. Rev. 119, 17–34.
Carrascal, L.M., Galvan, I., Gordo, O., 2009. Partial least squares regression as an alternative to current regression methods used in ecology. Oikos 118 (5), 681–690.
D'Agostino, R.B., Belanger, A., D'Agostino, J.R.B., 1990. A suggestion for using powerful and informative tests of normality. Am. Stat. 44 (4), 316–321.
de Vente, J., Poesen, J., Arabkhedri, M., Verstraeten, G., 2007. The sediment delivery problem revisited. Prog. Phys. Geogr. 31 (2), 155–178.
de Vente, J., Verduyn, R., Verstraeten, G., Vanmaercke, M., Poesen, J., 2011. Factors controlling sediment yield at the catchment scale in NW Mediterranean geoecosystems. J. Soil Sediments 11 (4), 690–707.
de Vente, J., Poesen, J., Verstraeten, G., Govers, G., Vanmaercke, M., Van Rompaey, A., Arabkhedri, M., Boix-Fayos, C., 2013. Predicting soil erosion and sediment yield at regional scales: where do we stand? Earth-Sci. Rev. 127, 16–29.
Fu, B.J., Wang, Y.F., Lu, Y.H., He, C.S., Chen, L.D., Song, C.J., 2009. The effects of land-use combinations on soil erosion: a case study in the Loess Plateau of China. Prog. Phys. Geogr. 33 (6), 793–804.
Gassman, P.W., Reyes, M.R., Green, C.H., Arnold, J.G., 2007. The soil and water assessment tool: historical development, applications, and future research directions. Trans. ASABE 50 (4), 1211–1250.
Haregeweyn, N., Poesen, J., Nyssen, J., Govers, G., Verstraeten, G., de Vente, J., Deckers, J., Moeyersons, J., Haile, M., 2008. Sediment yield variability in Northern Ethiopia: a quantitative analysis of its controlling factors. Catena 75 (1), 65–76.
Hassan, M.A., Church, M., Xu, J.X., Yan, Y.X., 2008. Spatial and temporal variation of sediment yield in the landscape: example of Huanghe (Yellow River). Geophys. Res. Lett. 35 L06401.
Jetten, V., Govers, G., Hessel, R., 2003. Erosion models: quality of spatial predictions. Hydrol. Process. 17 (5), 887–900.
King, R.S., Baker, M.E., Whigham, D.F., Weller, D.E., Jordan, T.E., Kazyak, P.F., Hurd, M.K., 2005. Spatial considerations for linking watershed land cover to ecological indicators in streams. Ecol. Appl. 15 (1), 137–153.
Kuhnert, P.M., Henderson, B.L., Lewis, S.E., Bainbridge, Z.T., Wilkinson, S.N., Brodie, J.E., 2012. Quantifying total suspended sediment export from the Burdekin River catchment using the loads regression estimator tool. Water Resour. Res. 48, W04533. http://dx.doi.org/10.1029/2011WR011080.
Lee, S.W., Hwang, S.J., Lee, S.B., Hwang, H.S., Sung, H.C., 2009. Landscape ecological pproach to the relationships of land use patterns in watersheds to water quality characteristics. Landsc. Urban Plan. 92, 80–89.
Lu, H., Moran, C.J., Sivapalan, M., 2005. A theoretical exploration of catchment-scale sediment delivery. Water Resour. Res. 41, W09415. http://dx.doi.org/10.1029/2005WR004018.
McGarigal, K., Cushman, S., Ene, E., 2012. FRAGSTATS: spatial pattern analysis program for categorical and continuous maps. University of Massachusetts, Amherst, MA. http://www.umass.edu/landeco/research/fragstats.html.
Memarian, H., Balasundram, S.K., Talib, J.B., Sood, A.M., Abbaspour, K.C., 2012. Trend analysis of water discharge and sediment load during the past three decades of development in the Langat basin, Malaysia. Hydrol. Sci. J. 57, 1207–1222.
Milliman, J.D., Syvitski, J.P., 1992. Geomorphic/tectonic control of sediment discharge to the ocean: the importance of small mountainous rivers. J. Geol. 100, 525–544.
Moriasi, D.N., Arnold, J.G., Van Liew, M.W., Bingner, R.L., Harmel, R.D., Veith, T.L., 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Trans. ASABE 50 (3), 885–900.
National Soil Survey Office, 1998. Chinese Soils. Agricultural Press, Beijing, (in chinese).
Onderka, M., Wrede, S., Rodny, M., Pfister, L., Hoffmann, L., Krein, A., 2012. Hydrogeologic and landscape controls of dissolved inorganic nitrogen (DIN) and dissolved silica (DSi) fluxes in heterogeneous catchments. J. Hydrol. 450, 36–47.
Ouyang, W., Hao, F.H., Skidmore, A.K., Toxopeus, A.G., 2010. Soil erosion and sediment yield and their relationships with vegetation cover in upper stream of the Yellow River. Sci. Total Environ. 409 (2), 396–403.
Renard, K.G., Foster, G.R, Weesies, G.A., McCool, D.K., Yoder, D.C., 1997. Predicting soil erosion by water: a guide to conservation planning with the Revised Universal Soil Loss Equation (RUSLE). Agric. Handb. No. 703. US Department of Agriculture, Washington, DC.
Restrepo, J.D., Kjerfve, B., Hermelin, M., Restrepo, J.C., 2006. Factors controlling sediment yield in a major South American drainage basin: the Magdalena River, Colombia. J. Hydrol. 316, 213–232.
Shi, Z.H., Ai, L., Li, X., Huang, X.D., Wu, G.L., Liao, W., 2013. Partial least-squares regression for linking land-cover patterns to soil erosion and sediment yield in watersheds. J. Hydrol. 498, 165–176.
Soil Survey Staff, 1999. Soil taxonomy. USDA-NRCS US Gov. Print. Office, Washington, DC.
Tamene, L., Park, S.J., Dikau, R., Vlek, P.L.G., 2006. Analysis of factors determining sediment yield variability in the highlands of northern Ethiopia. Geomorphology 76 (1–2), 76–91.
Tramblay, Y., Ouarda, T.B.M.J., St-Hilaire, A., Poulin, J., 2010. Regional estimation of extreme suspended sediment concentrations using watershed characteristics. J. Hydrol. 380 (3–4), 305–317.
Trimble, S.W., Crosson, P., 2000. US soil erosion rates—myth and reality. Science 289, 248–250.
Umetrics, A.B., 2012. User guide to SIMCA-P 13.0. Umetrics Inc., Kinnelon.
Van Oost, K., Govers, G., Desmet, P., 2000. Evaluating the effects of changes in landscape structure on soil erosion by water and tillage. Landscape Ecol. 15 (6), 577–589.
Verstraeten, G., Poesen, J., 2001. Factors controlling sediment yield from small intensively cultivated catchments in a temperate humid climate. Geomorphology 40 (1), 123–144.
Walling, D.E., 1983. The sediment delivery problem. J. Hydrol. 65 (1), 209–237.
Wang, G., Yang, H., Wang, L., Xu, Z., Xue, B., 2014. Using the SWAT model to assess impacts of land use changes on runoff generation in headwaters. Hydrol. Process. 28, 1032–1042.
Wei, W., Chen, L.D., Fu, B.J., Lu, Y.H., Gong, J., 2009. Responses of water erosion to rainfall extremes and vegetation types in a loess semiarid hilly area, NW China. Hydrol. Process. 23, 1780–1791.
Wei, W., Chen, L.D., Yang, L., Fu, B.J., Sun, R.H., 2012. Spatial scale effects of water erosion dynamics: complexities, variabilities, and uncertainties. Chin. Geogr. Sci. 22 (2), 127–143.
Williams, J.R., 1969. Flood routing with variable travel time or variable storage coefficients. Trans. ASAE 12 (1), 100–103.
Williams, J.R., 1975. Sediment Yield Prediction with Universal Equation using Runoff Energy Factor, ARS-S-40. Agricultrual Research Servive, USDA, Washington, DC.
Wold, S., Sjöström, M.L., Eriksson, L., 2001. PLS-regression: a basic tool of chemometrics. Chemometr. Intell. Lab. 58 (2), 109–130.
Wu, Y., Chen, J., 2012. Modeling of soil erosion and sediment transport in the East River Basin in southern China. Sci. Total Environ. 441, 159–168.
Xiao, H.G., Ji, W., 2007. Relating landscape characteristics to non-point source pollution in mine waste-located watersheds using geospatial techniques. J. Environ. Manag. 82 (1), 111–119.
Xin, Z.B., Yu, X.X., Lu, X.X., 2011. Factors controlling sediment yield in China's Loess Plateau. Earth Surf. Process. Landf. 36 (6), 816–826.
Yan, B., Fang, N.F., Zhang, P.C., Shi, Z.H., 2013. Impacts of land use change on watershed streamflow and sediment yield: an assessment using hydrologic modelling and partial least squares regression. J. Hydrol. 484, 26–37.
Ziegler, A.D., Giambelluca, T.W., Plondke, D., Leisz, S., Tran, L.T., Fox, J., Nullet, M.A., Vogler, J.B., Minh, T.D., Vien, T.D., 2007. Hydrological consequences of landscape fragmentation in mountainous northern Vietnam: buffering of Hortonian overland flow. J. Hydrol. 337, 52–67.