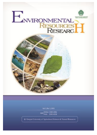

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Identification of critical sediment source areas across the Gharesou watershed, Northeastern Iran, using hydrological modeling

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Abstract

In this study, the process-based watershed model, Soil and Water Assessment Tool (SWAT), was used for simulating hydrology and sediment transport in the Gharesou watershed and for identifying critical areas of soil erosion and water pollution. After model calibration and uncertainty analysis using SUFI-2 (Sequential Uncertainty Fitting, ver. 2) method, the outputs of the calibrated model were used for assessing critical sediment source areas. Three pollution quantifying indices including a Load Impact Index (LII), a Concentration Impact Index (CII), and a load per nit area impact index (LUII), were computed based on the model outputs. The results indicated that despite lack and uncertainty of available data, SWAT model performance in simulating sediment transport in Gharesou watershed is quite acceptable. During calibration, the simulated monthly sediment loads matched the observed values with a Nash-Sutcliffe coefficient of 0.24 and PBIAS of -17%. The values for validation period were 0.2 and -12.1% respectively, indicating the model's weakness in simulating sediment dynamics and its capability in predicting average sediment load. Assessing spatial pattern of sediment indices showed that, in general, critical sub-watersheds based on LII are located in downstream areas of the watershed while sensitive sub-watersheds in terms of CII are situated in the middle part and critical areas with respect to LUII are in upstream. On the basis of LUAII, eight percent of the watershed area yields about 60% of sediment load. Implementation of appropriate conservation practices in the critical areas has the potential to significantly reduce erosion and sediment transport.

Keywords: Sediment transport; SWAT model; SUFI-2 method; Critical areas

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1. Introduction

Soil erosion is one of the most serious environmental degradation problem that adversely affects many natural and human-managed ecosystems. In agricultural watersheds, soil erosion not only removes nutrient-rich top soil on site, but also degrades water quality as a result of transported sediments off site (Lal, 1998; Zhu *et al.,* 2013). Therefore, it is a major cause of reduced agricultural productivity and water pollution.

Iran is among the most affected countries in the world in terms of the extent and intensity of soil erosion. Current estimates suggest that soil erosion in Iran is around 25 tons per hectare annually which is four times greater than that of the world average (Afshar *et al.,* 2010; Jalalian *et al.,* 1996; Moghadam *et al.,* 2015). Land use changes mostly from rangeland to dry farming, has led to an 800% increase in soil erosion between 1951 and 2002 (Ahmadi, 1999; Nosrati *et al.,* 2011). Gharesou watershed in the northeastern part of the country has long been subjected to land use changes from forest to agriculture and urban areas resulting in increased soil erosion. Gharesou River tributaries originate from high mountain streams on the northern slopes of the Elburz Mountain Range. When these streams reach the lowlands downstream, they pass through agricultural fields and urban areas. The main river collects tributary waters as it flows westward, and finally drains into the Gorgan Gulf in the southeastern part of the Caspian Sea. Gorgan Gulf is a semi-enclosed water body which is connected to the Caspian Sea through a narrow natural channel (Figure 1). It is an important natural ecosystem in the southern part of the Caspian Sea as it is the habitat for sturgeon and cartilaginous fish and many migratory birds in the region (Taheri *et al.,* 2012). However, because of its isolation and unique ecological conditions, this ecosystem is very fragile and prone to degradation. Runoff from agricultural fields adds nutrient-rich sediments to the Gharesou River water and contributes to water quality problems in the Gorgan Gulf. A high risk of eutrophication is expected in the Gulf because of increasing agricultural non-point sources (NPS) pollution, particularly as a result of phosphorus adsorbed into sediments. In recent years, algae blooms have been frequently reported in the region (Kideys *et al.,* 2008; Nasrollahzadeh *et al.,* 2008; Nasrollahzadeh *et al.,* 2011; Ramezanpour *et al.,* 2011; Soloviev, 2005).

Strategies and policies of watershed management and implementation of soil and water conservation practices could effectively control soil erosion which is the main cause of NPS pollution in the Gharesou watershed, and mitigate the negative impacts of NPS pollution in the Gorgan Gulf. However, prior to any planning, it is important to assess the extent and rate of soil erosion and identify erosion hot-spots within the watershed.

Since measured erosion and sediment data for the study area are scarce and the resources to conduct extensive field experiments are limited, hydrologic and water quality modeling provides the only feasible way for estimating runoff and soil erosion and also assessing their spatial variability in the watershed.

Process-based distributed watershed models that provide a realistic approximation of the watershed system are valuable tools for quantification and spatial distribution of runoff and soil loss processes across the watershed (Bieger *et al.,* 2014; Russell and William, 2001). During recent years, there has been an increase in the development and use of these models (Borah and Bera, 2004; Yang and Wang, 2010). One of the most widely applied watershed models is SWAT (Arnold *et al.,* 1998) which has been extensively used for simulating hydrologic and water quality processes in watersheds with a wide range of scales and environmental conditions (Arnold and Fohrer, 2005; Gassman *et al.,* 2007). Several past studies indicated that SWAT is capable of modeling data-scarce and ungauged watersheds with reasonable accuracy (Bieger *et al.,* 2014; Chaponniere *et al.,* 2008; Kumar *et al.,* 2015; Mekonnen *et al.,* 2009; Ndomba *et al.,* 2008; Nyeko, 2015; Panagopoulos *et al.,* 2011; Schmalz *et al.,* 2015; Stehr *et al.,* 2008).

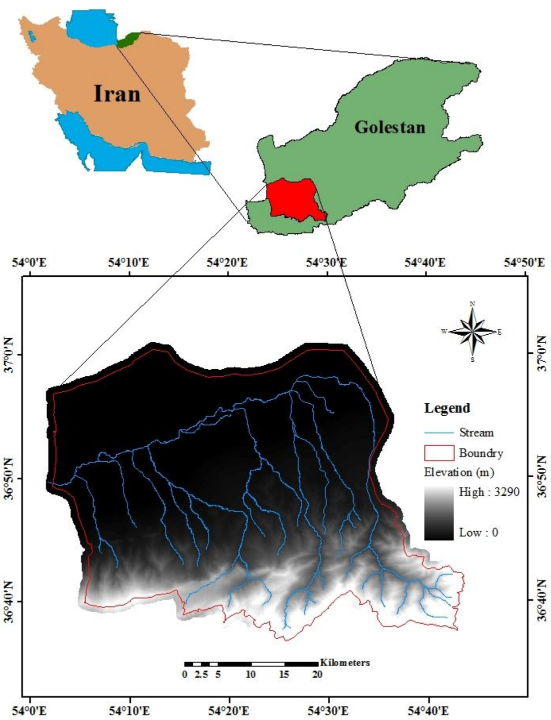
The goal of this study is to assess spatial distribution of soil erosion and sediment transport in the Gharesou watershed where there are limitations in terms of data availability. The specific study objectives are to (1) calibrate, validate, and perform uncertainty analysis of the SWAT model for the watershed, and (2) identify critical source areas of sediment in the watershed.

This is the first scientific study of its kind carried out in this watershed the results of which will provide useful information for soil and water management in the Gharesou watershed which will help improve ecological conditions within and downstream of the watershed.

2. Materials and methods

2.1. Study Area

The Gharesou River is located in the Golestan Province in the northeastern part of Iran. The river has a drainage area of about 161,473 hectares which lies between longitudes 54°00′ and 54°44′E and latitudes 36°36′ and 37°01′N (Figure 1). The watershed is characterized by highly variable topography composed of mountains, piedmont plains, and lowlands. Its elevation ranges from 3,359 meters above the mean of sea level (m.a.s.l) near the origin of the Gharesou River in the Elburz Mountains to 46 m.a.s.l. at the outlet of the river in the Gorgan Gulf. The Gorgan Gulf is a semi-enclosed water body in the southeastern part of the Caspian Sea with about 60 kilometers (km) length and 12-km width. This region is known for its high economic and ecological importance as a fishing and recreational area because of appropriate biological conditions for aquatic animals (Bagheri *et al.,* 2015). The underlying geology of the watershed is mainly limestone formations, alluvial deposits near streams, and quaternary sedimentary formations in the lowlands of the study area. The majority of the soils in the watershed are loess (windblown silts). In terms of their infiltration capacity or runoff potential, soils of the Gharesou watershed belong to hydrologic soil group B and C exhibiting moderate to low infiltration capacity. The main land use types in the watershed are agriculture (52%), forest (40%), rangelands (4.5%), and urban and rural residential (3%). Since the watershed is situated between the Caspian Sea and Elburz Mountains, the climate of this area is generally moderate; the average annual temperature is 17 degrees Celsius and the mean annual rainfall is about 650 mm. However, both temperature and precipitation exhibit a considerable temporal and spatial variability throughout the watershed. Annual rainfall totals, in general, decrease from south to north and precipitation mostly occurs in winter and spring. The sub-climatic classification of the region is as follows: moderate semi-dry in the north, moderate semi-dry to semi-wet in the central flat areas, and cold semi-wet to cold semi-dry in the southern mountainous areas. Discharge in the Gharesou River is relatively high during winter and spring, but low in summer and fall.



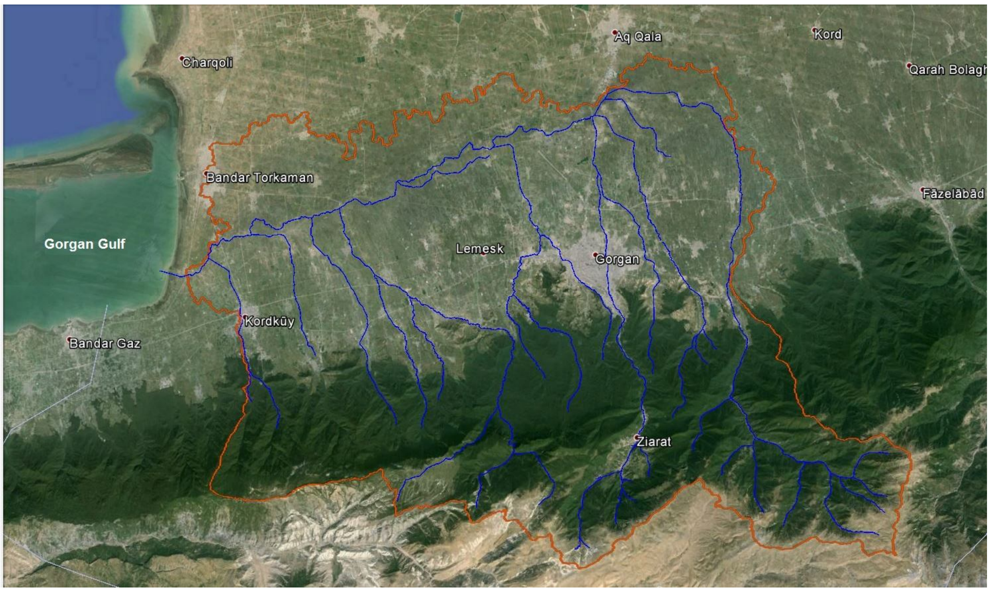


Figure 1. Location of the Gharesou watershed

2.2. Soil and Water Assessment Tool (SWAT)

SWAT is a process-based, semi-distributed, and continuous-time watershed-scale model that is designed to simulate hydrology as well as erosion and transport of sediment, nutrients, and agricultural chemicals in large ungauged watersheds (Neitsch *et al.,* 2011). The model is capable of simulating main eco-hydrological processes including water flow, erosion, sediment, nutrient and pesticide transport, and plant growth. The necessary input data for the model includes a digital elevation model (DEM), soil and land-use maps and their corresponding databases, land management information, and daily precipitation and temperature data. For simulating watershed processes, SWAT first divides the watershed into sub-basins which are then further subdivided into hydrologic response units (HRUs). HRUs represent lumped areas within a sub-basin with a unique combination of land use, soil type, and slope (Neitsch *et al.,* 2011). Simulation of the hydrologic cycle is separated into land and water phases. The simulation of the land phase is based on the water balance equation (Equation 1) which is calculated separately for each HRU. Some of the processes simulated in the land phase include evapotranspiration (ET), surface runoff, infiltration, soil storage, lateral flow, groundwater recharge, and groundwater flow.

$$SW_t = SW_0 + \sum_{i=1}^{t} (R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw})_i \tag{1}$$

here SW_t = final soil water content (millimeters); SW_0 = initial soil water content (millimeters); t = simulation period (days); R_{day} = amount of precipitation on the *i*th day (millimeters); Q_{surf} = amount of surface runoff on the *i*th day (millimeters); Ea = amount of evapotranspiration on the *i*th day (millimeters); W_{seep} = amount of water entering the vadose zone from the soil profile on the *i*th day (millimeters)' and Q_{gw} = amount of base flow on the *i*th day (millimeters). Runoff (as well as sediment and agricultural chemical yields) from all HRUs within a sub-basin are summed to calculate the amount of water reaching the main channel in each sub-basin. The water phase of the hydrologic cycle describes the routing of water in the river channel using the variable storage co-efficient method (Williams, 1969) or the Muskingum routing method (Linsley *et al.,* 1958). Sediment yield is estimated for each HRU using the empirical Modified Universal Soil Loss Equation (MUSLE; Williams, 1975).

$$Sed = 11.8 \times (Q_{surf} \times q_{peak} \times Area_{hru})^{0.56} \times K_{USLE} \times C_{USLE} \times P_{USLE} \times LS_{USLE} \times CFRG \quad (2)$$

where Sed = sediment yield on a given day (metric tons); Q_{surf} = surface runoff volume (millimeters per hectare); q_{peak} = peak runoff rate (cubic meters per second), $Area_{hru}$ = area of the HRU (hectare), K_{USLE} = universal soil loss equation (USLE) soil erodibility factor, C_{USLE} = USLE cover and management factor; P_{USLE} = USLE support practice factor, LS_{USLE} = USLE topographic factor, and C_{FRG} = coarse fragment factor. The modified rational method is used to estimate peak runoff rate. The transport of sediment in the channel is controlled by two simultaneous operations, degradation and deposition, which are estimated based on the stream power equation (Williams, 1975; Bagnold, 1977). The methods and equations of all model components are described in detail in Neitsch et al. (2011).

2.3. Data Availability and Preparation for SWAT Application

Lack of data availability and poor data quality were major issues hampering hydrologic modeling of the Gharesou watershed. In this research, we overcame data limitations by combining data from different sources together with inputs from stakeholders and experts.

As mentioned before, basic data required for the SWAT model include DEM, land-use, and soil and meteorological data. With regard to DEM, the Global Digital Elevation Model (GDEM) which is derived from Advanced Space borne Thermal Emission and Reflection Radiometer (ASTER) at 30 meter resolution was downloaded from the NASA reverb website (http://reverb.echo.nasa.gov). Land use and land cover data for the watershed were obtained from the Golestan Province Natural Resources Department. The data were interpreted from the LANDSAT imagery which was acquired in 2002. As we couldn't find any information about the detailed characteristics of the vegetation required by the SWAT model, the land cover map class descriptions were used to reclassify the map to match the SWAT land cover and crop growth database. In the Gharesou watershed, soil map and detailed information for soil properties were not available, thus we used a landform map provided by the Iranian Soil and Water Research Institute along with some soil profile data extracted from previous studies to represent soil information. Also, some soil parameters were extracted from the FAO global soil map of the Food and Agriculture Organization of the United Nations (FAO, 1995).

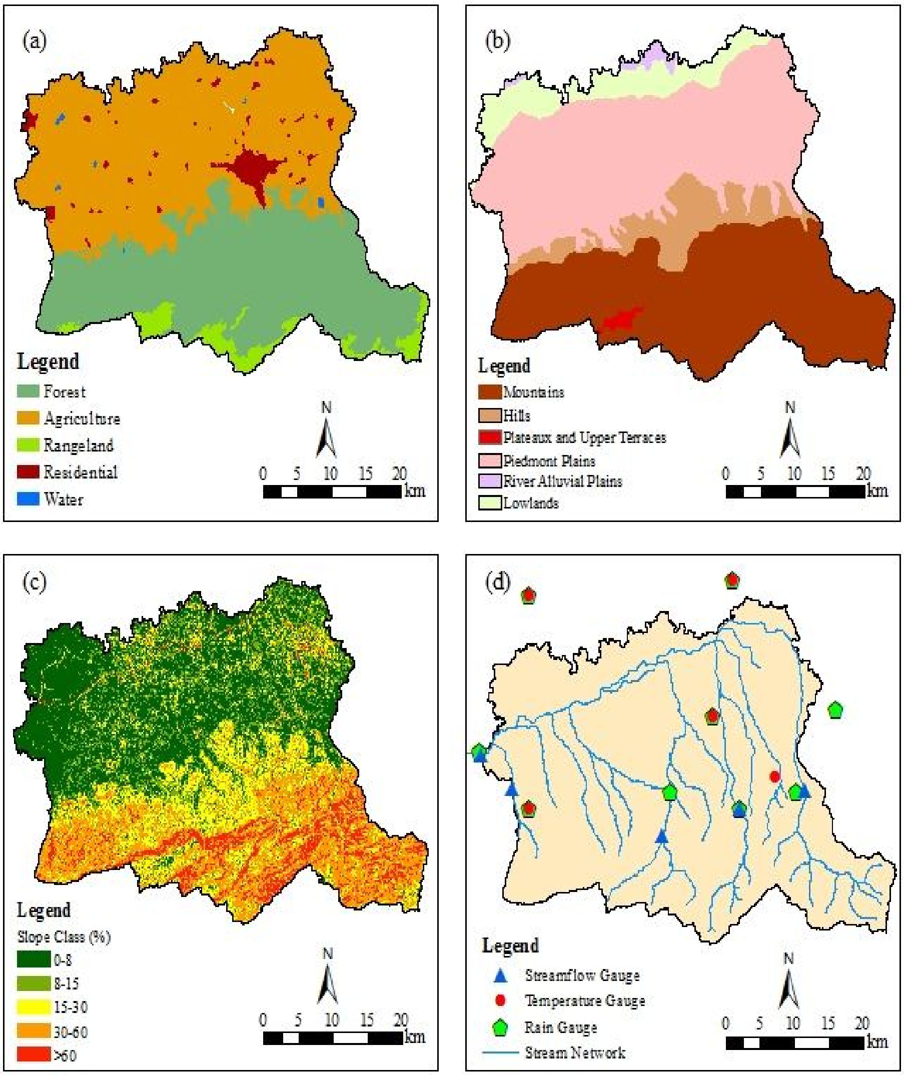


Figure 2. (a) Land use, (b) landforms, (c) slope classes, and (d) gauge location maps for the Gharesou watershed.

Regarding meteorological data, both daily precipitation and maximum and minimum of the temperatures were obtained from the Golestan Province Regional Water Authority. Also, daily relative humidity, wind speed, and solar radiation were estimated by the model's weather generator. The statistics used by the weather generator to simulate these variables were calculated using the time series of Gorgan synoptic station. Stream flow and sediment data for 5 gauges (4 within the watershed and 1 at the outlet) were available for model calibration and evaluation (Figure 2). Another data limitation was that the sediment measurements were normally conducted only once per month and in some cases a few times per year.

2.4. Model Setup and Parameterization

Using Arc SWAT 2012, the Gharesou watershed and its sub-basins were delineated based on the 30-m DEM. The minimum drainage area required to define the detail of watershed stream network was set to 1.5 % of the watershed area. When a river gauging station was available for calibration and validation of the model, an outlet was inserted. Automatic sub-basin delineation based on the given threshold areas and manual input of sub-basin outlets generated 71 sub-basins. Also, based on land use, soil, and slope classes, the watershed was subdivided into 388 HRUs (To define HRUs, 10% was selected as threshold for each land use, soil type, and slope class).

After making a SWAT project, the Arc SWAT interface writes default values to all the SWAT parameters, which are highly generic. So, we tried to estimate realistic values for as many parameters as possible (based on a calculation procedure, literature research, or expert knowledge) before calibrating the model. Some of the most important pre-calibration parameter changes that were carried out are as follows:

To account for the effect of elevation on temperature and rainfall (orographic effect) that is typically observed in mountainous regions, elevation bands were implemented in the SWAT model as proposed by Fontaine et al. (2002). We applied elevation bands to sub-basins that were located at higher elevations. The lapse rates of 6°C/km and 100 mm/km were applied to temperature and precipitation respectively based on the relationship between mean annual temperature (and precipitation) and elevation.

Since Gharesou watershed is an agricultural-dominated watershed, the processes affecting water balance and sediment yield are highly influenced by agricultural land management practices. Therefore, typical management parameters and data (such as crops grown, tillage, fertilizer application, irrigation, and harvest operations) for dominant crops in the watershed were collected from different sources and applied in the SWAT model (Information Center of Ministry of Jahade-Agriculture; Golestan Jihad-e-Agriculture Organization website; Torabi *et al.,* 2012; interview some local farmers).

Because our soil data lacked some important soil hydraulic properties necessary for SWAT (such as bulk density, available water capacity, and saturated hydraulic conductivity), we used the equations of Saxton et al. (1986) to calculate these parameters from soil texture. We also used Williams (1995) equation to calculate USLE soil erodibility factor (K).

The base flow filter program developed by Arnold et al. (1995) and modified by Arnold and Allen (1999) was used to separate surface runoff and base flow from daily stream flow data and give an estimate of the groundwater parameters alpha-bf (base flow alpha factor) and GW_DELAY (groundwater delay time).

After inputting all the data, the SWAT model was run for the Gharesou watershed. Based on the observed data available for model calibration and validation, an 18-year period (1990 to 2007) was selected for simulation. The first five years of the simulation (1990-1994) were used for model warm-up in order to minimize uncertainties due to initial conditions.

2.5. Model Calibration and Uncertainty Analysis

Calibration of process-based distributed watershed models like SWAT is a challenging task (especially in data-poor conditions) because there are a large number of parameters that can vary spatially. Ideally, calibration should be process-based (i.e., take into account different watershed processes, e.g. evapotranspiration, base-flow, sediment transport, crop growth etc.) and spatially-based to ensure thatvariability in the predominant processes for different landscapes or sub-watersheds is captured (instead of determining global watershed-wide processes) (Arnold *et al.,* 2012).

In this study, we tried to perform a careful calibration of the SWAT model for the Gharesou watershed and provide the best representation of hydrologic and sediment transport processes in the area. Calibration was performed at several steps. During the calibration, we checked different model components to make sure the predictions are reasonable for the study of the watershed and consistent with those of previous studies.

Following model simulation, the SWAT check program (White *et al.,* 2012) was used to examine the model outputs. This program reads outputs from a SWAT project, creates process-based figures for visualization, and performs many simple checks to identify potential model problems. At this step a rough manual calibration was done for average annual water balance as described by Arnold et al. (2011). Average annual values of major water balance components (including evapotranspiration, surface runoff, and base flow) for the Gharesou watershed were determined using data and information from the previous studies along with the Base flow filter program.

Next, the SUFI-2 method (Sequential Uncertainty Fitting version 2; Abbaspour, 2007) was used for auto-calibration; the SUFI-2 algorithm combines calibration with uncertainty analysis. In this method, initially, the user has to select a number of model parameters to be included in calibration and assign a set of meaningful parameter ranges to them. Then a set of Latin hypercube samples are drawn from the parameter ranges leading to *n* parameter combinations where *n* is the number of desired simulations. Next, SWAT is run *n* times and saves *n* time series of simulated output variables. The uncertainty which is referred to as the 95% prediction uncertainty (95PPU) is quantified at the 2.5% and 97.5% levels of the cumulative frequency distribution of all simulated output values. The goodness of model performance, in terms of calibration and uncertainty level, is evaluated using the P-factor and the R-factor indices. The P-factor is the percentage of the measured data bracketed by the 95PPU band. It ranges from 0 to 1 where 1 is ideal and means all of the measured data are within the uncertainty band (i.e., model prediction). The R-factor is the average width of the band divided by the standard deviation of the measured variable. It ranges from 0 to ∞ where 0 reflects a perfect match with the observation. Based on the experience, an R-factor of around 1 is usually desirable (Abbaspour *et al.,* 2007; Rouholahnejad *et al.,* 2012). SUFI-2 is a stochastic procedure and does not converge with any best simulation but it calculates standard goodness-of-fit measures such as R^2 and the Nash-Sutcliffe efficiency (NSE) for each of *n* model runs and indicates the best simulation among them.

Model calibration and validation was based on stream flow, sediment load, and wheat yield data. We adopted this multi-variable calibration approach because it was revealed that including more variables in calibration produces parameters reflecting more of the local processes, provides more realistic simulations (Gupta *et al.,* 1999; Beven, 2006; Abbaspour *et al.,* 2007; White and Chaubey., 2005; Cao *et al.,* 2006). Including crop yield data in calibration is believed to give greater confidence on the representation of the watershed hydrology (the partitioning of water between soil storage, actual evapotranspiration, and aquifer recharge) and water quality (Faramarzi *et al.,* 2009; Nair et al. 2011). The calibration process was started with yearly time-step focusing on those parameters that influence the amount of water, sediment load, and crop yield. After getting a relatively good match between predicted annual values and measured ones, we proceeded to monthly calibration and included some parameters that affected timing of the flow and sediment.

Daily stream flow and sediment data for calibration were obtained from the Golestan Province Regional Water Authority. Sediment data were based on collected grab samples which were used to measure suspended solids. These data were extrapolated into equivalent monthly loads using the Load Estimator (LOADEST) program (Runkel *et al.,* 2004). In this program, eleven regression models are available to estimate sediment load as a function of stream flow, sediment concentration, and other data inputs. The method is well- documented and accepted as a valid means of calculating pollutant loads from a limited number of water quality measurements (Gassman, 2008). Wheat yield data were obtained from Agricultural Statistics and Information Center of Ministry of Jihad-e-Agriculture of Iran. Data from 1995–2003 and 2004-2007 were used for calibration and validating the model respectively. The strength of calibration and uncertainty assessment was evaluated using P-factor and R-factor. In addition, three performance criteria including Nash-Sutcliffe efficiency (NSE), percent bias (PBIAS), and ratio of the root mean square error to the standard deviation of measured data (RSR) were calculated for simulations as a part of the model evaluation.

2.6. Identification and Prioritization of Critical Areas

The critical sub-watershed of the Gharesou watershed were identified based on average annual sediment outputs (loads and concentrations) by the calibrated SWAT model during the study (1995-2007). Three pollution quantifying indices were computed to facilitate the identification of critical areas: Load Impact Index (LII), Concentration Impact Index (CII), and Load per Unit Area Index (LUAII). The LII is based on sediment loads in the sub-watersheds' reaches and considers contributions of each sub-watershed as well as the entire upstream area. This index represents the cumulative effects of pollutant loading throughout the watershed (Tuppad and Srinivasan, 2008). The CII is based on sediment concentration level in the sub-watersheds' reaches and considers contributions from each sub-watershed as well as the entire upstream area. CII is useful in identifying localized pollution concerns in tributaries under high and low flow conditions especially concerning aquatic health (Tuppad and Srinivasan, 2008). The LUAII is based on the average sediment load per unit area from each sub-watershed. This index only accounts for contributions of individual sub-watersheds and is used to effectively assign a priority to each sub-watershed (Tuppad and Srinivasan, 2008).

Sub-watersheds were categorized into high, medium, and low priority areas using Natural Breaks method of classification (Jenks, 1967). Natural Breaks is a data clustering method designed to determine the best arrangement of values into different classes. The method seeks to minimize each class's average deviation from the class mean, while maximizing each class's deviation from the means of the other groups. In other words, the method seeks to reduce the variance within classes and maximize the variance between classes (McMaster, 1997).

To capture more detailed distribution of critical sediment source areas within the watershed, a similar analysis was performed at HRU-level.

3. Results and Discussion
3.1. Calibration/Validation of SWAT
3.1.1 Water Balance and Stream flow

The first model simulation predicted stream flow considerably higher than observed flows. Examining the model outputs using the SWAT check program revealed that the model was not able to correctly represent the hydrological balance of the Gharesou watershed. Surface runoff and lateral flow were overestimated while base flow was highly underestimated compared to those of the base flow filter program.

The most sensitive parameters affecting hydrological balance of the watershed were used in the calibration process with the SUFI-2 program; calibration was first performed for annual time step. Once the proportions of evapotranspiration, surface runoff, and subsurface flow were established, the model was further calibrated at monthly time step. Monthly calibration was started from the upstream gauges—namely, Pol Ordougah, Naharkhoran, Shastkola and Ghaz mahalleh—located in the outlet of the mountainous forest-dominated sub-basins (Figure 2) and showed poor results for these gauges. After a lot of iterations and parameter adjustments, there were still large discrepancies between simulated and observed hydrographs. Investigations suggested that the main cause of the poor results was attributed to inadequate representation of precipitation and temperature inputs for mountainous parts of the watershed. Because the precipitation and temperature gauges are located in the lower parts of the watershed (Figure 2), even after implementing elevation bands and precipitation and temperature laps rates, the model still could not capture the variability of temperature and precipitation caused by severe elevation variability. Another reason could be shortcomings of the SWAT model in simulating snow-dominated watersheds because snow parameters are not spatially defined (Fontaine *et al.,* 2002) and SCS method cannot accurately simulate runoff from melting snow and on frozen ground (Maidment, 1992).

Because the main sources of pollution in the Gharesou watershed are agricultural areas and the focus of this study was simulating runoff and erosion for the agricultural part of the watershed, in the end, it was decided to avoid modeling the upland forested sub-basins by including the four stream gauges as inlets in the SWAT project. After implementing the inlets, the simulation of lowland portion of the watershed resulted in a relatively good fit of the simulated and observed data. Calibration (validation) plots for monthly and annual flow at the Syahab gauge, at the watershed outlet, are shown in Figure 3. Model performance criteria for hydrologic calibration (validation) are given in Table 1.

Visual comparison of the hydrographs (Figure 3) and the model evaluation statistics (Table 1) indicate that the observed and simulated flow data match quite well during both calibration and validation periods. According to the general performance ratings proposed by Moriasi et al. (2007), the simulation of Gharesou

River flow at monthly time step can be evaluated as “satisfactory” with NSE > 0.50, RSR < 0.70, and PBIAS ± 25%. Specially, very low PBIAS values indicate that the average magnitude of simulated flows is very close to the observed ones. Uncertainty measures also indicate a good calibration result. The R-factor (thickness of uncertainty band) for calibration period is relatively small (around 1) and the P-factor shows that about 70 % of the observations are bracketed by the 95PPU. A careful examination of the hydrographs (Figure 3) indicates that magnitude and timing of high flows are simulated quite well, but the recession of flow peaks are not simulated accurately which could be due to the limitation of the model in rigorously simulating groundwater flow to streams. There are also significant uncertainties in the peak values on several occasions.

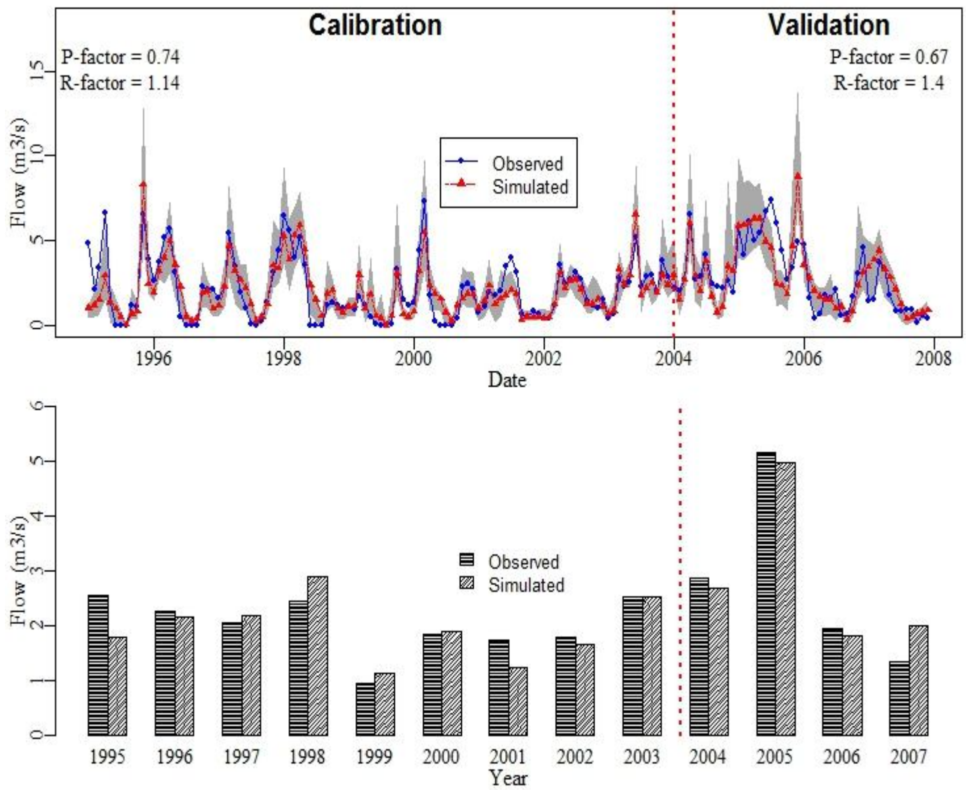


Figure 3. Plots of observed and simulated monthly stream flow (top) and annual stream flow (bottom) for Syahab gauging station; the shaded region on the monthly plot represents the uncertainty band corresponding to the final parameter ranges obtained in SUFI-2.

Table 1. Model performance statistics for monthly streamflow calibration (validation) results at Syahab gauging station

Statistic	Calibration Period		Validation Period	
	Observed	Simulated	Observed	Simulated
Mean (m^3/s)	2.02	1.94	2.83	2.86
Maximum peak (m3/s)	7.32	8.28	7.37	8.78
SD (m3/s)	1.77	1.5	1.91	1.93
R^2	0.7		0.58	
bR^2	0.59		0.54	
NSE	0.69		0.52	
PBIAS	-4.2		0.9	
RSR	0.55		0.69	
RMSE	0.98		1.32	
P-factor	0.74		0.67	
R-factor	1.14		1.4	

3.1.2. Sediment Loads

For calibrating the sediment yield component of the SWAT model, first we focused on the erosion process and sediment yield from the landscape. Calibration for average annual conditions was attempted first to ensure that annual sediment yields of different land uses were simulated reasonably. Sensitive parameters pertaining to sediment yield from the landscape (e.g., USLE_K, USLE_C, and HRU_SLP; definition of the parameters are given in Table 2) were adjusted until the specific sediment yield for forest and agricultural areas generally conformed to the reality. The channel parameters (e.g. CH_COV, CH_BNK_KD, CH_BNK_TC, etc.; Table 2) were then modified based on field observations and suggested the ranges defined in the literature, particularly SWAT model documentation. The calibration process was followed by a fine-tuning at the monthly time scale using sediment load data of the Syahab gauging station. Parameters used for the calibration of sediment load, their optimal ranges, and its final calibrated values are shown in Table 2.

Calibration (validation) plots for monthly and annual sediment load at the Syahab gauge are displayed in Figure 4. Model performance criteria are given in Table 3.

Simulation results for sediment load are not as good as those for stream flow. NSE for calibration and validation periods could not exceed the value of 0.5, indicating that, in terms of trends, the results are not satisfactory (Moriasi *et al.,* 2007; Panagopoulos *et al.,* 2011). However, PBIAS values are much less than ± 50% limit which provides evidence that the model successfully predicted sediment yields in the whole simulation period; RSR values for calibration and validation are relatively higher than the recommended 0.7 limit.

Table 2. Sensitive parameters for the calibration of sediment load and their optimal ranges and fitted values calculated using SUFI -2

Parameter Name[1]	Description	Min value	Max value	Fitted Value
r__USLE_K().sol______FRSD	USLE soil erodibility factor	-0.7	0	-0.116
r__USLE_C{7}.plant.dat	Min value of USLE C factor applicable to the land cover/plant	-0.3	0.1	-0.272
r__HRU_SLP.hru______FRSD	Average slope steepness (m/m)	-0.2	0	-0.023
r__SLSUBBSN.hru______FRSD	Average slope length (m)	-0.2	0	-0.113
r__USLE_P.mgt______FRSD	USLE support practice factor	-0.5	0	-0.371
r__USLE_K().sol______AGRL	USLE soil erodibility factor	-0.3	0	-0.169
r__USLE_C{28,56}.plant.dat	Min value of USLE C factor applicable to the land cover/plant	-0.25	0.1	0.091
r__USLE_P.mgt______AGRL	USLE support practice factor	-0.2	0.1	-0.137
v__CH_EQN.rte	Sediment routing methods (2 = Kodatie model)	2	2	2
v__CH_COV1.rte	Channel bank vegetation coefficient	1.5	2.5	1.933
v__CH_COV2.rte	Channel bed vegetation coefficient	1.5	2.5	2.077
v__CH_BNK_KD.rte	Erodibility of channel bank sediment	0.001	0.5	0.018
v__CH_BED_KD.rte	Erodibility of channel bed sediment	0.001	0.5	0.010
v__CH_BNK_TC.rte	Critical shear stress of channel bank (N/m^2)	100	400	200.6
v__CH_BED_TC.rte	Critical shear stress of channel bed (N/m2)	100	400	257.4

[1-] The qualifier (v__) refers to the substitution of a parameter by a value from the given range, while (r__) refers to a relative change in the parameter where the existing parameter value is multiplied by (1 + a given value); The extensions (e.g. .sol, .plant.dat, .hru, etc.) refer to the SWAT file type where the parameter occurs, AGRR = agricultural, FRST = forest, and additional information on formatting parameters for SUFI-2 calibration can be found in the SWAT-CUP user's manual (Abbaspour *et al.,* 2014).

Uncertainty analysis results indicate bracketing of around 70% of the observed data within the 95PPU band (Figure 4). The R-factors, however, are large (2.38 and 2.87 for calibration and validation periods respectively) which indicate substantial uncertainties. Visual inspection of the plots in Figure 4 especially shows very large uncertainties at extreme events during both calibration and validation periods. The inaccuracies and uncertainties could be due to the following reasons:

(1) Uncertainties in the input data especially poor representation of soil properties. As mentioned earlier, a soil map covering the entire watershed doesn't exist, so we had to use a landforms map to represent spatial distribution of soil types. Moreover, some important soil attributes (such as SOL_AWC and USLE_K) were estimated based on soil texture data sampled at a few points across the

watershed. These inaccuracies could have a significant impact on the model outputs.

(2) Uncertainties in the parameters. For some model parameters, particularly channel parameters (such as critical shear stress of channel bank and bed), direct measurement or exact estimation wasn't possible. We could only make rough estimates based on field visits and the literature. So, they were allowed to vary in a wider range during the calibration which led to high uncertainty in the outputs; this was also the case for some soil parameters.

(3) Dependence of sediment yield simulation on hydrologic simulation. The runoff and peak runoff rate are the main inputs of the MUSLE equation (Eq. 2) for erosion prediction. As a result, sediment simulation is directly linked to the runoff simulation. Consequently, the inaccuracies and uncertainties of runoff could propagate to sediment load prediction. Comparison of flow and sediment calibration (validation) plots (Figure 3 and Figure 4) clearly shows that large uncertainties in sediment load are often associated with high flow uncertainties.

(4) Uncertainties in the observed data. Considerable uncertainty in sediment simulation is likely to be introduced by the observed data used for model calibration and validation. As mentioned earlier, an observed data set of sediment loads was estimated on the basis of flow-concentration regression models. Although the regression models carefully calibrated and gave good results, they are not truly "observed" data. Ferguson (1986) indicated that most of the rating curve estimates of instantaneous load are biased and tend to underestimate the actual loads.

Table 3. Model performance statistics for monthly sediment load calibration (validation) results at Syahab gauging station

Statistic	Calibration Period		Validation Period	
	Observed	Simulated	Observed	Simulated
Mean (ton)	3244	2693	4574	4018
Maximum peak (ton)	21881	24430	22727	35510
SD (ton)	4530	4668	5353	6899
R^2	0.43		0.4	
bR^2	0.37		0.35	
NSE	0.24		0.2	
PBIAS	-17		-12.1	
RSR	0.76		0.85	
RMSE	3430		4721	
P-factor	0.76		0.65	
R-factor	2.38		2.87	

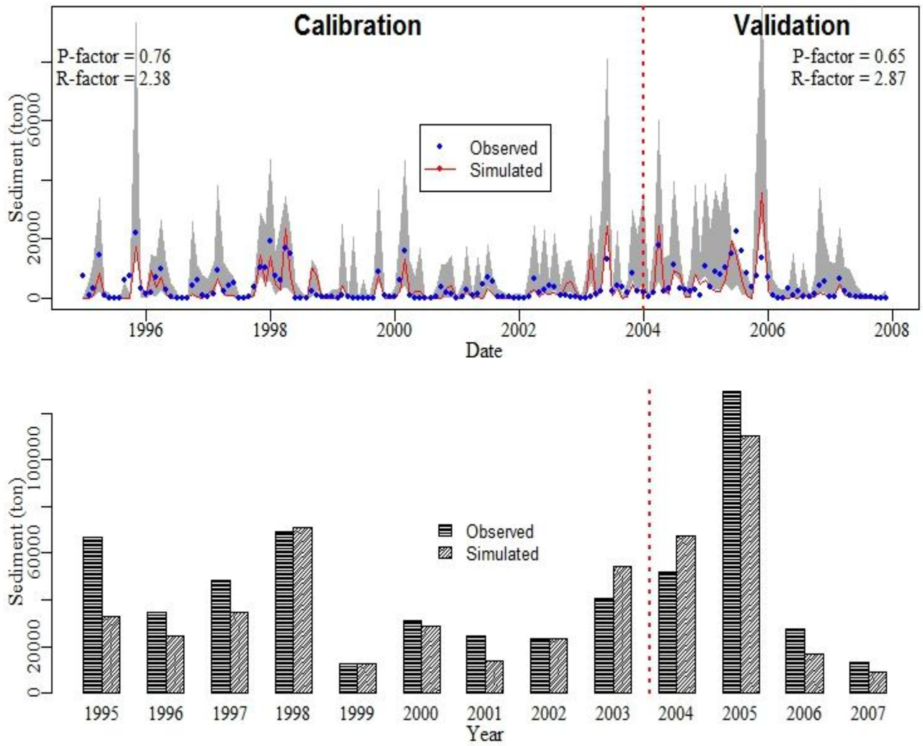


Figure 4. Plots of observed and simulated monthly sediment load (top) and annual sediment load (bottom) for Syahab gauging station; the shaded region on the monthly plot represents the uncertainty band corresponding to the final parameter ranges obtained in SUFI-2.

Overall, a relatively good temporal match between observed and simulated sediment loads (Figure 4) as well as low absolute values for PBIAS suggest that the calibrated SWAT model for the Gharesou watershed is fairly reliable especially for predicting the total volume of sediment yield on a long-term basis. It is noteworthy to mention that in this study our priority was to better represent the watershed processes during the model parameterization and calibration rather than performing a fully automatic calibration to produce better performance statistics.

Being a semi-distributed process-based model, SWAT considers the main factors and processes affecting hydrology and sediment yield as well as the relationships between them across the watershed. So, the calibrated SWAT model for the Gharesou watershed is believed to reasonably represent runoff and soil erosion processes in the watershed. It could therefore be used for identifying the spatial distribution of runoff and soil erosion and also for predicting the effects of alternative land management options in the watershed.

3.2 Identified Critical Sub-Watersheds

Figure 5 shows the sub-watersheds prioritized as high, medium, and low based on different types of impact indices.

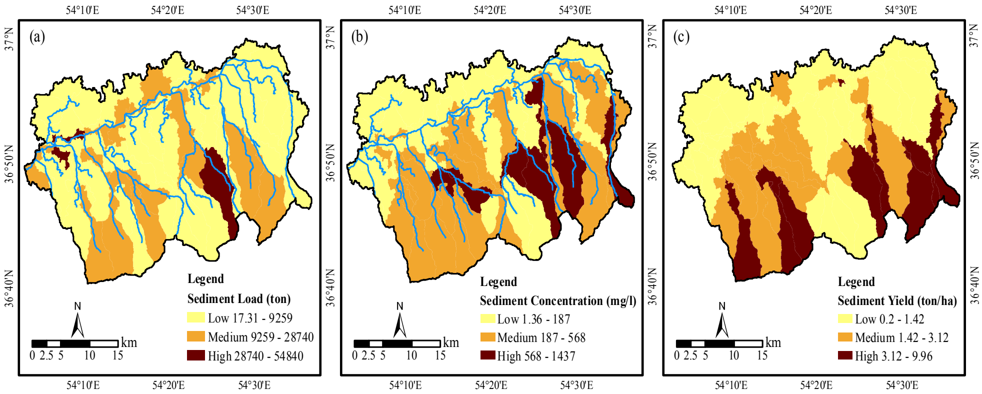


Figure 5. Sub-watersheds prioritization based on (a) LII, (b) CII, and (c) LUAII

Priority areas of LII were determined according to the sediment load for each reach. Out of 71 sub-watersheds delineated by ArcSWAT, 3 sub-watersheds fall under high, 21 sub-watersheds under moderate, and 47 sub-watersheds under low priority class. High priority areas are located near the watershed outlet and also near Gorgan city in the middle of the watershed.

For the CII, priority areas were identified based on the sediment concentration in the reach. CII analysis identified 8, 26, and 37 sub-watersheds as high, medium, and low priority areas respectively. The high priority sub-watersheds are generally located in the vicinity of Gorgan city where erosion from urban development sites as well as intensive agricultural works cause higher water pollution. Also, some tributaries may have high sediment concentrations because of relatively low flows. Appropriate in-stream conservation practices (e.g. check dams and constructed wetlands) could be implemented in the critical reaches identified by LII and CII to improve water quality.

In the LUAII method, the priority areas were identified based on the sediment load per area which normalizes each sub-watershed for comparison. From the LUAII analysis, it has been found that 10, 19, and 42 sub-watersheds fall under high, medium, and low sediment yield categories respectively. These sub-watersheds cover 20% of the watershed area and contribute 41% of sediment yield. However, every part of the sub-watersheds doesn't contribute the same amount of sediment yield to the stream. In most cases, there are only some portions of sub-watersheds which contribute to sediment yield highly the result of which causes sub-watershed to fall under critical zone. To identify these specific areas, HRU-based analysis was performed.

3.3 Identified Critical HRUs

Figure 6 presents the spatial distribution sediment yield (LUAII) at HRU-level in the Gharesou watershed.

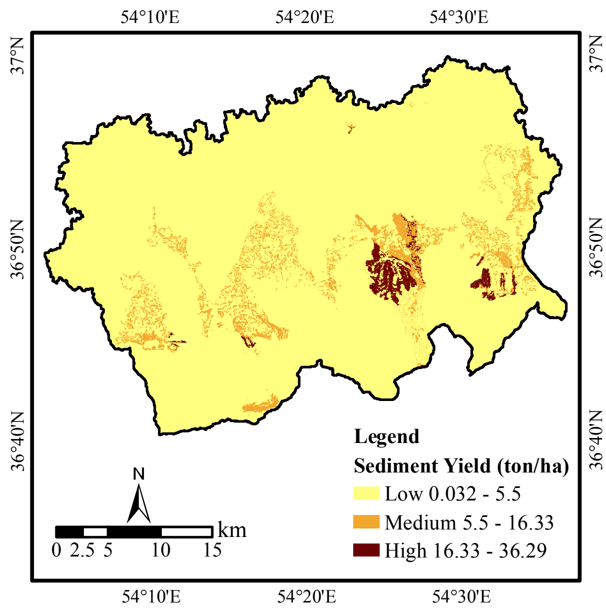


Figure 6. HRUs prioritization based on LUAII

Ten HRUs (out of the total 388 HRUs) were found to be critical hotspots of soil erosion in the watershed. These HRUs cover only 1.6% of the watershed area, but account for about 21% of the total soil loss from the watershed. Forty four HRUs covering about 6% of the watershed area are classified as medium priority areas contributing 37% of the total sediment. The remaining 334 HRUs which represent more than 92% of the watershed area fall under low priority category and produce about 42% of the total sediment. A plot showing cumulative percent of sediment yield versus the contributing watershed area is given in Figure 7. It can be seen that the slope of the curve decreases with increasing contributing area (i.e. the cumulative sediment yield increases slowly).

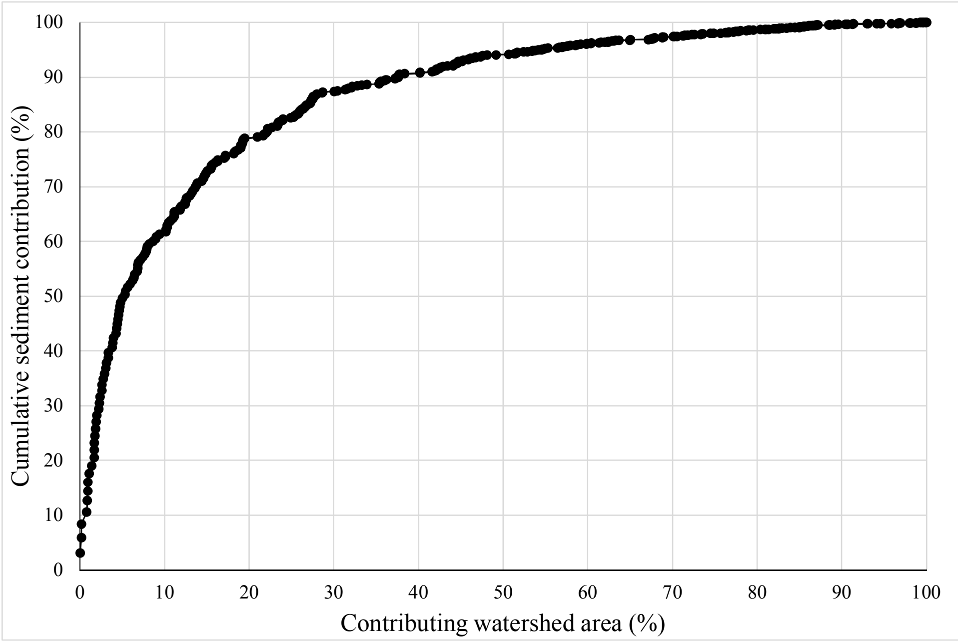


Figure 7. Cumulative percent of sediment yield by percent of contributing watershed area

Investigating spatial distribution of sediment yield across the watershed indicated that critical HRUs are mainly located in the upstream areas which are dominated by cultivated lands on steeper slopes and generally experience more and heavier rainfall events. This is in agreement with field observations in this study area. Implementation of on-farm BMPs (e.g. conservation tillage, contour farming, and terracing) is recommended in the critical areas to reduce soil erosion and sediment yield. LUAII-based prioritization at HRU-level contains more spatial detail than sub-watershed level, therefore, it could be more useful for soil and water conservation planning.

4. Conclusion

Hydrologic and water quality modeling of the Gharesou River watershed was conducted using the SWAT model to estimate water balance and sediment yield. Model parameterization and calibration procedures along with the techniques to overcome data limitations were described in the paper. Model evaluation results indicated that the Ghare -Sou watershed SWAT model is capable of providing reasonably accurate monthly stream flow prediction. However, its performance in predicting monthly sediment load is weak, although still fair and without serious bias as indicated by PBIAS statistic.

Using the calibrated SWAT model, critical areas of soil erosion and water pollution in the watershed were identified. Three types of impact indices were defined based on SWAT outputs of sediment load, sediment concentration, and sediment yield per unit area. Identified critical areas varied based on which impact index was used in the evaluation. It suggests that choosing a specific impact index should be based on managerial goals. For example, if the goal of a project is to protect aquatic health in the streams, it may be useful to use CII or if preventing sedimentation in the Gorgan gulf is most important, LII may be more appropriate. LUAII is useful to prioritize critical source areas irrespective of upstream influences. The LUAII demonstrated that some small areas are the source of disproportionately large amount of sediment and need most management interventions within the Gharesou watershed.

The outputs of this study may serve as a quick and accurate guide for targeting soil and water conservation practices in the watershed. Several practices that are suitable for the study of watershed are currently being assessed to come up with the best alternative scenarios in terms of implementation costs and reduction of soil erosion and water pollution.

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