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Identification and prioritization of critical sub-basins in a highly mountainous watershed using SWAT model

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Abstract

A few areas in a large watershed might be more critical and responsible for high amount of runoff and soil losses. For an effective and efficient implementation of watershed management practices, identification of these critical areas is vital. In this study, we used the Soil and Water Assessment Tool (SWAT, 2009) to identify and prioritize the critical sub-basins in a highly mountainous watershed with imprecise and uncertain data (Bazoft watershed, southwestern Iran). Three different SWAT models were first developed using different climate input data sets. The first data set (denoted as CRU) was derived from the climate research unit data set developed by the British Atmosphere Data Center (BADC). The second data set (denoted as CDW) was included the climate data obtained from the precipitation and air temperature stations in the study area. The third set (denoted as COM) was a combination of CRU and CDW climate data. The Generalized Likelihood Uncertainty Estimation (GLUE) program was used for calibrating and validating the SWAT model. Daily rainfall, temperature, and runoff data of 20 years (1989-2008) were used in this study. In results, the constructed SWAT model using COM data set simulated the runoff more satisfactorily than the two other developed SWAT models according to the statistical evaluation criteria. The correlation coefficient and Nash-Sutcliff values for the constructed SWAT model using COM data set were 0.40 and 0.38, respectively. The model simulated the runoff satisfactorily; however, the predicted runoff values were much more in agreement with the measured data for the calibration period than those for the validation period. Sub-basins S10, S12, and S13 were assigned as the most top critical sub-basins in runoff production in the watershed. The study revealed that the SWAT model could successfully be used for identifying the critical sub-basins in a watershed with imprecise and uncertain data for management purposes.

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Introduction

The Resource considerations for implementation of watershed management programs related to administration or even political considerations may limit the implementation of management programs to a few sub-basins of a watershed only. Even otherwise, it is always better to begin management measures from the most critical sub-basins, which makes it mandatory to prioritize the sub-basins available. In other word, identification of these critical areas is essential for an effective and efficient implementation of watershed management programs. Watershed prioritization is thus the ranking of different critical sub-basins of a

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watershed according to the order in which they have to be taken up for treatment and soil conservation measures (Tripathi et al., 2003).

Hydrometric stations are quite limited in Iran and many of them have sparse data. Therefore, management plans are difficult to develop due to the lack of measured data. Hence, identification of critical sub-basins plays a crucial role in the proper planning and development of local resources. Recently, mathematical models of watershed hydrology and transport processes have been employed to address a wide spectrum of environmental and water resources problems. In this study, a calibrated and validated Soil and Water Assessment Tool (SWAT) model was used to determine the critical sub-basins in a highly mountainous watershed with imprecise and uncertain data (the Bazoft watershed, southwestern Iran). The effects of different climate input data sets on prediction accuracy of the model were also evaluated.

Materials and Method

Study area

The study area was Bazoft watershed (31 37 to 32 39 N and 49 34 to 50 32 E) located in northern part of the Karun river basin in southwestern Iran (Fig. 1). The major river in the watershed is AbBazoft which is joined by Karun River at the outlet of the watershed. The elevation ranges from 880 m at the southern of the watershed to 4300 m on Zardkuh mountain. The long-term average rainfall and temperature in the region are around 800 mm and 10 °C, respectively. The slope class of 40-70 % is the major class of slope in this watershed which covers about 46 % of the study area. The dominant slope shape in the watershed is also convex. Approximately 56 % of the watershed is covered by pastures and the rest is covered by forest and bare lands.

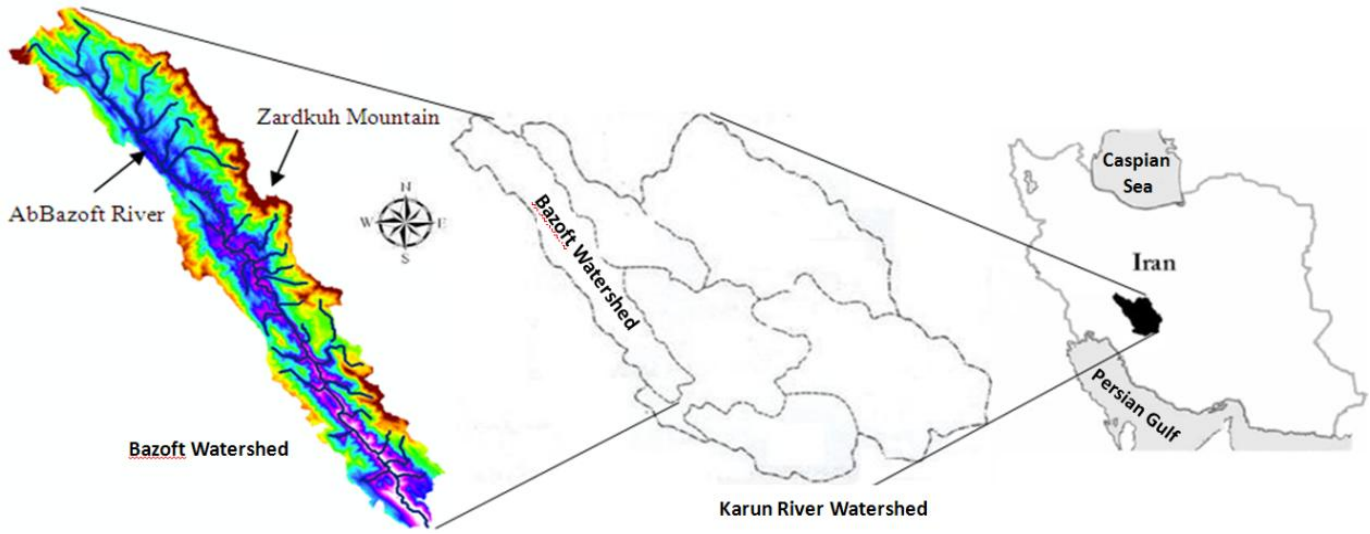

Fig. 1. Location of Bazoft watershed in south western of Iran (31 37 to 32 39 N and 49 34 to 50 32 E).

SWAT model

The ArcSWAT (2009) program was used to simulate runoff and sediment in the study area. The SWAT model is a basin-scale, continuous time model that operates on a daily time step and evaluates the impact of management practices on water, sediment and agricultural chemical yields in ungauged basins. The basic input data to SWAT are digital elevation model (DEM), stream network coverage, landuse, soil maps, and climate data. A DEM with grid size of 53m × 53m was used in this study. Stream network creation was done in the environment of ArcGIS using DEM. Soil data including sand, silt and clay contents, rock fragment content, organic carbon content, soil electrical conductivity (EC), water content, porosity, bulk density, saturated hydraulic conductivity (Ks), and soil hydrologic groups were obtained by studying soil profiles in the main landscape subunits. The land use map was prepared by interpretation of IRS-1D 2008 satellite image at a spatial resolution of 24 m by 24 m (Indian Space Applications Centre, Ahmedabad, India) in the ArcGIS software environment (Fig. 2). Based on the DEM and stream network maps, the SWAT delineates the watershed boundaries and divides it into sub-basins. By entrance of soil and land use maps into the model, sub-basins subdivide into the hydrologic response units (HRUs) which are assumed to be spatially uniform in terms of soil, landuse and, topographic characteristics. The watershed was subdivided into 55 sub-basins and 946 hydrological response units (HRUs).

Climate data sets

Three different climate input data sets were developed in this study. The first data set (denoted as CRU) was derived from the climate research unit (CRU) data set developed by the British Atmosphere Data Center (BADC). The BADC holds the CRU TS3.1 dataset for the period 1901-2009. The time-series datasets are month-by-month variation in climate over the last century or so. These are on high-resolution grids. They allow the comparison of variations in climate with variations in other phenomena. Variables include cloud cover, diurnal temperature range, frost day frequency, precipitation, daily mean temperature, monthly average daily maximum temperature, vapour pressure and wet day frequency. The second data set (denoted as CDW) was included the climate data obtained from the precipitation and air temperature stations in the study area. The third set (denoted as COM) was a combination of the CRU and CDW climate data sets.

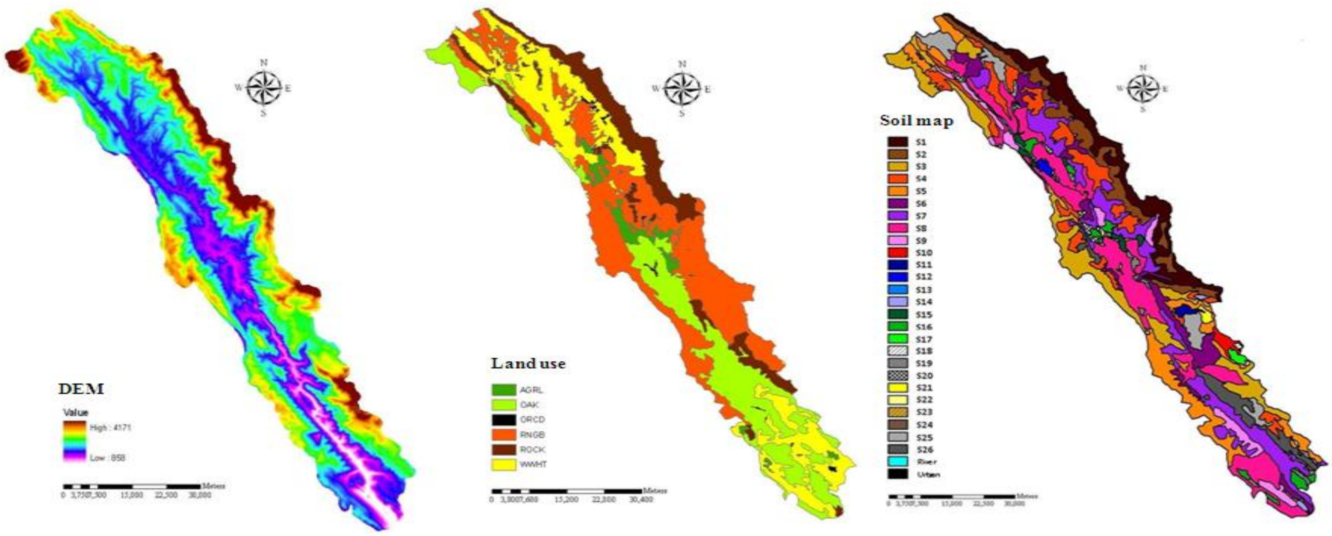

Fig. 2. The input maps to SWAT (DEM: digital elevation model, landuse, and soil maps)

GLUE algorithm description

Generalized Likelihood Uncertainty Estimation (GLUE) is an uncertainty analysis technique inspired by importance sampling and regional sensitivity analysis (RSA; Hornberger and Spear, 1981). In GLUE, parameter uncertainty accounts for all sources of uncertainty, i.e., input uncertainty, structural uncertainty, parameter uncertainty and response uncertainty, because ''the likelihood measure value is associated with a parameter set and reflects all these sources of error and any effects of the covariation of parameter values on model performance implicitly'' (Yang et al., 2008). Also, from a practical point of view, ''disaggregation of the error into its source components is difficult, particularly in cases common to hydrology where the model is non-linear and different sources of error may interact to produce the measured deviation'' (Gupta et al., 2005). In GLUE, parameter uncertainty is described as a set of discrete ''behavioral'' parameter sets with corresponding ''likelihood weights''. A GLUE analysis consists of the following three steps:

(1) After the definition of the ''generalized likelihood measure'', $L(\theta)$, a large number of parameter sets are randomly sampled from the prior distribution and each parameter set is assessed as either ''behavioral'' or ''non-behavioral'' through a comparison of the ''likelihood measure'' with a selected threshold value.

(2) Each behavioral parameter set is given a ''likelihood weight'' according to:

$$w_i = \frac{L(\theta)}{\sum_{k=1}^{n} L(\theta_k)} \tag{1}$$

where N is the number of behavioral parameter sets.

(3) Finally, prediction uncertainty is described by quantiles of the cumulative distribution realized from the weighted behavioral parameter sets (Abbaspour, 2009).

The most frequently used likelihood measure for GLUE, the Nash–Sutcliffe coefficient (NS), was also used in this study:

$$NS = 1 - \frac{\sum_{i=1}^{n}(Q_i - Q_i')^2}{\sum_{i=1}^{n}(Q_i - \mathrm{Q})^2} \quad (2)$$

where subscripts Q_i and $_i$ represent measured and simulated, respectively, and Q is the average of measured data.

Sensitivity analysis, calibration, and validation

An initial sensitivity analysis was done to determine sensitive parameters among the input parameters selected for the calibration of SWAT model (Table 1). The simulation time period was from 1989 to 2008, where the first three years were used as a warm-up. Two-third of the available daily runoff data for the station at the outlet of the watershed were used for calibration (from 1998-2008) and the remainders were used for validation (1992-1997). In combination with SWAT, the GLUE program was used to calibrate and validate the model using the daily river discharge (Abbaspour, 2009). The objective function was the Nash–Sutcliffe coefficient. The calibrated and validated SWAT model was then used to identify the critical sub-basins on the basis of average annual runoff production.

Table 1. Description of SWAT (2009) input parameters selected for calibration.

Parameter	**Description**	**Range**	
		Min	**Max**
*r_CN2.mgt	Curve number for moisture condition II	-0.4	0.4
r_SOL_BD.sol	Soil bulk density	-0.3	0.3
r_SOL_AWC.sol	Soil available water storage capacity	-0.3	0.3
r_SOL_K.sol	Soil hydraulic conductivity	-0.8	0.8
r_SOL_ALB.sol	Moist soil albedo	-0.5	0.5
v_ALPHA_BF.gw	Baseflow alpha factor	0	1
v_GW_DELAY.gw	Groundwater delay time	0	400
v_REVAPMN.gw	Threshold water in shallow aquifer	0	100
v_GW_REVAP.gw	Revap coefficient	0.02	0.2
v_SHALLST.gw	Initial depth of water in the shallow aquifer	0	1000
v_RCHRG_DP.gw	Deep aquifer percolation fraction	0	1
v_GWQMN.gw	Threshold depth of water in the shallow aquifer required for return flow to occur.	0	500
v_EPCO.hru	Plant uptake compensation factor	0.01	0.2
v_ESCO.hru	Soil evaporation compensation factor	0.01	0.3
v_SLSUBBSN.hru	Average slope length	10	150
v_OV_N.hru	Manning's *n* value for overland flow	0	0.8
v_CH_N2.rte	Manning's *n* value for the main channel	0	0.3
v_CH_K2.rte	Main channel conductivity	0	150
v_SFTMP.bsn	Snowmelt temperature	-5	5
v_SMTMP.bsn	Snowmelt base temperature	-5	5
v_SMFMX.bsn	Melt factor for snow on 21 June	0	10
v_SMFMN.bsn	Melt factor for snow on 21 December	0	10
v_TIMP.bsn	Snow pack temperature lag factor	0.01	1
v_MSK_CO1.bsn	Muskingum coefficient	0	10
v_MSK_CO2.bsn	Muskingum coefficient	0	10
v_SURLAG.bsn	Surface runoff lag coefficient	1	24
r_PCPMM.wgn	Average amount of precipitation falling in month	-0.5	0.5
r_PCPSKW.wgn	Skew coefficient for daily precipitation in month	-0.5	0.5

r_PCPSTD.wgn	Standard deviation for daily precipitation in month	-0.5	0.5

* r_ means the existing parameter value is multiplied by (1 plus a given value) and v_ means the default parameter is replaced by a given value

Results and Discussion

SWAT models

The SWAT model constructed using a combination of the CRU data and the climate data obtained from the precipitation and air temperature stations in the study area (i.e. COM climate data set) had higher prediction accuracy than the other two developed SWAT models (Fig. 3). The correlation coefficient and Nash-Sutcliff values for the constructed SWAT model using COM data set were 0.40 and 0.38, respectively. Furthermore, simulated runoff values by the constructed SWAT model using CDW data set were more in agreement with the measured values than those simulated by the constructed SWAT model using CRU data set (Fig. 3).

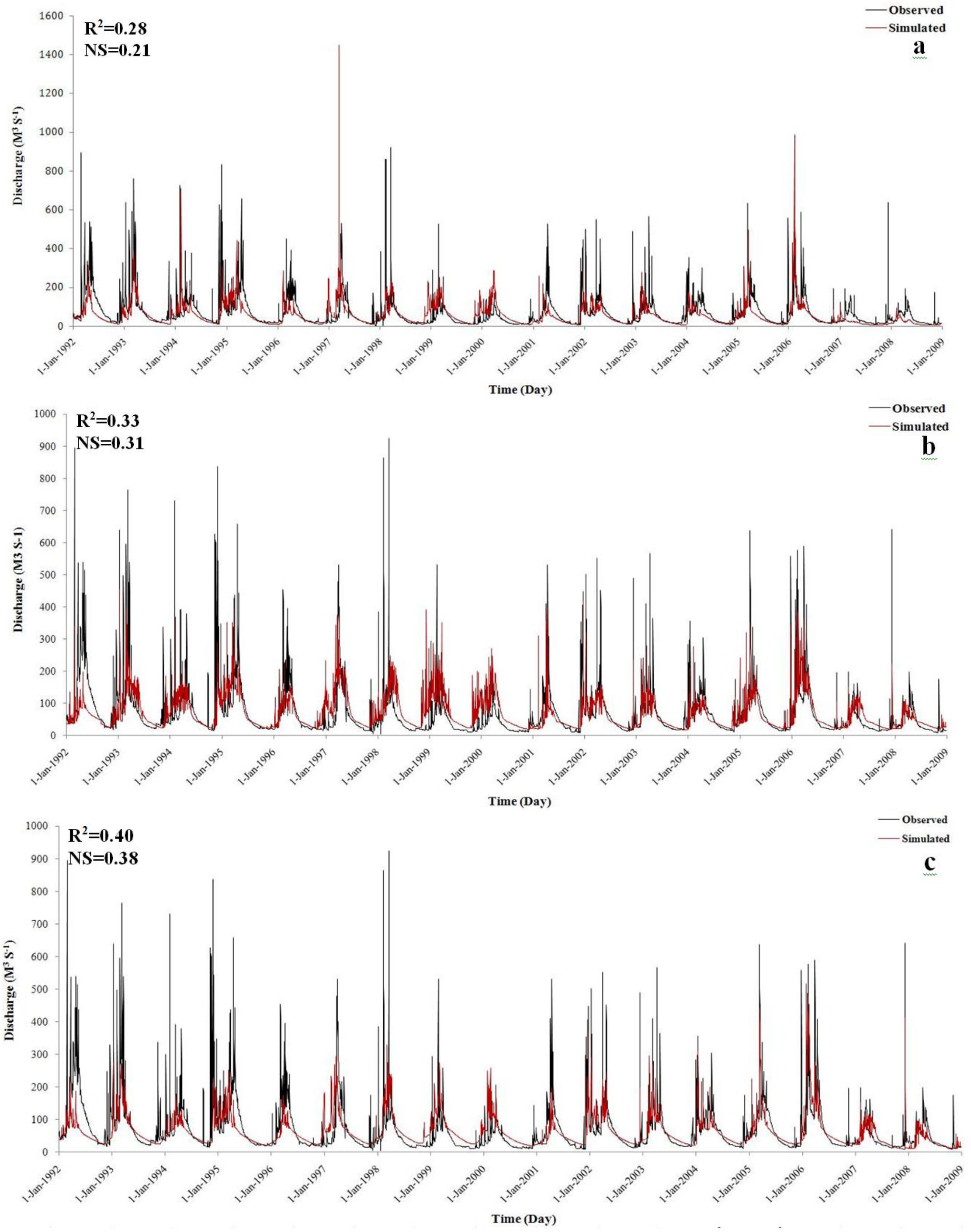

Fig. 3. Daily runoff prediction using SWAT models developed by different input climate data sets (a: CRU, b: CDW, and c: COM). R^2: coefficient of determination and NS: Nash-Sutcliff coefficient.

Calibration and validation of the model

The results of daily runoff calibration and validation using GLUE algorithm are presented in Table 2. The model simulated the runoff satisfactorily; however, the predicted runoff values were much more in agreement with the observed data for the calibration period than those for the validation period. The R^2 and NS coefficients for the calibration period were 0.54 and 0.51, respectively; while, they were 0.48 and 0.47 for the validation period, respectively. Although the simulation of daily runoff was satisfactory during the calibration period, the model exhibited larger uncertainties in the calibration period. The *P* factor (percentage of data being bracketed by 95PPU) for the calibration period was 0.64, while it was 0.73 for the validation period (Table 2).

Table 2. Summery statistic results for the daily runoff calibration and validation periods.

Evaluation criteria	Calibration	Validation
R^2	0.54	0.48
NS	0.51	0.47
P factor	0.64	0.73

R^2: coefficient of determination, NS: Nash-Sutcliff coefficient, and *P* factor: percentage of data being bracketed by 95PPU.

Identification of the critical sub-basins

Fig. 4 shows location of the 3 most top critical sub-basins in Bazoft watershed according to the SWAT model results. Based on the spatial distribution of the runoff production hazard in the watershed, sub-basins S10, S12, and S13 were assigned as most top critical sub-basins in runoff production in the study area. The high runoff production rate predicted in these sub-basins may be attributed to insufficient use of the land, scanty vegetative cover, steep sloping areas, high population pressure, cultivating of the steep-lands, and other environmental problems. These 3 critical sub-basins were, hence, assigned as the top priorities and were recommended to be considered for the future conservation plans.

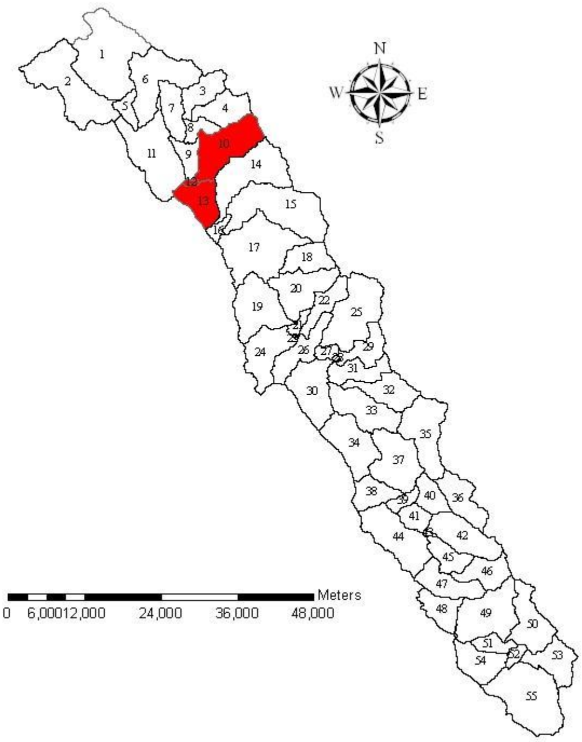

Fig. 3. Location of the 3 critical sub-basins in Bazoft watershed according to the SWAT model results.

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