ISSN: 2476-6909; ECOPERSIA . 2020;8(3):169-180

Quantifying the Long-Term Flood Regulation Ecosystem Service under Climate Change Using SWAT Model

ARTICLE INFO

Article Type
Original Research

Authors
Norouzi Nazar M.[1] *MSc,*
Asgari E.[2] *MSc,*
Baaghideh M.*[2] *PhD,*
Lotfi S.[3] *MSc*

How to cite this article
Norouzi Nazar M, Asgari E, Baaghideh M, Lotfi S. Quantifying the Long-Term Flood Regulation Ecosystem Service under Climate Change Using SWAT Model. ECOPERSIA. 2020;8-(3):169-180.

[1]Civil Engineering Department, Engineering Faculty, University of Sistan and Baluchestan, Zahedan, Iran
[2]Climatology & Geomorphology Department, Geography & Environmental Sciences Faculty, Hakim Sabzevari University, Sabzevar, Iran
[3]School of Civil Engineering, College of Engineering, University of Tehran, Tehran, Iran

****Correspondence***
Address: Room 127, Geography & Environmental Sciences Faculty, Hakim Sabzevari University, Tohidshahr, Sabzevar, Khorasan Razavi Province, Iran. Postal code: 9617976487
Phone: +98 (51) 44013270
Fax: +98 (51) 44013271
m.baaghideh @hsu.ac.ir

Article History
Received: September 26, 2019
Accepted: January 9, 2020
ePublished: September 20, 2020

ABSTRACT

Aims In recent years, interest in quantifying ecosystem services (ESs) has dramatically grown among the scientific society. By increasing global environmental crises as a result of population growth, it is becoming increasingly essential to quantify the impacts that human activities have on ESs. Soil and water assessment tool (SWAT) is a process-based distributed hydrological model that has been widely recommended to quantify the ESs. The purpose of the present study is to employ the SWAT model for quantifying the flood regulation ecosystem service in one of the highest flood prone watersheds in the west of Iran.
Materials & Methods In this study, after calibration and validation of daily and monthly discharge using SUFI-2 algorithm, the flood regulation index (FRI) was calculated for each year of simulation period (1989-2017).
Findings The results show that climate variables such as precipitation could severely affect the quantities of FRI in different years. According to middle of 95PPU, the FRI varies from 0.22 in the wettest year of 1994 to 0.72 in the driest year of 2017 with precipitation values of 1080 and 380mm, respectively. The results also indicate that lower, middle, and upper limits of FRI 95PPU show the correlation coefficient of 28, 66, and 72% with the precipitation values in different years.
Conclusion The available knowledge on the application of SWAT model in addressing ESs can be similarly used in the regions with corresponding environmental challenges of the low delivery level of regulation ESs.

Keywords SWAT; Flood; Regulation Services; Sufi-2; Uncertainty Analysis

CITATION LINKS

[1] The economics of ecosystems and biodiversity: Ecological and economic ... [2] Impacts of land-use and climate change on ecosystem service in ... [3] Climate-and land use-induced risks to watershed services ... [4] A quantitative approach to evaluating ecosystem ... [5] Using the Soil and Water Assessment Tool ... [6] Hyrcanian forests conservation based on ecosystem services ... [7] The Multiscale Integrated Model of Ecosystem Services (MIMES): ... [8] Trading off agriculture with nature's other benefits ... [9] State-of-the-art report on integrated valuation of ecosystem ... [10] A comparison of tools for modeling freshwater ecosystem ... [11] Large area hydrologic modeling and assessment part I: Model ... [12] Possible change in Korean streamflow ... [13] Assessing, quantifying and valuing the ecosystem services of coastal ... [14] Investigating the impacts of climate changes on floods ... [15] Flow modelling in great Karun sub-basins in terms of future ... [16] Design ... [17] Studies on soil physics, part 1, the flow of air and ... [18] Model for predicting evaporation from a row crop with ... [19] Reference crop evapotranspiration from ... [20] On the assessment of surface heat flux and evaporation using ... [21] Evaporation and the ... [22] The soil and water assessment tool: Historical development ... [23] earthexplorer.usgs ... [24] Estimation of freshwater availability in the West African ... [25] Calibration and validation of swat model for Kunthipuzha basin using ... [26] Modelling hydrology and water quality in the pre-alpine/alpine Thur ... [27] A continental-scale hydrology and water quality model for ... [28] Evaluating the use of "goodness-of-fit" measures in hydrologic and ... [29] River flow forecasting through conceptual models part I-A ... [30] Status of automatic calibration for hydrologic ... [31] Model evaluation guidelines for systematic quantification of accuracy in ... [32] Application of SWAT model to investigate nitrate leaching in Hamadan-Bahar Watershed ... [33] Assessment of SWAT hydrological model in catchments' water balance simulation located in semi-arid ... [34] Using SWAT model to determine runoff, sediment yield and nitrate loss in gorganrood ... [35] Estimation of hydrologic budget for Gharasou Watershed ...

Introduction

Ecosystem services (ESs) are the collective benefits that human communities gain from ecosystems, and are classified into four types of provisioning, regulating, supporting, and cultural services [1]. Over the past three decades, global warming and climate change have dramatically influenced the level of ESs delivery [2]. Therefore, understanding the impacts of climate change on ESs is of significance and it can help decision-makers to analyze various strategies and policies [3, 4]. In recent years, the quantification of ESs has been an innovative and sustainable approach to addressing the effects of climate change on ecosystems [5]. Quantification of ESs could provide valuable insights for decision and policy-makers, and they can evaluate and compare the possible results of decisions that they might take [6].

To quantify the effects of ecosystem changes on ESs, using tools and models is inevitable. There are two classes of emerging tools that are being used for ESs assessment: ESs specific tools and traditional hydrological tools. The multi-scale integrated model of ecosystem services (MIMES) [7], the artificial intelligence for ecosystem services (ARIES) [8], and the integrated valuation of ecosystem services and tradeoffs (InVEST) [9] are among the most popular ESs specific tools, focusing mainly on end services and visualization of these services across a landscape [10]. An example of traditional hydrological models is the soil and water assessment tool (SWAT) which is unable to directly simulate the ESs and needs post processing analysis [11]. Hence, some researchers have attempted to develop various indices for quantifying ESs using SWAT outputs [4].

In response to various climate change policies, ESs assessment has attracted the considerable attention of scientific community in different ecosystems around the world. Gathenya *et al.* [3] used SWAT model to investigate sediment and flood regulatory ESs in Nyando river basin in Kenya. They reported that a 10% increase in rainfall would increase flood risk by 50% increase in flow at the outlet of the basin. Jung *et al.* [12] conducted an ecosystem assessment study in South Korea and they concluded that climate change and global warming would bring a decrease in water availability and an increase in flood risk. Tang *et al.* [2] indicated that climate change had a dramatic impact on ESs in Eastern Tibetan Plateau in China. They reported that 35% of the study area showed increase in ESs and the other 65% decrease. Newton *et al.* [13] stated that increases in frequency and intensity of extreme weather events resulting from climate change are the main changes that affect ESs in different coastal lagoons around the worlds.

The present study aims to use SWAT model to assess the flood regulation ES under past climate change in Dez watershed in Khuzestan Province, western Iran. One of the most important environmental challenges in this region is the increasing occurrence of severe and destructive floods which has been greatly affected by climate change in recent years [14, 15]. Khuzestan Province is one of the highest flood prone provinces in Iran, in which the occurrence of devastating floods has caused human casualties and economic losses over the past 50 years. For example, in the last flood of March 2019, over 50000 people were forced to leave their houses and the flood caused about 138 million dollars economic losses.

One of the biggest challenges of using SWAT model is the uncertainty associated with the modeling outputs. Miserably, the previous studies in Iran which have used SWAT model for environmental modeling have reported the final results according to the best fitted parameters. This is wrong and misleading, because this cannot express the uncertainty of simulated variables. In this study, the simulation results were presented as 95PPU to express the uncertainty of SWAT parameters and structure. This is the first study in Iran that uses SWAT model to quantify the effects of climate change on flood regulation ES addressing the modeling uncertainty.

The main objective of this study is to calculate the Flood Regulation Index (FRI) for each year of the simulation period (1989-2017) to understand how climate variables such as precipitation could affect it. The purpose of the present study is also to show that available knowledge on the application of SWAT model in addressing ESs can be similarly used in the regions with corresponding environmental challenges of the low delivery level of regulation ESs.

Materials and Methods

Study area

The study area is a part of Dez watershed in Lorestan Province, western Iran (Figure 1). It is located on the western slopes of the Zagros Mountains between 48.3-50.3 °E and 32.4-34.1 °N with an area approximately of 17611km^2. Bakhtiari and Sezar are the main tributaries of Dez watershed which join together to form the main river of Dez. northern parts of the watershed are predominantly covered with agriculture and rangeland. Also, the predominant landuse in the south are rangeland and Oak forest. The topography of the basin is characterized by mountains in the east and north with the elevation up to 4075m and plains in the west and south with the elevation down to 92m. The region is affected by Mediterranean climate conditions with monsoon season from November to May. The average annual precipitation is around 705mm which more than 93% of which occurs in the rainy season. Because of the mountainous nature of most parts of the region, precipitation mainly falls in the form of snow in autumn and winter. The average annual discharge in Talezang station located at the near of the basin's outlet is 293m^3/s and 148m^3/s for the wet and dry seasons, respectively, with the maximum value of 514m^3/s in April and the minimum one of 72.5m^3/s in September (Figure 1).

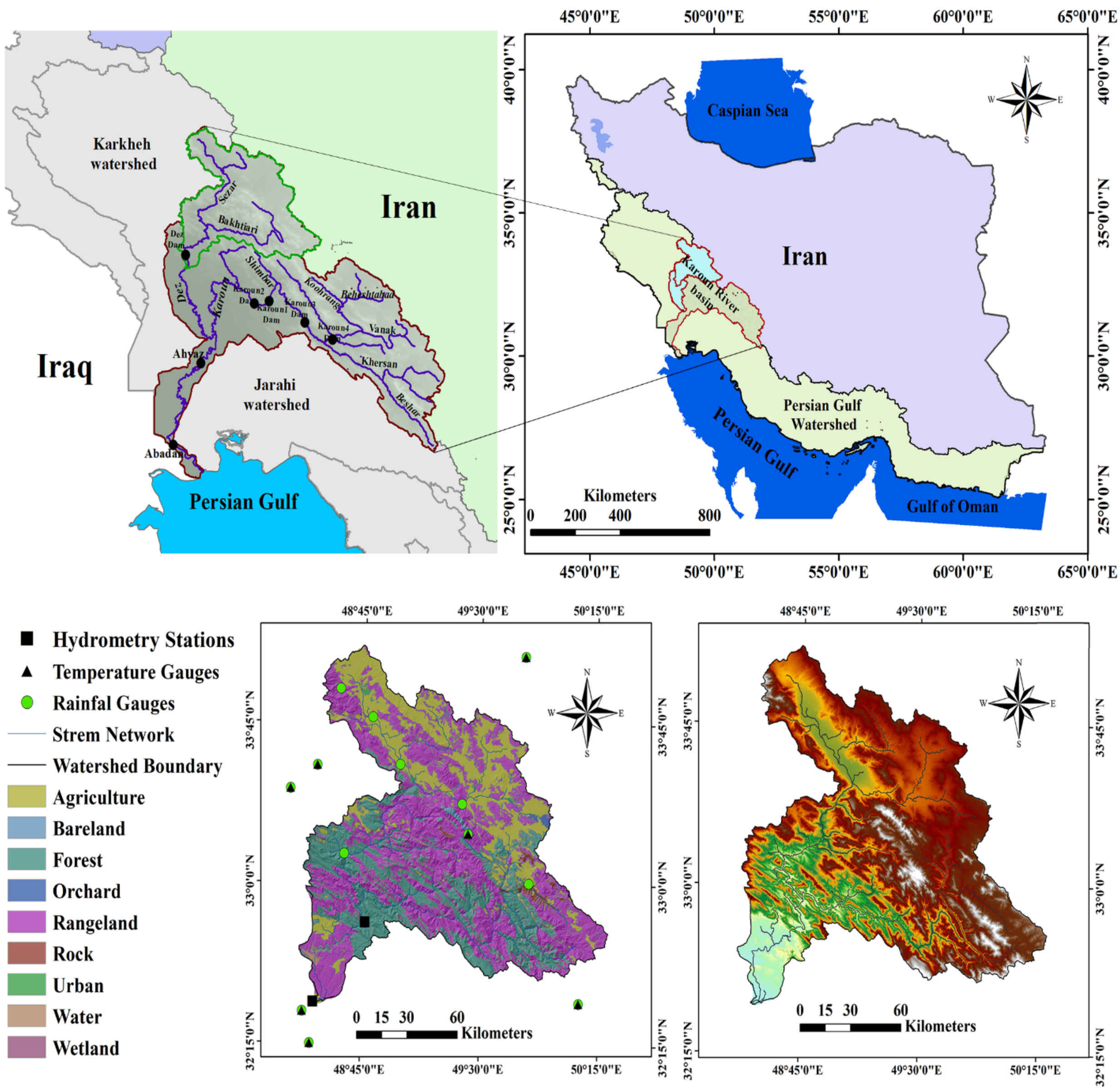

Figure 1) Location of watershed, drainage network, river and climate gage stations

Description of hydrology simulator

Soil and water assessment tool (SWAT) is a robust watershed scale model which is developed by Jeff Arnold [11] for the United States Department of Agriculture (USDA), Agricultural Research Service (ARS). As the most popular hydrological model, SWAT has been used in different parts of the world for hydrological modeling of watersheds. SWAT is a time-continuous and physical-based model that operates on the daily time step. It is able to simulate the impact of land management practices on water quantity and quality in large, complex watersheds. There are 10 major components in SWAT, including hydrology, sedimentation, weather, soil temperature, crop growths, nutrients, pesticides, agricultural management, channel routing, and reservoir routing. SWAT uses a digital elevation model to generate stream network channels and partition the watershed into a number of sub-watersheds. The smallest spatial unit in SWAT is hydrological response unit (HRU) which is unique in landuse, soil types and topography characteristics. SWAT simulates the hydrology of a watershed in the two following steps. The first step is the simulation of water quantity and quality in each sub-basins and the second step is routing of the calculated components through the channel network to the outlet of watershed. The following equation is used by SWAT to simulate the components of hydrology in a watershed:

$$SW_t = SW_0 + \sum_{i=1}^{t}(R_{day} - Q_{sur} - ET_a - w_{seep} - Q_{gw})$$

Where SW_t is soil water content at time step t, SW_0 is initial soil water content, R_{day} is daily precipitation, Q_{sur} is surface runoff, Et_a is evapotranspiration, w_{seep} is percolation, and Q_{gw} is groundwater flow.

SWAT offers two methods for computation of surface runoff; modified SCS Curve Number [16] and Green and Ampt infiltration equation [17]. It uses a methodology described by Ritchie [18] to calculate actual evapotranspiration. Also, there are three options in SWAT for estimating the potential of evapotranspiration; Hargreaves [19], Priestly-Taylor [20], and Penman-Monteith [21]. A detailed description of SWAT can be found in the studies of Arnold *et al.* [11] and Gassman *et al.* [22].

Model inputs and set up

Input data description

The required temporal and spatial data for SWAT calibration and validation were obtained from diverse sources. Digital elevation model (DEM) was extracted from Aster Global DEM with a resolution of 30m which is available through the USGS Earth Explorer site [23]. DEM is used by SWAT for watershed delineation, stream channel network definition, and calculation of sub-basin's topographic characteristics such as area, slop and slop length. A landuse/landcover map created by the Iranian Space Agency (ISA) was also used to develop the hydrological model. It has a resolution of 1:2500000 and represents 9 various landuse classes. The soil type map of the study area was constructed from the soil map of the world provided by FAO-UNESCO (FAO, 1974) with a spatial resolution of 5km. Based on the FAO classification, there are 6 different soil types in the region. Various physical and chemical soil properties for different layers were obtained from a study by Schuol *et al.* [24] to complete the soil databases file within the model. In addition, the observed meteorological data including daily precipitation and minimum and maximum air temperature from January 1986 to December 2013 were collected from two sources including the Iranian Meteorological Organization (IMO) and the Iranian Water Resources Management Organization (IWRMO). River daily discharge at Talezang hydrometric station was also obtained from the IWRMO for the time period of 1989-2013 for model calibration and validation. Figure 1 illustrates the geographic locations of meteorological and hydrological stations in the study area.

Model set up

After collection of the above data, a value of 10000ha was selected for drainage threshold area to delineate the watershed. Selection of smaller values for drainage threshold area is resulted in more number of sub-basins, finer stream network definition, and longer time for running the model. The multiple HRU's (Hydrological Response Units) and single slope options within the model were also used to generate HRU's. With these specifications, the watershed area was characterized into the 100 sub-basins and 258 HRU's. Considering the data availability, two SWAT projects were built in Arc SWAT 2012 for the period of 1989-2013 at daily and monthly timescales. The initial 3 years of simulation period were regarded as the warm-up to minimize the undesirable effect of default parameters values within the model.

Sensitivity analysis

Calibration of a model with a large number of parameters is difficult [25]. Therefore, identification of the most sensitive parameters to an output SWAT variable is an optional but highly recommended procedure before the calibration [26]. Sensitivity analysis is a method that reveals and ranks the contribution of each input parameter to an output variable. Two types of sensitivity analysis are available within the SWAT-CUP program: Global sensitivity analysis which allows all parameters change at a time and one-at-a-time sensitivity analysis which allows one parameter changes at a time, while all other parameters are kept constant. In the present study, both types of them were performed. Global sensitivity analysis provides two statistics of t-test and p-value to quantify the relative significance and sensitivity of each parameter, respectively. In absolute value, the higher value of t-test and the smaller p-value indicate the more significant and the more sensitive parameter, respectively.

Model calibration, validation and uncertainty analysis

Calibration is the process of adjustment and optimization of sensitive model parameters in order to get a reasonable match between simulation and observation. Computer modeling works are rife with various sources of errors and uncertainties. Thus, it is necessary to quantify the uncertainty in model predictions. Without consideration of uncertainty, calibration of a model is meaningless. Hence, any analysis using a calibrated model needs to include the uncertainty in the results. SUFI-2 is an optimization algorithm within the SWAT-CUP program which allows the sensitivity analysis, combined calibration-uncertainty process and validation of SWAT model. It is developed by Dr. Abbaspour [26] for the Swiss Federal Institute of Aquatic Science and Technology (Eawag). In SUFI-2, all the sources of uncertainties are considered by the propagation of uncertainty in the model parameters, expressed as ranges. Assigning the uncertainty in the input parameters is resulted in uncertainty in the model output variables, which expressed as uncertainty band. The uncertainty band is generated at 2.5% and 97.5% levels of the cumulative distribution of an output variable which is simulated by Latin hypercube sampling (LHS) from the parameter ranges (95PPU). In the present study, in order to show the impact of uncertainty in model structure and model parameters, the 95PPU box plots for the flood regulation service were calculated and presented.

There are two factors that assess the outcomes of uncertainty analysis: P-factor which is the percentage of observed data enveloped by 95PPU and R-factor which is the average thickness of 95PPU divided by the standard deviation of measured data. The value of P-factor ranges from zero to 1, while the value of R-factor varies from zero to ∞. According to some studies, values of P-factor >0.7 and R-factor around 1 are satisfactory for discharge calibration [26, 27]. Furthermore, the three following statistical indices were calculated to evaluate the performance of model in simulating discharge: Coefficient of determination (R^2) [28], Nash-Sutcliffe efficiency (NSE) [29], and percent bias (PBIAS) [30]. R^2 ranges from zero to 1, where the higher values denote the higher agreement between simulation and observation. NSE varies between -∞ and 1, where the value of 1 indicates the perfect model prediction. PBIAS falls within -∞ and +∞ with the optimal value of zero, where the smaller values represent better simulation. The equations for R^2, NSE, and PBIAS are as follows:

$$R^2 = \frac{[\sum_i (Q_{m,i}-\bar{Q}_m)(Q_{s,i}-\bar{Q}_s)]^2}{\sum_i (Q_{m,i}-\bar{Q}_m)^2 \sum_i (Q_{s,i}-\bar{Q}_s)^2}$$

$$NSE = 1-\frac{\sum_i (Q_m-Q_s)_i^2}{\sum_i (Q_{m,i}-\bar{Q}_m)^2}$$

$$PBIAS = 100 \times \frac{\sum_i (Q_m-Q_s)_i}{\sum_i Q_{m,i}}$$

Where Q_m is the measured variable (discharge or sediment), Q_s is the simulated variable, $\bar{Q}_m$ is the mean of measured variable and $\bar{Q}_s$ is the mean of simulated variable for each time step i. The performance of model in simulating monthly discharge is considered very good when PBIAS falls within ±15 and NSE is above 0.75 (Table 1) [31].

Table 1) The criteria for assessing the performance of SWAT model (Moriasi *et al.*) [31]

Performance Rating	NSE	PBIAS (%)
Very good	0.75<NSE≤1.00	PBIAS<±10
Good	0.65<NSE≤0.75	±10≤PBIAS<±15
Satisfactory	0.5<NSE≤0.65	±15≤PBIAS<±25
Unsatisfactory	NSE≤0.5	PBIAS≥±25

Quantifying the flood regulation ecosystem services

In the present study, a methodology by Logsdon and Chaubey [4] was used to quantify the flood regulation ES. In this method, the flood regulation ES is determined according to the three components of quantity, duration, and the extent of flooding events. The following equation provides the flood regulation index (ERI) where DF is the duration of flood (day), QF is the magnitude of flood, RF is the number of flood per year, w_1, w_2, and w_3 are the user weights added for each components of flood (where the summation of weights is 1), and LT subscript indicates the calculation of each components using historical long-term data. First, the historical flow data at Talezang station at the outlet of the watershed was used to calculate flood flow (Q_{10} of the flow), and then this was used to determine the three long-term historical components of flood. In general, the FRI varies between zero and 1, where the value of 1 indicates that there is no flood in a given year and the magnitude less than 1 suggests diminished flood regulation service.

$$RRI=\frac{1}{\exp[w_1\left(\frac{DF}{DF_{LT}}\right)+w_2\left(\frac{QF}{QF_{LT}}\right)+w_3\left(\frac{RF}{RF_{LT}}\right)]}$$

Findings and Discussion

Sensitivity analysis results

Initially, 25 parameters that had effect on discharge were chosen from the previous studies in the literature and were used in sensitivity analysis [32-35]. Then, 14 most sensitive parameters were selected for the calibration-uncertainty process according to the results of the sensitivity analysis (Table 2). The parameters attributed to the surface runoff (CN2.mgt), snow process (SMTMP.bsn, SFTMP.bsn, SMFMN.bsn, SMFMX.bsn), physical channel characteristics (ALPHA_BNK.rte, CH_K2.rte, CH_N2.rte), water movement in aquifers (GW_REVAP.gw, GWQMN.gw, RCHRG_DP.gw), and HRUs properties (CANMX.hru, EPCO.hru, SLSUBBSN.hru) were found as the most influential parameters on discharge. The most sensitive parameter was "SCS runoff curve number for moisture condition II" (CN2.mgt), followed by "baseflow alpha factor for bank storage" (ALPHA_BNK.rte) and "effective hydraulic conductivity in the main channel" (CH_K2.rte).

Calibration-uncertainty analysis results

The model calibration and validation were carried out using the daily and monthly observed discharge at Talezang station. First, the model was calibrated from 1989 to 2006 by adjusting the selected influential parameters from the sensitivity analysis in the previous step (Diagrams 1 and 2). Then, the model was validated from 2007 to 2013 using the calibrated parameter ranges without any further changes (Diagrams 3 and 4). The calibrated parameters and their optimal values are listed in Table 2. The efficiency statistics of R^2, NSE, and PBIAS for the monthly and daily discharge simulations are summarized in Table 3. The NSE value of >0.8 and PBIAS value of <10% indicate a very good performance of SWAT model in simulating monthly discharge for both calibration and validation periods according to the guidelines suggested by Moriasi *et al.* [31]. The performance of model was also evaluated satisfactory for the calibration and validation of daily discharge. It is obvious that the performance of model has been better for monthly discharge simulation than daily discharge.

According to the results of uncertainty analysis, more than 85% of daily and monthly observations were captured in the 95PPU band for both calibration and validation (Table 3). The R-factor values were also obtained around 1 for both calibration and validation for both daily and monthly time scales. These values are reasonable values for uncertainty analysis, according to the suggestions by Abbaspour *et al.* [26].

SWAT performance in quantifying FRI

The three components of flooding events (magnitude, duration, and number) were calculated using the SWAT simulated daily discharge at the outlet of the watershed for each year of the simulation period. The values of components and the corresponding calculated FRIs are listed in Table 4. The FRI quantities were also determined using the observed discharge data. Diagram 5 graphically compares the simulated (depicted as 95PPU) with the observed FRIs. As seen in Diagram 5, the simulated FRIs 95PPU captured most of FRIs calculated with the observed data. Only the observed FRI in 3 years of 2005, 2007, and 2015 have not been fallen within the FRI 95PPU box. The results also show that middle of 95PPU (as a representative of simulated FRIs) correlates 78% with the observed FRI quantities (Diagram 6-a). So, the SWAT outputs can be satisfactorily used in modeling the flood regulation ES in Dez watershed.

Table 2) The most sensitive parameters to streamflow and their optimal values

Parameters*	Description	File	Final value
r_CN2	Curve number	.mgt	[-0.1, 0.1]
v_GWQMN	Threshold depth of water for return flow to occur	.gw	[550, 850]
v_GW_REVAP	Groundwater "revap" coefficient	.gw	[0, 0.05]
v_RCHRG_DP	Deep aquifer percolation fraction	.gw	[0.7, 0.9]
v_SLSUBBSN	Average slope length	.hru	[115, 135]
v_ALPHA_BNK	Baseflow alpha factor for bank storage	.rte	[0.05, 0.25]
v_CH_K2	Effective hyd. Cond. in the main channel	.rte	[105, 125]
v_CH_N2	Maanning's n value foe the main channel	.rte	[0.09, 0.16]
v_EPCO	Plant uptake compensation factor	.hru	[0.7, 0.9]
v_SFTMP	Snowfall temperature	.bsn	[1.5]
v_SMTMP	Snowmelt base temperature	.bsn	[3.5]
v_SMFMX	Melt factor for snow on June 21	.bsn	[7.5]
v_SMFMN	Melt factor for snow on December 21	.bsn	[2.5]
v_CANMX_RANGE	Maximum canopy storage for range	.hru	[79]

* r_ means that the existing parameter value is multiplied by (1+a given value), while v_ means that the default parameter is replaced by a given value.

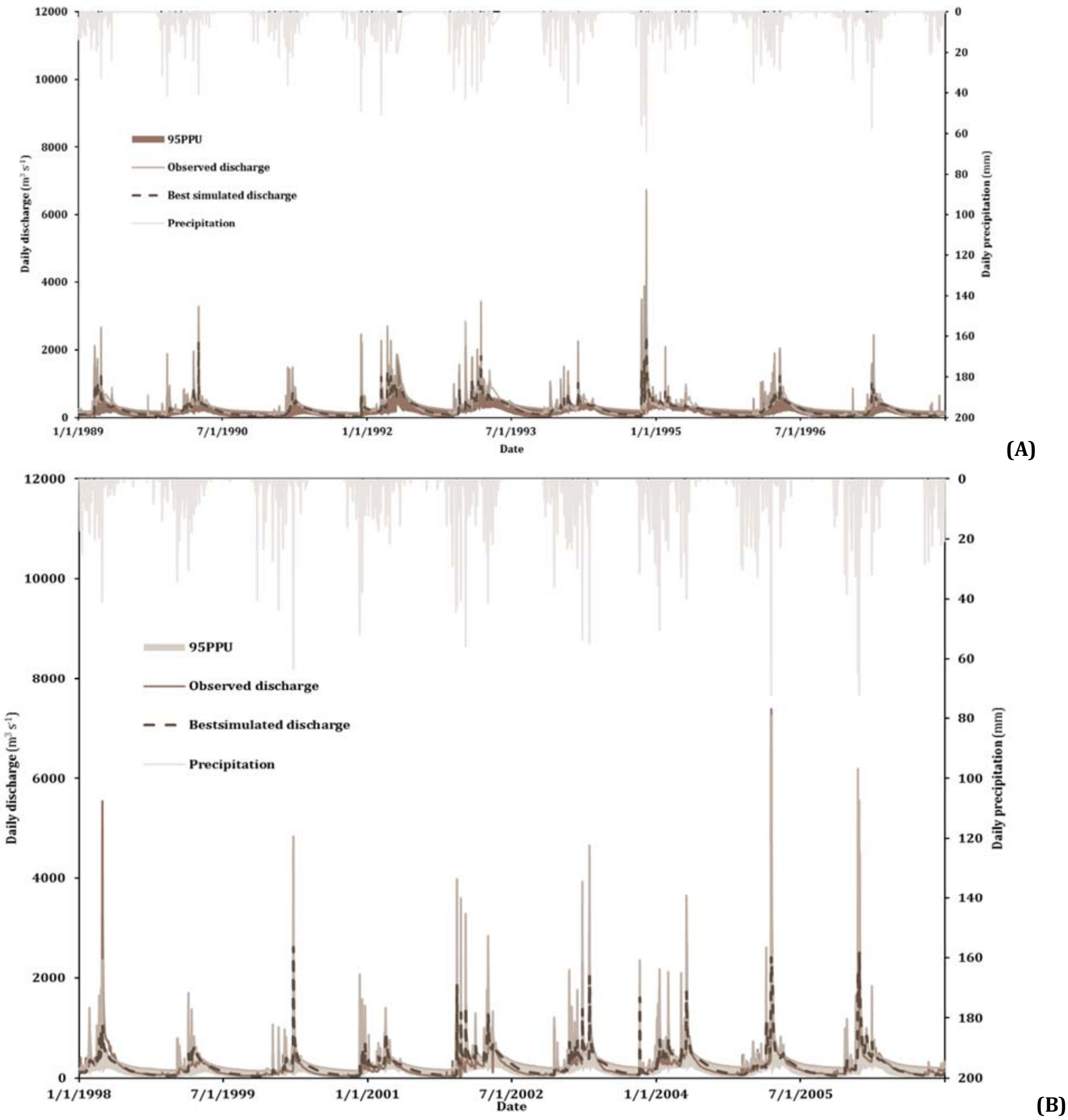

Diagram 1) Precipitation (upper) and comparison between the observed and simulated daily streamflow (lower) from 1989 to 1998 (A) and from 1998 to 2006 (B)

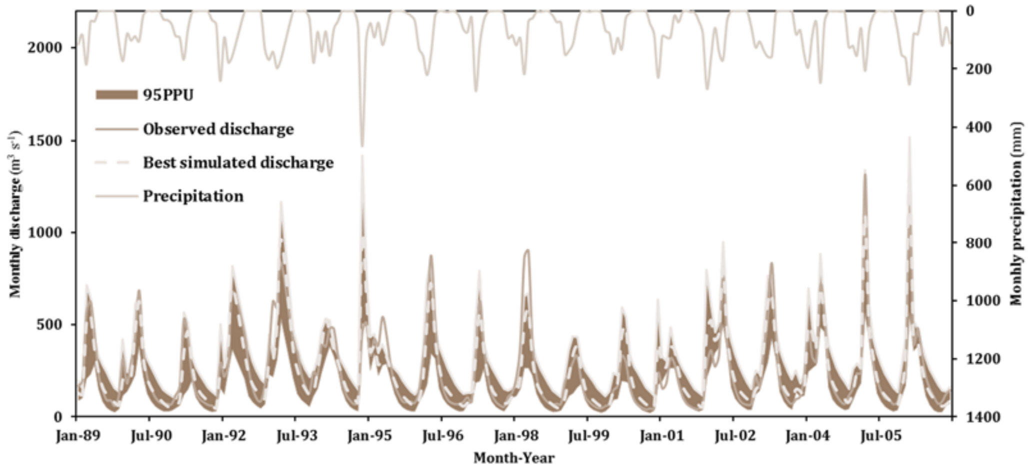

Diagram 2) Precipitation (upper) and comparison between the observed and simulated monthly streamflow (lower) from 1989 to 2006 (calibration period)

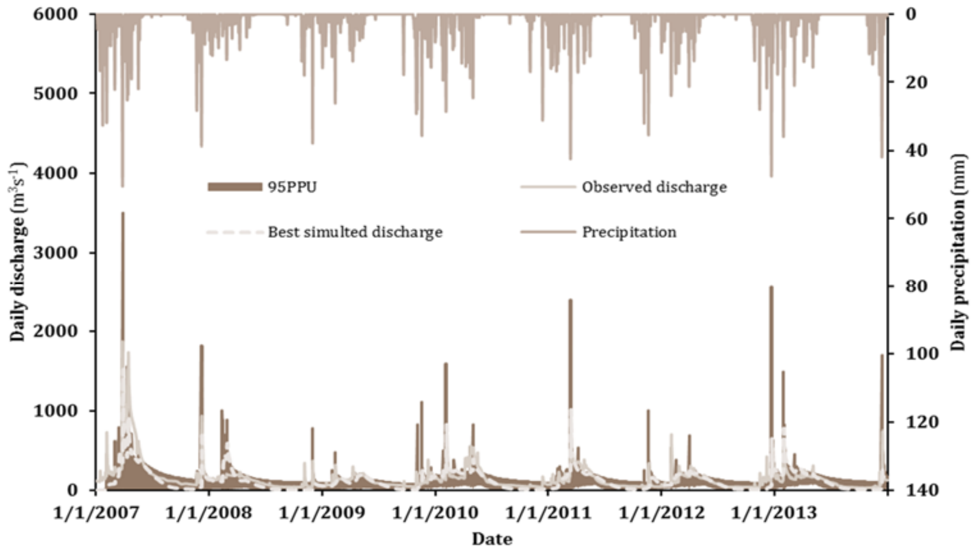

Diagram 3) Precipitation (upper) and comparison between the observed and simulated daily streamflow (lower) from 2007 to 2013 (validation period)

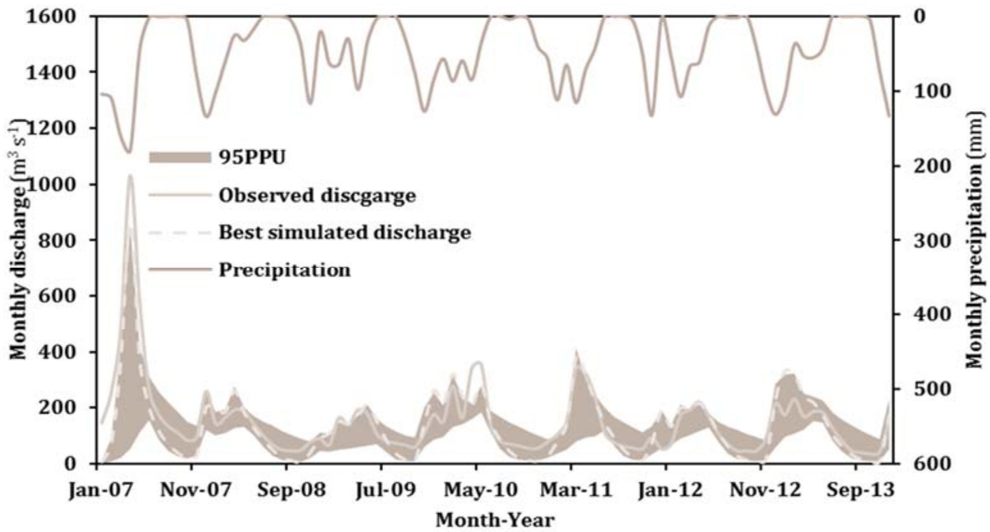

Diagram 4) Precipitation (upper) and comparison between the observed and simulated monthly streamflow (lower) from 2007 to 2013 (validation period)

Table 3) Results of calibration, validation, and uncertainty analysis

Time step and process	R^2	NSE	PBIAS	P-factor	R-factor
Monthly					
Calibration	0.84	0.83	-0.4	0.92	0.93
Validation	0.81	0.80	+9.2	0.89	0.60
Daily					
Calibration	0.62	0.62	+2.4	0.91	0.99
Validation	0.64	0.60	+22.7	0.84	1.02

Table 4) The components of flood and the FRI quantities for each year

Year	Magnitude of flood ($m^3 s^{-1}$)			Duration of flood (Day)			Number of flood			FRI		
	L.	M.	U.	L.	M.	U.	L.	M.	U.	L.	M.	U.
1989	0	1180	2754	0.0	1.8	5.0	0	4	5	0.13	0.36	1.00
1990	1624	1341	1162	1.0	2.0	2.7	1	2	4	0.34	0.40	0.43
1991	0	1137	1294	0.0	1.0	2.4	0	3	5	0.21	0.43	1.00
1992	0	1098	1244	0.0	3.1	6.0	0	7	6	0.21	0.25	1.00
1993	1264	1039	1142	1.0	3.8	4.3	1	6	9	0.19	0.27	0.50
1994	1309	1346	2365	1.0	5.4	2.2	3	8	8	0.15	0.22	0.40
1995	0	1279	1515	0.0	1.0	1.0	0	1	2	0.41	0.50	1.00
1996	0	1131	1126	0.0	1.7	2.7	0	3	7	0.26	0.41	1.00
1997	0	1160	1042	0.0	1.5	6.5	0	2	2	0.32	0.45	1.00
1998	0	1229	1461	0.0	1.7	2.5	0	3	6	0.25	0.39	1.00
1999	0	949	983	0.0	1.0	1.8	0	1	5	0.36	0.57	1.00
2000	1307	1114	1248	1.0	1.7	2.2	1	4	9	0.21	0.37	0.49
2001	1293	1872	1169	1.0	1.0	3.5	1	3	6	0.26	0.32	0.49
2002	824	1130	1164	1.0	1.8	3.8	1	5	7	0.23	0.34	0.60
2003	1420	1347	1421	1.0	1.8	2.9	2	6	8	0.2	0.28	0.43
2004	1180	1266	1550	1.0	3.0	3.8	1	3	8	0.19	0.35	0.52
2005	1473	1459	1213	2.0	7.0	5.7	1	2	6	0.21	0.26	0.42
2006	1369	1082	1465	1.5	4.3	8.3	2	4	4	0.19	0.31	0.42
2007	0	1126	1457	0.0	1.0	2.3	0	4	4	0.31	0.4	1.00
2008	0	0	889	0.0	0.0	1.0	0	0	4	0.43	1.00	1.00
2009	0	0	969	0.0	0.0	1.0	0	0	2	0.51	1.00	1.00
2010	0	894	1203	0.0	1.0	1.0	0	1	2	0.45	0.58	1.00
2011	0	1257	1475	0.0	1.0	1.5	0	1	2	0.4	0.50	1.00
2012	0	1107	2554	0.0	1.0	1.0	0	1	1	0.29	0.71	1.00
2013	0	857	1103	0.0	1.0	1.7	0	1	3	0.42	0.69	1.00
2014	0	1237	1515	0.0	1.0	1.2	0	1	2	0.45	0.55	1.00
2015	0	1245	1413	0.0	1.0	1.6	0	0	3	0.4	0.5	1.00
2016	0	1298	1565	1.0	1.0	1.1	0	1	3	0.43	0.53	1.00
2017	0	760	1050	0.0	1.0	1.0	0	1	1	0.5	0.72	1.00

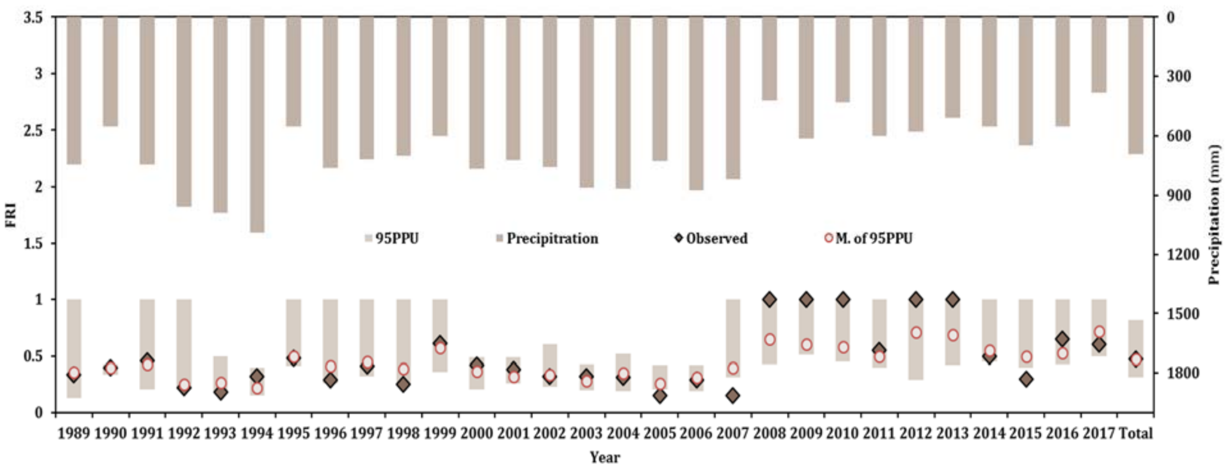

Diagram 5) Precipitation (upper) and simulated FRI 95PPU (lower)

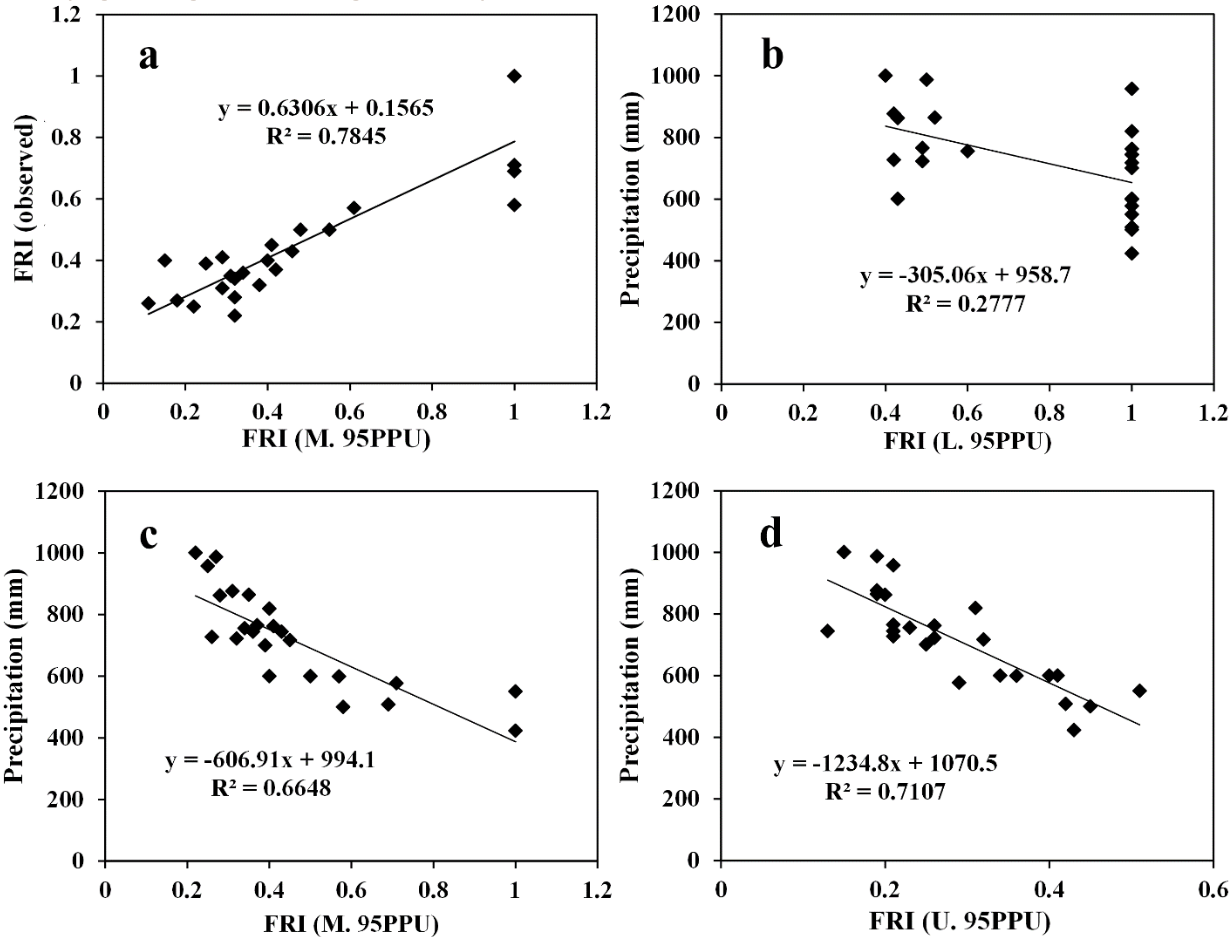

Diagram 6) (a) Correlation between observed and simulated FRI and the correlation between precipitation and (b) lower limit of FRI, (c) middle limit of FRI and (d) upper limit of FRI

SWAT uncertainty in quantifying FRI

The height of FRI 95PPU box varies in different years, indicating different uncertainties in quantifying the flood regulation ES due to changing climate variables. For example, the uncertainty in quantifying FRI for the years of 2000-2006 is lower than the one for the years 1995-1999 with smaller height of 95PPU and the nearly equal observed FRIs. The height of 95PPU box ranges from a minimum of 0.1 in 1990 to a maximum of 0.87 in 1989. The best performance of model is observed for 1990, where the height of 95PPU box is too small but captures the observed FRI. These results suggest that climate variables could severely affect the uncertainty of modeled FRI.

Impact of climate change on FRI

According to the middle of 95PPU results, the FRI quantity varies from 0.22 in the wettest year of 1994 to 0.72 in the driest year of 2017 with precipitation values of 1080mm and 380mm, respectively. The notable change in FRI values in different years results from only change in climate variables and it indicates that the delivery level of flood regulation ES could be severely affected by climate change. This also can be seen in Diagrams 6-b to 6-d, illustrating the correlation coefficients of 28, 66, and 72% between the lower, middle, and upper limits of FRI 95PPU and precipitation.

In a further analysis, the average annual FRI was also determined for the dry, average, and wet years during the simulation period (Diagram 7). According to the middle of 95PPU results, the average annual FRI was 0.66, 0.37, and 0.3 for dry, average, and wet years with the average annual precipitation of 539, 737, and 922mm, respectively. Also, the average annual FRI was 0.44 for the total simulation period with the average annual precipitation of 710mm.

FRI relative variation compared to the long-term average

Diagram 8 depicts the relative annual variation of FRI and the precipitation compared to the long-term historical average ones (FRI= 0.44 and Precipitation= 710mm/year). It can be seen that the years with a relative decrease in precipitation experience a relative increase in FRI, and on the contrary the years with a relative increase in precipitation experience a relative decrease in FRI. For example, the maximum decrease in precipitation by 46% in the driest year of 2017 led to an increase in FRI by 64%, whereas, in the wettest year of 1994, the maximum precipitation increase by 53% resulting in a decrease in FRI by 50%.

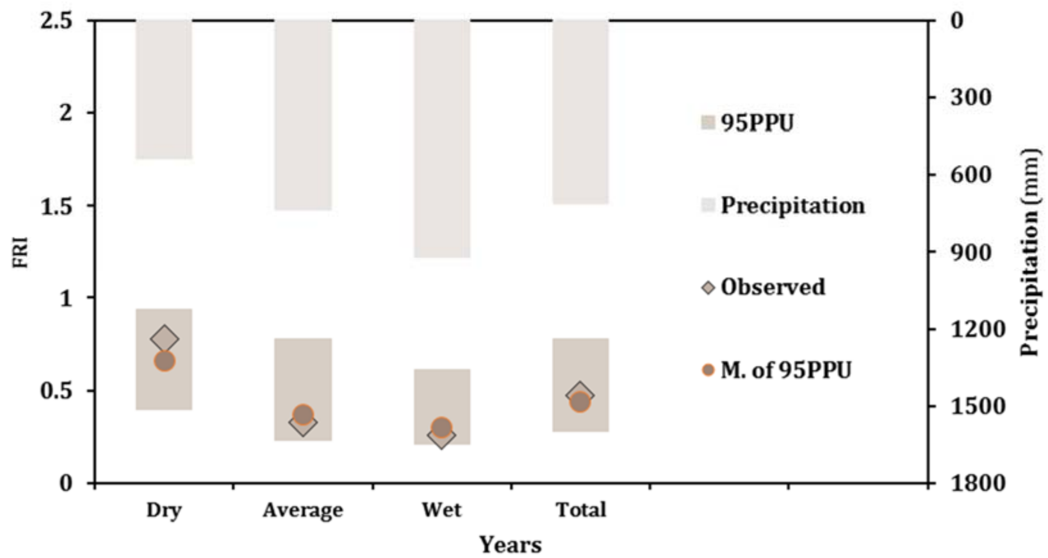

Diagram 7) The long-term annual FRI for the dry, average and wet years

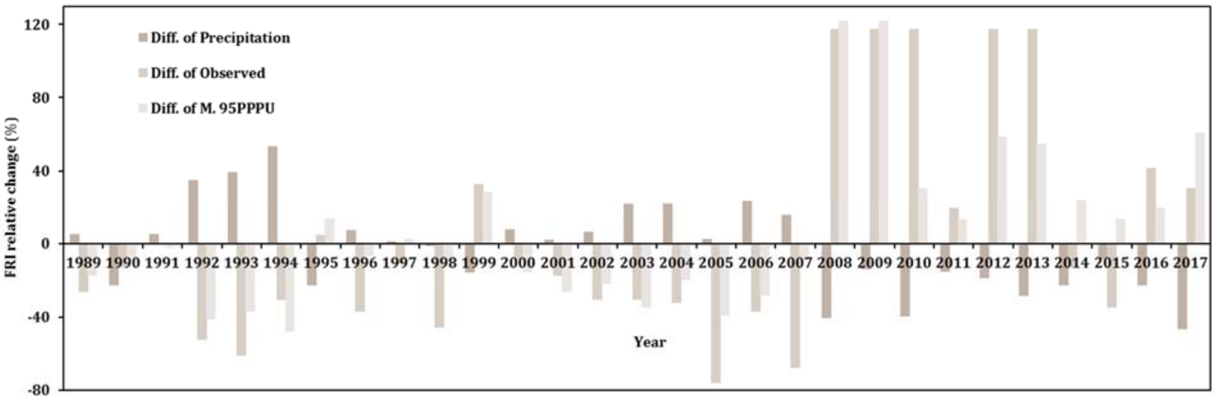

Diagram 8) Variation of precipitation and FRI quantities compared to the long-term average annual ones

Conclusion

In the present study, the SWAT model was used to quantify FRI in Dez watershed, in the west of Iran. The results of this study showed that simulated FRI 95PPU boxes bracketed most of the FRI calculated with the observed data. The outcomes also indicated that the delivery level of flood regulation ES could be severely influenced by climate change. This study could be useful for the SWAT users to address the modeling uncertainty in their future research projects and studies. Furthermore, the available knowledge on the application of SWAT model in addressing ESs can be similarly used in regions with corresponding environmental challenges of the low delivery level of regulation ESs.

Acknowledgement: The Authors would like to sincerely appreciate Dr. Zahra Asadolahi for her valuable technical support.

Ethnical Permission: The case was not declared by the authors.

Conflict of Interests: The authors state that there is no conflict of interest.

Authors' Contribution: Mohammad Sadegh Norouzi Nazar (First author), Introduction author/Methodologist/Original researcher (40%); Elaheh Asgari (Second author), Statistical analysis/Discussion author (30%); Mohammad Baaghideh, (Third author), Assistant (15%); Saeed Lotfi (Forth author), Assistant (15%)

Funding/Support: The authors would like to thank the University of Hakim Sabzevari for its financial support for the research project. Grant recipient was Dr. Mohammad Baaghideh.

References

1- Kumar P, editor. The economics of ecosystems and biodiversity: Ecological and economic foundations. Nairobi: UNEP; 2010.
2- Tang Z, Sun G, Zhang N, He J, Wu N. Impacts of land-use and climate change on ecosystem service in Eastern Tibetan Plateau, China. Sustainability. 2018;10(2):467.
3- Gathenya M, Mwangi H, Coe R, Sang J. Climate-and land use-induced risks to watershed services in the Nyando River Basin, Kenya. Exp Agric. 2011;47(2):339-56.
4- Logsdon RA, Chaubey I. A quantitative approach to evaluating ecosystem services. Ecol Model. 2013;257:57-65.
5- Francesconi W, Srinivasan R, Pérez-Miñana E, Willcock SP, Quintero M. Using the Soil and Water Assessment Tool (SWAT) to model ecosystem services: A systematic review. J Hydrol. 2016;535:625-36.
6- Asadolahi Z, Salmanmahiny A, Sakieh Y. Hyrcanian forests conservation based on ecosystem services approach. Environ Earth Sci. 2017;76(10):365.
7- Boumans R, Roman J, Altman I, Kaufman L. The Multiscale Integrated Model of Ecosystem Services (MIMES): Simulating the interactions of coupled human and natural systems. Ecosyst Serv. 2015;12:30-41.
8- Mulligan M. Trading off agriculture with nature's other benefits, spatially. In: Zolin CA, Rodrigues R, editors. Impact of climate change on water resources in agriculture. Boca Raton: CRC Press; 2015. pp. 184-204.
9- Gómez-Baggethun E, Martín-López B, Barton D, Braat L, Kelemen E, Garcia-Llorente M, et al. State-of-the-art report on integrated valuation of ecosystem services [Report]. Bellatera: EU FP7 OpenNESS Project; 2014 July. Report No.: D 4.1. Contract N.: 308428.
10- Vigerstol KL, Aukema JE. A comparison of tools for modeling freshwater ecosystem services. J Environ Manag. 2011;92(10):2403-9.
11- Arnold JG, Srinivasan R, Muttiah RS, Williams JR. Large area hydrologic modeling and assessment part I: Model development 1. J Am Water Resour Assoc. 1998;34(1):73-89.
12- Jung IW, Bae DH, Lee BJ. Possible change in Korean streamflow seasonality based on multi-model climate projections. Hydrol Process. 2013;27(7):1033-45.
13- Newton A, Brito AC, Icely JD, Derolez V, Clara I, Angus S, et al. Assessing, quantifying and valuing the ecosystem services of coastal lagoons. J Nat Conserv. 2018;44:50-65.
14- Hejazizadeh Z, Fatahi E, Massah Bavani A, Naserzadeh M. Investigating the impacts of climate changes on floods using the atmospheric circulation model (AOGCM). Geography. 2012;10(34):5-24. [Persian]
15- Kayhanpanah M, Zare Bidaki R, Bazrafshan J. Flow modelling in great Karun sub-basins in terms of future climate. Echo Hydrol. 2018;4(4):1033-47. [Persian]
16- Mockus V. Design hydrographs. In: United States. Soil Conservation Service. National engineering handbook hydrology. Washington D.C.: USDA; 1972. pp. 2-12.
17- Heber Green W, Ampt GA. Studies on soil physics, part 1, the flow of air and water through soils. J Agric Sci. 1911;4(1):1-24.
18- Ritchie JT. Model for predicting evaporation from a row crop with incomplete cover. Water Resour Res. 1972;8(5):1204-13.
19- Hargreaves GH, Samani ZA. Reference crop evapotranspiration from temperature. Appl Eng Agric. 1985;1(2):96-9.
20- Priestley CH, Taylor RJ. On the assessment of surface heat flux and evaporation using large-scale parameters. Mon Weather Rev. 1972;100(2):81-92.
21- Monteith JL. Evaporation and the environment. Symp Soc Exp Biol. 1965;19:205-34.
22- Gassman PW, Reyes MR, Green CH, Arnold JG. The soil and water assessment tool: Historical development, applications, and future research directions. Trans ASABE. 2007;50(4):1211-50.
23- earthexplorer.usgs.gov [Internet]. Reston: United States geological survey agency; 1879 [cited 2011 March 15]. Available from: https://earthexplorer.usgs.gov/
24- Schuol J, Abbaspour KC, Srinivasan R, Yang H. Estimation of freshwater availability in the West African sub-continent using the SWAT hydrologic model. J Hydrol. 2008;352(1-2):30-49.
25- Tejaswini V, Sathian KK. Calibration and validation of swat model for Kunthipuzha basin using SUFI-2 algorithm. Int J Curr Microbiol Appl Sci. 2018;7(1):2162-72.
26- Abbaspour KC, Yang J, Maximov I, Siber R, Bogner K, Mieleitner J, et al. Modelling hydrology and water quality in the pre-alpine/alpine Thur watershed using SWAT. J Hydrol. 2007;333(2-4):413-30.
27- Abbaspour KC, Rouholahnejad E, Vaghefi SR, Srinivasan R, Yang H, Kløve B. A continental-scale hydrology and water quality model for Europe: Calibration and uncertainty of a high-resolution large-scale SWAT model. J Hydrol. 2015;524:733-52.
28- Legates DR, McCabe Jr GJ. Evaluating the use of "goodness-of-fit" measures in hydrologic and hydroclimatic model validation. Water Resour Res. 1999;35(1):233-41.
29- Nash JE, Sutcliffe JV. River flow forecasting through conceptual models part I-A discussion of principles. J Hydrol. 1970;10(3):282-90.
30- Gupta HV, Sorooshian S, Yapo PO. Status of automatic calibration for hydrologic models: Comparison with multilevel expert calibration. J Hydrol Eng. 1999;4(2):135-43.
31- Moriasi DN, Arnold JG, Van Liew MW, Bingner RL, Harmel RD, Veith TL. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Trans ASABE. 2007;50(3):885-900.
32- Akhavan S, Abedi-Koupai J, Mousavi SF, Afyuni M, Eslamian SS, Abbaspour KC. Application of SWAT model to investigate nitrate leaching in Hamadan-Bahar Watershed, Iran. Agric Ecosyst Environ. 2010;139(4):675-88.
33- Amini MA, Torkan G, Eslamian E, Zareian MJ, Besalatpour AA. Assessment of SWAT hydrological model in catchments' water balance simulation located in semi-arid regions (case study: Zayandeh-Rud River Basin). J Water Soil. 2018;32(5):849-63. [Persian]
34- Mahzari S, Kiani F, Azimi M, Khormali F. Using SWAT model to determine runoff, sediment yield and nitrate loss in gorganrood watershed, Iran. ECOPERSIA. 2016;4(2):1359-77.
35- Hosseini M, Ghafouri M, Tabatabaei M, Ebrahimi N, Zare Garizi A. Estimation of hydrologic budget for Gharasou Watershed, Iran. ECOPERSIA. 2016;4(3):1455-69.