



Determining the spatial contributions of land use changes on the streamflow and sediment transport regimes: a case study of the Gorganroud watershed in Iran

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Abstract

Human activities and climate change are recognized as two of the most important drivers of hydrologic variability and have attracted the interest of researchers over the past decade. Changes in land use, dam construction, agricultural development, and global warming are forces that directly or indirectly impact the global and local hydrologic regime. This study examines the effects of these drivers on streamflow and sediment transport in the Gorganroud watershed, located in the north of Iran. In addition, the most sensitive land use patterns are detected using statistical approaches and a hydrologic model. The current study's principal argument is based on the variability of land use patterns during the modeling procedure (2007–2019). The Soil and Water Assessment Tool (SWAT) model is used to consider the land use dynamics during the simulation period based on the hydrological regime of the reference period. The Simple Differential Method (SDM) and Climate Elasticity Method (CEM) are utilized to estimate the contribution rates of land use and climate change in streamflow and sediment transport changes. The results indicate that changes in land use have contributed more than 60% to streamflow and sediment regime changes in all subbasins. A sensitivity analysis of land uses and the spatial distribution of the Human Contribution Rate (HCR) over the study area reveal that an increase in orchard land use (8.7% during the computational period) is primarily responsible for these significant changes.

Keywords Human activities · Land use change · Climate change · SWAT · Gorganroud watershed · Simple Differential Method · Climate Elasticity Method

Introduction

As a multiscale phenomenon, climate change has caused various changes in global, regional, and local hydrologic regimes and has altered ecosystems consistently and systematically. Enviro-climate variables such as temperature, precipitation, wind speed, relative humidity, and solar radiation determine the interaction of hydrologic components and

how they are affected by these changes. River discharges and sediment yields are among the variables susceptible to climate variables (Ashrafi et al. 2022a, b; Naz et al. 2018; Nilawar and Waikar 2019; Zhao et al. 2019). In addition, certain human activities on the land surface cause direct disturbances. Changes in land use, deforestation, dam constructions, and water transfers directly affect hydrologic components, particularly river discharge and sediment transport (Hendriks et al. 2020; Tjiedeman et al. 2018; Yan et al. 2018). Therefore, human activities and climate change are two major drivers of hydrologic behavior. In some cases, these drivers occur simultaneously but with different intensities.

Three different analytical approaches have been used in the literature to analyze the causes and impacts of hydrological variabilities changes, including direct/indirect human activities. In the first approach, researchers compare the hydrological regime of a watershed with other watersheds in which climate is the major driver (Serieyssel et al. 2009; Déry et al. 2009; Wang et al. 2017; Putnam and Broecker

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2017; Dinpashoh et al. 2019; Hidalgo et al. 2009; Kirchmeier-Young et al. 2019; Vogel et al. 2019). In the second approach, the research focuses on identifying land use changes as the major human activities that have the greatest impact on hydrologic variability changes. Therefore, an important presumption is that other human activities, such as farming or dam construction, have little to no effect on hydrological responses (Bai et al. 2018; Dudley et al. 2020; Jodar-Abellan et al. 2019; Llana et al. 2019; Melland et al. 2018; Wang et al. 2018; Yang and Lu 2018; Zhao et al. 2020).

In some cases, there is no comparable watershed, and different human activities likely cause hydrological change; thus, a more detailed and accurate approach is required. Consequently, the third approach is aimed at separating the contributions of the climate and direct human activities (Zhang and Lu 2009; Modaresi et al. 2010; Li et al. 2020; Zeng et al. 2020; Ziyang et al. 2020). This approach is based on the assumption that the computational period consists of two subperiods. In the first or reference period, the climate is the significant driving force. In the second or antecedent period, climate and direct human activities are significant driving forces that substantially impact the hydrologic procedure.

Different hydrological models have been used to determine the interaction of climatic and hydrologic conditions in the literature. Yan et al. (2013) employed the coupled Soil and Water Assessment Tool (SWAT) model and Partial Least Square (PLS) to quantify the contribution of each land use change in streamflow and sediment transport in the Upper Du watershed in China. The most significant land use change occurred in farmlands, forests, and urban areas. They reported that the SWAT model performed adequately. According to the findings, farmlands and forests were primarily accountable for dramatic hydrologic changes.

Zeng et al. (2015) used SWAT and SIMHYD models to assess the contribution of human and climate change on the variation of streamflow of the Luan River basin in China. They noted that both models performed well and that the contribution of human activities is significantly greater than that of climatic forcings. Haleem et al. (2022) used the SWAT model to simulate the interaction of climate variables and streamflow in Upper Indus Basin in Pakistan. The results indicated that climate change had contributed more than direct human interventions to sudden streamflow disturbances, and both drivers increased the streamflow. They also projected future climate and land use to simulate future changes in streamflow.

Different methods, including Simple Differential Method (SDM) (Zhang and Lu 2009; Bao et al. 2012; Zheng et al. 2019; Huang et al. 2020), the Fixing and Changing Method (FCM) (Wang et al. 2009; Farsi and Mahjouri 2019; Zhang et al. 2020), and the Climate Elasticity Method (CEM) (Liu

et al. 2017; Xin et al. 2019; Xin et al. 2019; Zhang et al. 2020) have been proposed in the literature to estimate the contribution of hydrologic drivers.

Zhang and Lu (2009) analyzed the streamflow and sediment yield changes in the Luodingjiang River. They utilized statistical techniques to determine the year of change in their recorded time series. The observed time series breaks into two subperiods considering the detected change point. The hydrologic behavior in the second period was projected using the detected relationship between hydrologic and climate components in the reference period. Using a simple comparison, the relative contribution of climate and direct human activities was estimated.

The FCM is another method proposed by Zhang (2004) to calculate the contributions of the mentioned drivers. Due to the necessity of calibrating hydrologic models for the reference and antecedent periods, the FCM requires more computational resources than the SDM (for more information, please see Wang et al. (2009)). Unlike SDM and FCM, CEM can estimate drivers' contribution rates without using a hydrologic model. This method assumes that the desired hydrologic variable is a function of climate and human activities.

In numerous watersheds around the globe, it is evident that both climate change and direct human intervention are concurrently occurring. Consequently, it is necessary to develop reliable frameworks for evaluating the simultaneous effects of both drivers. The change point determination that does not account for human activities in previous research appears to be a significant shortcoming. In other words, human activities in a basin must be considered to confirm the change points that have been detected. A more precise approach must be carefully considered to assign a change point in these kinds of environmental studies.

Moreover, previous studies failed to refer to land use dynamics during the reference period. In this period, land use dynamics could substantially affect the calibration of the hydrological model. Thus, the impact of land use changes in the study area is considered spatiotemporally in the current study. Based on the points above, the objectives of the present study are as follows:

- Investigating the probable change point of streamflow throughout the study area,
- Semidistributed simulation of streamflow and sediment yield in different subbasins
- Estimation of the relative contribution of climate/land use change on the streamflow
- Detection of the most influential land use type on streamflow changes

The remainder of this paper is organized as follows. “Materials and methods” introduces the study area,

materials, and methods. “[Determining the contribution rates](#)” presents a flowchart of the developed framework and introduces various parts of the proposed methodology. “[Modeling and results](#)” and “[Discussion](#)” present and discuss the results of the developed framework. Finally, the paper is concluded in “[Conclusion](#).”

Materials and methods

Study area

Gorganroud watershed is one of the second-level watersheds in the east north of Iran located between latitudes 36° 30' and 37° 50' and longitudes 54° 5' and 56° 30'. Gorganroud River originates from the northeastern part of the Alborz Mountains and reaches the Caspian Sea after traveling about 300 km with a drainage area of 11,889 km². According to the Digital Elevation Model (DEM) of STRM (<https://srtm.cgiar.org/>), the elevation of the watershed considerably varies from the southern and southeastern parts of the watershed (with at a high altitude of about 1000 to 2500 m AMSL) to the western part (with a low altitude of about 30 m AMSL) at the watershed outlet.

According to Kottek et al. (2006), its climate is mainly semiarid. Historical frequented flood events, land use changes, deforestation, and climate change and their effects on the hydrological process in this watershed are discussed in various studies (Safaripour et al. 2012; Hajibigloo et al. 2017; Karami Jozani et al. 2019; Arabameri et al. 2020; Moradi 2020; Akbari and Rahimi 2021).

The study area of the current research was the headwaters of the Gorganroud watershed, extended to the latitude of 36° 57' and longitude of 55° 17' with an area of approximately 5100 km². According to the Food and Agriculture Organization of the United Nations (FAO) (<https://www.fao.org>), the study area’s dominant soil is I-Rc-Yk-c, comprising

calic soil. The variation of minimum, maximum, and average streamflow and rainfall over the study area is shown in Fig. 1. As can be seen, about 70% of both precipitation and streamflow occur in winter and spring. Three rivers known as Gorganroud River (the main branch which passes the Tamer station), Dough River (which passes Pole-Kouseh station), and Ghareh-Shour River (which passes the Ghareh-Shour station) are located in the study area (Fig. 2). In addition, two reservoirs, Golestan and Boostan, with normal volumes of 47.73 and 29.02 mcm, are present in the study area.

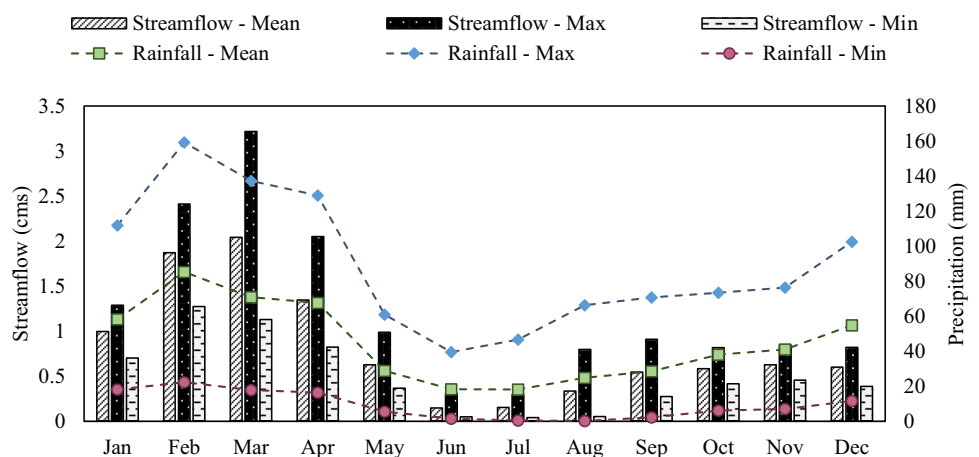
Ground information

Locations of reservoirs and meteorological, climatological, and hydrometric stations are depicted in Fig. 2. Four meteorological variables, including relative humidity (RH), wind speed (WS), maximum and minimum temperature (Tmax, Tmin), and solar radiation (SR), were collected from Iran Meteorological Organization (IRIMO) (www.irimo.ir). In addition, precipitation data from 2007 to 2019 were obtained from Iran Water Resources Management Company (www.wrm.ir). Table S1 of the supplementary materials provides climate data statistics.

Land use information

The Moderate Resolution Imaging Spectroradiometer (MODIS) Land Cover Type Product (MCD12Q1) was used to extract historical land use patterns (Sulla-Menashe and Friedl 2018). This product contains global annual land use images with a resolution of 500 m, obtained by supervised classification of MODIS Terra and Aqua reflectance data. Using a system established by the International Geosphere-Biosphere Program (IGBP), the MCD12Q1 product can locate the geographic distribution of 17 different land cover classes. Figure 3 shows the spatiotemporal variations of land use/land covers (LULC) in various stations of the study area.

Fig. 1 The variation of maximum, minimum, and average of streamflow and precipitation over the watershed



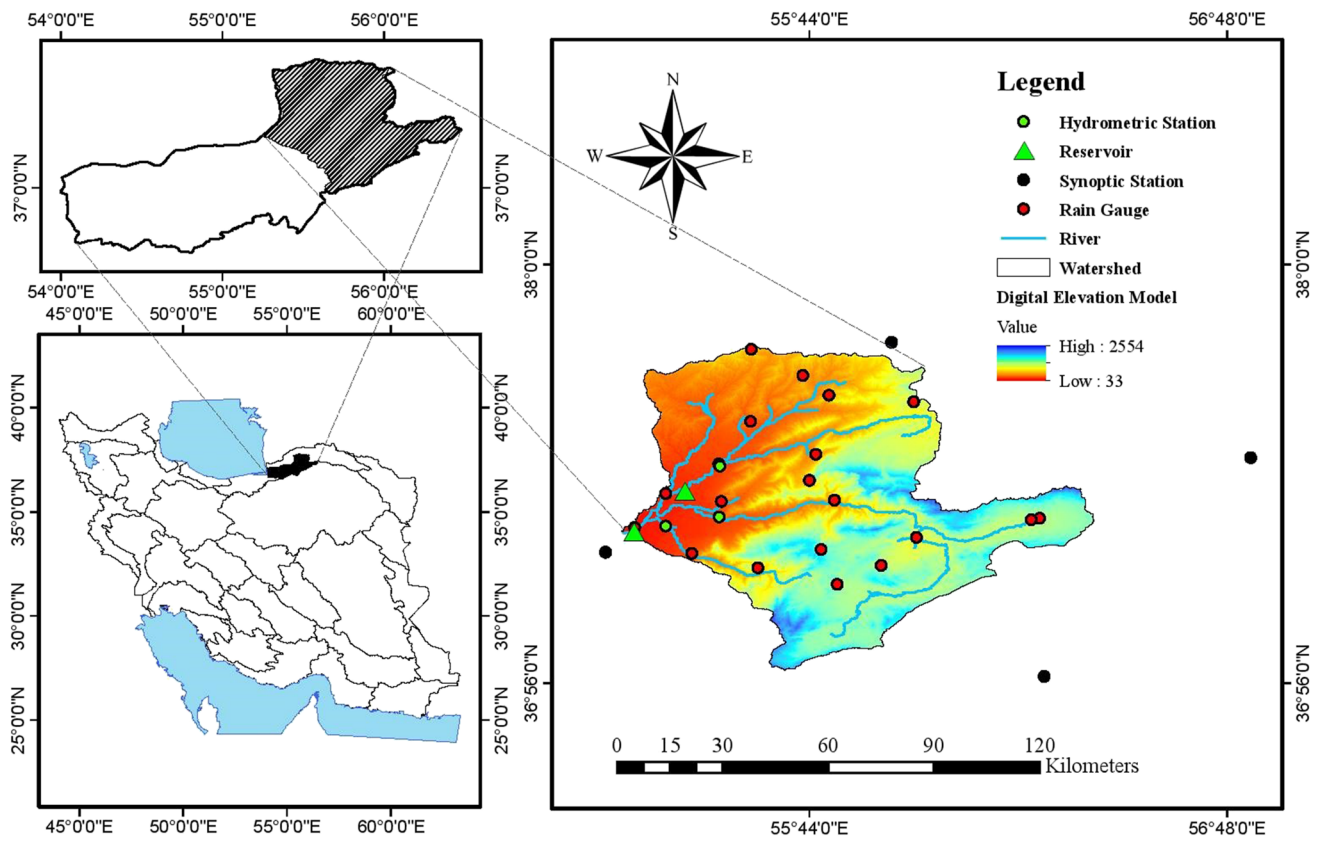


Fig. 2 Location of watershed of interest, its climatological, and hydrometric networks

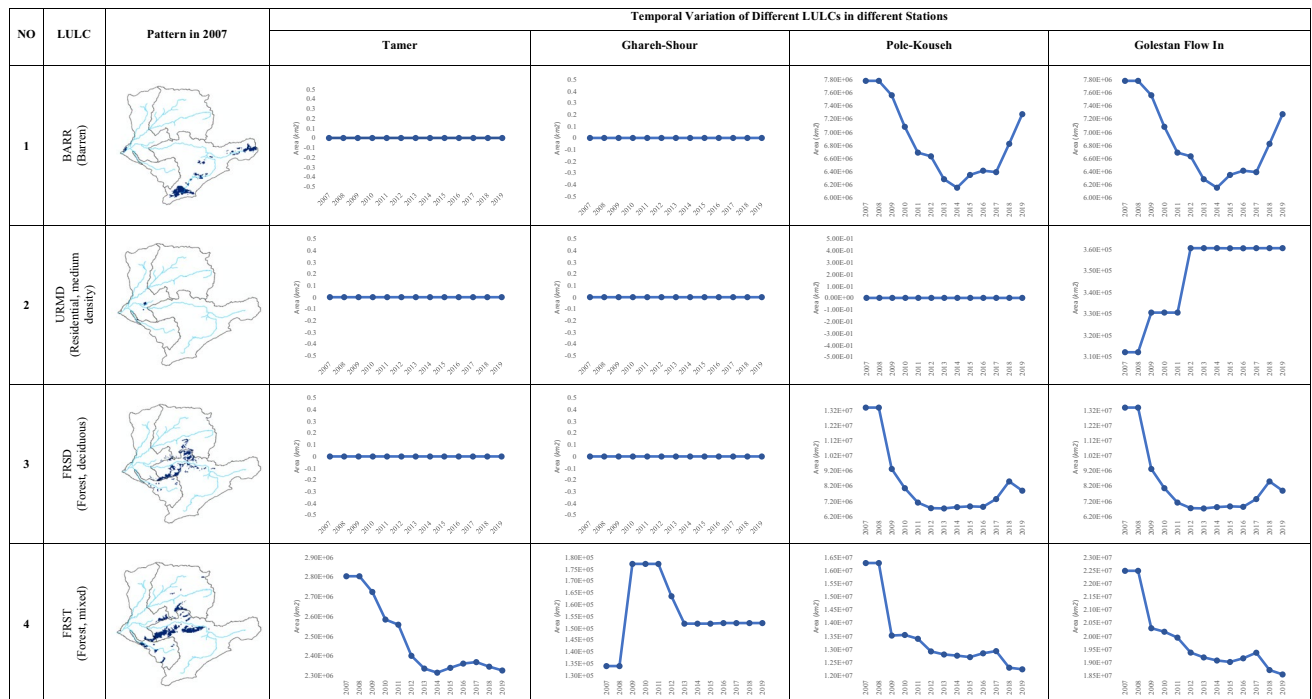


Fig. 3 Spatial and temporal variation of LULCs in different stations

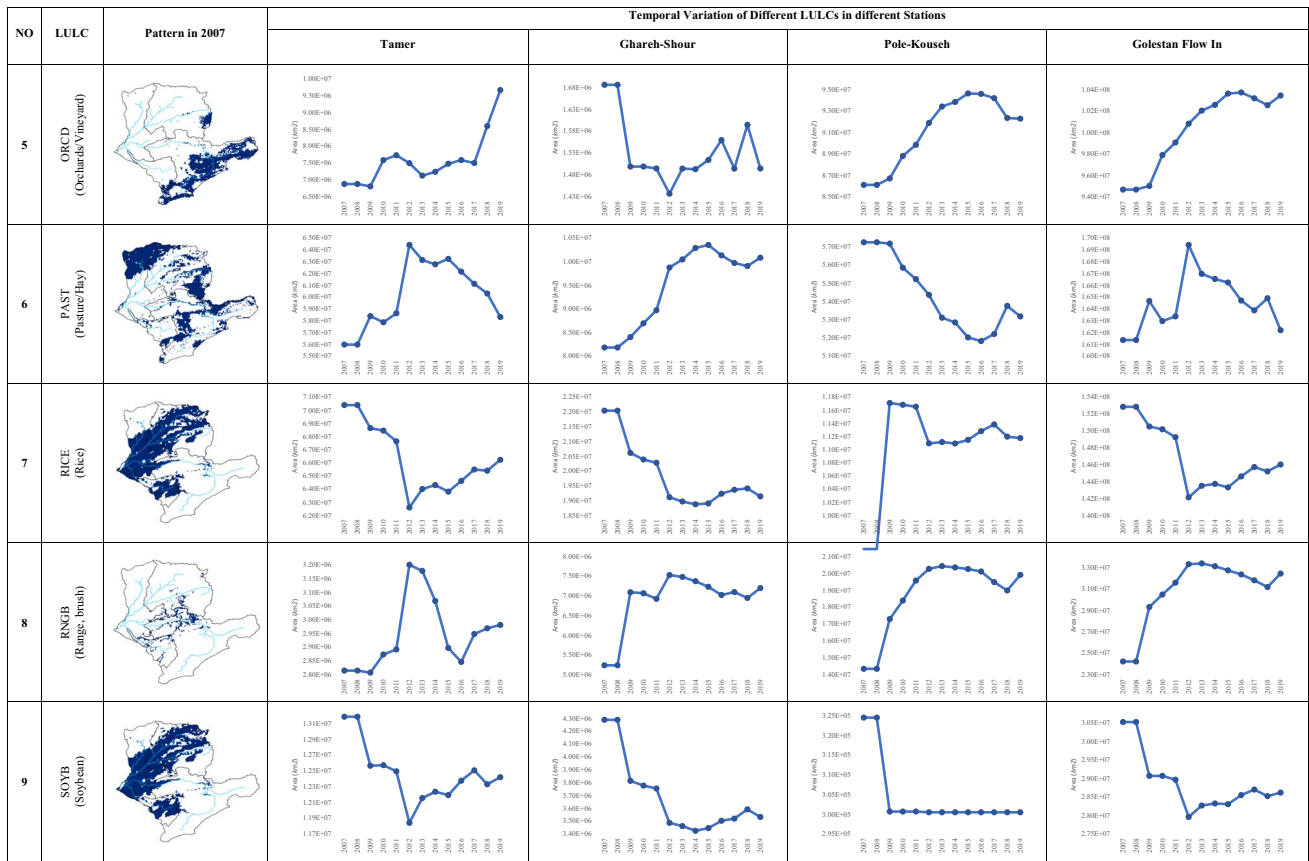


Fig. 3 (continued)

Based on this figure, nine distinct land uses were identified within the watershed: BARR (barren), URMD (residential-medium density), FRSD (forest-deciduous), FRST (forest-mixed), ORCD (orchard), PAST (pasture), RICE (rice), RNGB (range-brush), and SOYB (soybean) (soybean).

Soil and Water Assessment Tool (SWAT)

The SWAT was used to model the watershed hydrology via conceptual and semidistributed methods (Neitsch et al. 2011). Due to the model’s appropriate conceptual framework for simulating streamflow and sediment regimes (simultaneously), numerous studies have been conducted utilizing the SWAT capabilities worldwide. SWAT’s comprehensive capacity to implement dynamic land use and management practices on a watershed scale is the model’s most significant advantage over other hydrological models (Zhang et al. 2016; Haleem et al. 2022) (please see the literature review of SWAT applications at https://www.card.iastate.edu/swat_articles/). Hydrologic Response Units (HRUs) are delineated based on the unique combination of land use, soil types, and slope to simulate the hydrological components’ behavior

in the SWAT (Arnold et al. 1998; Yan et al. 2013). Then, a water balance equation is performed in each HRU, and hydrological components are calculated utilizing the weighted average method based on the area of each HRU within each subbasin (Neitsch et al. 2011). Equation 1 demonstrates the water balance relationship and its components, which are utilized in SWAT:

$$SW_t = SW_0 + \sum_{i=1}^t (P_i - ET_i - Q_{i,seep} - Q_{i,surf} - Q_{i,gw}) \quad (1)$$

where SW_t denotes soil moisture (mm) at time t , SW_0 represents initial soil moisture (mm), i is the temporal indicator, P_i denotes precipitation (mm), ET_i is evapotranspiration (mm), $Q_{i,seep}$ represents water percolation (mm), $Q_{i,surf}$ denotes surface runoff (mm), and $Q_{i,gw}$ is groundwater return flow (mm).

The SWAT model was set up to simulate streamflow and sediment regimes in the upstream of the Boustan Dam in the Gorganroud watershed. In the first modeling step, 46 subwatersheds were delineated based on the DEM of the watershed. A soil map was fed to the model to define the basins’ soil properties. Furthermore, MCD12Q1 products were utilized from 2007 to 2018 to conduct the

hydrological model. The lack of data necessitated that the modeling start year was set as 2007, so the land use map of 2007 was used as the base map, and the remaining maps were processed to be used in the “lup.dat” add-in to consider land use dynamics.

During the final step of the hydrological model, 453 HRUs were extracted from land use, soil, and slope maps of the watershed. After HRU calculation, climate data from four synoptic stations, including maximum and minimum temperatures, wind speed, solar radiation, and humidity, were added to the model. The final step provided data on crop management operations, dam geometries/operations, land use update data, and pothole information. Since the initial assumption regarding depression areas in rice paddies was disproved, the source code was modified so that the pothole area was considered the same for all water levels (please see further information on modeling section of the SWAT in Neitsch et al. 2011).

SWAT Calibration and Uncertainty Programs (SWAT-CUP) was used to calibrate the SWAT model. It can calibrate and validate the assembled hydrology model using numerous algorithms, including SUFI-2, Particle Swarm Optimization (PSO), Generalized Likelihood Uncertainty Estimation (GLUE), ParaSol, and Markov Chain Monte Carlo (MCMC) (Abbaspour 2015). In the current article, the SUFI-2 algorithm was selected to determine the optimal model and parameter performance. The most relative and sensitive parameters to both water yield and sediment yield were obtained from Neitsch et al. (2011) and related studies in the same study area (Salmani et al. 2012; Mahzari 2014; Moradi et al. 2018).

Statistical evaluation

Four statistics, including Nash–Sutcliffe (NSE) (Nash and Sutcliffe 1970), Kling–Gupta Efficiency (KGE) (Gupta et al. 2009), Root Mean Square Error (RMSE), and Correlation Coefficient (CC), were used to evaluate the model performance. Equations 2–5 show their formulations, respectively.

$$NSE = 1 - \left[\frac{\sum_{i=1}^n (Q_i^{obs} - Q_i^{sim})^2}{\sum_{i=1}^n (Q_i^{obs} - \bar{Q}_{obs})^2} \right] \quad (2)$$

$$KGE = 1 - \sqrt{(CC - 1)^2 + \left(\frac{\sigma_{sim}}{\sigma_{obs}} - 1\right)^2 + \left(\frac{\mu_{sim}}{\mu_{obs}} - 1\right)^2} \quad (3)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (Q_i^{obs} - Q_i^{sim})^2}{n}} \quad (4)$$

$$CC = \frac{\sum_{i=1}^n (Q_i^{sim} - \bar{Q}_i^{sim})(Q_i^{obs} - \bar{Q}_i^{obs})}{\sqrt{\sum_{i=1}^n (Q_i^{sim} - \bar{Q}_i^{sim})^2 \sum_{i=1}^n (Q_i^{obs} - \bar{Q}_i^{obs})^2}} \quad (5)$$

where Q denotes the hydrologic variable of interest, CC represents the linear correlation coefficient between observed (obs) and simulated (sim) values, n is the number of samples, and σ and μ denote the standard deviation and mean of the parameter of interest, respectively.

NSE and KGE vary between $[-\infty, 1]$, with the greater value indicating a more accurate simulation. Consequently, the optimal values of NSE and KGE are 1. The negative value of NSE shows the model’s poor performance, and its acceptable value must be higher than 0.5 (Moriassi et al. 2007). KGE differs slightly from NSE in that it may be negative but have greater accuracy than the mean of the observations. In other words, according to Knoben et al. (2019), the KGE value of -0.41 indicates that the model has the same accuracy as the mean of the observations, and higher values will make the model more accurate than the mean.

The KGE values between 0.5 and 0.74 indicate a suitable simulation, while values above 0.75 suggest an excellent simulation (Towner et al. 2019). CC is a similarity metric that shows how closely the simulation matches the observed trend. It returns values between $[-1, 1]$. The absolute value indicates the power, while the sign indicates their relationship type. Consequently, a value of -1 indicates a strong indirect linear relationship, a value of 0 indicates no linear relationship, and a value of 1 indicates a strong direct linear relationship between simulation and observation, so a greater value of CC indicates a more accurate simulation. Except for RMSE, all the metrics are nondimensional values. RMSE, which represents a model error, has the same dimensions as the variable of interest.

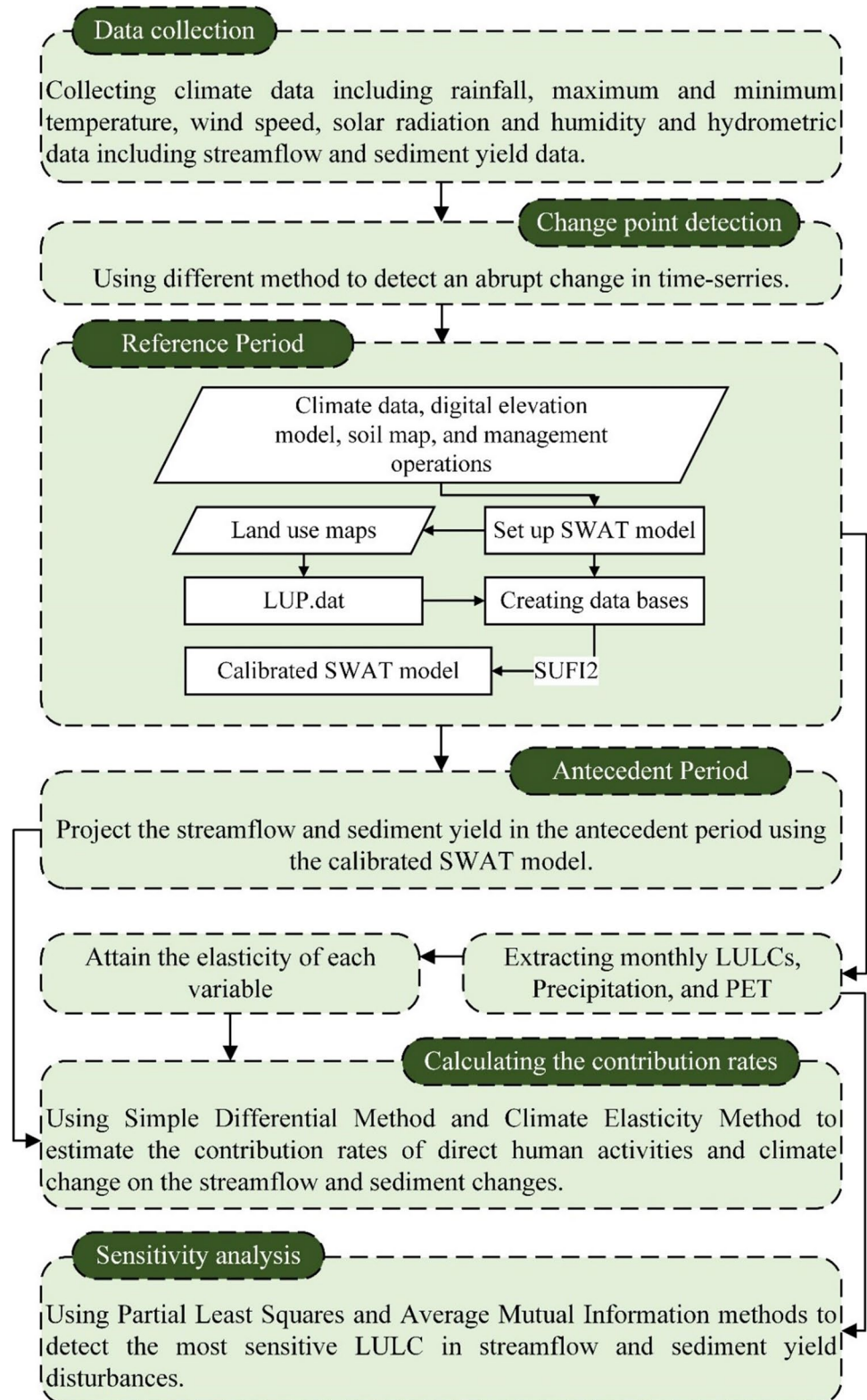
Determining the contribution rates

The combination of statistical and modeling methods was used to calculate the contribution rates of human and climate alternations in streamflow and sediment values. Initially, a change point was determined using various statistical techniques to identify the start of the affected period. Determining the beginning of the affected period informs the modeler of the year in which human activities altered the hydrologic regime. The current study utilized the SWAT model to determine the hydroclimatic procedure and simulate the affected period if no additional development load were present. The model’s result for the affected period was compared to the observed and calculated values to determine the contribution rates. The Climate Elasticity

Method was also used to validate the results of the preceding method. In addition, statistical methods were employed to identify the most sensitive land uses. The

methods mentioned above are briefly explained below. Figure 4 depicts the proposed research procedure used in the current study.

Fig. 4 Proposed flow diagram of the modeling procedure and steps in the current steps



Change point detection

A temporal change point is a point in time (year, month, and day) when the behavior of a time series changes considerably. The literature assumes that a change point signifies the beginning of a new period in which climate and direct human activities influenced hydrology significantly. Change point detection methods identify abrupt changes based on a variety of criteria. They are sensitive to abrupt changes in the mean, the trend, and the standard deviation. Other methods employ hybrid statistical metrics, such as standard deviation and mean to capture sudden changes or trends in a time series. In the present study, four distinct change point detection methods, including the Pettitt test (Pettitt 1979), ordinary clustering (Ping and Yong 2005), Standard Normal Homogeneity Test (Marcolini et al. 2017), and the Bernaola-Galvan Clustering test (Bernaola-Galvan et al. 2001), have been used to determine change point year in the recorded discharges of all hydrometric stations.

In the Pettitt test, input data are divided into two sections and compared to determine if they have the same distribution. This method is prevalent in the literature for determining the shift position of hydrologic time series (Zhang and Lu 2009; Gao et al. 2016; Shahid et al. 2018). The ordinary clustering method detects sudden shifts in the mean value, similar to the Pettitt test, using a different formula. Although these methods only consider mean shifts, human activities could also impose changes on the standard deviation. The standard normal homogeneity test (Ho Ming and Yusof 2012; Marcolini et al. 2017) and Bernaola-Galvan clustering (Bernaola-Galvan et al. 2001) methods break the time series for each element and define a new statistic which brings into play both the mean and standard deviation (please see the supplementary materials for more information about implemented methods and their corresponding formula).

Contribution analysis

Two distinct methods for estimating the contribution rates of various drivers are presented below.

Simple Differential Method (SDM)

After detecting a change point, the selected hydrologic model (physically based, conceptual, or black box model) should be calibrated and validated during the reference period to understand the relationship between climate and hydrology. In this situation, the model could be used to determine the hydrologic state during the affected period if there were no human activities. Due to the prominence of

human activities in the affected period, model simulation and observational differences in the second (affected) period are attributed to human activities. If $Q_{sim,p1}$ is the mean of the hydrologic variable for the first (reference) period, $Q_{sim,p2}$ represents the mean of the simulated variable for the affected period, and $Q_{obs,p1}$ is the mean of the observations for the reference period, then the relative contribution of human and climate change can be calculated as follows:

$$\Delta Q_{Climate} = Q_{sim,p2} - Q_{sim,p1} \quad (6)$$

$$\Delta Q_{Human} = Q_{sim,p2} - Q_{obs,p2} \quad (7)$$

$$CR_{Climate} = \frac{\Delta Q_{Climate}}{\Delta Q_{Climate} + \Delta Q_{Human}} \times 100 \quad (8)$$

$$CR_{Human} = \frac{\Delta Q_{Human}}{\Delta Q_{Climate} + \Delta Q_{Human}} \times 100 \quad (9)$$

where $\Delta Q_{Climate}$ denotes the changes in the hydrologic variable by climate, ΔQ_{Human} represents the changes by humans, $CR_{Climate}$ is the contribution rate of climate activities, and CR_{Human} is the contribution rate of human activities. After calibrating the SWAT model in the reference period and simulating it in the affected period, this study used SDM for contribution analysis to calculate the relative contribution of climate change and human activities.

Climate Elasticity Method (CEM)

Climate elasticity is a conceptual approach introduced by Schaake (1990) to measure the most sensitive climatic variable in changing streamflow. In this method, it is assumed that the streamflow is a function of climate and human activities as follows:

$$Q = f(\text{climate}, \text{human}) \quad (10)$$

Precipitation (P) and potential evapotranspiration (PET) could be utilized to evaluate the climate effect. Because the potential evapotranspiration embeds most environmental forcing factors (such as temperature, wind speed, solar radiation, and relative humidity), it is deemed a good indicator of climate variabilities. Changes in the LULC area could be suitable for incorporating human activities (V). To this end, Eq. 11 could be rewritten as follows:

$$Q = f(P, PET, V) \quad (11)$$

Consequently, changes in hydrologic variable of interest can be estimated via Eq. 12 based on relative changes of independent variables:

$$\Delta Q = f'_p \Delta P + f'_{PET} \Delta PET + f'_V \Delta V \tag{12}$$

where f'_p , f'_{PET} , and f'_V are the first derivatives of climate concerning precipitation, potential evapotranspiration, and LULC area, respectively. Using the elasticity definition, Eq. 13 is expressed as follows:

$$\Delta Q = \left(\varepsilon_P \frac{\Delta P}{P} + \varepsilon_{PET} \frac{\Delta PET}{PET} + \varepsilon_V \frac{\Delta V}{V} \right) \tag{13}$$

where ε denotes the elasticity of the variable. The first, second, and third terms in Eq. 13 represent the changes in hydrologic variables due to changes in precipitation, potential evapotranspiration, and human activities, respectively. Thus, the sum of the first and second terms can be used to estimate the relative changes caused by climate dynamics, and the contributions of each driver can be calculated.

Sensitivity analysis of LULC

Using statistical methods, a sensitivity analysis of various land uses was conducted to identify more effective LULC for changing streamflow and sediment regimes. This section briefly presents two sensitivity analysis methods used in this research.

Partial Least Squares (PLS)

PLS is a way to apply a linear model within a set of dependent and independent variable(s). The current research determined the sensitive LULCs for streamflow and sediment yield by applying PLS. PLS is used when the number of observations is small or independent variables are colinear. It decomposes both variables and searches for the optimal regression model, which yields the optimal outcome with the fewest components. In addition, Variable Importance for Projection (VIP) is a useful metric that can be calculated in the PLS procedure (Abdi and Williams 2013; Farrés et al. 2015; Ng 2013; Sengupta et al. 2015) and assists researchers in determining whether an independent variable is significant or not. With a greater value of VIP, the corresponding variable carries information that is more valuable.

Average Mutual Information (AMI)

The AMI index is a measure of the mutual dependency and relation between variables, widely used in different studies (Asghari and Nasserri 2014; Wallot and Mønster 2018). It has two significant advantages over PLS: filtering before modeling and capturing nonlinear relationships. If X and Y are two random variables, then the amount of information they provide about one another is referred to as the AMI and is calculated per Eq. 14:

$$I(Y;X) = H(Y) - H(Y|X) = - \sum_{y \in Y} p(y) \log(p(y)) + \sum_{x \in X} \sum_{y \in Y} p(y, x) \log_2(p(y|x)) \tag{14}$$

where $H(Y)$ denotes the entropy of Y and $H(Y|X)$ is the conditional entropy and is calculated via Eqs. 15 and 16:

$$H(Y) = - \sum_{y \in Y} p(y) \log(p(y)) \tag{15}$$

$$H(Y|X) = - \sum_{x \in X} \sum_{y \in Y} p(y, x) \log_2(p(y|x)) \tag{16}$$

If X and Y are independent, then the AMI would be zero.

Modeling and results

The proposed research methodology evaluates the contribution of human activities and climate variability to changes in flow and sediment based on Fig. 4. The subsequent sections detail the modeling procedure and its results.

Detection of change points

During the first step, change points of the recorded hydrometric values were determined using data from various hydrometric stations and approaches. Table S2 (in the supplementary materials) displays the outcomes of the methods used to detect the change points for all hydrometric stations in the basin. The recorded values indicated that all stations experienced an abrupt change confirming the streamflow alteration by human activities. It is preferable to focus on upstream stations when determining a break because human activities at the upstream will affect downstream areas. According to the findings, change points are roughly concentrated around 1965 and 2013/2014, with a greater emphasis on the latter. As a result, the second change point was chosen for further consideration. Consequently, the historical period was divided into the reference (before 2014) and the affected (from 2014 to 2018).

Hydrological modeling and results

The study area’s streamflow and sediment yield were simulated using the SWAT model. Two-thirds of the observed hydrological time series were used to calibrate the SWAT model, and the remaining part was utilized to validate the modeling process. The calibration step attempted to select stations located on each river with larger drainage areas in the watershed. Finally, the northeastern section was

calibrated using observed, recorded values at Tamer station (code 12–005); the eastern and southeastern sections were calibrated using observations at Pole-Kouseh station (code 12–003); the southwestern section was calibrated using observed streamflow values at Ghareh-Shour station (code 12–076); and some remaining subwatersheds were calibrated using Golestan Dam inflow values.

Optimized values of the selected parameters are reported in Table S3. As shown, several parameters are considered global, including SMFMX, SMTMP, SMFMN, SFTMP, and TIMP. These parameters have the same values in all subwatersheds. However, the rest of the parameters are spatially distributed and possess different values in each subbasin. Global and local parameters are important considerations when calibrating a watershed, which includes subbasins with varying hydrological characteristics, as in the current case. Tamer station, for example, has seen less CN2 decline, indicating that the subbasin has more potential to generate runoff. The ESCO parameter, which ranges from 0.01 to 1, is another example introduced for each HRU and controls the rate of evaporation from the soil surface. Evaporation in HRU increases as ESCO decreases. Therefore, it can be inferred that more effort was expended during the calibration to reduce the evaporation rate in the Tamer subbasin

than in other subbasins. Figure 5 compares the simulated flow and sediment diagrams to the relevant observations during two calibration and validation periods. The vertical dashed line separates the calibration and validation periods.

Figure 5 shows the monthly simulated streamflow and sediment (for both calibration and validation periods) at the Tamer, Ghareh-Shour, and Pole-Kouseh stations and the upstream station of Golestan Dam. Although the streamflow at Tamer station is simulated well during wet seasons, the model's performance during dry seasons is poor. In dry seasons, the model overestimates the streamflow; consequently, the same issue exists with the simulated sediment discharge. The simulated flow at the Ghareh-Shour station followed the trend more accurately than the simulated sediment discharge, which was underestimated. SWAT uses various sediment transport functions with varying performances (Lu and Chiang 2019; Yen et al. 2017), and the model was permitted to use these functions.

SWAT accurately simulated the streamflow in Pole-Kouseh, but the streamflow is overestimated during certain wet seasons. Lastly, the model's performance in simulating the inflow to Golestan Dam is superior to other simulations in the current work.

The statistics of the simulated streamflow and sediment discharge at selected stations are presented in Table 1.

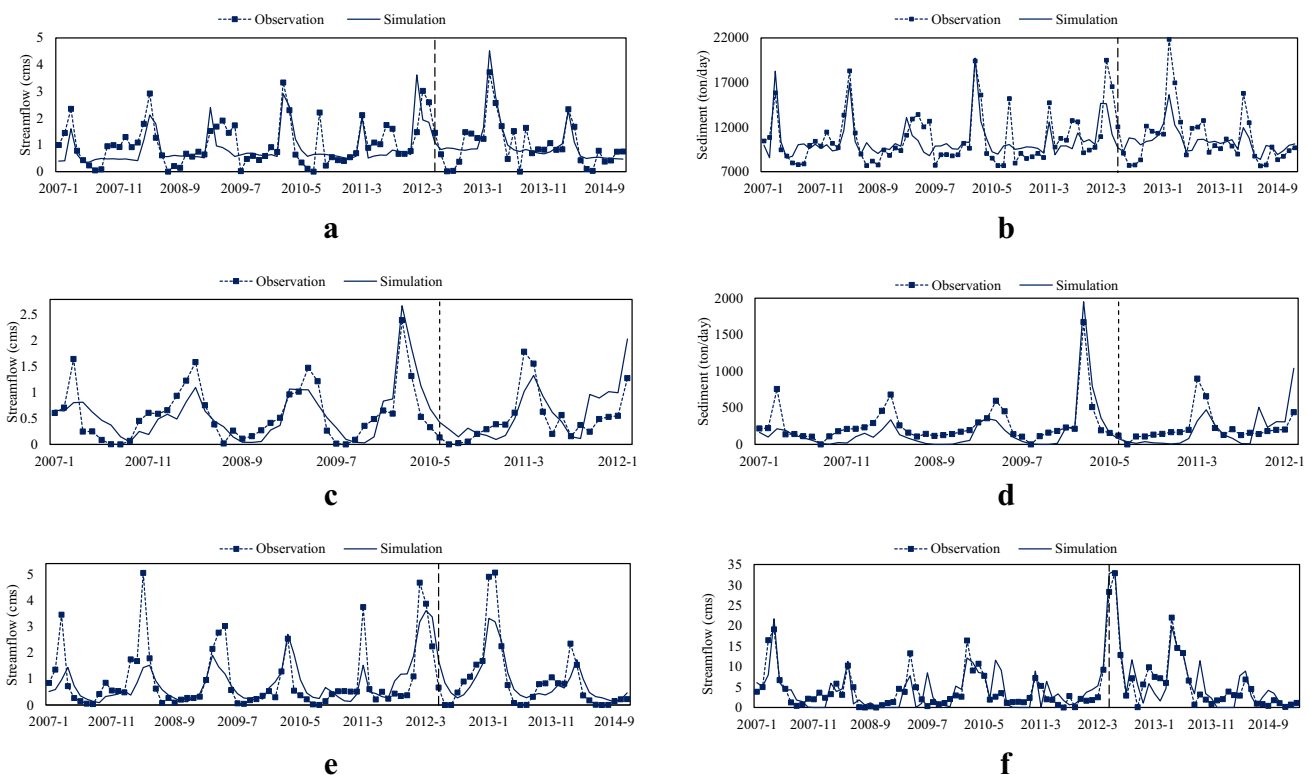


Fig. 5 Simulation and observation time series of streamflow and sediment yield in calibration and validation periods. **a** Streamflow in Tamer. **b** Sediment yield in Tamer. **c** Streamflow in Ghareh-Shour.

d Sediment yield in Ghareh-Shour. **e** Streamflow in Pole-Kouseh. **f** Inflow of Golestan dam

Table 1 Value of goodness of fit indices in calibration and validation period

Station	Station Number	Variable	Period	NSE	CC	KGE	RMSE
Tamer	12–005	Streamflow	Calibration	0.38	0.59	0.67	0.62
			Validation	0.67	0.83	0.84	0.46
		Sediment	Calibration	0.56	0.57	0.75	1920.60
			Validation	0.52	-0.28	0.83	2053.10
Pole-Kouseh	12–003	Streamflow	Calibration	0.49	0.40	0.71	0.84
			Validation	0.74	0.46	0.89	0.63
Ghareh-Shour	12–076	Streamflow	Calibration	0.63	0.81	0.81	0.32
			Validation	0.34	0.66	0.71	0.38
		Sediment	Calibration	0.63	0.49	0.89	168.16
			Validation	-0.26	0.46	0.52	223.18
Golestan Dam	-	Streamflow	Calibration	0.77	0.88	0.89	3.00
			Validation	0.61	0.81	0.81	3.11

Table 2 Relative contribution of human and climate on flow and sediment based on SDM and CEM

Station Code	Variable	Relative Contributions Based on SDM		Relative Contributions Based on CEM	
		Human	Climate	Human	Climate
12–005	Flow out	61	39	32.5	67.5
	Sediment out	76	24	60.2	39.8
12–003	Flow out	92	8	60.7	39.2
12–076	Flow out	71	29	68.5	31.5
	Sediment out	61	39	73	27
Golestan dam	Flow in	86	14	81	19

According to this table, 75% of NSE values are greater than 0.5, which is an acceptable performance. All simulations attain acceptable KGE values, with over 60% of KGE results indicating high quality. This suggests that SWAT obtained a reliable simulation of the area under study. In addition, the performance of the model is calculated during wet and dry periods. Metrics indicate that the SWAT model’s performance in dry seasons is acceptable. In wet seasons, nearly all simulations exhibit favorable performance (please see Table S4 in the supplementary materials for further information).

Contributions and LULC sensitivity analysis

Two approaches, including SDM and CEM methods, were used to quantify the contributions of direct and indirect human activities on the watershed scale. The calibrated SWAT model was used to project flow and sediment discharges in the affected period based on the climate conditions to determine how they would respond if human interventions in the second period were eliminated. Then, the relative contributions of humans and climate were computed

using the methodology mentioned in “Contribution analysis.” The calculated contribution rates are reported in Table 2 using the simple differential method.

Based on the results, the contribution of direct human activities to streamflow and sediment disturbances is over 50%, meaning they have contributed more than climate dynamics at the stations. They account for 92% and 86% of the changes in streamflow at the Pole-Kouseh and Golestan Dam stations, respectively. Clearly, the streamflow in Pole-Kouseh and Golestan Dam has been significantly impacted by human activities. According to the findings, 70% of the changes in streamflow at the Ghareh-Shour station can be attributed to direct human activities. Figure 3 shows that the orchard LULCs are more focused at the southeastern part of the study area where the river leading to the Pole-Kouseh and Ghareh-Shour stations flow through; therefore, it is expected that direct human activities in orchards have more influence on streamflow generation.

Direct human activities at Tamar station had the least effect (60% of changes), with fewer orchards. The spatial variation of direct human activities contribution is shown in Fig. 6. Due to differences in the actual processes of streamflow and sediment generation, it is anticipated that their contribution rates will vary. Among all stations, streamflow in Tamer and sediment discharge in Ghareh-Shour appear to have at least a 60% direct human contribution rate.

Time series of the observed precipitation, potential evapotranspiration, and LULC areas were collected for use in the Climate Elasticity Method. The results of climate elasticity are depicted in Table 2 and exhibit a close relationship with the previous rates. All values are consistent with previous findings, confirming that direct human activities play a central role in streamflow and sediment discharge generation. Comparing the results of the two methods in Table 2, only one calculated rate is inconsistent at Station 12–005 (Tamer). Direct human activities are responsible for approximately 32% of streamflow changes in this case. In other words, CEM

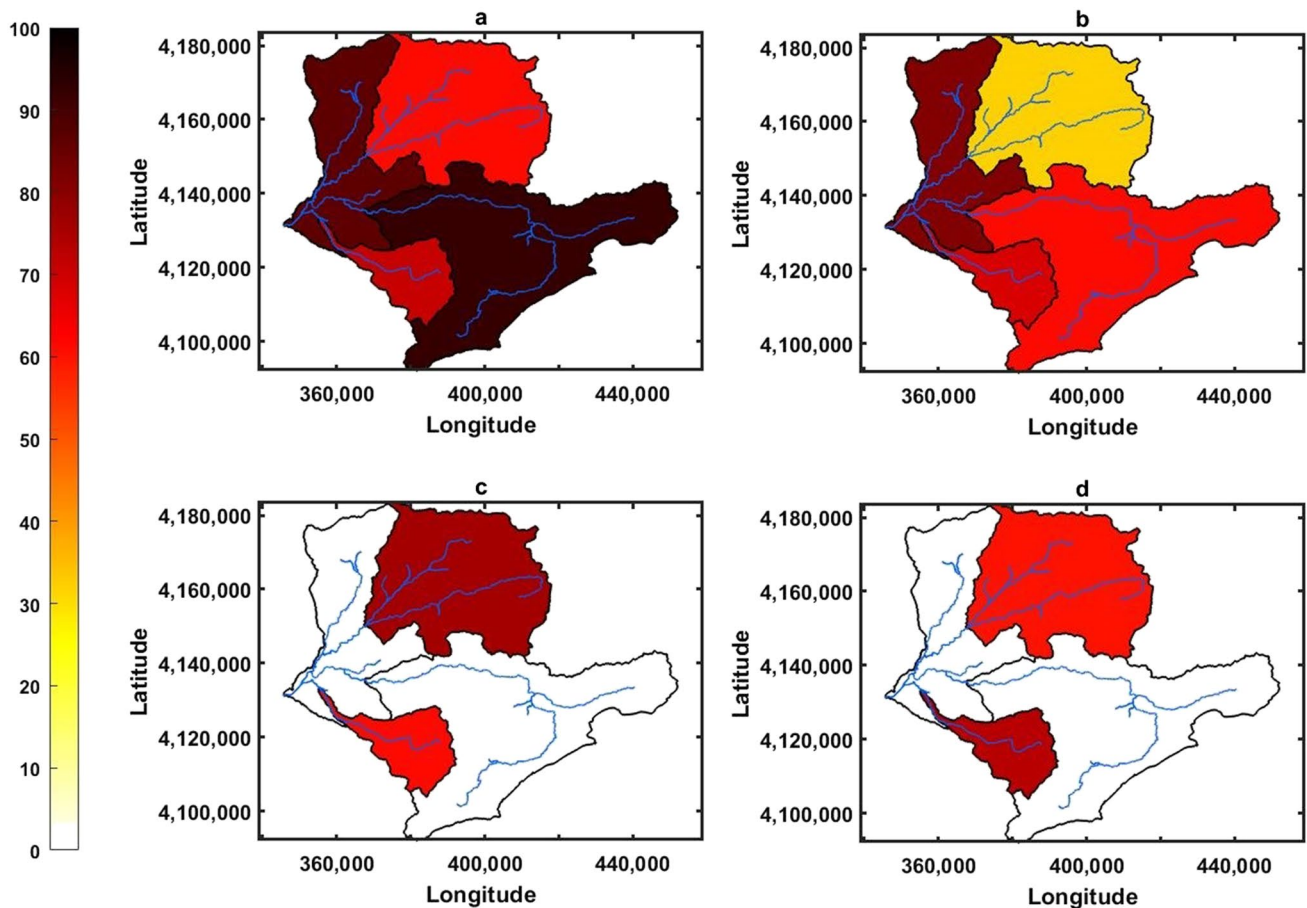


Fig. 6 Spatial variation of land use changes on streamflow and sediment among the watershed. **a** Flow by SDM. **b** Flow by CEM. **c** Sediment by SDM. **d** Sediment by CEM

favors climate dynamics over SDM when analyzing streamflow changes at Tamer Station. For the Golestan Dam, 86% and 81% of streamflow changes were generated from direct human activities, according to SDM and CEM, respectively. The close contribution rates evidence the significant role of human activities. Overall, land use changes in the study area play an important role in sediment and streamflow changes in the watershed, as shown in Table 2.

In the final step, the sensitivity of each LULC was evaluated to detect the impact of LULC on streamflow and sediment discharges with greater accuracy. According to Fig. 3, a significant part of the watershed is covered by agricultural activities located in the center, close to the river, and extends from east to west. As can be seen, the extent of the majority of land uses has changed, but certain trends stand out among them. In the first year, rice and soybean fields occupied a significant portion of the watershed and were present in all subbasins. They are concentrated mostly around the main river and have experienced a decreasing trend over time.

On the other hand, two subbasins in the south and southwest of the watershed have experienced a growing area of

orchards primarily located at higher elevations. The urban portion of the watershed's land use pattern is very small and has experienced an upward trend. Despite the existence of LULC of forests in all subbasins, they have experienced a declining trend through deforestation. To evaluate the sensitivity of each LULC, two statistical measures, PLS and AMI, were employed. LULC areas were considered independent variables, whereas streamflow and sediment were considered dependent variables. Based on the metrics, the streamflow appears to be more sensitive to LULC than to climatological forcings. The results are shown in Table 3.

Table 3 shows ORCD and FRST gain the highest value of VIP at the Tamer station, indicating the highest LULC class sensitivity to streamflow. ORCD reaches the maximum value of AMI as well. The alignment of sediment sensitivity values with streamflow indicates that ORCD was the responsible LULC for the change in sediment yield. The expansion of the ORCD in the Tamer subbasin over time is evident in Fig. 3, whereas other significant effective LULCs exhibit a decreasing trend. As a result, it can be inferred

Table 3 The sensitivity of streamflow and sediment on LULCs in sub-watersheds

LULC	12–005		12–076		12–003	Golestan Dam
	Streamflow	Sediment	Streamflow	Sediment	Streamflow	Streamflow
VIP Method						
BARR	0	0	0	0	0.59	1.05
URMD	0	0	0	0	0	0.85
FRSD	0	0	0	0	0.77	0.83
FRST	0.91	0.41	0.5	0.36	0.53	0.93
ORCD	0.85	0.7	0.18	0.27	1.04	0.72
PAST	0.55	0.4	0.83	0.74	0.75	0.68
RICE	0.67	0.4	0.95	0.88	0.63	0.64
RNGB	0.42	0.35	0.51	0.47	0.98	0.95
SOYB	0.45	0.33	0.32	0.28	1.09	0.6
AMI Method						
BARR	0	0	0	0	0.08	0.07
BERM	0	0	0	0	0	0.03
FRSD	0	0	0	0	0.05	0.03
FRST	0.04	0.05	0.05	0.04	0.04	0.05
ORCD	0.05	0.07	0.07	0.06	0.07	0.05
PAST	0.05	0.05	0.06	0.05	0.06	0.07
RICE	0.04	0.07	0.05	0.05	0.04	0.07
RNGB	0.04	0.08	0.04	0.04	0.04	0.04
SOYB	0.04	0.05	0.04	0.04	0.01	0.05

that deforestation to expand orchards has contributed more than any other factor to changes in streamflow and sediment. Overall, agricultural activities appear to significantly impact streamflow and sediment yield in the Tamer basin, based on both VIP and AMI results.

Streamflow and sediment yield at the Ghareh-Shour station is highly sensitive to PAST, RICE, and ORCD land uses, as shown in Table 3. According to LULC classes, RICE and ORCD were declining while PAST was growing. Also, at Pole-Kouseh station, it appears that ORCD is responsible for LULC. SOYB has achieved the maximum value using the VIP method, but the maximum AMI values depend on BARR and PAST. According to Fig. 3, agricultural activities in RICE and ORCD LULCs increased, while other effective LULCs decreased at Pole-Kouseh station.

According to the results, agricultural activities, particularly orchard expansions, appear to be more responsible for altering streamflow and sediment discharges. Ultimately, streamflow variations at the entrance of Golestan Dam are more sensitive to BARR changes using both methods. According to land use maps, the BARR LULC area declined over time. During the simulation period, orchards, urban areas, and barren regions increased at this station, whereas forests, pastures, and barren areas decreased.

Discussion

This study used different statistical methods to detect a sudden change in streamflow behavior. The results showed that almost all stations throughout the study area had been disturbed. The observed land use patterns of the watershed also confirmed the occurrence of human interventions. In all subbasins, most LULCs withstood a trend reversal or change around 2013, indicating that the change point was around 2014.

In four stations, the impact of climate change on streamflow and sediment yield disturbances was evaluated. The results indicate that, excluding the Ghareh-Shour station, the effect of climate change on streamflow disturbances is 16% greater than that of sediment yield. The results also suggest that the relative contribution of climate change to the variation of streamflow downstream is approximately 50% greater than its contribution upstream. Comparing SDM and CEM demonstrates that the CEM method contributes at least 8% more to climate change.

The results revealed that direct human activities are responsible for at least 60% of the changes in streamflow and sediment yield at each station. Due to the different streamflow and sediment generation processes, it is logical that the contribution of each driver to the dynamics of

streamflow and sediment yield differ. The results indicate that land use changes play a significantly larger role in streamflow modification than sediment changes. Except for the Tamer station, the results of the SDM and CEM methods are comparable, confirming that human activities play a significant role in changing the hydrologic regime.

Considering AMI and VIP metrics, orchard cultivation appears to be more responsible for changes in streamflow and sediment. In certain stations, such as Tamer and Pole-Kouseh, orchards achieved the first or second value of effectiveness and experienced an upward trend, whereas the other most effective LULC experienced a downward trend. The high sensitivity of streamflow and sediment changes to changes in orchard land uses, as well as the spatial map of the human contribution rate to disturbances in both variables, indicate that orchard development is likely the most responsible activity in the study area. For example, Pole-Kouseh station, which drains many orchard lands, has a human contribution rate of approximately 92% and 60% in SDM and CEL methods, respectively, whereas Tamer station, which drains about ten times fewer orchard lands, has a human contribution rate of around 61% and 32% in each method, respectively.

Conclusion

In this study, the relative contribution of human activities (with a particular emphasis on land use changes) and climate change to streamflow and sediment yield disturbances in the Gorganroud watershed, an important watershed in the north of Iran that experiences numerous flood events, was evaluated. The first step employed a new method to detect a watershed change point. Previous studies typically used a single method-station approach to detect a sudden change in the watershed's hydrological behavior (Bao et al. 2012; Huang et al. 2020). In this study, however, a multi-method-station approach was introduced and utilized, considering the land use dynamics of the study area. The results indicated that almost all stations experienced a sudden change in streamflow history, implying that human activities significantly influence the study area.

The SWAT model was used in the study area to simulate streamflow and sediment yield. During the simulation, the SWAT's land use pattern was updated annually to produce a more accurate model. Various goodness-of-fit criteria were employed to demonstrate the performance of the simulation. The results showed that the SWAT model could simultaneously simulate water and sediment yield over the watershed. The least accurate stimulation was associated with the Tamer station, while the best simulation was attributed to the Golestan Dam inflow. SWAT was also used to estimate the streamflow and sediment yield during the affected period,

during which climate change and human activities simultaneously affect the hydrological behavior.

Two methods were used to evaluate the relative reliability of the drivers' contributions. Human activities have had a greater impact on streamflow and sediment yield than climate change, based on the results of the SDM as the initial method. The method results that human activities have had the least impact on streamflow at the Tamer station and sediment yield at the Ghareh-Shour station (with 61%) and the greatest impact on streamflow at the Pole-Kouseh station (with 92%). The second method largely validates past contribution rates. In this method, climate change has had a greater effect on the changes in streamflow at Tamer station. According to the results of the second method, the maximum rate of human contribution to Golestan Dam inflow is achieved. Comparing human contribution rates between two variables reveals that human activities contribute more to sediment yield in the basin.

Finally, the most sensitive land use patterns on hydrologic alterations are identified using feature selection approaches to identify the most disruptive human activity. A preliminary analysis of the results revealed that the expansion of agricultural activities, specifically orchards, throughout the watershed is responsible for these changes. In addition, the spatial pattern of human contribution rates confirms this reality, as stations that drain a greater proportion of orchard land use receive greater human contributions.

This study's findings may interest water resources managers, particularly in the Gorganroud watershed. It should be noted that studies have demonstrated that human activities can affect water quality and quantity (Melland et al. 2018; Dudley et al. 2020). Since human interventions affect the stability of the watershed's water quality and quantity regime, determining the contribution rates in the basin's intermediate- and long-term plans is highly effective. It is strongly recommended that changes in water quantity and quality caused by human activities be considered when investigating the future conditions of a watershed.

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