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ORIGINAL ARTICLE

Estimation of flow regime for a spatially varied Himalayan watershed using improved multi-site calibration of the Soil and Water Assessment Tool (SWAT) model

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Abstract

Due to the influential role in global climate, the hydrologic modeling of the watersheds in Himalayan mountain range is critically important for the socioeconomy and livelihood of surrounding regions. As these watersheds usually have snow-driven hydrology and abrupt changes in orography, the challenges in hydrologic model are acknowledged in scientific community. In this study, we addressed this challenge by implementing an improved multivariable and multi-site approach to calibration and validation of the Soil Water Assessment Tool (SWAT) model for determining its ability to mimic flow regime of the watershed. In the improved multi-site approach, the model was successfully calibrated using 1980–1985 streamflow data and validated using 1990–1995 data for the daily time steps. Combination of different performance metrics indicates that the improved method increased the efficiency of daily prediction of Karnali River discharge. We utilized 30 years of streamflow data from four discharge stations to explore the changes in flow pattern at the decadal scales. Groundwater flow decreased in monsoon season compared to other season where the changes in flow regimes were insignificant within the decadal scale. The proposed calibration method can be used to any other large mountainous watershed to improve the estimation of the hydrologic processes.

Keywords SWAT · Calibration · Himalayan watershed · Flow regime · Climate

Introduction

Mountains, one of the primary sources of stream flows, are the storehouse of biodiversity and vital to coupled ocean–atmosphere and terrestrial system (Viviroli et al. 2007). The assessment of hydrologic processes in mountain terrain received special attentions in recent years due to its importance in water resource management and local and regional economics (De Jong et al. 2005; Nolin 2012). Accurate quantification of this process in mountainous terrain through numerical modeling is considered to be a challenging task due to its steep elevation gradient, coarse in situ information, and complex snow water dynamics (Sorooshian 2008). In case of Himalayan mountain range, such challenge is paramount hydro-climatic impacts on water resources and extreme environments are poorly understood.

The hydro-climatic assessment of Himalaya and its downstream plains is essential for socioeconomic development and future policy-making, where about one-tenth global population live (Immerzeel et al. 2010; Tiwari and Joshi 2012). The mountain range is the largest cryospheric system outside the polar region and nourishes more than 12,000 glaciers (Thayyen and Gergan 2010). Nepal, a country that resides in the central Himalayan region, requires robust valuation of mountain hydrology for its future socioeconomic growth (Dewan 2015). Therefore, hydrologic studies of Himalayan watersheds and their ecological flow are not only a prime interest for the scientific community, but also essential for local stockholders. Even with the advancement of numerical and hydrologic models in recent years, precise estimation of hydrologic process such as river runoff still faces challenges and uncertainty.

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The Soil and Water Assessment Tool (SWAT) model, one of the widely used distributed parameter models, can simulate surface and subsurface flows and be applicable for mountainous watershed modeling (Arnold et al. 2012). However, high altitude watershed modeling associates some uncertainties in prediction of flow, which could be dealt by using various modeling approach and calibration strategies. Most of the models require optimization of a set of parameters to simulate particular processes, which are selected depending on the objective of a study. In the application of watershed models like SWAT, it is crucial for the model to pass a careful calibration for accurate estimation of river runoff.

The model calibration is usually based on a comparison between the simulated and observed streamflows. Nevertheless, the potential for equifinality or non-uniqueness in complex, spatially distributed models with numerous calibration parameters has shown that a large number of alternative parameterizations can produce acceptable results (Beven and Binley 1992; Beven and Freer 2001). In case of large watershed of mountainous region, SWAT can be calibrated using single-site or multi-site method. In the single-site calibration, parameterization is often done considering one single set of optimizing variables (Devkota and Gyawali 2015; Narsimlu et al. 2013; Neupane et al. 2015). On the other hand, in simultaneous multi-site calibration, although the analysis is conducted over multiple sites, the parameterization still utilizes single set of common calibrating variables (Cao et al. 2006; Santhi et al. 2008; Easton et al. 2010; Zhang et al. 2010; Bai et al. 2017). However, the underlying sub-basins of a large watershed have different hydrologic characteristics from each other; thus, a separate conceptualization of parameters for each sub-basin could be appropriate for accurate calibration of the larger basin. Some multi-site calibration studies related to SWAT model considered sub-basinwise parameterization, but the calibration process was conducted separately for each sub-basin (Chaibou Begou et al. 2016; Teshager et al. 2016; Shrestha et al. 2016). There is no reported study in our knowledge that considered the multi-site parameterization as well as multi-site calibration of SWAT model simultaneously to calibrate the primary outlet of a large watershed. This study conducted a multi-site multi-segment hydrologic analysis using semi-distributed SWAT model in a vulnerable watershed of Himalayas and therefore adds additional knowledge base to the existing literature in hydrologic modeling.

It is evident that the natural flow variation—ranging from base flow to high flow pulses and floods—plays important ecological roles in a river ecosystem (Mathews and Richter 2007; Aldous et al. 2011). Under ongoing climate change, evaluating the existing condition as well as future changes of environmental flow is crucial for the Himalayan Rivers. A well-calibrated hydrologic model such as SWAT can be utilized to estimate both present and future environmental flows over the areas. Therefore, the first step to understanding hydrology of the watershed using SWAT model is to calibrate streamflow to calculate environmental flows of a climate-vulnerable mountainous watershed.

The quantification of environmental flow requires daily discharge information. Most of the modeling studies over the Himalayan region have been conducted at a monthly time scale with no further analysis on streamflow parameters pertaining to environmental flows. Estimation of daily flow through modeling is not only useful for providing meaningful information to decision makers on ecological services, but also plays substantial role in quantifying the extreme events such as droughts and floods. In this context, we improvised our model development at a daily scale to conduct a comprehensive hydrologic modeling over this region.

Therefore, in this study, we implemented an improved technique of calibration for a large mountainous watershed of Himalaya to accurately quantify environmental flow regime. As a case study, we selected one of the watersheds of Western Nepal, Karnali River watershed, where downstream of the watershed has experienced devastating floods in recent years (Smith et al. 2017). The importance of the study area is explained in the following section.

Study area

The Karnali River originates in the Tibetan plateau and runs through the Himalayan Mountains in western Nepal before connecting with Ganges River in India covering an area of 127,950 km^2. The river runs through the snowmelt-driven High Himalaya, High Mountain, and Middle Mountain and the monsoon-driven Siwalik and Terai plains physiographic zones (Gautam and Acharya 2012) with an annual average discharge of 43.9 billion m^3 (Siderius et al. 2013).

The study area includes the headwaters in the Tibetan plateau through the Chisapani outlet in Nepal for a total area of 38,569 km^2. The river runs from an elevation of 7664 m in the Tibetan plateau to 185 m near the Chisapani outlet and covers the High Himalaya, High Mountain, and Middle Mountain physiographic regions (Hannah et al. 2005). This watershed is unregulated, which means that it has not been affected by important hydraulic structures that would otherwise significantly modify its flow regime.

We used observed discharge data from four stations shown in Fig. 1: Lalighat (215), Bangga (260), Jamu (270), and Chisapani (280). These watershed stations are referred as C215, C260, C270, and C280, respectively, in rest of the study. Lalighat measures runoff from 15,200 km^2; Bangga measures runoff from 7460 km^2; Jamu measures runoff from 12,290 km^2; and Chisapani measures runoff from 42,890 km^2 from respective sub-watershed. Chisapani is

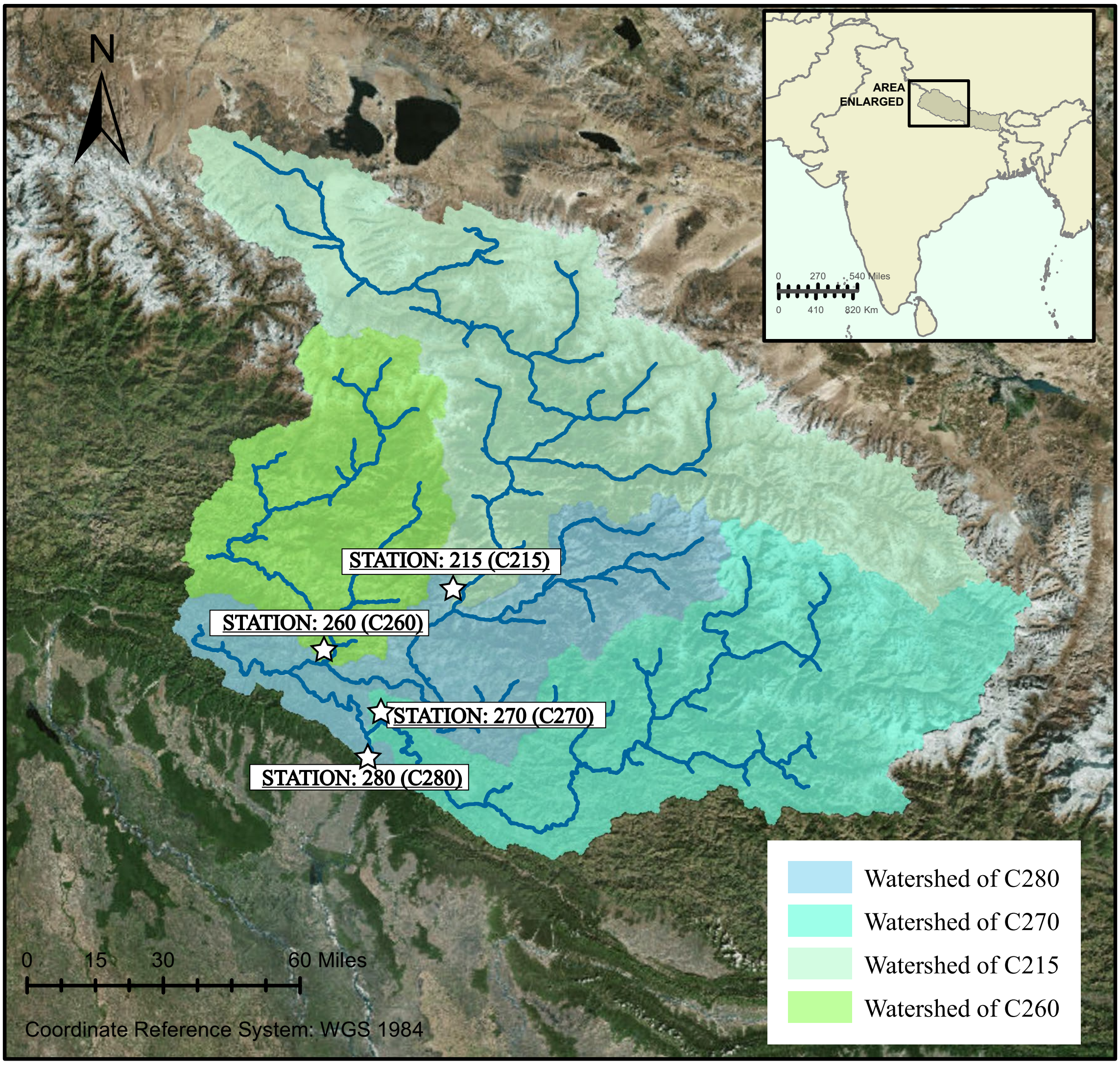

Fig. 1 Watershed area of Karnali watershed with shaded sub-watershed

the downstream gauging station; measures combined flow of all sub-watersheds.

Methodology

Soil and Water Assessment Tool (SWAT) is a semi-distributed hydrologic model that can function on a daily to sub-daily time step and utilizes physically based algorithms to describe many important components of the hydrologic cycle. SWAT is computationally efficient, applies readily available inputs, allows users to study long-term impacts (Neitsch et al. 2011), and is originally developed by United States Department of Agriculture (USDA) to model the impact of land management practices on water, sediment, and crops. SWAT has been widely used to simulate long-term hydrology, sediment mass transport, agricultural chemical yields, and land management at the sub-basin level (Muleta and Nicklow 2005; Gassman et al. 2007; Arnold et al. 2012).

In SWAT, a watershed is divided into sub-basins, which are then further subdivided into hydrologic response units (HRUs) that consist of unique combinations of land cover and soils (Neitsch et al. 2011). SWAT accounts for a number of different hydrologic routines for solving physical processes. The hydrologic component of SWAT is based on the water balance equation of soil:

$$\mathrm{SW_t} = \mathrm{SW_0} + \sum_{i=1}^{t} (R_{\mathrm{day}} - Q_{\mathrm{surf}} - \mathrm{ET_a} - W_{\mathrm{seep}} - Q_{\mathrm{gw}}) \quad (1)$$

where $\mathrm{SW_t}$ is the final soil water content (mm), $\mathrm{SW_0}$ is the initial soil water content (mm), t is time in days, R_{day} is the amount of precipitation (mm), Q_{surf} indicates the amount of surface runoff (mm), ET_a is the amount of evapotranspiration (mm), W_{seep} is the amount of water entering the vadose zone from the soil profile (mm), and Q_{gw} is the amount of return flow (mm). We used the curve number method of the Soil Conservation Service (SCS) to estimate surface runoff volume for the selected basins. The SCS curve number equation is:

$$Q_{surf} = \frac{(R_{day} - 0.2\,S)^2}{(R_{day} + 0.8\,S)} \tag{2}$$

where Q_{surf} is the accumulated runoff or rainfall excess (mm), R_{day} is the rainfall depth for the day (mm), and S is the retention parameter (mm) (Loague and Freeze 1985). Potential evapotranspiration (PET) was estimated using Penman–Monteith procedure (Monteith 1965) which is based on the energy balance components. Snowmelt in the model is estimated through temperature-index or degree-day approach. In the routing phase of SWAT, water is routed using kinematic wave model (Chow et al. 1988).

SWAT can be simulated with ArcGIS with an extension called 'ArcSWAT' which provides an easy-to-use graphical interface (Winchell et al. 2013). We used the ArcSWAT, to model the streamflow of the Karnali watershed in this study.

Input data

SWAT uses spatial data on topography, land use and soil, weather and climate, and stream discharge to model streamflow. The resolution of input data—both spatial and temporal—and data quality ensures the accuracy of the model output.

We used a 30-m digital elevation model (DEM) produced by the Shuttle Radar Topographic Mission (SRTM), obtained from the United States Geological Survey's (USGS's) earth explorer (http://earthexplorer.usgs.gov/), and processed at 1 arc sec/30 m in the WGS84 datum and Lambert conformal conic projection system for the entire Karnali watershed. Missing values in the 30-m DEM in the higher elevations were filled by disaggregating the older 90-m SRTM version of elevation data.

The land use map of the Karnali watershed area with a resolution of 400 m was generated based on Global Land Cover Characterization database (https://lta.cr.usgs.gov/GLCC). The 400-m spatial resolution soil data compiled in 2004 by the Food and Agriculture Organization (FAO) and the Survey Department of Nepal were obtained from the Nepal's Soil and Terrain database (SOTER) (Dijkshoorn and Huting 2009). The soil categories were reclassified according to the FAO's soil classification (IWG WRBFAO 2007); eight different types of soils were identified from the 1:5 million scale raster data of which two soil types cover more than 65% of the watershed.

As precipitation is the key input variable that drives flow and mass transport of a watershed, precision is critical for modeling output accuracy (e.g., Beven 1983; Hamlin 1983; Shah et al. 1996). The gauge-based Asian Precipitation-Highly Resolved Observational Data Integration Towards Evaluation of Water Resources (APHRODITE) precipitation data are proved to be one of the more accurate precipitation products over the South Asian region (Yasutomi et al. 2011; Yatagai et al. 2012; Khandu et al. 2015). APHRODITE data are not only spatially uniform, but also have a long historical record—since 1950—thus, it is well suited as input data for this study. Daily precipitation was obtained from APHRODITE for 1979–2007.

Additional meteorological variables like maximum and minimum temperatures, net radiation, wind speed, and relative humidity were obtained from the Climate Forecast System Reanalysis data produced by the National Centers for Environmental Prediction (NCEP) for 46 stations that fall within or adjacent to the Karnali watershed boundary covering the study period of 1979–2007.

Daily discharge measurements in the Karnali watershed were obtained from the Nepal Department of Hydrology and Meteorology (GON-DHM 2008). Flow records for 1979–2007 were used in calibration and validation. The simulation was run in two seven-year period segments: 1980–1985 was used to calibrate the model, and 1990–1995 was used for validation. Additional 2 years were used for model initialization, 1979 for calibration and 1989 for validation. Due to some missing discharge data from 1986 to 1988, there is a gap between calibration and validation.

Model setup

The two-step discretization process allows the spatial heterogeneity of a watershed to be well captured (Geza and McCray 2008). At the beginning of watershed delineation process, a watershed can be divided into sub-basins, and then, each sub-basin can be further divided into multiple Hydrologic Response Units (HRUs).

We delineated the Karnali watershed into 151 sub-basins based on the DEM with a minimum drainage area threshold value of 140 km^2. The delineated river channel length and watershed boundaries were validated using the secondary literature and map description from Water and Energy Commission Secreteriat of Nepal (WECS 2011). Sub-basin outlet locations were delineated in a way that it represents actual discharge station locations.

Land use, soil, and slope categories were combined to determine the Hydrologic Response Units (HRUs) for each sub-basin. The default land use and soil database in SWAT2012, crop database, and the user soil database of ArcSWAT were updated using land use and soil data for the study area and were reclassified. Slope was reclassified into four categories by considering the multi-slope option. The elevation bands in each sub-basin each representing approximately 750 m in elevation were used to account for orographic precipitation with snow accumulation and melt processes in the steep Karnali watershed. We applied a 10% minimum area threshold value for each land use, soil, and slope categories to define 1146 HRUs for the watershed. Lastly, precipitation and weather data files were overlaid before writing and finalizing all input files.

Calibration

Hydrologic models such as SWAT have some parameters that cannot be measured directly due to measurement limits and scale issues. Therefore, calibration process of the model is the crucial part in watershed modeling. Identification of key parameters based on objective of a study is an essential step for model calibration (Ma et al. 2000). A set of 19 parameters for calibration, focusing on discharge quantity, were adopted from Muleta and Nicklow (2005), Rajib et al. (2016) and Rostamian et al. (2008). The detailed list of the parameters is presented in Table 2.

The implication of parameterization in different spatial extent of a watershed can influence the performance of the watershed model. The downstream discharge of a large watershed is combined flow of smaller sub-basins where each incorporates a river outlet. Therefore, if the flow of the upstream sub-basins is calibrated well, the combined flow of main watershed outlet will be accurately represented. For spatially varied watershed like Karnali, parameters within each sub-basin can significantly vary. Previously, studies have focused their work on calibrating similarly large watershed, considering a single outlet station with a single set of parameters for the calibration (Narsimlu et al. 2013; Devkota and Gyawali 2015; Neupane et al. 2015). Others also utilized multiple discharge stations together to calibrate the model where a common set of calibration parameters were employed (Cao et al. 2006; Zhang et al. 2008; Jiang et al. 2015). However, there is no study about applied calibration parameters for each individual segment of a large watershed by considering the heterogeneity of parameterization of distinguishable sub-basins. Therefore, our research focused on a multi-site multi-segmented approach to calibrate the spatially varied Himalayan watershed. We also did a comparative performance analysis to assess the effectiveness of proposed calibration techniques. Three cases were formulated for the analysis: single set of parameterization with single site (CASE1), single set parameter with multi-sites (CASE2), and multi-set parameters with multi-sites calibration (CASE3).

In the calibration and validation process, objective function requires iteration of the model to converge the parameterization to optimum calibration parameter. However, if the number of calibration parameter increases, it requires more iteration to converge toward the accurate solution. Simultaneously, higher number of parameters can cause more chances of equifinality (Lu et al. 2009). To address this problem, we also incorporated a rank correction method for multiple trial of calibration process to remove such problem of equifinality in the context of multi-site calibration. Detailed description of the process is presented in later sections.

As a first step to initializing SWAT model, we calibrated the Karnali watershed streamflow from 1979 to 2007 using a single outlet approach and compared the output models to our multi-site calibration technique. All three calibration cases in this study were done using the Sequential Uncertainty Fitting version-2 (SUFI-2) procedure. SUFI-2 is an inverse optimization approach that uses the Latin hypercube sampling (LHS) procedure along with a global search algorithm to examine the behavior of objective functions. The LHS method is a multi-dimensional random variable sampling technique that ensures equal probability of selection of the random variable parameter values (Iman et al. 2008). Uncertainty analysis by Yang et al. (2008) suggests that SUFI-2 is a more flexible method for calibration since it allows arbitrary objective functions while providing satisfactory results in model calibration. The method is currently linked to SWAT in the calibration package SWAT Calibration Uncertainty Procedures (SWAT-CUP) (Abbaspour 2007).

Calibration cases

The Karnali watershed, in this study, is divided into four sub-watersheds shown in Fig. 1. The discharge data of each sub-watershed outlet were available from 1963 to 2007 Department Of Hydrology and Meteorology Nepal (DHM 2017). The discharge stations of C280, C270, C215, and C260 are located over Lower Karnali, Bheri, Upper Karnali, and Seti rivers, respectively.

To conduct our calibration, we utilized SWAT-CUP, a widely calibration tool for SWAT model. We defined the three calibration techniques as cases (CASE1–CASE3). In CASE1, the model was calibrated only for the downstream gauge of the watershed, i.e., C280. Therefore, in SWAT-CUP, each watershed was calibrated separately with a defined objective function. In CASE2, the model was calibrated at all four gauge stations simultaneously, using a common set of selected hydrologic parameters. In this case, we implemented the objective function for multiple discharge stations within the SWAT-CUP. The input parameter range is common for all basins, and we utilized maximum possible iteration in SUFI method to calibrate streamflow. However, in the output we extracted the simulated discharges for each selected station. In both CASE1 and CASE2, we considered 19 parameters as stated in previous section. In CASE1, the result of main outlet was improved and in CASE2 did a better model simulation in finding the optimum solution for all four outlets. Therefore, the optimized parameter of CASE1 differed from optimized parameter of CASE2.

In CASE3, we calibrated all the sub-basins separately. The best parameter ranges from all the four separately calibrated sub-basins were then used as the initial calibration range for the subsequent second calibration, which we referred to as a multi-site multi-segment calibration and discussed more below.

Multi-site multi-segment calibration

A new model calibration was done considering all four watersheds where best-fitted parameter range is applied to corresponding area of later watershed. In this calibration process, the selected hydrologic parameters were modified from five kinds of files, namely .HRU, .MGT, .GW, .Sol, and .BSN files. The .HRU files contain information related to a diversity of features within the HRU. The .MGT or the management files contain information about planting, harvest, and irrigation applications of watershed. The .GW or groundwater file has the information of the properties of groundwater movement. The .Sol files define the physical properties for all layers in the soil. The .BSN file defines the global watershed attributes such as the temperature of snow melting or freezing. The first four (refers as HMGS in later sections) file types, namely .HRU, .MGT, .GW and .Sol, have unique values in each individual sub-basin. Therefore, in later part of the calibration process, we applied optimized parameters from HMGS file types of each sub-basin to their corresponding sub-basin files of larger watershed. Hence, 13 out of 19 parameters (or HMGS parameters) were applied separately based on their sub-basin location. However, parameters from BSN file are global watershed scale file for all sub-basin units in any SWAT simulation. Therefore, it cannot be applied at a sub-basin level. To alleviate such problem, we took the best range of optimization parameters of BSN file from CASE2 simulation and applied it as common BSN parameter of CASE3 calibration. Nonetheless, such BSN parameters are different from each sub-basin BSN parameter. We fixed the values of HMGS parameters from each individual sub-basin with different BSN parameters, which resulted in a shift of independent optimization of corresponding sub-basins. Thus, instead of using the fixed best values of sub-basin simulation, we took the best parameter range after 1500 iteration to keep the simulation close to optimum solution. In this context, we formulated a ranked sensitivity method to incorporate sub-basin parameter range to main basin calibration.

SWAT-CUP, a calibration tool, was utilized to explore the sensitivity of different parameters (Abbaspour 2007). Typically, after a calibration simulation, the tool can provide a new range of calibration where one can refine the parameter optimization for further improvement. It also provides a sensitivity matrix with p-values of each parameter. In our ranked method, sensitivity matrix of each individual calibration was obtained and ranked according to their p-values. Based on the descending rank of p-values, we first weighted the parameter ranges of individual sub-basins. Higher sensitive parameters should have a larger range for calibration, where insignificant parameters (significant level of 95%) can be ignored in calibration process. Weighted matrix then multiplied by optimized range and all HGSM parameters are combined in a single input file for the final calibration. The final calibration simulation ended up to a total 58 parameters, where 13×3 parameters of HRU, GW, Sol, and MGT were adopted from each sub-basin simulation, and remaining six parameters of BSN were adopted from multi-site multi-segment simulation. Although we have a large number of calibration parameters, by applying optimized range and sensitivity ranked technique, we were able to reduce the problem of equifinality for the integrated simulation. After calibration, we validated streamflow using 7-year data period.

Model evaluation

Performance of CASES was evaluated and compared using three statistics of model fit and efficiency—referred to as our objective functions: coefficient of determination (R^2), the Nash–Sutcliffe efficiency (NSE) (Nash and Sutcliffe 1970), and standard deviation of measured data (RSR) (Moriasi and Arnold 2007). The R^2 is a measure of correlation between simulated and measured data, NSE measures how well the model fits the observed data compared to the observed average, and the RSR is the standard deviation of the difference between simulated and measured data. In addition to this, we also incorporated Kling–Gupta efficiency (KGE) (Gupta et al. 2009) and Percentage Bias (PBIAS) as the goodness of the fit parameters. The KGE one of the robust model evaluation criteria can be decomposed in the contribution of mean, variance, and correlation on model performance. We reported all the selected statistics for both calibration and validation runs.

We modeled and compared streamflow for all CASES in the monthly and daily timescales. The model is known to be performing well if in the monthly timescale, the objective function of R^2 and NSE is greater than 0.5 and less than 0.5 for RSR.

Flow regime

The characteristics of river flow can be classified based on magnitude, frequency, and duration. In this analysis, we have adopted five hydrologic flow matrixes from Zhang et al. (2012) to quantify the flow regime. These indices also represent environment flow of certain watershed (Poff et al. 1997; Richter et al. 2003). We utilized R statistical software to calculate these hydrologic matrixes (Dierauer et al. 2017). To represent the magnitude of flow, we considered Q75 (high flow), Q50 (mean flow), and Q25 (low flow) indices, which represents the 75th, 50th, and 25th percentile of annual daily flow, respectively. To characterize the duration of flow regime, we adopted the 'Duration' index, which represents the number of days from low flow (Q25) to high flow (Q75). Finally, to characterize the proportion of base flow from total flow, we utilized the 'MeanBFI' index in the analysis. Details about 'MeanBFI' and its base flow separation algorithm can be found in Eckhardt (2012). By utilizing these indices, we quantified the flow regimes of the Karnali River.

Result and discussion

Karnali watershed model development and performance of all three cases are presented in Table 1. From the model evaluation, it was found that the CASE3 performed better in all three performance metrics. For station 280 (downstream location within Karnali watershed), CASE1 showed R^2 and NSE of 0.80 and 0.73, and the PBIAS was above acceptable range. However, for CASE2, both the indicators were relatively higher, but *p*-bias did not change much. Although the R^2 and NSE values are considered satisfactory, the model performance is considered satisfactory when R^2 and NSE are combined with less PBIAS. The good R^2 and NSE do not always prove the model to be performing well. For instance, the model might capture the pattern of flow, but might be either overestimated or underestimated. Therefore, using PBIAS helps to understand any deviation in the magnitude of the streamflow from the observed flow. As one of the objectives of this study was to conduct environmental flow analysis in daily time scale, such assumption needed to be rationalized. In this context, we selected KGE values as an additional objective function, to incorporate all performance metrics. In CASE3 with new improved method, the result was satisfactory also in terms of PBIAS. All three performance indicators increased from previous cases and thus conferred that CASE3 method is the best method for large-scale watershed modeling. For 260, in CASE2, model underperformed compared to CASE1. This could be attributed to the fact that simulation was conducted in this station considering only the sub-basin of C260, whereas in CASE2 simulation was conducted considering optimized value of the entire watershed. Both CASE1 and CASE2 did not perform well which could possibly due to the variability in elevation of the study watershed and unavailability of snow information to initialize model (Gupta et al. 2009).

Optimized parameters after calibration of CASE3 are presented in Table 2. Parameters such as GWQMN, ALPHA_BF, and REVAPMN showed a significant difference between the sub-watersheds, thus validating the need of unique parameterization for each of the watersheds.

Effect of rainfall over modeled and observed data was examined using KGE performance coefficient. We found that the model flow of C280 watershed follows almost identical flow pattern of observed data (Fig. 2). However, the recession of the flow occurs faster in the model compared to actual flow. This could be due to coarse land use and soil information as ground water retention coefficient of the model needs more fine-scale information (Arnold et al. 2012). Both floods of 1983 and 2001 were well captured by the model where the floods occurred due to excess rainfall during those periods. The model performance of the C270 watershed and C260 was also found to be in satisfactory range where both models were underestimating streamflow in dry periods. On the other hand, the C215 watershed produced more streamflow than the observed one. This is possible due to the inadequate formation of snow process in higher elevation areas of the model.

We compared decadal characteristics of different components of water balance equation (Fig. 3). Precipitation during the month of July was lower on later decades. Surface runoff during July, August, and September was also reduced over all four watersheds. Prominent reduction in ground water flow as well as deep percolation was observed over the C260 watershed. Reduction amount was higher during the monsoon season compared to other seasons. Ashraf (2013) showed a reduction in groundwater over Himalayan watershed from 1990 to 2010, which agrees our findings. There was an increase in PET during 2000s, which could cancel out the decreasing effects of other flows.

Table 1 Evaluation parameters in daily scale for the selected cases over Karnali Basin

Station names	CASE1 (individual)				CASE2 (multi-site)				CASE3 (multi-calibration)			
	R^2	NS	PB	KGE	R^2	NS	PB	KGE	R^2	NS	PB	KGE
280	0.80	0.73	28.5	0.69	0.92	0.80	29.0	0.60	0.87	0.83	19.2	0.75
260	0.83	0.65	30.2	0.45	0.82	0.67	32.1	0.48	0.5	0.67	28.8	0.62
270	0.78	0.75	17.3	0.70	0.80	0.79	12.2	0.75	0.74	0.67	− 0.48	0.76
215	0.71	0.47	48.6	0.48	0.79	0.50	47.7	0.40	0.29	0.14	49.9	0.41

Table 2 Optimized parameters in CASE3 calibration over Karnali Basin

Parameters	Description of parameter	File type	Chisapani (st 280)	Jamu (st 270)	Belgaon (st 260)	Tholtada (st 215)
CN2	Initial SCS CN II value	.mgt	1.89	0.02	0.93	− 1.71
OV_N	Manning's '*n*' value for overland flow.	.hru	− 0.62	0.20	− 0.83	0.28
ALPHA_BF	Baseflow alpha factor	.gw	0.26	0.64	0.43	0.70
GW_DELAY	Groundwater delay	.gw	87.35	15.92	146.41	4.24
GWQMN	Threshold depth of water in the shallow aquifer required for return flow to occur	.gw	1965.35	496.81	2172.25	349.71
GW_REVAP	Groundwater 'revap' coefficient	.gw	0.08	0.05	0.04	0.05
RCHRG_DP	Deep aquifer percolation fraction.	.gw	0.63	0.10	0.72	0.20
REVAPMN	Threshold depth of water in the shallow aquifer.	.gw	235.29	77.95	43.67	59.82
CH_N2	Manning's '*n*' value for the main channel.	.rte	0.16	0.12	0.22	0.08
ESCO	Soil evaporation compensation factor	.hru	0.40	1.00	0.84	0.95
EPCO	Plant uptake compensation factor	.hru	0.26	0.93	0.64	0.84
TLAPS	Temperature lapse rate.	.sub	5.68	− 8.19	− 9.21	− 7.00
SOL_AWC	Available water capacity of the soil layer	.sol	− 0.20	− 1.29	− 1.36	− 0.92
SMTMP	Snowfall temperature	.bsn	3.55			
SMFMX	Snow melt base temperature	.bsn	0.26			
SMFMN	Melt factor for snow on June 21	.bsn	7.02			
SFTMP	Melt factor for snow on December 21	.bsn	− 0.56			
TIMP	Snow pack temperature lag factor	.bsn	0.47			
SURLAG	Surface runoff lag time	.bsn	7.04			

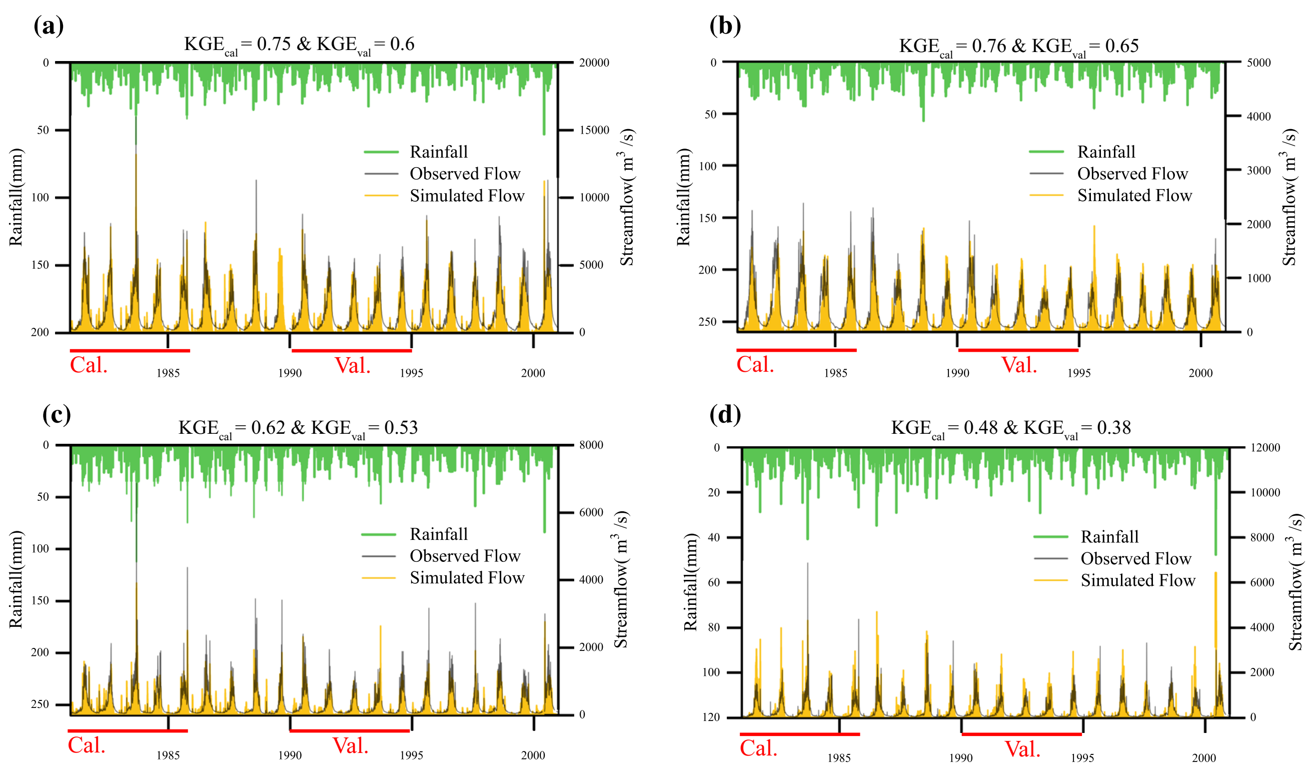

Fig. 2 Observed and model stream flow against observed rainfall over **a** C280, **b** C270, **c** C260, and **d** C215 watershed. KGE values of calibration (KGECal) and validation (KGEval) are also shown in each section of the figure. The two red lines in each subplot represent the calibration (as Cal.) and validation (as Val.) period

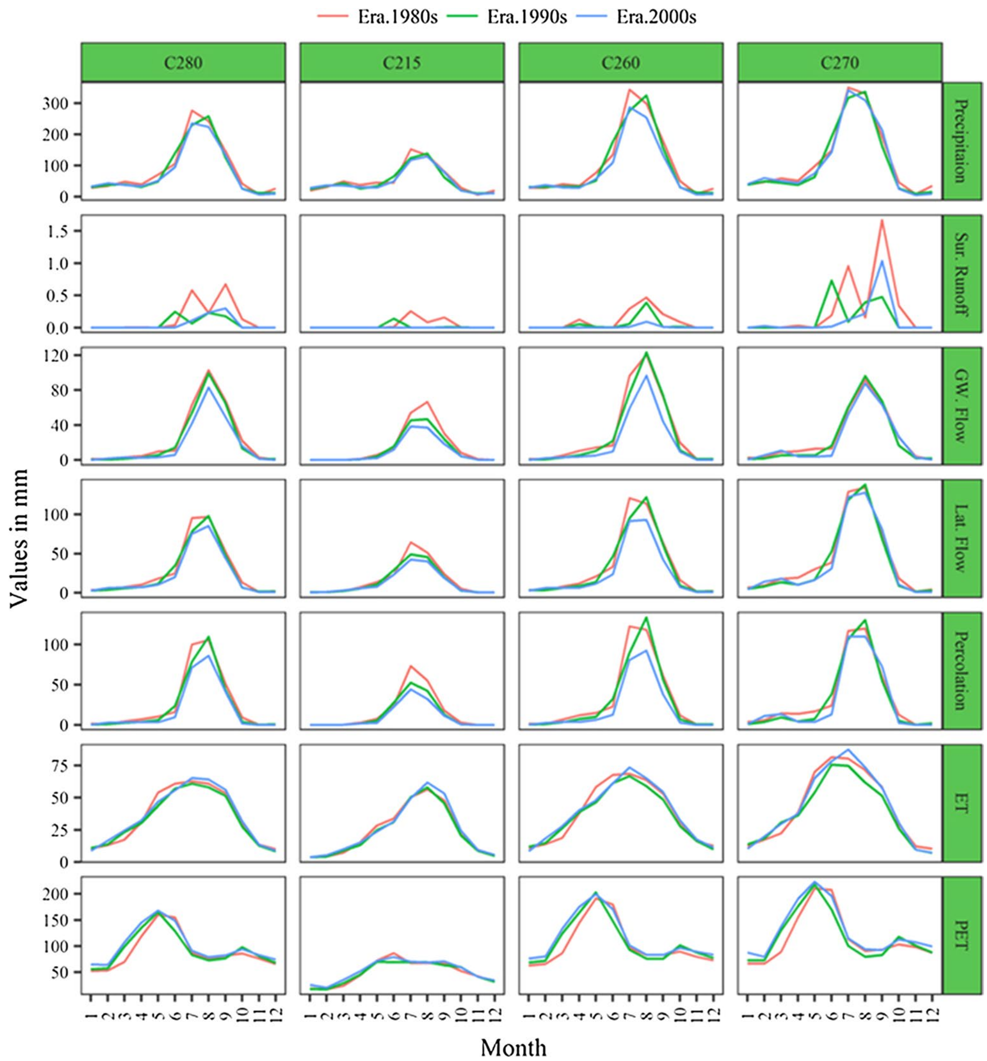

Fig. 3 Characteristics of different components of water balance over the watershed of station C280, C215, C260, and C270 in three time slices, namely Era-1980s (1971–1980), Era-1990s (1981–1990), and Era-2000s (1991–2000)

The effect of ET over Karnali watersheds is shown in Fig. 4a. All the watersheds show similar pattern of ET–rainfall ratio during the selected time period. However, snow-dominated watershed like the watershed of C215 shows more ET contribution than the rest of the watersheds. The mean trend of ET/rainfall reveals a gradual increase in

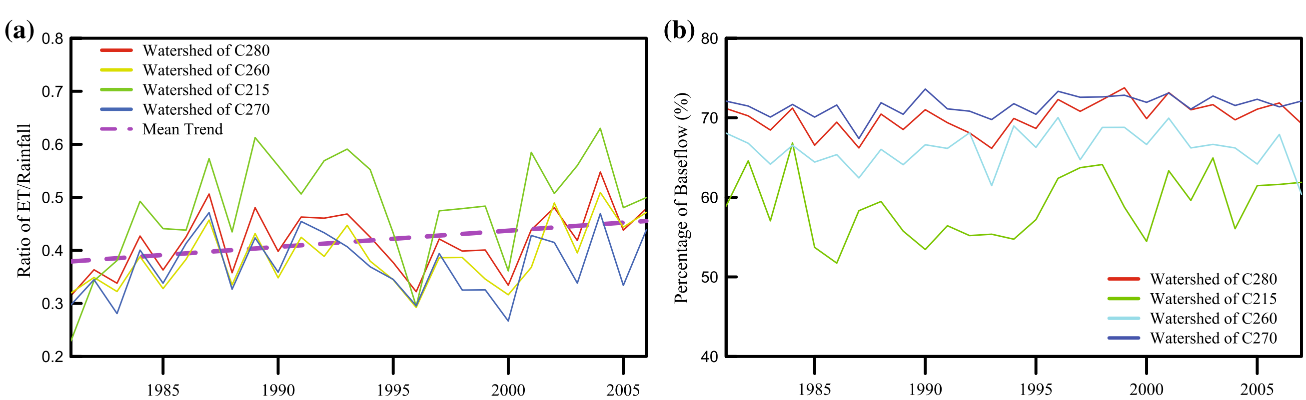

Fig. 4 **a** Ratio of ET and rainfall and **b** the contribution of base flow in the total flow from CASE3 model simulation over the four selected watershed

ET over the study area. The probable cause of this rise can be attributed to global warming as increased heat flux results in increased ET.

To evaluate the characteristics of flow regime, we calculated the base flow contribution in the total flow of the model. The average contribution of base flow over entire study area ranges from 65 to 75% of total flow annually (Fig. 4b). The watershed with more snow cover showed lower contribution of base flow than other watershed. Huang et al. (2016) showed that, in mountainous watershed, land use changes like forest to agricultural land could increase the contribution of base flow. Similar reasoning could be made for C215 which had relatively low baseflow. The mean annual groundwater contribution in the entire study area is about 30% in comparison with the total flow.

To identify the flow regime and its decadal changes, we selected five hydrologic indicators that are presented in Fig. 5. The duration of flow regime is characterized with 'Dur' index (the duration between Q25 and Q75 flows), which is found to exhibit similar pattern for both modeled results and observed data. The index did not show any significant changes among the three selected time chunks. Different magnitude of the flow regime, which is represented by Q75, Q50, and Q25, is detected reasonable well in model compared to the observed values. It should be noted that, during 1987–1988, there were missing values in the observed data. Therefore, observed flow matrix showed some unusual changes during that time. In that context, the modeled streamflow helped to determine the actual characteristics of river flow, which could not be achieved by simple interpolation methods. The MeanBFI index showed satisfactory agreement between model and observed data which is one of the indicators for the environmental flow regime. In terms of capturing the duration between high flow and low flow, model underestimated the duration between two flows. However, the model replicated other characteristics of flow regime more accurately in our analysis. In terms of changes in decadal scale, no

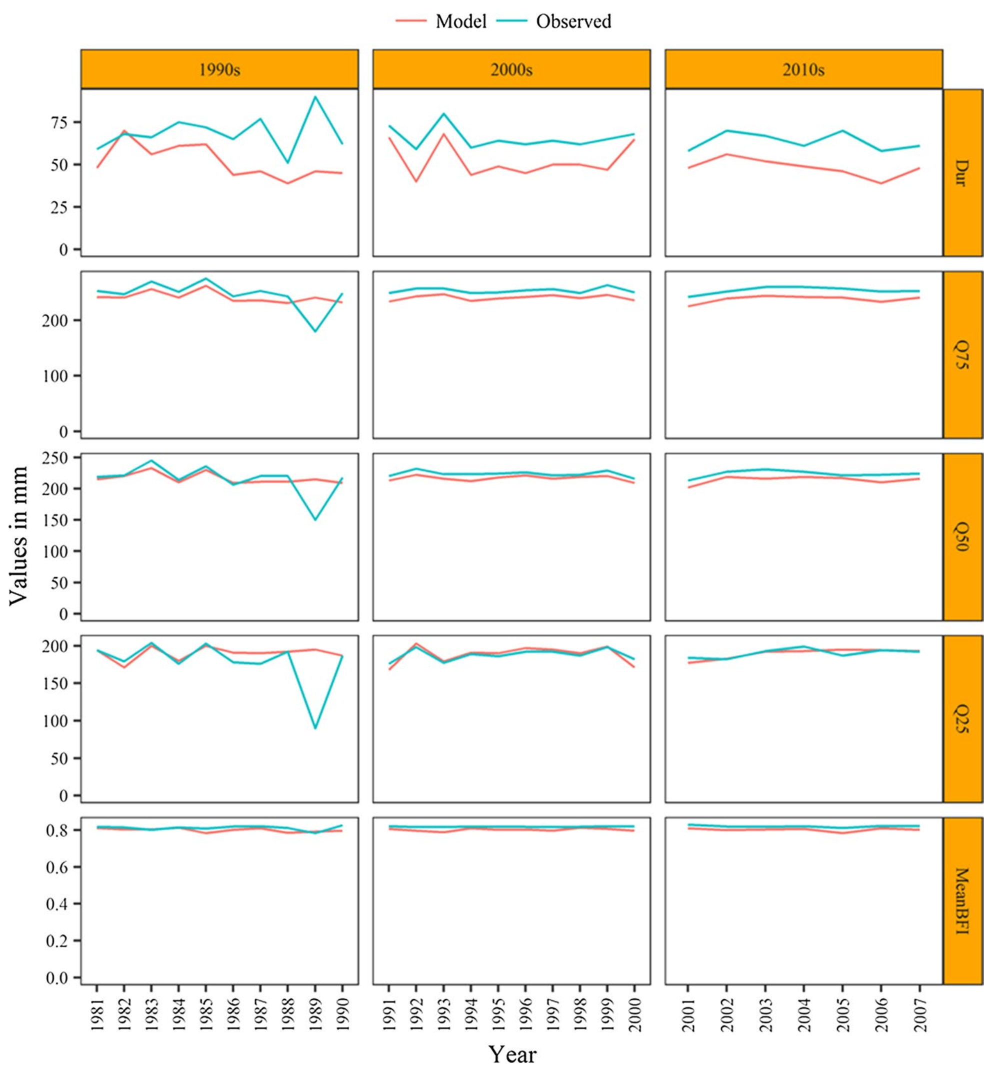

Fig. 5 Model performance in different environmental flow regime

significant changes are found in any of the selected environmental flow matrixes.

Conclusion

We calibrated the Karnali watershed using an improved multi-site multi-segment calibration technique. We also assessed the performance of the environmental flow regime in previous climate period. The key findings are summarized in the following paragraph:

The new methods of calibration for large watershed in this study were found to be more effective in estimating river discharge compared to other conventional calibration techniques. In terms of magnitude of the flow regime, the model-generated discharge was able to capture both low flow (Q25) and high flow (Q75) matrices reasonably well. The model also accurately replicated the proportion of base flow (Mean-BFI) in comparison with observed data. The calibrated model is also successful in generating similar frequency pattern ('Dur' index). However, the model underestimated the 'Dur' index with respect to observed values. In summary, the performance of the model in reproducing all five selected environmental flow regime parameters was found to be acceptable. In the decadal trend analysis, it is found that the ET proportion in rainfall is increasing in recent years which supports the ongoing effect of global warming.

This modeling practice enables a basis for the estimation of flows for mountainous watershed accurately in daily scale. As the present study explored the observed condition of environmental flow, with the help of climate projections, similar methodology can be implemented to explore the future condition of the flow in any mountainous watershed.

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