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A multi-model approach for analyzing water balance dynamics in Kathmandu Valley, Nepal

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ABSTRACT

Study region: : Kathmandu Valley, Capital city of Nepal
Study focus: : This study applied three hydrological models (i.e., SWAT, HBV, and BTOPMC) to analyze the water balance components and their temporal and seasonal variations in the Kathmandu Valley, Nepal. The water balance components were investigated using the same precipitation, climatic data, and potential evapotranspiration (PET) as input variables for each model. The yearly and seasonal variations in each component and the interactions among them were analyzed. There was a close agreement between the monthly observed and calibrated runoff at the watershed scale, and all the three models captured well the flow patterns for most of the seasons.
New hydrological insights for the region: : The average annual runoff in the study watershed calculated by the SWAT, HBV, and BTOPMC models was 887, 834, and 865 mm, corresponding to 59%, 55%, and 57% of the annual precipitation, respectively. The average annual evapotranspiration (ET) was 625, 623, and 718 mm, and the estimated yearly average total water storage (TWS) was 5, −35, and 29 mm, respectively. The long-term average TWS component was similar in all three models. ET had the lowest inter-annual variation and runoff had the greatest inter-annual variation in all models. Predictive analysis using the three models suggested a reasonable range for estimates of runoff, ET, and TWS.

Although there was variation in the estimates among the different models, our results indicate a possible range of variation for those values, which is a useful finding for the short- and long-term planning of water resource development projects in the study area. The effects of historical water use, water stress, and climatic projections using multi-model water balance approaches offer a useful direction for future studies to enhance our understanding of anthropogenic effects in the Kathmandu Valley.

1. Introduction

Water in the natural environment is in almost continuous motion as various components of the hydrological cycle change its state from liquid to solid or vapor and vice-versa under appropriate conditions. Knowledge on the water storage and movements within the components of the hydrological cycle can help characterize the interactions among the primary

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components of the cycle to assess the current status and trends, partitioning of green and blue waters, human–environment relationships, and sustainability of water resources (Sokolov and Chapman, 1974; Boughton, 2004; Anderson et al., 2006; Healy et al., 2007; Moriarty et al., 2007) over a specific period of time. Such information provides a resource for policy makers, decision-makers, and other relevant stakeholders to quantify the different types of water security threats (Sunsnik, 2010), and devise strategies for better allocation, utilization, and management of freshwater resources; management of wastewater; and prediction of floods (Boughton and Hill, 1997; Anderson et al., 2006). For example, in Iran, water balance studies are customary for allocating financial budgets to water resource policies and projects (Ghandhari and Alavi moghaddam, 2011). Furthermore, such information can provide feedback for redefining scenarios; support systems for decision-making, strategies, and policies in the design and assessment of alternative water resource management plans; and help prioritize investments in water infrastructures. In addition, water balance studies can help refine the optimized allocation of limited water resources, quantify environmental and economic impacts, and diffuse potential water security issues (Sunsnik, 2010).

Techniques for estimating water balance range from very simple methods, such as lumped models and field-experiment techniques, to highly complex computer-based models that can calculate water balance at various temporal (e.g., hourly, daily, monthly, and yearly) and spatial scales (Xu and Singh, 1998; Zhang et al., 2002; Ghandhari and Moghaddam, 2011). Selection of an appropriate technique depends on the objectives of the study and availability of data (Zhang et al., 2002). Increasing a model's complexity does not necessarily improve its accuracy (Walker and Zhang, 2001), and simple lumped models may also be equally well or better than more complex alternatives (Jakeman and Hornberger, 1993). Monthly water balance models were first developed by Thornthwaite in 1940, and later revised by Thornthwaite and Mather (1955) (Xu and Singh, 1998). Between 1959 and 1966 computer-based hydrological models evolved with SWM models (Crawford and Linsley, 1966) that focused on the estimation of runoff. Today, numerous models with different assumptions and parameterizations are available for water balance computations, such as the NAM Module for MIKE-11 (Celleri et al., 2000), WATBAL (Starr, 1999), WaSim-ETH (Schulla and Jasper, 2007), HBV (Bergstrom, 1976; Bergstrom, 1992), YHyM/BTOPMC (Takeuchi et al., 1999), SWAT (Arnold et al., 1998), and TWBM (Thornthwaite and Mather, 1955). These models include temporal and spatial features that make them useful as tools for water resource management, groundwater modeling, and urban and rural watershed management under different climatic conditions (Vandewiele et al., 1992; Makhlouf and Michel, 1994; Vandewiele and Elias, 1995; Xu et al., 1996; Xiong and Guo, 1999; Legesse et al., 2010). Over the last four decades, researchers have attempted to reproduce the different characteristics of catchments in models, resulting in a large number of mathematical models for watershed simulation (Alam et al., 2011). The features of basin-wide climate, geology, socioeconomic development, and land use play significant roles in shaping the quantity, quality, and timing of stream flow. Integrated and interdisciplinary approaches that simultaneously address problems of the environment and water resources in the context of these factors increasingly require the use of suitable mathematical models (Tokar and Johnson, 1999).

Based on the degree of complexity to be considered, various types of models are available for simulating rainfall-runoff and water balance analyses. A physically based model is a scaled-down form of a real system (Brooks et al., 1991; Salarpour et al., 2011), which serves as a better tool to support decision-making for related project implementation, but its large data requirement may limit its use in many circumstances (Singh and Frevert, 2006). Field-experiment techniques for water balance estimations cannot by themselves adequately represent the impacts of complex dynamics (e.g., land-use and land-cover changes) in the watershed due to the high costs associated with such techniques. Fundamental conceptualization of the system is based on an understanding of the hydrological cycle, and varies from the control volume principle that considers the watershed as a lumped system, to complex models incorporating soil moisture dynamics. There are always trade-offs among the models, and selection of the most appropriate one depends upon the objectives and data availability. Some of the challenges with complex models include the need for more data, more computational time, and careful attention to represent complex interactions among processes and parameters, over-parameterization (Jakeman and Hornberger, 1993), and difficulty in interpreting the results. However, complex models decrease systematic errors and are flexible in the sense that they can accept different types of variables/parameters as stocks, converters, flows, and so forth (Sunsnik, 2010). In contrast, simple models can use readily available data (e.g., rainfall and runoff), are easy to perform, produce results that are simple to interpret, and are manageable with only a basic knowledge of hydrology. However, they can cause systematic errors resulting from simplified assumptions (Zhang et al., 2002), and may not be useful for estimating all of the water balance components. Despite the effort and resources invested in developing better hydrological models, no single model is superior in capturing hydrological processes under all conditions and for all cases (Beven, 2006; Duan et al., 2007). Therefore, definitive conclusions should not be based on the results of a single model realization, and hence multi-model analysis is highly preferred to add confidence in the model results (Fritsch et al., 2000; Haddeland et al., 2011; Nasseri et al., 2014).

Kathmandu Valley (KV) (Fig. 1) in central Nepal suffers from an acute shortage of water, which is primarily due to the growth in population from 1.11 million in 1991–1.65 million in 2001 (CBS, 2003) to 2.53 million in 2011 (CBS, 2012). The corresponding urbanization, which has resulted in a decrease in agricultural land area in the valley from 62% to 42% from 1984 to 2000 (ICIMOD, 2007), alters the dynamics of the hydrological environment. Climate and land-use changes (Thapa et al., 2008) and sand extraction (NTNC, 2008) have greatly influenced the hydrological responses and water resource planning in the valley, resulting in water shortages, inter-sectoral water conflicts (Shukla et al., 2010), and deteriorating water quality with subsequent impacts on public health (NTNC, 2008). The potable water demand of KV has increased from 35.1 million liters per day (MLD) in 1988 (Gyawali, 1988) to 155 MLD in 2000 (Moench and Janakarajan, 2006) to 370 MLD in 2015 (KUKL, 2015). Kathmandu Upatyaka Khanepani Limited (KUKL), the utility responsible for water supply in the valley, supplies only 115 MLD during the wet season and 69 MLD during the dry season, and the deficit is met

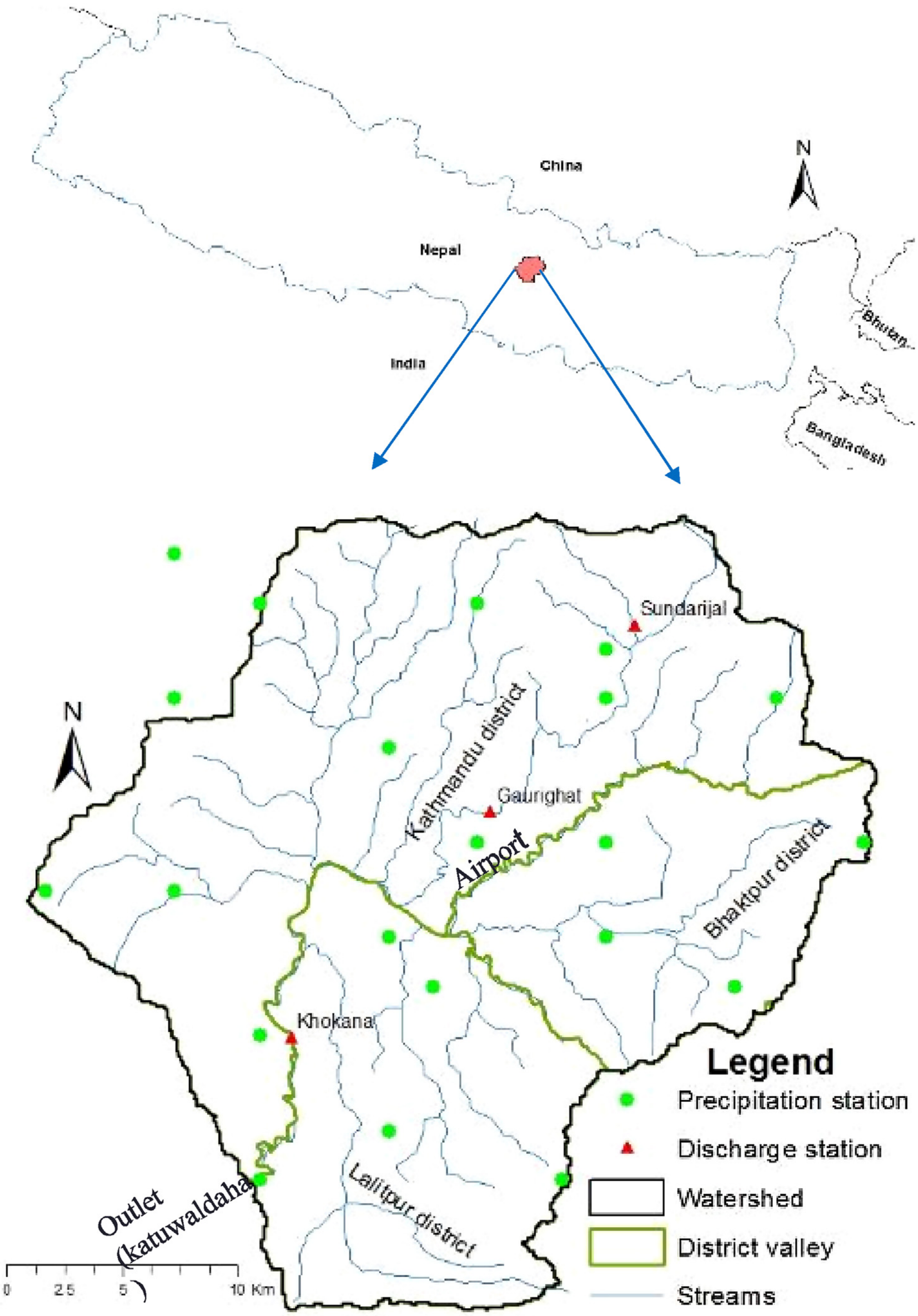

Fig. 1. Location of study area with major tributaries, rainfall stations and discharge gauging stations.

through groundwater pumping, traditional water spouts, wells, supplies from private water vendors (which was estimated at more than 450 tankers operating in 2009; Shrestha and Shukla, 2010), and bottled water companies. Udmale et al. (2016) projected a deficit of 322 MLD by 2021, and Thapa et al. (2016a) estimated a 40% reduction in the total water supply due to the 2015 Gorkha Earthquake. Surface water available at the intake of water supply systems is insufficient to meet potable water demand (both domestic and commercial) leading to water deficits (MoPPW, 2004) in the valley. For the short term solution to meet these deficit could be done by harvesting additional 67 MLD in dry season and 87 MLD in wet season from mountainous region of KV (Thapa et al., 2016b). Furthermore, the availability of water could decrease in the dry season and increase in the wet season due to climate change, resulting in an increase in annual water availability (Babel et al., 2013) and change in flood patterns (Sharma and Shakya, 2006). All of these scenarios indicate that significant variability in the

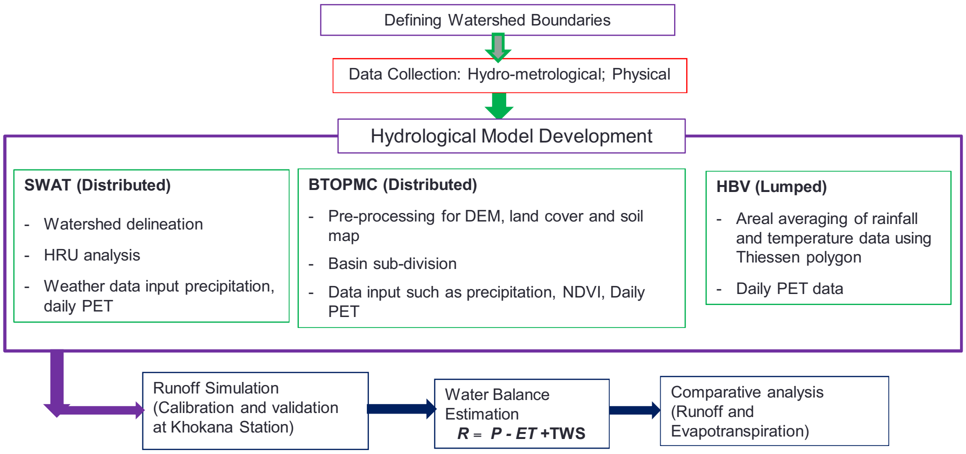

Fig. 2. Overall methodological framework for estimating water balance using multi-model approach (*DEM is digital elevation model, NDVI is normalized difference vegetation index, PET is potential evapotranspiration, P is Precipitation, R is runoff, ET is evapotranspiration, TWS is total water storage).*

available water in different components of the hydrological cycle has created insecurity in the potable water supply in the KV.

Very few studies to date have used a holistic approach to examine the amount of available water in the different components of the hydrological cycle, however, none of the studies have reported the range to which those values may vary in the KV watershed. This study aims to address the gap by estimating and evaluating the water balance for the study area using three hydrological models. The results will be useful for tackling human-induced water scarcity issues in the area by supporting informed decision-making. The multi-model analysis offers an approach for defining possible ranges within which the water stored in different components of the hydrological cycle may vary for a watershed of interest.

2. Materials and methods

2.1. Study area

KV watershed is located between 27°32′13′′ and 27°49′10′′N and 85°11′31′′ and 85°31′38′′E. The elevation of the watershed ranges from 1212 to 2722 m above mean sea level according to the 30 m ASTER global digital elevation map (GDEM), and covers an area of 664 km^2. The valley is bowl-shaped and surrounded by hills (which are the origin of most of the valley's tributaries) acting as natural forts to protect the valley. The major rivers traversing the valley are the Bagmati, Bishnumati, Hanumante, Dhobi, and Manohara. The outer periphery (hilly area) of KV is covered by mixed forest, peri-urban areas are composed of a mix of agricultural and built-up land, and the central core of the valley is covered by built-up area. The surface runoff of the entire valley drains through the Bagmati River with its outlet at Katuwaldaha, located at the southern tip of the valley. The climate in the valley is characterized as warm temperate with warm days followed by cool nights and mornings. The average precipitation ranges from 1500 mm (city area) to 1800 mm (surrounding hills), the average summer temperature varies from 28 °C to 30 °C, the average winter temperature is around 10 °C, and the average humidity is 75% according to data for 2000–2010 provided by the Nepalese Department of Hydrology and Meteorology (DHM). The rainfall is mostly monsoon-based, with 65% of the total rainfall concentrated during the monsoon months of June to August. Rainfall is highly variable and has unpredictable anomalies based on the DHM data for 2000–2010.

2.2. Methodology

This study applied a multi-model approach to estimate the water balance in the KV watershed using the physical and hydro-meteorological data. The overall methodological framework adopted in this study is shown in Fig. 2.

2.2.1. Watershed delineation

The watershed boundary was defined above the outlet of the Bagmati River at Katuwaldaha (Fig. 1) using the 30 m ASTER GDEM. The entire watershed was divided into three sub-basins to represent spatial variabilities within the three models mentioned in Fig. 2. The sub-divisions were made above the three hydrological stations available along the main river in the valley (Fig. 1).

Table 1
Main characteristics of the three hydrological models used in this study.

Model name	Model type	Model time steps	Metrological forcing variables	Hydrological. processes	Smallest spatial unit	Runoff schemes	Refs.
SWAT	D	Daily	P,DEM,LC,SM, PET	Physical	HRU	SCS, CN	Arnold et al. (1998)
BTOPMC	D	Daily	P,NDVI,DEM,SM,LC, PET	Physical	Grid (Water balance: Sub-basin)	TOPMODEL concept	Takeuchi et al. (1999)
HBV	L	Daily	P, T_{mean}, PET	Conceptual	Basin	SE/Beta function	Bergström (1976)

P is precipitation, DEM is digital elevation map, LC is land cover type, SM is soil map, VP is vapor pressure, CC is cloud cover, NDVI is normalized differences vegetation index, T_{mean} is average air temperature, PET is Potential Evapotranspiration (calculated by Snyder's equation using pan evaporation data), HRU is hydrological response unit (unique combination of soil type, land use and slope), CN is curve number, D is distributed, L is lumped.

2.2.2. Selection of hydrological models

Three types of models, both lumped and distributed types as mentioned in Fig. 2, were developed for the KV watershed to estimate water availability in the different components of the hydrological cycle. They are discussed briefly below, and their key characteristics are summarized in Table 1.

SWAT (Arnold et al., 1998): The SWAT model is a distributed parameter, continuous time model that was developed to help water resource managers assess water supplies and non-point-source pollution in small to large river catchments. The model uses digital maps on an ArcGIS interface for pre- and post-processing, and processes the results as maps, tables, or text files. The Soil Conservation Service (SCS) curve number method is used to estimate surface runoff from daily precipitation (SCS, 1972) and variable storage for channel routing. Evapotranspiration (ET; the atmospheric demand of water) includes all processes (transpiration and evaporation) that convert water at the Earth's surface to water vapor (Allen et al., 1998). While accurate estimation of the ET is important for hydrological studies and water resource management, it is generally the least known variable. It is difficult to measure the ET directly at the catchment scale (Aouissi et al., 2016). Many researchers have concluded that calculating potential evapotranspiration (PET) is acceptable for use in water budgets and models (Xu and Chen, 2005; Earls and Dixon, 2007). In the SWAT model, the temperature-based Hargreaves (HA) method (Hargreaves and Saman, 1985), radiation-based Pristely and Taylor (PT) method (Priestley and Taylor, 1972), and the combined Penman-Monteith (PM) method (Penman, 1956; Monteith, 1965) are incorporated to estimate PET. There is also a provision to read PET data directly as an input. In this study, we adopted the latter option, calculated PET outside the model from Snyder's equation (Snyder's, 1992) using observed pan daily evaporation data as input, and then read as input to the model. Evaporation of free water from the canopy was subtracted from the PET, known as adjusted PET. The ET was calculated as a function of the adjusted PET, leaf area index, and water content; it varies with plant growth. Similarly, the ET was calculated as a function of the adjusted PET, soil cover, soil depth, and plant water uptake (Neitsch et al., 2005).

BTOPMC (Takeuchi et al., 1999): The BTOPMC model is a physically based distributed hydrological model based on block-wise use of TOPMODEL and the Muskingum-Cunge method that combines the advantages of both lumped and distributed models. The TOPMODEL concept (Beven and Kirjby, 1979) is used to estimate runoff. In the model, the local saturation deficit is controlled by the soil-topographic index and average saturation deficit of the sub-basin. The discharge in each cell is composed of both overland flow and base flow, and both are dependent on the local saturation deficit (Takeuchi et al., 2007). The physically based Muskingum-Cunge method was adopted as a flow routing method, taking advantage of the computational simplicity and physical soundness of simulating flood wave diffusion (Takeuchi et al., 1999). In the BTOPMC model, the SW method (Shuttleworth and Wallace, 1985) is available as a sub-module for estimating PET, or PET can be directly read as an input. The SW method is an extension of the Penman-Monteith method that includes sparse vegetation by considering two coupled sources in a resistance network (transpiration from vegetation and evaporation from substrate soil) and is applicable at the global scale, particularly in data-poor or ungauged large basins (Zhou et al., 2006). In this study, PET was calculated outside the model from Snyder's equation (Snyder's, 1992) using observed pan daily evaporation data. The calculated PET was then provided with the model as input to estimate ET. ET is considered to occur from the root zone according to the PET and the availability of water in the root zone. ET is calculated as the minimum of either the fraction of PET or the root zone storage available for evapotranspiration as described in detail by Takeuchi et al. (2007) and Zhou et al. (2006). The fraction value is a unitless drying function related to the soil moisture wetness in the root zone, which limits the ET (Vorosmarty et al., 1998).

HBV (Bergstrom, 1976): The HBV model is a widely used conceptual rainfall-runoff model that includes conceptual numerical descriptions of hydrological processes at the catchment scale and requires less data than other models. To estimate runoff, the runoff response module includes two conceptual reservoirs, in which the upper reservoir has two outlets to estimate the near-surface flow, and the lower reservoir simulates the base flow (groundwater flow). A constant percolation rate is used to connect the reservoirs, and the runoff response routine transforms the excess water from the soil moisture routine to discharge for each reservoir. In this study, PET calculated outside the model from Snyder's equation (same as both SWAT and BTOPMC model) was then provided as input to the HBV model to estimate ET. To estimate ET, the daily estimated PET was adjusted for temperature deviation based on mean daily air temperatures and the long-term average as described in detail by Lindstrom and Bergstrom (1992).

Table 2
Calibration strategies and parameters used in the three hydrological models.

Model Name	Calibration Strategy	Calibration Parameter	Performance Indicator	Optimization Technique
SWAT	Regionalization	CN2, GW_DELAY, CH_K2, CH_K1, OV_N,CH_N1, CH_N2, GW_REVAP,GWQMN,CANMX	R^2, NSE, and PBIAS	Manual
BTOPMC	Regionalization	m,n0,alpha, SDbar,T0, Srmax	R^2, NSE, and PBIAS	Manual
HBV	Regionalization	FC, LP, BETA, PERC,UZL, K0, K1, K2, MAXBAS	R^2, NSE, and PBIAS	Manual

CN2 is initial Soil conservation service curve number for moisture condition II, GW_DELAY is groundwater delay time, CH_K2 is effective hydraulic conductivity in main channel, CH_K1 is effective hydraulic conductivity in tributary channel, OV_N is manning's "n" value for overland flow, CH_N1 is manning's "n' value for the tributary channel, CH_N2 is manning's 'n' value for main channel GW_REVAP is groundwater revap coefficient, GWQMN is threshold depth of water in the shallow aquifer required for return flow to occur, CANMX is maximum canopy storage, m is decay coefficient, n0 is manning's roughness parameter, alpha is empirical constant of drying function in evapotranspiration module (Vorosmarty et al., 1998), SDbar is initial value of average saturation deficit of each sub-basin, T0 is saturated transmissivity of soil, Srmax is vegetation rooting depth, FC is maximum soil storage, LP is factor defining reduction of evaporation, BETA is shape parameter, PERC is percolation rate, UZL is limiting factor, K0, K1 and K2 is recession coefficient, MAXBS is triangular weighting function, R^2 is correlation coefficient, NSE is Nash Sutcliffe Efficiency, PBIAS is percentage biasness, GAP is genetic algorithm optimization.

2.2.3. Model calibration strategies and performance indices

The hydrological models were calibrated based on the observed runoff at Khokana station (Fig. 1) located near the outlet of the KV watershed. Model parameters were adjusted manually until a reasonable statistical agreement between the observed and simulated runoff was obtained at Khokana. The calibration parameters, performance indicators, optimization techniques, and calibration strategies used in model calibration for all three models are summarized in Table 2. All of the models were run with a daily time step using the same rainfall and PET as inputs, and were individually calibrated and validated based on available observational data. Parameters were regionalized based on the soil and land-cover type in the SWAT and BTOPMC models (the parameterization was based on the discretized sub-basin, hydrological response unit, and grid size), whereas in the HBV model simulation, the parameters were regionalized for the sub-basin.

All three models were calibrated for the period 2001–2007. Three performance indicators, the Nash-Sutcliffe efficiency (NS), percent volumetric bias (PBIAS), and coefficient of determination (R^2), were used to evaluate the performance of the models.

2.2.4. Model validation

The same three performance indicators as used in model calibration were used for validation of the models using the same parameters as in the calibration for the period 2008–2010.

2.2.5. Water balance estimation

Water balance was estimated based on the principle of conservation of mass (i.e., the water entering an area must leave the area or be stored within the area) and the annual partitioning of precipitation into ET and runoff, which is controlled by the temporal distribution of water supply (precipitation) and demand (ET) and is balanced by water storage in the soil (Sokolov and Chapman, 1974; Kwadijk, 1993; Milly, 1994). The snow and ice components were not used as they were not relevant to the study area. Thus, the water balance can be expressed as:

$$R = P - ET + \mathrm{TWS}$$

where *R* is river runoff, P is precipitation, *ET* is evapotranspiration, and *TWS* is total water storage (vegetation, snow and glacier, surface detention, soil, and groundwater).

To determine the water availability in the different components of the hydrological cycle, the estimated values from the models of all of the components should be reasonably accurate. In reality, there are always discrepancies between the observed values and model predictions due to measurement errors, inadequate data capture networks, and the difficulty of representing real-life complex spatial heterogeneity in the model. However, we attempted to verify the model results with each component of the hydrological cycle such as precipitation, runoff, PET, and so forth. Observed precipitation data that had been adequately checked for continuity and consistency were used in the simulations. River runoff was estimated using the three different models and compared to observed runoff. PET values estimated from Snyder's equation using measured pan evaporation data at Kathmandu Airport as inputs were used with all the three models. The groundwater and surface water withdrawals for consumptive and non-consumptive uses are not considered in this study. Each water balance component in the watershed was estimated using the simple water balance equation, and the model results were analyzed and compared. The results are useful for scenario visioning and planning with stakeholders in the context of water scarcity in KV. Based on the measured precipitation data and observed PET, the percentage runoff generation (runoff fraction) and conversion of

Table 3
Description of data and sources.

Type	Description	Source	Original resolution	Model	Remarks
Physical data	Digital Elevation Model (DEM)	USGS	30 × 30 s (~1 × 1 km)	SWAT, BTOPMC	Global data
	Land use	LRMP	90 m x 90 m	SWAT	1998
	Land cover map	IGBP	30 × 30 s (~1 × 1 km)	BTOPMC	Global data
	Soil map	FAO	0.25 × 0.25deg. (~25 × 25 km)	SWAT, BTOPMC	
	NDVI	Vito Earth	8 × 8 km	BTOPMC	
Hydro- meteorological data	Precipitation (23 stations)	DHM	daily data	SWAT, BTOPMC, HBV	2000–2010
	Mean temperature (7 stations)	DHM	daily data	HBV	2000–2010
	Pan evaporation (1 station)	DHM	daily data	SWAT, BTOPMC, HBV	2000–2010
	Observed discharge (3 stations)	DHM	daily data	SWAT, BTOPMC, HBV	2000–2010

USGS is United States of Geological Survey, LRMP: land reform mapping project, IGBP is international geosphere-biosphere program, FAO is Food and Agricultural Organization, NDVI is normalized difference vegetation index, DHM is Department of Hydrology and Meteorology.

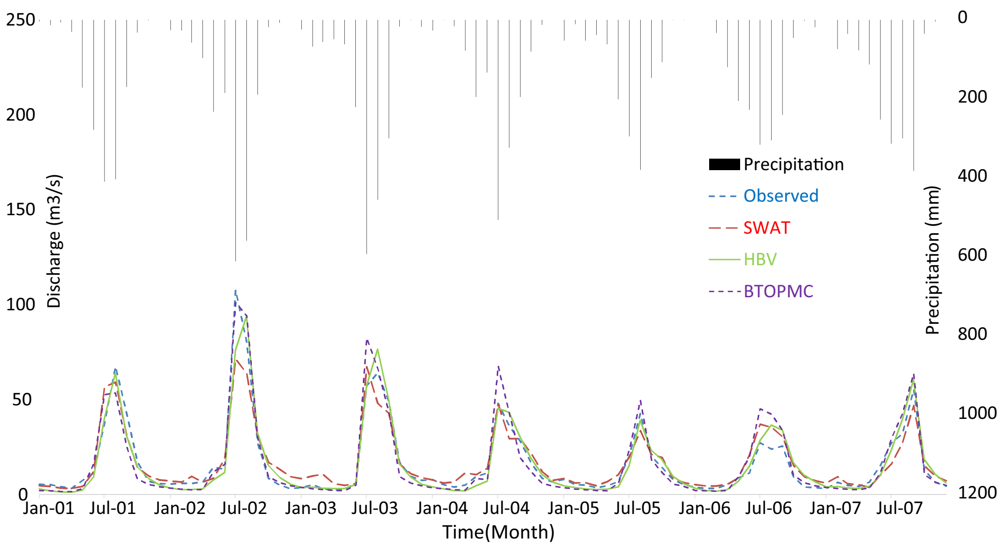

Fig. 3. Plot of simulated (by three models) and observed monthly runoff at Khokana (Station ID: 550.05) during calibration period (2001–2007).

PET to ET were estimated. The runoff fraction is the percentage of total precipitation that is converted into runoff, and is calculated as the ratio of runoff to total precipitation in the study watershed.

2.2.6. Data and sources

The three models use different types of input files for the hydrological simulation. Details of the data used in this study, including their extent, spatial resolution, and the data sources, are listed in Table 3. Records of precipitation, pan evaporation data, and runoff published by the DHM were used as the basic data, and the areal coverage of each meteorological station for calculating the total precipitation in the basin was calculated using the Thiessen polygon technique with GIS. Observed flows near the outlet of the basin at Khokana station (Fig. 1) were used to evaluate the performance of the models.

3. Results and discussion

All three models were calibrated and validated at the outlet of the basin, capturing flows generated at almost all the parts of the valley and reflecting the results of all of the flow processes and their interactions occurring in the entire valley. Monthly simulated runoff values were compared to observed runoff values from the three models, and performance indicators were calculated and summarized.

3.1. Model calibration

Plots of the runoff simulated by the three hydrological models with the observed runoff at the outlet (i.e., Khokana station) for the entire calibration period (2001–2007) are shown in Fig. 3. All three models adequately simulated the general

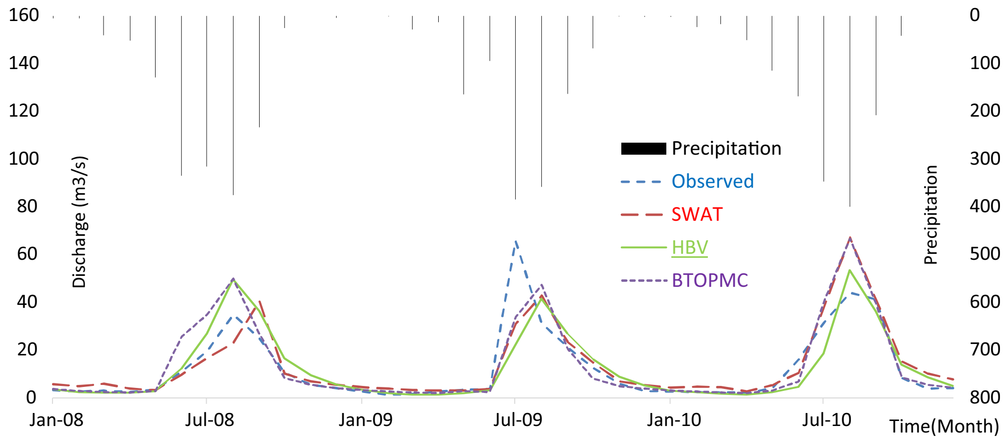

Fig. 4. Plot of simulated (by three models) and observed monthly runoff at Khokana (Station ID-550.05) during validation period (2008–2010).

Table 4
Statistical analysis of observed and simulated runoff at Khokana (Station ID: 550.05).

S.N.	Items	Calibration Period (2001–2007)				Validation Period (2008–2010)			
		Observed	SWAT	HBV	BTOPMC	Observed	SWAT	HBV	BTOPMC
1	Mean monthly runoff (m^3/s)	16.30	16.91	15.02	15.56	12.52	13.90	12.76	13.76
2	Minimum monthly runoff (m^3/s)	2.39	3.27	1.19	1.61	1.50	2.94	1.43	2.20
3	Maximum monthly runoff (m^3/s)	107.76	71.35	93.85	101.18	66.01	67.37	53.63	66.92
4	Standard deviation of runoff	19.65	16.16	18.43	20.96	15.23	15.13	14.66	17.24
5	Coefficient of determination (R^2)		0.89	0.92	0.92		0.72	0.65	0.75
6	Nash Sutcliffe Efficiency (NSE)		0.88	0.92	0.89		0.69	0.63	0.67
7	% PBIAS		−0.04	0.02	0.00		−0.11	−0.02	−0.10

trends in runoff fluctuations in the KV watershed and responded well to rainfall events (Figs. 3 and 4). All three models simulated average monthly runoff during the lean season better than the peak season flows. In addition, NSE values were 0.88, 0.92, and 0.89, and PBIAS values were −0.04, 0.02, and 0.0 in the SWAT, HBV, and BTOPMC models, respectively (Table 4). No generally agreed absolute thresholds exist for the performance indicators; however, based on published studies, hydrological simulation of monthly values with NSE above 0.65 can be considered satisfactory (Moriasi et al., 2007). Values of performance indicators and the reasonably well-correlated plots of simulated versus observed monthly runoff in this study suggest satisfactory performance of all the three hydrological models for the purpose of water resource assessment and water balance analysis.

The simulated mean monthly runoff was 16.91 m^3/s in the SWAT model, 15.02 m^3/s in the HBV model, and 15.56 m^3/s in the BTOPMC model during the calibration period. The difference in mean runoff during the calibration period was 0.61 m^3/s, 1.28 m^3/s, and 0.73 m^3/s in SWAT, HBV, and BTOPMC models, respectively. Predictive analysis showed that the runoff was underestimated by the HBV and BTOPMC models, and overestimated by SWAT during the calibration period. Although comparison of the performance indicators and statistical analyses with the observed runoff suggested reasonably good simulation of monthly flow by all the three models. The focus during calibration was mainly on storm fitting for lean season flow and performance for the entire period of calibration. Because of the reason, there are differences in estimation on yearly basis, such as underestimation of general trend of peak flow in wet year (e.g., 2002) and overestimation in dry year (e.g., 2006). As the performance were evaluated for average conditions, the model results are useful for the purpose of water resources assessment and not for flood-related studies.

3.2. Model validation

The calibrated parameters were used with all the three models to simulate runoff for the validation period of 2008–2010. Performance of the models during the validation are shown in Fig. 4 and Table 4. The annual precipitation is less than the average precipitation over the basin for all the three years considered for validation. For year 2008 and 2010, all the three models overestimated the peak flow, as in calibration, for dry year but for year 2009 it is not following the general pattern. The reason behind could be variation in precipitation pattern in the year 2009 compared to other years considered in validation. To be more precise, precipitation in June 2009 was very low compared to the same months in other years. As a result, all three models underestimated peak flow during June 2009 (Fig. 4).However, overall performance to simulate average hydrological conditions seems reasonably well during validation as well with the NSE values of 0.69, 0.63, and 0.67; the PBAIS of −0.11, −0.02, and −0.10; and R^2 of 0.72, 0.65, and 0.75 for SWAT, HBV, and BTOPMC models, respectively. The

Table 5
Differences between mean monthly observed and simulated runoff at Khokana (550.05) from 2001 to 2010 (m^3/s).

Item (m^3/s)/month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Observed	4.70	4.36	3.81	3.88	6.58	10.74	44.36	45.75	33.58	12.87	6.46	4.86
SWAT	6.30	6.13	6.15	5.30	6.03	11.73	40.23	43.02	33.82	16.04	9.88	7.40
HBV	3.63	2.84	2.33	2.28	3.94	8.25	35.37	53.75	36.08	16.62	9.49	5.70
BTOPMC	3.29	3.45	3.60	4.81	10.65	19.85	48.05	46.03	29.49	11.13	5.63	4.06

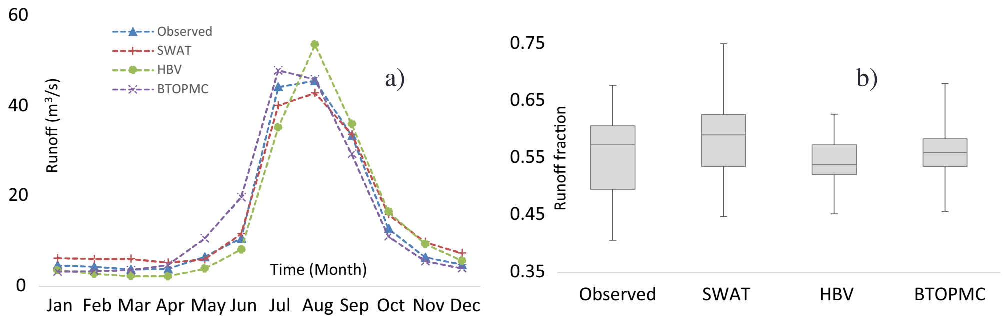

Fig. 5. a) Multi-model mean monthly runoff in comparison with observed runoff values, b) Box plots illustrating the smallest annual runoff fraction (runoff/precipitation), lower quartiles, medians, upper quartiles, and the largest runoff fraction values for observed and participated model from year 2001–2010.

simulated mean discharges were 13.90, 12.76, and 13.76 m^3/s (as shown in Table 4), respectively, for the validation period. The differences in mean runoff during the validation period are 1.38 m^3/s for SWAT, 0.24 m^3/s for HBV, and 1.24 m^3/s for BTOPMC model.

3.3. Comparison of runoff

The monthly averaged runoff volumes produced by the three models are listed in Table 5. The absolute difference between the long-term average (2001–2010) for the observed and simulated runoff was higher during August, September, October, and November for the SWAT model; during June, July, August, October, and November for the HBV model; and during May, June, July, and September for the BTOPMC model. These results show the differences in the seasonal fluctuation for each model from the range of values of runoff for each month. The difference in runoff from the long-term average was small from December to April in all three models, indicating that the dry season values were well-reproduced by the models relative to the observed values. The main focus of this study was water resource assessment rather than flood forecasting, and in this context, all three models provided reasonable values for the water balance components.

In addition to mean monthly flows, we also investigated whether the variabilities in the observed time series were reproduced well by the models. The values of significance for the differences among mean monthly discharges and the box plot of the runoff coefficient for 2001–2010 shown in Fig. 5a) & b) indicate that the SWAT model overestimated the total runoff component with a large range of variation, whereas BTOPMC model overestimated total runoff with a small range of variation and HBV model underestimated the total runoff values with a small range of variation compared to the observed values. The peak flow of runoff estimated by the HBV model was slightly to the right with higher values than the other two models and the observed values. The receding limbs of runoff generated by the SWAT and HBV models overestimated the observed values and they were shifted to the right, whereas the values produced by the BTOPMC model closely matched the observed values. However, the simulated rising limbs from the SWAT and HBV models closely matched the observed values, whereas they were overestimated and shifted towards the left in the BTOPMC model. The mean monthly runoff plots and annual variation in the runoff fraction (2001–2010) showed that all models provided reasonable fits and close correlations relative to observational data

3.4. Comparison of evapotranspiration

Although all three models used the same observed precipitation data and PET as inputs, and the same indicators (NS, PBIAS, and R^2) to evaluate their performance, they used different methods to calculate ET based on the model characteristics. PET for 2001–2010 was estimated from a pan evaporation equation (Snyder's, 1992) using measured pan evaporation data from Kathmandu Airport station located in the central part of the watershed (Fig. 1).

The average monthly seasonal fluctuation in ET estimated by the SWAT and BTOPMC models showed similar trends, whereas the values estimated by the HBV model were different (Fig. 6**b**). The ET estimated by the HBV model for October to March was higher than that produced by the other two models, and in the other months, the ET estimated by the HBV model was smaller than that for the other two models. In general, the average annual ET estimated by the HBV model was

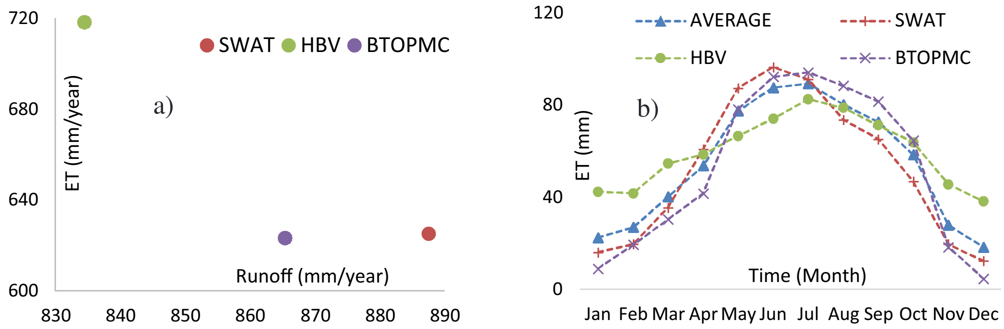

Fig. 6. a) mean model predicted runoff and (ET) evapotranspiration values in mm/year b) Mean monthly ET (Evapotranspiration) in mm for the 10 years simulation period (2001–2010).

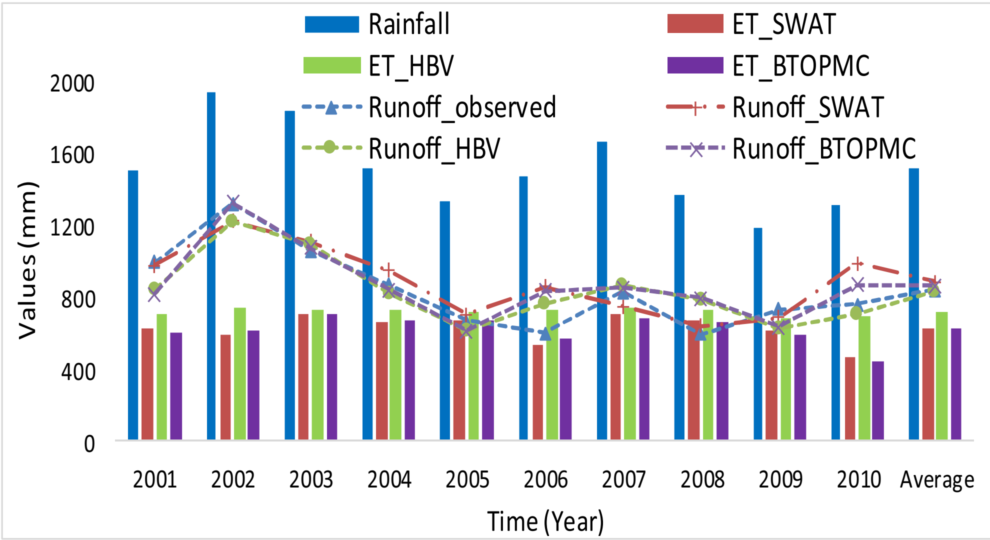

Fig. 7. Temporal variation of water balance component by three model in Kathmandu valley watershed for 2001–2010 (values in mm).

higher than that estimated by the other two models. The average ET estimated by the SWAT model was 625 mm/y, and the value estimated by the BTOPMC model was 623 mm/y, but the value estimated by the HBV model was 718 mm/y. The seasonal fluctuation in ET was greater in the SWAT model in April, and greater in the BTOPMC model in August, September, and October; in the other months, there was close agreement between the BTOPMC and SWAT models but not with the HBV model. The average ET used in Fig. 6**b** is the average of ET calculated by all three model.

3.5. Comparison of annual water balance component

Plots of calibration, validation, significance tests, runoff plots, and ET showed that the SWAT, HBV, and BTOPMC models were suitable for water resource assessment in the KV watershed. The ranges of values of the water balance components estimated by the models combined with the average values from both temporal and seasonal variation could be useful for water resource planning, development, and management in the KV. Hence, the temporal and seasonal fluctuations of the water balance components are discussed here in more detail.

The models used to quantify the water balance components are based on the following equation:

$$R = P - ET + TWS$$

where P is precipitation, R is runoff, ET is evapotranspiration, and TWS is total water storage, which is the total storage of water in soil (SW), the surface (SS), and groundwater (G). The difference between precipitation and the sum of runoff and ET is lumped as the total water storage within the watershed.

Annual precipitation in the KV fluctuated between 1188 and 1947 mm from 2001 to 2010, and the fluctuation displayed no statistically significant trend (Fig. 7**)**. The simulated runoffs from the three models were similar for each year and comparable with the observed data (Table 6 and Fig. 7). Because the calibration process was primarily based on storm fitting rather than annual runoff fitting, the overall annual runoff was overestimated by the SWAT and BTOPMC models, and underestimated by

Table 6
Components of annual water balance in the Kathmandu Valley watershed for 2001–2010.

Year	Precipitation (P), mm/y	Runoff (R), in mm/y				Evapotranspiration (ET) in mm/y			TWS in mm/y			PET (Observed), mm/y
		Observed	SWAT	HBV	BTOPMC	SWAT	HBV	BTOPMC	SWAT	HBV	BTOPMC	
2001	1508	996	980	844	818	626	701	604	−98	−38	85	918
2002	1947	1320	1221	1220	1325	591	739	614	135	−13	8	741
2003	1839	1056	1110	1097	1075	711	728	711	17	13	52	983
2004	1518	868	947	823	841	660	726	674	−90	−31	2	835
2005	1345	666	702	609	614	670	717	677	−27	20	54	845
2006	1479	601	855	761	835	532	733	570	93	−14	75	707
2007	1667	827	748	866	850	710	739	682	209	62	135	895
2008	1369	592	638	792	794	669	724	665	62	−146	−90	895
2009	1188	731	686	626	634	610	684	593	−108	−122	−38	892
2010	1318	762	988	707	866	472	694	443	−142	−82	9	669
Average	1518	842	887	834	865	625	718	623	5	−35	29	853

Potential Evapotranspiration (PET) observed means the estimated PET by Snyder's equation using pan evaporation observed data.

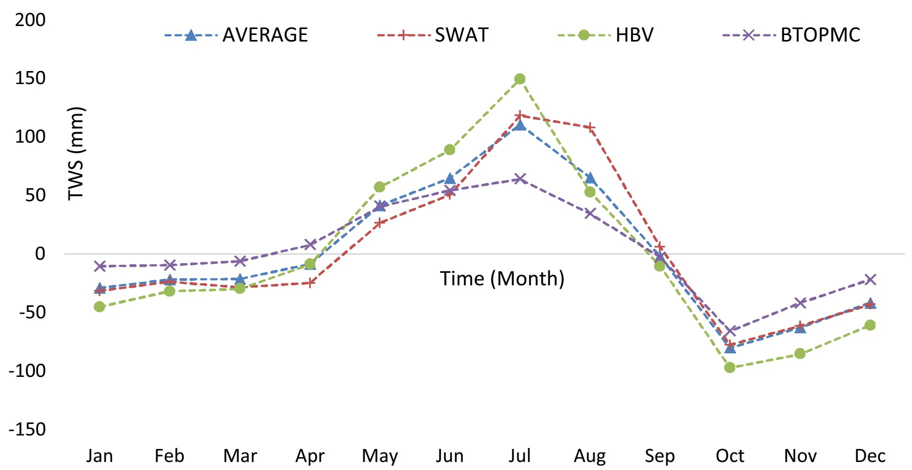

Fig. 8. Monthly average total water storage (TWS) component by three models and average values in Kathmandu Valley watershed for 2001–2010.

the HBV model. The annual runoff was overestimated by all three models in 2006, and underestimated in 2009. The annual runoff fraction for the simulation period varied from 0.41 to 0.68 in observation data and 0.45–0.75 in the SWAT model, 0.45–0.63 in the HBV model, and 0.46–0.68 in the BTOPMC model, reflecting temporal variation in the runoff components in different years and their ranges. The average annual runoff in the watershed was 887 mm for the SWAT model, 834 mm for the HBV model, and 865 mm for the BTOPMC model, which is 59%, 55%, and 57% of annual precipitation, respectively

The PET calculated from Snyder's equation varied from 38% to 75% during the simulation period, and the average value was 56% of the total precipitation. The average estimated ET in the watershed ranged from 472 to 711 mm/y for the SWAT model, 684–739 mm/y for the HBV model, and 443–711 mm/y for the BTOPMC model. The average ET estimated by the SWAT, HBV, and BTOPMC models was 41%, 47%, and 41% of the annual precipitation respectively, which was 0.75, 0.87, and 0.75 times the observed PET. The highest ET was given by the HBV model, followed by the SWAT and BTOPMC models. The differences among the models might be due to the different methods used by each model to estimate the ET from the same observational data. The HBV model gave higher values of ET for each year, which might be due to the temperature anomaly correction factor used for estimating ET from PET.

The average TWS component was balanced in all three models, and showed inter-annual variation; i.e., it was positive in some years, and negative in others (Table 6). Predictive analysis showed that the estimated TWS component varied from +209 to −108 mm/y in the SWAT model, +62 to −146 mm/y in the HBV model, and +135 to −90 mm/y in the BTOPMC model. The minimum and maximum estimated TWS component varied between ±10% and ±14% of the total annual precipitation. The average TWS component for the period 2000–2010 was 5 mm/y in the SWAT model, −35 mm/y in the HBV model, and 29 mm/y in the BTOPMC model, which was 0.34%, 2.3%, and 1.9% of the average annual precipitation. Predictive analysis of all three models showed that the average TWS component was well reproduced over the long term. Precipitation, the only source of water for recharge and storage in the study area, is concentrated from mid-May to mid-September in the KV. Fig. 8 shows the seasonal fluctuation in the TWS component, which was negative in January–March and October–December, and positive in June–August in all three models. The TWS estimated by the BTOPMC model for April was positive; it was negative for the other two models. Similarly, for September, the TWS estimated by the SWAT model was positive. The average TWS value in Fig. 8 is the average of values calculated by all three model. The analyses of the mean monthly average water balance components indicate that, from October through March, streams are supplemented by groundwater, and for the rest of the year, groundwater is recharged by the precipitation falling in the watershed. In all three models, the month with the most negative water storage was October followed by November and December. The month with the most positive water storage was July followed by August and June. These analyses reveal greater water storage in the rainy season, and less storage in the driest season. Therefore, when planning any water resource development project, developers and decision-makers should take into account the temporal and seasonal fluctuations in all of the water balance components to plan for sustainable use of water.

5. Conclusions

The performance indicators NS, PBIAS, and R^2 had similar indicator values in the three models used in this study, and the models showed satisfactory performance for runoff simulation. There was close agreement between the monthly observed and calibrated runoff at the watershed scale, and the models accurately captured the flow patterns for most seasons. Although the three models used similar performance indicators for runoff, the estimated yearly runoff, ET and TWS component values differed among the models.

There were negligible differences in the simulated and observed runoff for the averaged seasonal flow for all the three models, but overestimation of the overall annual runoff by SWAT and BTOPMC and underestimation by the HBV. This may be due to different methods adopted by the three models for the estimation of ET as described in the Section 2.2.2. The runoff simulation was performed based primarily on storm fitting rather than annual total runoff fitting. The runoff fraction varied from 0.55 to 0.59, and the ET component varied from 0.41 to 0.47 of the total precipitation in the three models. The yearly fluctuation in TWS varied from $\pm 9\%$ to $\pm 14\%$ of the total precipitation. Considering the variation in the water balance components in the three models, ET had the lowest inter-annual variation, and runoff had the greatest variation. The ET component is primarily driven by radiation and temperature, which does not vary significantly from year to year. The runoff component is primarily driven by precipitation, and relatively small differences in rainfall have a significant impact. The calculation of ET using only temperature as an adjusting parameter in the HBV model led to significantly different results than in the other two models. We used same precipitation, PET, and other climatic parameters, number of sub-basins, and calibration method for all three models. Predictive analyses showed reasonable ranges relative to observational values for runoff, ET, and TWS in all three models. These estimated ranges of values in the water balance components, which can have significant impacts on the available water resources in the KV, provide useful information to guide planning of water resource development projects. Estimates from such model simulations of the available water resources combined with climate impact studies can provide reliable information for water-resource management projects.

The multi-model techniques representing different runoff, evaporation, and energy balance schemes can be used for more accurate representation of water balance in any basin, and to obtain the ranges of values of each water balance component. In the KV, a possible next step for achieving more reliable water resource assessments would be multi-model analyses that include historical water use and water stress as well as future climate projections.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.ejrh.2016.12.080.

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