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Simulation of Hydrologic Processes through SWAT and Modis ET for Sirsa RiverBasin in Western Himalaya

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Abstract: In this paper an attempt has been made to simulate hydrologic processes by calibrating SWAT model with MODIS evapotranspiration data for Sirsa River Basin, an unguaged basin, in Western Himalayas. The study used remote sensing data derived evapotranspiration to parameterize SWAT model through manual calibration. For this study twelve subasins using fifth order stream as threshold were delineated from Aster DEM. These were further subdivided into 179 HRUs by overlaying land use/landcover, soil and slope layers. Climate input parameters were loaded to run the model for the period of 2001-2008, considering first three years as warm-up period. After initial SWAT run, sensitivity analysis was performed based on Latin LH-OAT method. From sensitivity analysis groundwater related parameters (GWQMN, REVAPMN, GW_REVAP and RCHR_DP), soil related parameters (SOL_Z, SOL_AWC and SOL_K) and HRU related parameters (EPCO, ESCO and CANMX) were found to be most sensitive. In the basin, 50% and 42% of mean annual precipitation is contributed as ET and streamflow, respectively; and 8% as deep aquifer recharge. About 64%, 11% and 23% of streamflow is contributed from SURQ, LATQ and GWQ, 90% of annual streamflow is generated during monsoon period (July – September). Contribution of baseflow to streamflow is maximum in post-monsoon period (October - December).

Key words: Hydrological model・MODIS・SWAT

INTRODUCTION

Quantitative information of hydrological components not only helps to understand governing processes, but is also essential to manage water resources under changing environmental conditions. Among all hydrological components, runoff is commonly measured at several points on main stream. Though, data is readily available in developed countries, but is poorly maintained in developing countries. Hence, for sustainable water resources management, quantification of rainfall-runoff relation and other hydrological components areessential, but a challenging task. To overcome this challenge hydrological modelling has emerged as a potent tool. Several hydrological and environmental models have been developed recently to quantify hydrological components and probe the hydrologic response to human activity [1,2].

Hydrologic models, especially rainfall-runoff models are 'simplifications of the real-world system under investigation' [3]. Based on the hydrological process description, hydrological models can be either lumped (conceptual), fully distributed or semi-distributed. Since last two decades, integrating with geospatial tools and remotely sensed data, ample distributed and semi-distributed models have been developed to estimate water quality and quantity [4]. Among various models, Soil and Water Assessment Tool (SWAT) model has been popularly applied worldwide for various range of watersheds varying topography, climate, soil and management conditions over long periods of time [5,6,7]. SWAT model [8] is a physically based semi-distributed, basin-scale and continuous-time model. It is suitably used for estimating water balance components [4,9], sediment and nutrition loss [10,11], impact of nonpoint-source pollution and water management [12], land use change [13,14,15] and climate change [16,17,18] on water quality

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and quantity. In this study SWAT model is opted as it offers: (a) detail surface and sub-surface hydrologic processes, (b) spatial heterogeneity in the model input-output, (c) long-term hydrologic simulation with limited data, even for ungauged basin also, (d) simple and user-friendly platform, good documentation and solution feedback from large number of user community etc.

Physically-based models, like SWAT, incorporate huge number of parameters, of which most are not physically measurable. It is obtained through a process of adjustment with field data (observed), known as calibration. But, adjustment of such huge parameters is cumbersome and labour-intensive [19]. Hence, identification of key parameters and the parameter precision is required for calibration [20, 21]. Sensitivity analysis helps to identify most influential parametersthat have significant influence on model output [22]. A combined method of Latin Hypercube (LH) sampling and One-Factor-At-a-Time (OAT) is popularly used for sensitivity analysis in which each model parameter is changed at predefined interval, while others are kept constant at their nominal value [23,24,25,26]. This LH-OAT approach embedded in SWAT interface is used in this study. However, understanding of variation in model output with change in sensitive parameter value is utmost important for manual calibration. Few studies experimented model accuracy by manually varying SWAT parameters. For example, Wu and Johnston, [18] evaluated the effect ofplant uptake compensation factor (EPCO) and soil evaporation compensation coefficient (ESCO) on deviation of discharge values under dry and average climate condition. Kannan *et al*., [27] tested the effect of four most sensitive parameters on streamflow components by varying OAT at low, medium and high parameter values. Mosbahi *et al*.,[28] compared Nash-Sutcliffe coefficients of simulated runoff at various points in a range of sensitive parameter values by varying OAT.

In gauged basins, availability of observed data makes it easier for realistic simulation. But, for the ungauged basin accurate estimation of hydrologic variables is difficult and challenging task [23]. The studies that simulated hydrologic behaviour of ungauged basins are either based on physical considerations or other theories, like Grey information theory, fuzzy theory etc. [29,30]. International Association of Hydrological Sciences (IAHS) adopted the ‘Predictions in Ungauged Basins’ (PUB) in 2003 to improve research on hydrologic simulation for ungauged basins [31]. Several studies found regionalization approach as most suitable method for estimation of runoff in ungauged basin [23,32,33,34,35,36]. In this approach, hydrologic information, i.e., model parameters or model structure are transferred from gauged (donor) to ungauged (target) catchment based on similarity in catchment characteristics or spatial proximity [35,37]. But, this approach is not applicable for an ungauged basin, if a donor basin is not available. Moreover, uncertainty in simulation may arise either due to equifinality problems from optimisation with limited number of gauge points [38], or parameter transfer through regionalization approach [39]. Hence, hydrological parametersmeasured using satellite data could provide a viable solution to calibrate hydrological model for data scarce region [19].

Application of remote sensing data derived hydrological components like, evapotranspiration and soil moisture for parameterization of hydrological models in ungauged basin is recently getting momentum in hydrological engineering [19,40,41,42,43,44]. Most of these studies, used Moderate Resolution Imaging Spectroradiometer (MODIS) product of land cover and vegetation cover (NDVI, LAI) to estimate evapotranspiration (ET) based on the Surface Energy Balance Algorithm (SEBAL) for calibration of SWAT model or other hydrological model [19,41,42,44]. Stehr *et al*., [43] combined MODIS snow products with SWAT model to estimate monthly flows in a basin located in Andes mountain where snowmelt significantly contributes to streamflow. Overall, these studies satisfactorily used MODIS products for data scarce regions. However, calculation of long-term ET from NDVI and LAI through SEBAL algorithm is quite complex and cumbersome. MODIS product (MOD16A2) of global ET data prepared by Mu. *et al*. [45] and [46] at 1 km spatial resolution can be used to calibrate SWAT model [47].

Hydrological information in developing countries, like India are limitedly available. Additionally, alteration of land use practice, climate change, industrialization and high rate of water consumption has raised big question on water quality and its availability for future. Hence, hydrological modeling for data scarce basins is required by planners and managers for sustainable management of water resources. In the present study, water balance components were simulated with SWAT model for Sirsa river basin, an ungauged tributary basin of Satluj river in the western Himalaya, India. This study is mainly focused to develop a simple and efficient approach for calibration of physically based hydrological model in data limited and ungauged basin. The study used remote sensing data

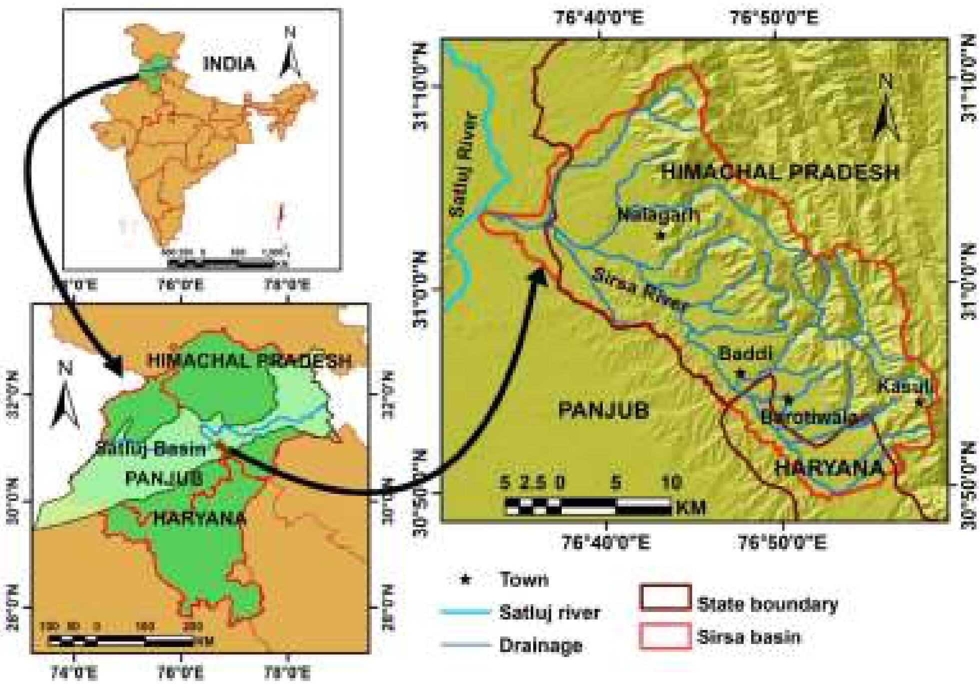

Fig. 1: Location Map

derived evapotranspiration to parameterize SWAT model through manual calibration. Variation in modeled hydrological components with changes in sensitive parameter values was also experimented.

Study Site: The Sirsa river basin, a downstream tributary channel of Satluj river, flows through Himachal Pradesh, Haryana and Punjab states in India. The study site covers approximately 670 km^2 area,of which 75% lies in Solan district of Himachal Pradesh. The basin extends from 30°49'22? to 31°11'00? N latitudes and 76°32'48? to 76°59'22? E longitudes in western Himalaya at the fringe of Ganga plain. The basin is an intermontane river system, bounded by outer Siwalik range in the south-west and Kasauli–Ramshahr Tertiary ranges in the north-east (Figure 1). Elevation of the basin varies between 250 and 1900 m, almost half of which is characterized by intermontane valley (Nalagarh valley). The basin landscape is characterized by ridge and valley topography, eroded undulating surface, flat alluvial fan etc. The tributaries of Sirsa River that originate from Kasauli–Ramshahr ranges are long; while rivulets developed in the outer Siwalik are too short. The drainage morphometry indicates that the basin is elongated and well drained with an average drainage density of 3 km/km^2 [48].

The study basin is located in sub-tropical monsoon climate with a mean annual temperature of 23.5ºC and an annual mean rainfall of 900mm. About 80% of annual precipitation is received during summer monsoon (June - September). The dominant land use land cover (LULC) classes in the basin are dense forest, open forest and agricultural land.The major soil type of the study basin is sandy loam (Central Ground Water Board 2007). The valley region (Dun) is dominantly covered by sandy loam soil, while loamy skeletal soil is found in Kasauli–Ramshahr ranges. Soil layers are quite thick in the intermontane valley and outer Himalaya than Kasauli–Ramshahr ranges. Soils are characterized by low to moderate permeability. Major industrial hub of Himachal Pradesh, i.e. Baddi-Barotiwala-Nalagarh corridor is located in the study basin. Rapid industrialization and urbanization has increased water demand and intervening hydrologic process of the basin.

Materials and methods

SWAT Model: The Soil and Water Assessment Tool (SWAT) model has been used in this study (SWAT version 2005). SWAT is a continuous time, physically based semi-distributed hydrologic model that simulates hydrologic components on daily basis.The model accountsfor large-scale spatial variability of hydrologic processes partitioning a basin into a numbers of land parcels in two phases. Initially, based on topography, the basin is divided into numerous sub-basins, considering drainage area threshold. Then, sub-basins are further segregated into numerous conceptual homogeneous land parcels, known as hydrologic response units (HRUs) combining slope, soil and land use layers.

Water budget of surface, sub-surface and deep aquifer is calculated for each HRU and routed at basin and sub-basins. SWAT model simulates various hydrological components, like evapotranspiration, surface runoff, lateral flow, baseflow, deep aquifer recharge etc. based on water balance equation expressed as follows:

$$SW_t = SW_0 + \sum_{i=1}^{t}\left(R_{day} - Q_{surf} - E_a - w_{seep} - Q_{gw}\right)$$

where, SWt is the final soil water content (mm), SW0 is the initial soil water content on day i (mm), Rday, Qsurf, Ea, wseepandQgware precipitation (mm), surface runoff (mm), evapotranspiration (mm), seepage flow (mm) and return flow (mm) on day i, respectively.

SWAT model offers two methods for surface runoff simulation, of which SCS Curve Number method [8] was opted in this study. Potential evapotranspiration (PET) is calculated using Penman–Monteith method [49] and Hargreaves method [50], though Priestley-Taylor method isalso offered by the model. Percolation is estimated by storage routing method, while muskingum method is used for channel routing. Most importantly, SWAT system embedded within GIS interface is morehelpful to integrate several spatial information, including topography, soil, land cover, climate etc [15]. A more detailed description of the model is found in Neitsch *et al.*, [29] and online documentation (http://swatmodel.tamu.edu/).

Data Preparation: Topographic data, land use and soil data, meteorological data are essentially required for SWAT model setup. To input topographic information, Advanced Spaceborne Thermal Emission and Reflection Radiometer Global Digital Elevation Model (ASTER GDEM) of 1 arc-second resolution was used. A soil map of 1:125,000 scale was acquired from National Bureau of Soil Survey and Land Use Planning (NBSS & LUP). Soil classes were reclassified according to SWAT soil database. Land use/land cover (LULC) information was acquired from Landsat TM image. A LULC map of 2009

Table 1: Statistics of parameters used for calibration.

	Sensitivity report		
Parameter	Rank	Mean value	Calibrated final value
GWQMN	1	0.26	46.44
ALPHA_BF	2	0.22	0.2
REVAPMN	3	0.19	46.5
GW_REVAP	4	0.06	0.03
RCHR_DP	5	0.056	0.36
CN2	6	0.041	*
CANMX	7	0.035	5
EPCO	8	0.022	0.6
SOL_AWC	9	0.01	0.09
SOL_Z	10	0.009	480
SOL_K	11	0.006	10
ESCO	12	0.005	0.3
GW_DELAY	13	0.005	18

* Varies with LULC and soil types

was prepared from Landsat data based on supervised classification. In absence of long term in-situ meteorological data, gridded raster climatic data of NCEP/NCAR Global Reanalysis Products of Global Meteorological Forcing Dataset for Land Surface Modelling (ds314) was used in this study. Global gridded datasets of 1o spatial resolution was collected from Computational and Information Systems Laboratory (CISL) archive (http://rda.ucar.edu/datasets/ds314.0/). The meteorological data, that included minimum and maximum temperature, precipitation, solar radiation, wind speed and relative humidity, were collected for two grid locations with the help of python programmingfor the period of 2003–2008.Climate data was prepared in suitable format for SWAT2005 as guided by Neitsch *et al.*, [51].

As Sirsa basin is ungauged, hydrograph data was unavailable to calibrate SWAT model. Hence, the model was parameterized by comparing SWAT simulated ET with MODIS ET. MODIS evapotranspiration data product at 1-km spatial resolution for the period of 2004–2008 (MOD16A2, 8-day interval) acquired fromftp://ftp.ntsg.umt.edu/pub/MODIS/NTSG_Products/MOD16/. The datasets were prepared by Mu. *et al.*, [45,46] for the globe. Coupling MODIS land cover, albedo, Leaf Area Index (LAI) data and daily global meteorological reanalysis data (GMAO) of 1.00°×1.25° resolution, land surface ET datasetwas prepared at an 8-day interval. Based on Penman-Monteith method [49] ET was calculated considering, soil heat flux, evaporation from wet and moist soil, day and nighttime transpiration etc. [45,46]. However, MODIS ET data was considered as actual ET for calibration and validation of SWAT model.

Parameter Sensitivity and Adjustment: For this study, twelve sub-basins were delineated from DEM, considering 2000 ha minimum drainage area and fifth order stream as threshold. Overlaying LULC, soil and slope layers sub-basins were further divided into 179 HRUs.Afterwards, climate input parameters were loaded to run the model for the period of 2001-2008, considering first three year as warm-upperiod. After initial SWAT run, sensitivity analysis was performed based on Latin LH-OAT method. To make calibration process easier, most sensitive parameters were manually varied once-at-a-time (OAT) within the range as suggested in the SWAT user's manual. The analysis was carried out for 20 model parameters with 10 intervals in Latin hypercube (LH) sampling.The rate of change in selected hydrological components (model output) with respect to change in each parameter values was tested to identify suitable parameter values.

Calibration and Validation: In this study, calibration of SWAT model parameters was performed by comparing SWAT simulated ET with MODIS ET, due to lack of measured stream-flow data. The SWAT simulated daily ET data were assembled at 8-day and monthly interval to calibrate for the periods of 2004 – 2006 and validate for periods 2007 – 2008.The model is calibrated manually by editing sensitive parameters for all plausible hydrological components [14]. However, the knowledge of rate of change in hydrologic components with variation of model parameters values increased the efficiency of the calibration procedure. During calibration, groundwater parameters (.gw), soil parameters (.sol) and HRU parameters (.hru) were iteratively modified until simulated ETclosely match with MODIS ET. Initially, comparisons between SWAT ET and MODIS ET were made for annual values. Afterwards, parameters were fine-tuned for monthly and daily (8-day) values until the modeled ET was acceptable according to performance ratings proposed by Moriasi, D.N., *et al*., [52]. As parameters were adjusted by only comparing ET, uncertainty in separation of streamflow components was likely to subsist in simulation. Hence, simulated results were checked with SWAT Check program [20]. Based on the error report, surface runoff, lateral flow, baseflow and deep aquifer recharge was adjusted by varying model parameters until satisfactory results were obtained. Finally, model performance for most suitable set of parameters values was again tested and validated.

RESULTS AND DISCUSSIONS

Sensitivity Analysis: LH-OAT based sensitivity analysis was performed to identify and choose influential parameters by ignoring redundant parameters. The most sensitive parameters found in this study are: curve number (CN), soil available water capacity (SOL_AWC), soil depth (SOL_Z), soil evaporation compensation factor (ESCO), saturated hydraulic conductivity (SOL_K), threshold depth of water in the shallow aquifer required for return flow (GWQMN), groundwater 'revap' coefficient (GW_REVAP), groundwater recession factor (ALPHA_BF) etc. Table 1 lists rank of sensitive parameters and their final values. The sensitivity of groundwater parameter (.gw), soil parameter (.sol) and HRU parameter (.hru) to surface runoff, stream-flow, baseflow, deep aquifer recharge and evapotranspiration are discussed in this section. During this process, one parameter was changed randomly, while others were kept constant.

Groundwater Parameters (.gw): The sensitivity of groundwater parameters, particularly GWQMN, REVAPMN, GW_REVAP and RCHR.DP on hydrological components are presented in Figure-2. Parameters are found sensitive to baseflow and consequently to stream-flow.

GWQMN: Variations in water balance components for changes in GWQMN valuesarepresented in Figure -2a. It is clear that with the increase of GWQMN, water yield and baseflow decreased. For high values of GWQMN a considerable portion of infiltrated water is stored in soil; while, at a low value of GWQMN, SWAT produces more baseflow that, in turn, increases stream flow also [27]. Noticeably, at initial value of GWQMN(up to 60) the rate of decrease in baseflow and stream flow is low to moderate. But, afterwards rate of decrease increases abruptly up to GWQMN value of 175. Baseflow and streamflow remain constant while GWQMN value exceeds 500. Kannan,.*et al*., [27] recommended low GWQMN for realistic prediction of daily stream flow.

REVAPMN: REVAPMN is the threshold depth of water in shallow aquifer that controls water movement to unsaturated zone for re-evaporation to occur. With the increase of REVAPMN, baseflow as well as streamflow increased (Figure-2b). But after a certain value (REVAPMN=60), both remain constant.

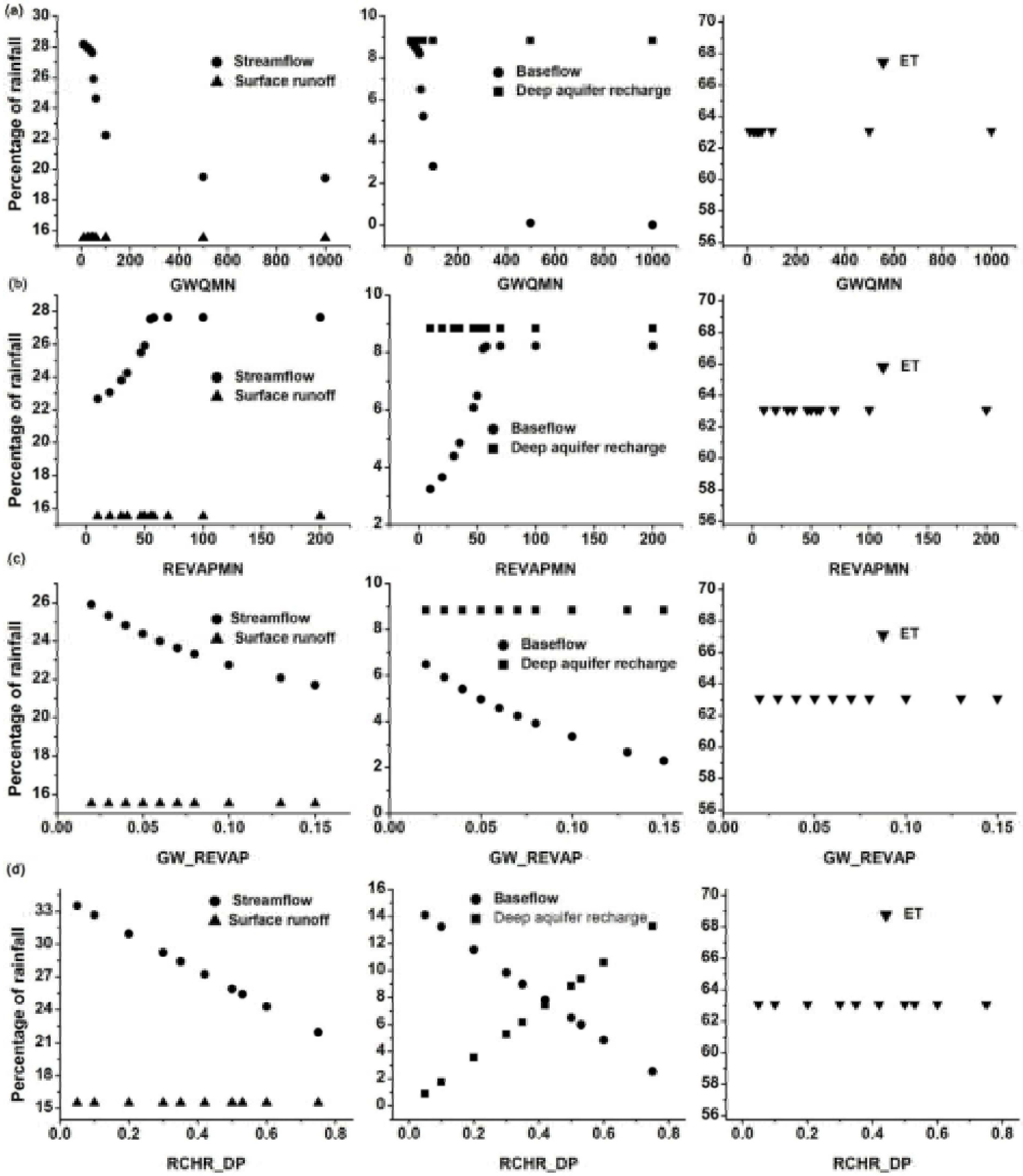

Fig. 2: Sensitivity of groundwater parameters to different water balance components

Because at this certain threshold value no 'revap' will occur for the basin. At low REVAPMN, as 'revap' from the soil is high, the contribution of baseflow to streamflow is very low. In this study, the REVAPN value was finally adjusted close to GWQMN.

GW_REVAP: Groundwater 'revap' coefficient (GW_REVAP) controls the amount of water that will 'revap' to upper soil layer. GW_REVAP value ranges from 0.02 to 0.2. For a high value of the parameter, the model returns water to root zone for 'revap', hence,baseflow

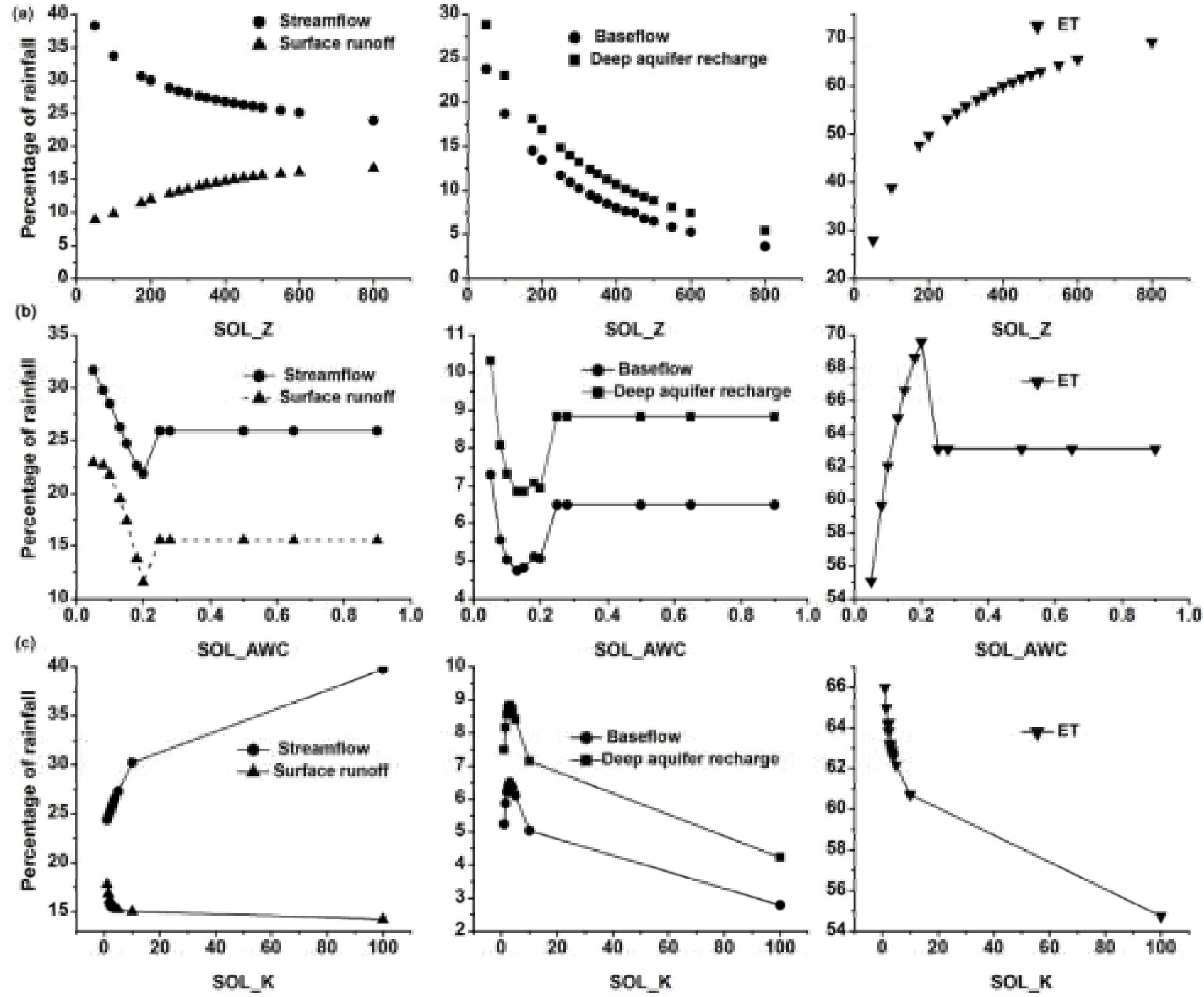

Fig. 3: Sensitivity of soil parameters to different water balance components

contribution to streamflow decreased. This parameter moderately controlled baseflow and streamflow in this study (Figure-2c).However, GW_REVAP value was finally set to 0.03 for this study.

RCHR_DP: RCHR_DP controls the amount of water that will move from shallow aquifer to deep aquifer. It was found fifth-rank sensitive parameters in this study. With the increase of parameter value amount of baseflow, as well as streamflow decreases and deep aquifer recharge increases linearly (Figure 2d).This parameter is most significant for separation between shallow and deep aquifer recharge.

However, adjustment of groundwater configuration parameters was very challenging task, as the parameters did not affect ET that was considered for comparison during calibration. Based on extensive literature findings these parameters were adjusted in 'trial and error' method and verified repeatedly with SWATCheck program.

Soil Parameters (.sol): Soil parameters, mainly SOL_Z, SOL_AWC and SOL_K showed significant control on each water balance components (Figure -3). The sensitivity results of these three parameters are discussed below.

SOL_Z: Hydrologic components showed curvilinear relation with SOL_Z values(depth of soil layer). An increase in SOL_Z value increased surface runoff and evapotranspiration and decreased total streamflow, baseflow and deep aquifer recharge (Figure -3a).

As soil depth increases, root zone depth and soil profile depth increases. It increases water holding capacity, as well as, water availability in the soil profile that, in turn, increased evaporation from soil profile and transpiration from plants. Thus, increase of vadose zone depth caused decrease in shallow and deep aquifer recharge and increase in evapotranspiration (ET). In the SWAT model, less depth of soil profile helps in quick downward movement of water from lowest soil layer to shallow aquifer. With increase of soil depth, delay in water movement to shallow aquifer will increase. Thus, groundwater recharge decrease and ET will increase. From the Figure -3a it is assumed that with the increase of soil water content due to increase of soil depth, surface runoff increased. But, as the rate of decrease of baseflow was higher than increase of surface runoff, streamflow trimmed down. However, interaction of this parameter with other soil and groundwater parameters can change its influence to hydrologic components.

SOL_AWC: SOL_AWC (available water capacity in soil) is one of crucial parameters that determine field capacity of soil, ranges between 0-1. In this study, SOL_AWC was found sensitive to various water balance components in a similar pattern (Figure 6.3b).Initially, surface runoff, stream-flow, baseflow and deep aquifer recharge was decreased and evapotranspiration increased with the increase of SOL_AWC value up to 0.2. But, in betweenSOL_AWC value of 0.2 and 0.3, response of each component is reversed. Finally, beyond SOL_AWC value 0.3, the parameters show no sensitivity to the water balance components.It can be concluded that with a fractional increase in SOL_AWC, evapotranspiration from soil and canopy increases as soil moisture increases. But, after a critical point (here 0.2), with the increase of SOL_AWC percolation to shallow and deep aquifer increased.

SOL_K: Saturated hydraulic conductivity of soil (SOL_K) plays a significant role in hydrologic processes. The infiltration and percolation capacity of soil is directly proportional to the soil saturated hydraulic conductivity (Neitsch et al., 2005a).At low value range (0-10) SOL_K was found very sensitive to all hydrological components. When SOL_K approaching 0 to 10, streamflow, baseflow and deep aquifer recharge increased, though, surface flow and ET decreased (Figure 3c).But, when the value increased from moderate to high, value of these components decreased, except streamflow. The results are quite similar with the findings of Kannan *et al*. [27]. Till SOL_K value approaches 10, baseflow, streamflow and groundwater recharge increased significantly as infiltration and percolation capacity increased. But beyond SOL_K value 10, most part of infiltrated water converted as lateral flow, rather than ground water recharge. Albeit, the contribution of surface flow and baseflow to streamflow is reduced, but substantialincrease in lateral flow hiked streamflow(Figure 3c).

HRU Parameters (.hru): EPCO, ESCO and CANMX were found most sensitive HRU configuration parameters in this study. These parameters were found comparatively less sensitive for water balance components (Figure 4).

EPCO: The plant uptake compensationfunction (EPCO) controls ET through allowing plant to uptake water from layers within rooting zone [18] (Wu and Johnston, 2007). The value of EPCO ranges between 0 and 1. At low EPCO value, model allows plant to uptake water from top soil layer; but, as EPCO approaches 1.0, plant water uptake demand will be met from deep soil layer also. In this study, with the increase in EPCO value ET increased linearly, though the rate of increase is less (Figure 4a).As for higher EPCO value, model allows to meet the more water uptake demand of plant from lower soil layer, ET increased marginally.

ESCO: The soil evaporation compensation factor (ESCO) controls evaporation from soil by modifying depth distribution in soil profile. ESCO is found sensitive to all water balance components(Figure 4b). ET decreased in curvilinear shape with the increased of parameter value and rest components increased with moderate rate (Figure 4b). As the value of ESCO is reduced, the model is able to extract more of the evaporative demand from lower level [34], resulting an increase in ET. For high ESCO values, ET decreased and consequently surface runoff, baseflow and other components increased. The sensitivity of this parameter is quite similar to previous studies [18,27].

CANMX: A change in the value of the maximum canopy storage (CANMX) affects ET and other water balance components. Figure 4c shows that CANMX is less to moderately sensitive to all components. With the increase in CANMAX, ET has increased slightly; whereas other components have decreased but at a low rate. As maximum canopy storage is increased, interception is

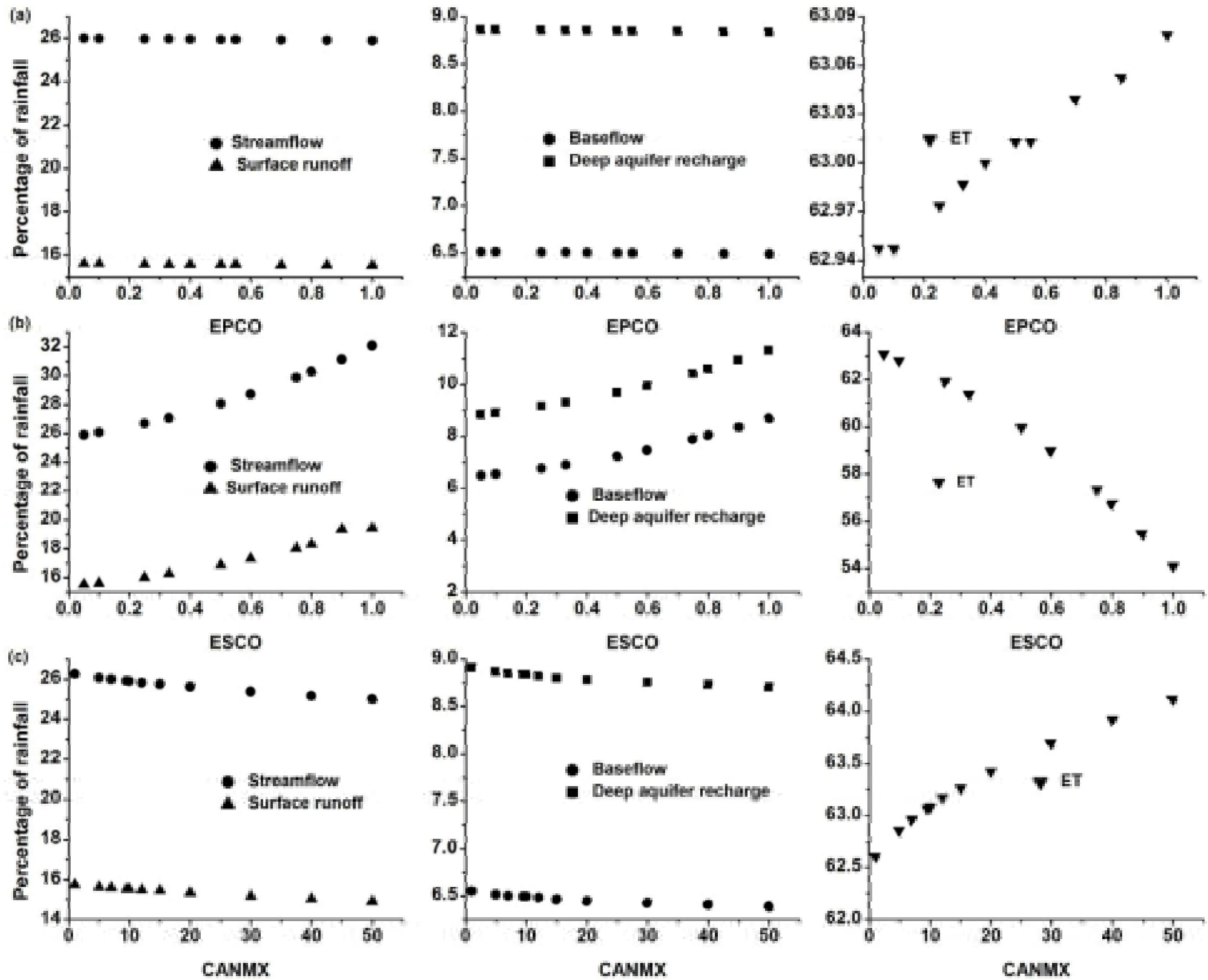

Fig. 4: Sensitivity of HRU parameters to different water balance components

increased. As a result, surface runoff, baseflow and deep aquifer recharge have decreased and concomitantly the amount of evaporation of intercepted water is increased. However,CANMX found less sensitive to all components as compared to other parameters.

Calibration and Validation: Modelled ET, simulated using Penman-Monteith and Hargreaves methods, was compared with MODIS ET for calibration (2004–2006) and validation (2007–2008) and illustrated in Figure 5. The statistical performances of the SWAT model using these two methods are presented in Table 2.The daily and monthly validation results of SWAT simulation showed better than calibration results.The overall statistical performance of the model was found 'good' for daily (8-day composite) simulations and 'very good' for monthly simulations, according to the criteria provided by Moriasi *et al.* [52].The coefficient of determination (R2) values for daily simulations range from 0.74 to 0.77 and monthly values range from 0.81 to 0.91.Likewise, Nash-Sutcliffe efficiency (ENS) varies from 0.53 to 0.72 for daily and 0.71 to 0.91 for monthly calibrations and validations.RSR of daily and monthly simulations varies in range of 0.53-0.68 and 0.33-0.54, respectively. Though, percent bias (PBIAS) showed relatively better performance of Penman-Monteith method than Hargraves method, but R2, ENS and RSR are found better for Hargraves method. During calibration, positive values of PBIAS for Hargraves method indicate underestimation of bias and negative values for Penman-Monteith method (Table 2) indicate overestimation of bias [3]. However, actual deviation of SWAT simulation from MODIS ET needed to asses to chose best method for ET simulation.

Table 2: Statistical performance of SWAT model during calibration of validation of ET result

		R^2		RSR		PBIAS (%)		E_{NS}	
		HAR	PM	HAR	PM	HAR	PM	HAR	PM
Daily	Calibration	0.75	0.74	0.57	0.68	2.84	-1.97	0.67	0.53
	Validation	0.75	0.77	0.53	0.54	2.43	0.21	0.72	0.70
Monthly	Calibration	0.81	0.82	0.48	0.54	2.84	-1.97	0.76	0.71
	Validation	0.89	0.91	0.33	0.31	2.43	0.21	0.89	0.91

Note: HAR- Hargreaves method, PM- Penman-Monteith method

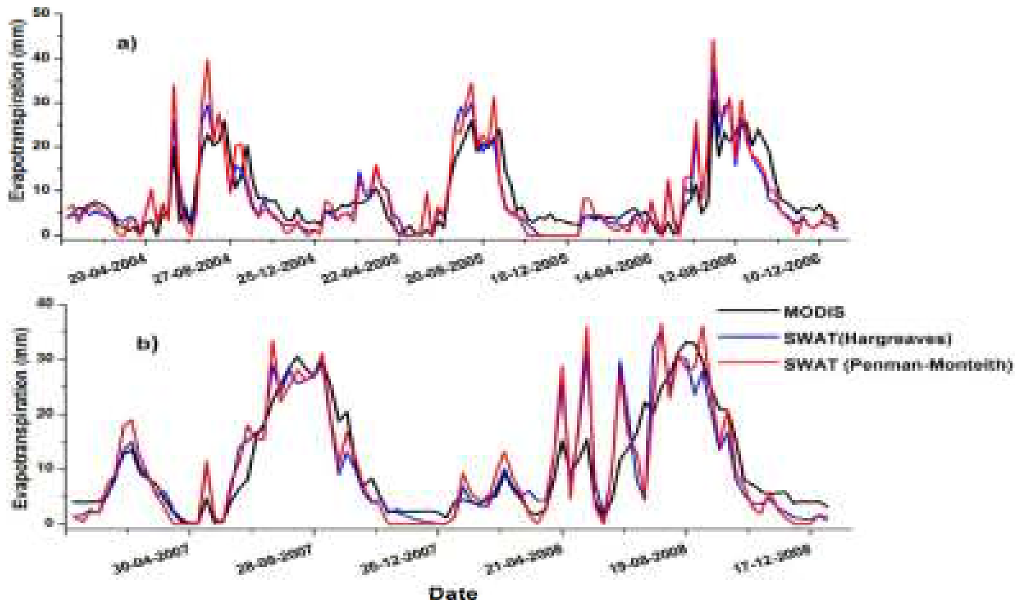

Fig. 5: Comparison of the daily (8-day composite) ET between SWAT simulation and MODIS data, (a) calibration (2004-2006) and (b) validation (2007-2008) period.

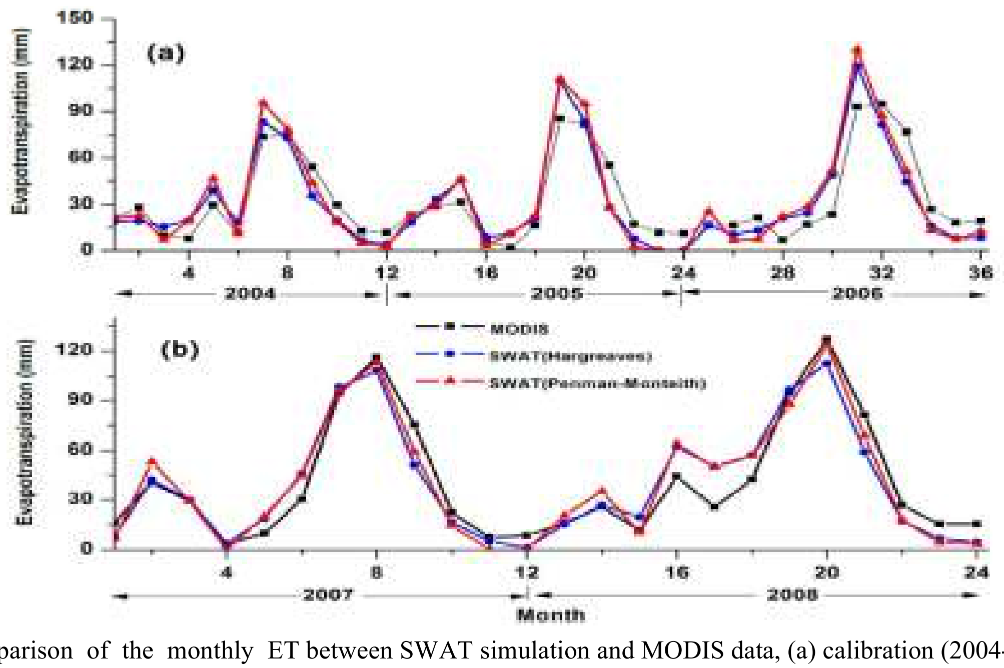

Fig. 6: Comparison of the monthly ET between SWAT simulation and MODIS data, (a) calibration (2004-2006) and (b) validation (2007-2008) period.

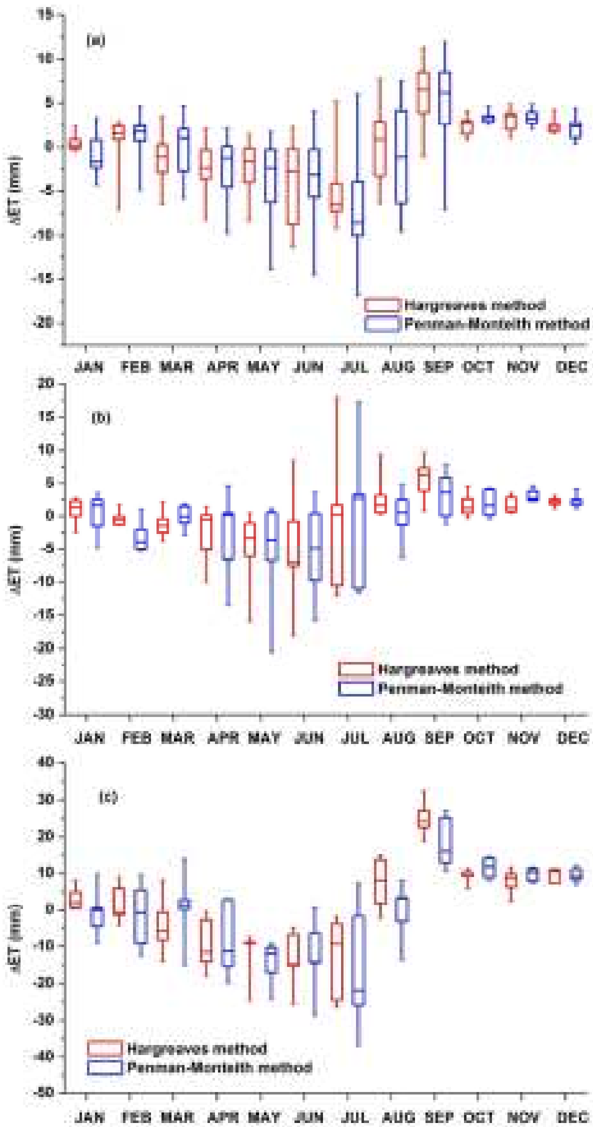

Fig. 7: Box whisker plot of daily (8-day cumulative) differences in ET, ?ET (MODIS-SWAT) during (a) calibration, (b) validation and (c) monthly difference for each month. The box-whisker plots show the median, first and third quartiles. The caps at the end of the boxes show the extreme values. MODIS – SWAT (Hargreaves method) in red and MODIS – SWAT (Penman-Monteith method) in blue.

During calibration of daily simulation, the differences between MODIS and SWAT ET ranged as 0–11.35 mm/8-day (mean 3.31 mm) and 0.05–16.80 mm/8-day (mean 3.94 mm) for Hargreaves and Penman-Monteith method, respectively. Similar statistics for monthlycalibration (Figure-6) varied in a range of 0.3 –32.42 mm/month (mean 10.81 mm) and 0.5–36.86 mm/month (mean 11.92mm) for Hargreaves and Penman-Monteith method, respectively. During validation period, the difference varied as 0–18 mm/8-day (mean 3.31mm) and 0.03–20.55 mm/8-day (mean 3.55 mm) for Hargreaves and Penman-Monteith method, respectively, in daily simulation. While, for monthly validation deviation of Hargreaves and Penman-Monteith method 0.44–24.62 mm/month (mean 9.24 mm) and 0.13–24.13 mm/month (mean 9.30mm), respectively.

Monthly difference between SWAT simulated ET and MODIS ET for daily and monthly simulation shown in box-whisker plots (Figure 7). The simulated ET (by both methods) deviates from MODIS ET by very less amount during August–March whereas it increases during April–July. During the calibration of daily ET, less variation is observed in post-monsoon and winter season, with median close to zero (Figure 7a).While, deviation is moderate (-8 to 5) during spring and it increases from summer to monsoon (wet) period.From Figure 7a, it is also observed that the deviation of simulated ET from MODIS ET is comparatively less while using Hargreaves method rather than Penman-Monteith method.The box-whisker plot of daily simulation shows comparatively better result (less deviation) during validation period (Figure 7b) than during calibration period. However, in both, daily calibration and validation period, difference of model simulated ET from MODIS ET is less in late monsoon period.Likely to daily simulation, the monthly difference between SWAT ET and MODIS ET (Figure 7c)for monthly simulation is very less during post monsoon period and winter period (October–January), but positive.

It indicates underestimation of the model with at consistent low magnitude. The average monthly difference during October–December is 8.9 mm/month and 10 mm/month for Hargreaves and Penman-Monteith method, respectively. In April–July, the median of difference by both methods is negative, indicating overestimation by the model. In the month of July, the median of difference in Hargreaves method is quite less (<-10 mm/month) than Penman-Monteith method (>-20 mm/month). It indicates that Hargreaves method simulates more closely to MODIS ET than Penman-Monteith method during peak rainfall period. However, deviation in model simulation is minimum in December and maximum in July.

The underestimation by the model is maximum during August – September i.e. late monsoon period. The deviation of simulated ET from MODIS data is maximum in Hargreaves method during this period. However, from Figure 6.7c, it is clear that the model simulates accurately during winter season, overestimates during spring and mid-monsoon period and underestimates during post monsoon and early winter period. This analysis could be verified from Figure 6.8a in which average monthly ET, simulated from SWAT (Hargreaves and Penman-Monteith method) and MODIS data for the period of 2004 – 2008 is plotted. The scatter plot of monthly simulated ET against MODIS ET indicates that SWAT simulation using Hargreaves method and Penman-Monteith method reasonably match with MODIS ET (Figure 6.8b). In Figure 6.9, monthly cumulative plot of SWAT simulation using both methods and MODIS for the period 2004 – 2008 are shown. It also shows that the SWAT simulation is closer to MODIS ET data. The calibration and validation results also indicate that the SWAT model could be effectively applied for simulation of other hydrologic components.

Hydrologic Simulations (Water Balance): Calibrated parameters were finally used for hydrologic simulation of Sirsa basin for the period of 2003–2008. On average 51% and 39 % of total rainfall is contributed as ET and streamflow. Annual streamflow varies in range of 105 mm (2004) to 496 mm (2006). The average monthly streamflow varies between less than 1 mm (December) and 90 mm (August).About 78% (240 mm) of total annual streamflow is yielded during July to September, while negligible streamflow noticed in early winter and pre-monsoon period.Annually, water yield is dominantly contributed from surface runoff (60%).Lateral flow and baseflow contributes to streamflow by only 13% and 27%, respectively.During winter (January-February) and monsoon (June-September) period, about 57% of total streamflow is contributed from surface runoff, because of maximum precipitation. During post-monsoonperiod, though streamflow noticed very negligible amount, but mostly(80%) contributed from baseflow. Net contribution of lateral flow and baseflow maximally noticed in July-August and August-September, respectively. The monthly ET varies between 4.60 mm (December) and 91.50 mm (July).Only during the monsoon period the average monthly ET is above 40 mm, while during the rest of period, especially winter and post monsoon period ET is very low. March–April (spring) and October–November (post-monsoon) months are the water stressed period during which ET exceeds rainfall.The rainfall in these months was insufficient to met vegetation and crop water demand and supplied from soil water storage.

Limitations: However, there might be some uncertainty in model simulation raised from error in input data, calibration approach etc. due to unavailability of observed meteorological data, the study used gridded reanalysis data that was coarse in resolution for this study. Moreover, climate data used in this study and used for MODIS ET calculation are collected from two different sources. It may arise ambiguity in parameterization process

CONCLUSIONS

Hydrologic modelling in mountainous regions is challenging because of scarcity of climatic data, extreme elevation gradients and orographic effects. In this study SWAT model together with MODIS ET have been used to simulate the hydrological response. Modelled ET, simulated using Penman-Monteith and Hargreaves methods, was compared with MODIS ET for calibration (2004–2006) and validation (2007–2008).The daily and monthly validation results of SWAT simulation showed better than calibration results.The overall statistical performance of the model was found ‘good’ for daily (8-day composite) simulations and ‘very good’ for monthly simulations, according to the criteria provided by Moriasi *et al*. [52]. The coefficient of determination (R2) values for daily simulations range from 0.74 to 0.77 and monthly values range from 0.81 to 0.91.Likewise, Nash-Sutcliffe efficiency (ENS) varies from 0.53 to 0.72 for daily and 0.71 to 0.91 for monthly calibrations and validations.RSR of daily and monthly simulations varies in range of 0.53-0.68 and 0.33-0.54, respectively.Though, percent bias (PBIAS)showed relatively better performance of Penman-Monteith method than Hargraves method, but R2, ENS and RSR are found better for Hargreaves method. Prior to calibration, sensitivity analysis was performed. The most sensitive parameters were randomly varied manually within predefined boundary to understand their sensitivity to various hydrologic components. The most sensitive parameters for this study basin are groundwater related parameters (GWQMN, REVAPMN, GW_REVAP and RCHR_DP), soil related parameters (SOL_Z, SOL_AWC and SOL_K) and HRU related parameters (EPCO, ESCO and CANMX).Generally, it is an efficient and simple approach for identification of sensitive parameters and calibration of model parameters for data scarce region. However, there might be some uncertainty in model simulation raised from error in input data, calibration approach etc. due to unavailability of observed meteorological data, the study used gridded reanalysis data that was course in resolution for this study. Moreover, climate data used in this study and used for MODIS ET calculation are collected from two different sources. It may arise ambiguity in parameterization process.

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