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Validation of SWAT model using satellite-derived evapotranspiration data

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ABSTRACT

Efficient groundwater management through judicious irrigation scheduling can be accomplished by using the data of actual evapotranspiration (ETact), deep percolation loss (DPL) and surface runoff (SR). In data-scarce regions, the water budgeting approach using satellite-derived evapotranspiration can be an alternative approach to estimate different water balancing parameters. In the present study the operational simplified surface energy balance (SSEBop) model derived ETact data based on moderate resolution imaging spectroradiometer evapotranspiration (MODIS ET) fractions was used to calibrate and validate the SWAT model for five districts *viz.,* Barnala, Sangrur, Moga, Patiala and Ludhiana of central Punjab, India. It was observed that coefficient of determination (R^2) and the model efficiency of the calibrated and validated SWAT model varied from 0.65 to 0.75 and 0.50 to 0.60, respectively. Moreover, the district-wise AET values estimated by the validated SWAT model were 409.3 mm yr^{-1}, 557.5 mm yr^{-1}, 454 mm yr^{-1}, 425.2 mm yr^{-1} and 548 mm yr^{-1} for Moga, Patiala, Sangrur, Barnala and Ludhiana, respectively. Further, the highest DPL rate estimated by the validated SWAT model was 9.6% of average rainfall for the Patiala district and other districts, it varied from 1.1% to 8.8%. Nonetheless, it was ascertained that the satellite-derived evapotranspiration data can be successfully used for calibration and validation of SWAT model besides estimation of DPL and SR for efficient groundwater management at a regional scale.

1. INTRODUCTION

Groundwater is a major source of irrigation in most parts of India (Chindarkar and Grafton 2019). In central Punjab districts of India, rice-wheatis the dominant cropping system where groundwater is extracted for irrigation of field crops. Unfortunately, due to the overdraft of groundwater resources, the water table has depleted critically in the region over past decades (Kumar *et al.,* 2021). Keeping this in view, it is imperative to come up with crop-specific irrigation schedules to save water and reduce the groundwater draft in the region. In order to accomplish this, the water budgeting components *viz.,* rainfall, SR, ET and percolation losses (PL) need to be quantified (Chatterjee *et al.,* 2021; Debnath *et al.,* 2021; Chatterjee *et al.,* 2019). However, the information of SR, ETact and PL are generally not available to perform the water budgeting analysis at regional scales. Though the hydrological models are capable of simulating such parameters, in ungauged watershed systems due to non-availability of measured runoff and other parameters, it becomes difficult to calibrate and validate such models. In such scenarios, the satellite-derived ETact values can be used to calibrate and validate the hydrologic models besides generation of a hydrologic response and flux-related parameters of water budgeting. The soil and water assessment tool (SWAT) is being extensively used by hydrologists for the assessment of SR and groundwater quality parameters at a regional scale (Mondal *et al.,* 2021; Tufa and Sime, 2021; Guug *et al.,* 2020; Patil *et al.,* 2019; Bhatt *et al.,* 2016; Kiptala *et al.,* 2014; Gamage and Danaka, 2015). Sirisena *et al.,* 2020 have compared two different calibration approaches of the SWAT model, one with a single variable *viz.,* streamflow and satellite-derived ET separately and the other with streamflow and ET data in combination. They reported that blending of streamflow and ET data resulted in better model performance with nash-sutcliffe efficiencies (NSE) >0.85 for streamflow estimation, whereas NSE values for streamflow estimations were 0.98 and 0.63 while model was calibrated using streamflow and ET data separately. ETact data derived by MODIS ETact, which isavailable as opensourceand used by researchers alongwith water balance models forestimation of hydrologic responses (Poméon *et al.,* 2018). Miranda *et al.* (2017) compared eddy-covariance system measured ET data with MODIS derived (MOD 16A2) daily, monthly ET data and found a correlation of 0.82 between the eddy covariance method measured ET and MODIS derived monthly ET values. They suggested that MODIS derived freely available and easy to use ET data can be successfully used for meteorological and hydrological studies.

Parajuli *et al.* (2018) used a streamflow-based approach, MODIS ET-based approach and both the FLOW-ET-based approach for SWAT model calibration and validation in sunflower river watershed, north-western Mississippi. They reported an overestimation of SWAT estimated ET by 8% as compared to MODIS derived ET and concluded that MODIS ET data can be used for SWAT model calibration and validation and successful estimation of SWAT based streamflow and ET in data-scarce watersheds. Abiodun *et al.* (2018) compared SWAT model estimated ET with MODIS (MOD16) satellite-derived ET estimates for the Sixth Creek catchment of the Western Mount Lofty Ranges, South Australia and reported differences of 31, 19, 15, 11 and 9% in ET estimation between the SWAT and MOD16 methods. They concluded that for complex terrain situations SWAT estimated ET and MODIS satellite-derived ET were well correlated up to 4 km^2 catchment size. Dash, 2018 calibrated SWAT model using (MODIS -MOD16A2) ET data at daily (8-day composite) and monthly intervals for ungauged Sirsa river basin in north-west Himalaya, India. It was reported from the study that SWAT model estimated ET was in good agreement with MODIS-derived monthly ET data. The study suggested the use of remotely sensed ET data for calibration and validation of SWAT model with acceptable accuracy in ungauged large river basins.

Keeping in view of the reviewed literature pertaining to use of satellite-derived ETact computation using hydrological models, the present study was undertaken to calibrate and validate SWAT using MODIS ET fractions based ETact data derived through operational simplified surface energy balance (SSEBop) model version 5.0 for five districts *viz.,* Moga, Barnala, Sangrur, Patiala, and Ludhiana of Central Punjab, India. Further, the validated SWAT model was used for estimation of SR and DPL for water budgeting analysis at a regional scale.

2. MATERIALS AND METHODS

Study Area

The present study was undertaken for five districts of Punjab state, India *viz.,* Barnala, Moga, Sangrur, Patiala and Ludhiana located in 29.9°N-31.07°N latitudes to 74.9°E-76.8°E longitudes (Fig.1). Satluj is the major river crossing near the boundary of Ludhiana districts from north-east to the north-western direction. River Sutlej in the north and river Ghaggar in the south alongwith Sirhind and Bhakracanal irrigation system form the drainage network in the study area. Rice-wheat are the major crops cultivated in these districts. Soil of the study districts is mainly the alluvial soil. The three main seasons of these districts are the summer season (April to June), the rainy season (July to September) and the winter season (December to February). Canal and ground water are the two sources of irrigation in the study area. Despite the presence of the canal command, about 89% and 11% of the net sown area is irrigated by tubewells and canal networks, respectively. So, a majority of cropped area in the region is irrigated by ground water resources. Further, the region is having land use and land cover (LU/LC) (Fig. 2) with 6.9% buit-up area (URMD), 81.15% agricultural crop land (AGCL), 6.12% current fallow land (PAST), 0.5% plantation area (ORCD), 0.6% deciduous forest (FRSD), 0.02% scrub forest (SHRB), 3.8% waste land (BSVG) and 0.8% water bodies (WATB).

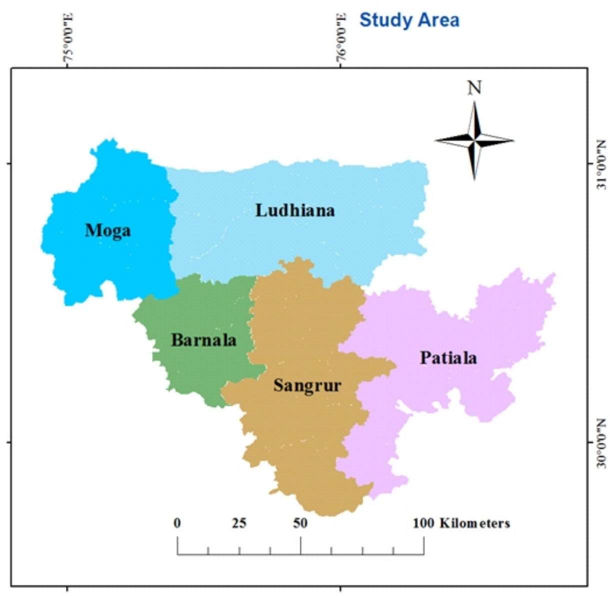

Fig. 1. Map of the study region comprising of five districts of central Punjab

Data Used in the Study

Input data required for operation of SWAT model and estimation of hydrological fluxes include rainfall (RF), maximum temperature (MaxT), minimum temperature (MinT), relative humidity (RH), sunshine hours (SSH), wind velocity (WV), LU/LC, soil textural classification, crop management data and digital elevation model (DEM) data. Sources of acquired data for analysis and their resolution are presented in Table 1.

Input Data Preparation for SWAT Model

The R software was used for extracting the IMD gridded RF, MaxT and MinT data for the study districts. All the required raster soil data, LU/LC data and DEM data were preprocessed and were extracted as per the study area boundary. All the maps were converted to the same resolution of 90 m for running the SWAT model.

The soil map depicting SWAT soil class and texture and the LU/LC maps of the study region are shown in Fig. 2.

Delineation of Watershed, sub-basins and Generation of Hydrologic Response Units (HRU)

SWAT compatible files were prepared for the study region and imported into the model. Outlets were chosen manually to generate the natural drainage network (NDN). NDNs were generated automatically by selecting the DEM-based stream generation module of SWAT and the generated streams were verified using Google™ earth images. Three slope classes *viz,.* 0-2%, 2-10%, >10% and the threshold values of land use percentage at 15%, 10% and 5%, respectively (Kalcic *et al.,* 2015) were generated. The HRUs and sub-basins were generated considering the threshold values of land use percentage over sub-basin area, soil class percentage over land use area and the slope class percentage over soil area as 15%, 10% and 5%, respectively. SWAT model was run from year 2003-2013 using initial 3 years (2000-2002) as the model warm-up period. The USDA SCS curve number method (USDA, 1972), Penman- Monteith method (Monteith, 1965) and the Ritchie method (Ritchie, 1972) were selected for estimation of the SR, ET_0 and AET during SWAT simulations. The PL which is the downward percolation flux entering the vadose zone from the soil profile (mm) was estimated by SWAT model using water balance approach.

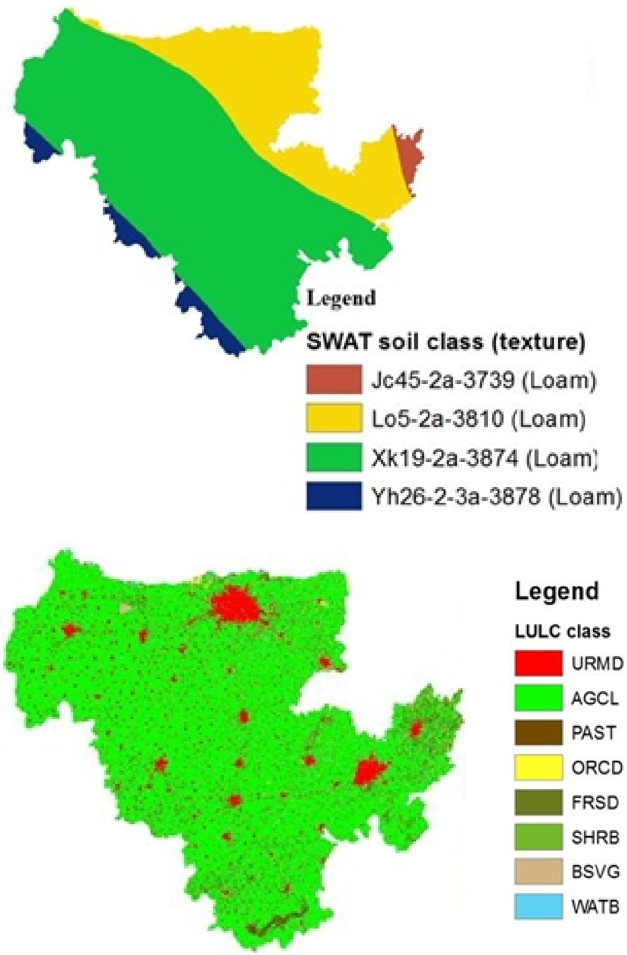

Fig. 2. Soil and LU/LC map of the study region

SWAT Model Calibration and Validation

The MODIS ET fractions based monthly ETact data at ~500 m resolution were extracted using R software. SWAT parameters were optimized using SWAT-CUP module. SUFI-2 algorithm was used to optimize the values of sixty three parameters pertaining to soil, basin, plant and groundwater components used for calibrating the model. Calibration was achieved for individual years from 2003-13 for the 15 randomly selected HRUs. The model was then validated by combining data from 2003-13 and 15 HRUs. The median values of the optimized parameter under model calibration were used for model validation. The calibration and validation was carried out using the SWAT CUP module of SWAT model. The Bayesian approach of SWAT CUP (Tasdighi *et al.,* 2018; Abbaspour *et al.,* 2007) assisted in identification of parameter space specifically applicable for an observation data series (ETact). During this process, the uncertainty in prediction (MODIS ETact product) was based on spatial cell where the target major crop also included a few other landuse system and represented a composite system response. By adopting this Bayesian approach, a parameter space was first ascertained and the mean value was used for validation across the whole set of

Table: 1
Description and sources of data used in SWAT model

Data used	Data sources	Data resolution
MaxT, MinT, RF	IMD Gridded data	RF (0.25 × 0.25 degree), Temp (1 × 1 degree)
LU/LC map	National Remote Sensing Centre, ISRO, Bhuvan portal	1:250000 scale
SRTM DEM	SRTM official website	90 m resolution
Soil map	FAO 30 arc-second harmonized world soil (HWSD) raster database *https://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/harmonized-world-soil-database-v12/en/*	1:5000000 scale

years *i.e.* from 2003-13. The approach used in SWAT CUP appears to embrace comparably satisfactory performance and is observed to be a pragmatic approach (Tasdighi *et al.,* 2018). The values of 63 parameters pertaining to soil, basin, plant and groundwater components used for optimization are shown in three separate graphs in Fig. 3. The ranges and fitted values of these 63 parameters under model calibration are given in Table 2 and the details of the optimized parame-

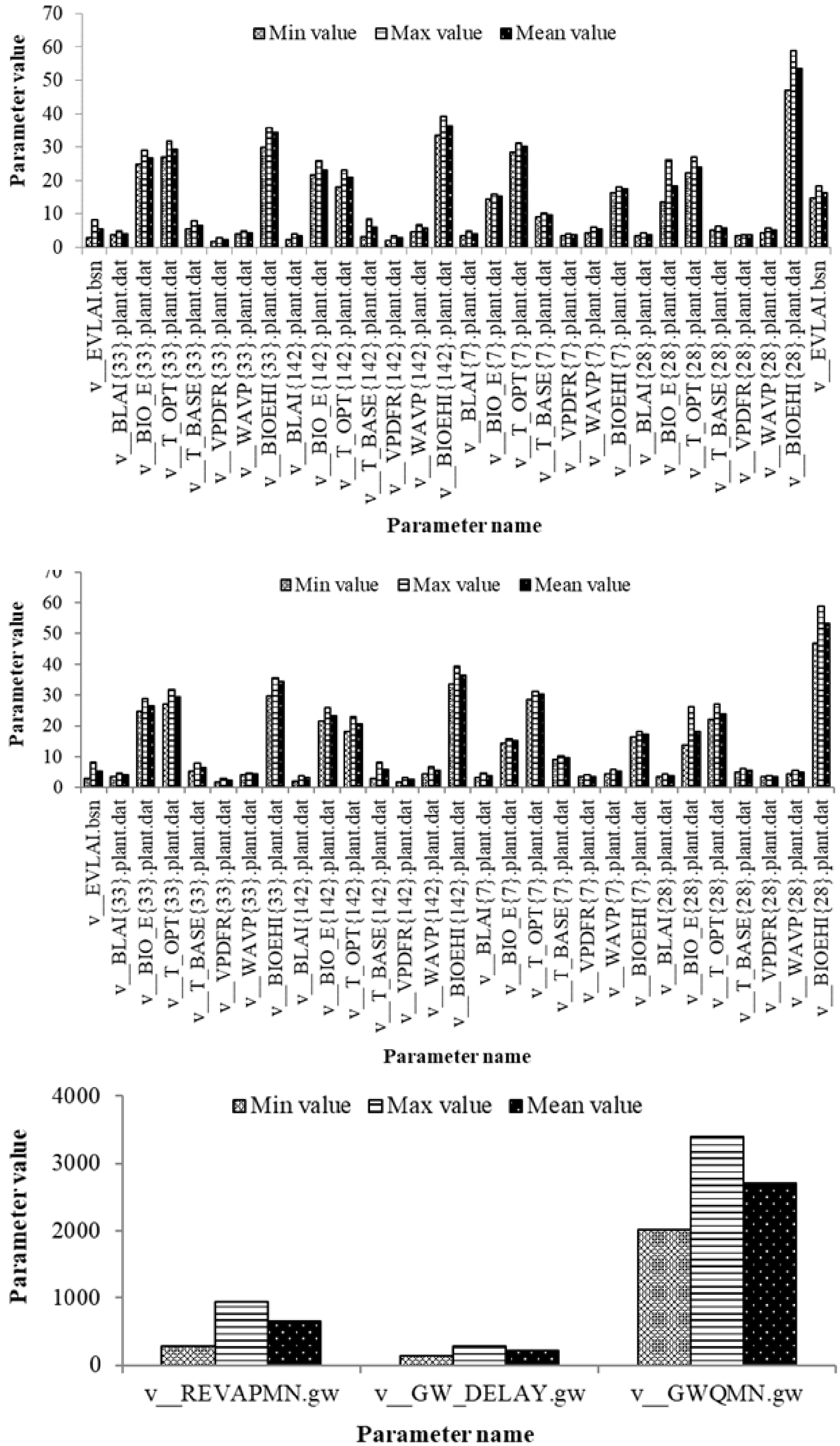

Fig. 3. Parameter ranges and optimized parameters for calibration and validation of SWAT

Table: 2
Ranges of 63 parameters during SWAT calibration

S.No.	Parameters	Lower value	Upper value	Average of fitted values
1.	v__ESCO.hru	0.00	0.54	0.17
2.	v__EPCO.hru	0.30	1.00	0.74
3.	v__REVAPMN.gw	250.00	1000.00	652.27
4.	r__SOL_K().sol	0.00	1.00	0.50
5.	r__SOL_AWC().sol	0.00	1.00	0.62
6.	r__SOL_BD().sol	0.00	0.39	0.06
7.	v__ALPHA_BF.gw	0.64	1.13	0.81
8.	v__CANMX.hru	0.00	65.00	44.55
9.	r__SLSUBBSN.hru	-1.00	0.00	-0.47
10.	v__GW_DELAY.gw	120.00	300.00	224.24
11.	v__GWQMN.gw	1800.00	3500.00	2710.27
12.	v__GW_REVAP.gw	0.00	0.10	0.03
13.	v__EVLAI.bsn	2.05	8.68	5.34
14.	v__SURLAG.bsn	0.32	17.44	8.13
15.	v__ESCO.bsn	0.31	0.77	0.58
16.	v__EPCO.bsn	0.00	0.43	0.20
17.	r__CH_N2.rte	-0.76	0.08	-0.47
18.	r__CH_K2.rte	-0.09	0.74	0.43
19.	v__ALPHA_BNK.rte	0.17	0.72	0.51
20.	v__BLAI{33}.plant.dat	3.12	5.04	4.12
21.	v__BIO_E{33}.plant.dat	23.06	29.20	26.68
22.	v__HVSTI{33}.plant.dat	0.28	0.43	0.36
23.	v__FRGRW1{33}.plant.dat	0.13	0.28	0.20
24.	v__T_OPT{33}.plant.dat	26.08	32.23	29.43
25.	v__T_BASE{33}.plant.dat	5.13	8.38	6.65
26.	v__GSI{33}.plant.dat	0.01	0.01	0.01
27.	v__VPDFR{33}.plant.dat	1.53	3.51	2.37
28.	v__FRGMAX{33}.plant.dat	0.71	1.12	0.96
29.	v__WAVP{33}.plant.dat	3.95	4.85	4.34
30.	v__BIOEHI{33}.plant.dat	28.73	35.84	34.38
31.	v__BLAI{142}.plant.dat	1.68	4.56	3.39
32.	v__BIO_E{142}.plant.dat	19.84	26.59	23.25
33.	v__HVSTI{142}.plant.dat	0.36	0.58	0.49
34.	v__FRGRW1{142}.plant.dat	0.29	0.34	0.31
35.	v__T_OPT{142}.plant.dat	15.67	25.23	20.80
36.	v__T_BASE{142}.plant.dat	1.74	8.58	5.93
37.	v__GSI{142}.plant.dat	0.01	0.01	0.01
38.	v__VPDFR{142}.plant.dat	1.52	3.84	2.82
39.	v__FRGMAX{142}.plant.dat	0.30	0.77	0.54
40.	v__WAVP{142}.plant.dat	4.42	7.25	5.57
41.	v__BIOEHI{142}.plant.dat	33.26	39.87	36.34
42.	v__BLAI{7}.plant.dat	3.18	5.06	3.98
43.	v__BIO_E{7}.plant.dat	14.24	15.86	15.23
44.	v__HVSTI{7}.plant.dat	0.85	1.06	0.94
45.	v__FRGRW1{7}.plant.dat	0.05	0.06	0.05
46.	v__T_OPT{7}.plant.dat	28.06	32.24	30.30
47.	v__T_BASE{7}.plant.dat	9.02	10.70	9.70
48.	v__GSI{7}.plant.dat	0.00	0.00	0.00
49.	v__VPDFR{7}.plant.dat	3.50	4.10	3.73
50.	v__FRGMAX{7}.plant.dat	0.42	0.64	0.49
51.	v__WAVP{7}.plant.dat	4.10	6.75	5.46
52.	v__BIOEHI{7}.plant.dat	16.15	18.56	17.41
53.	v__BLAI{28}.plant.dat	3.32	4.44	3.80
54.	v__BIO_E{28}.plant.dat	13.47	27.82	18.28
55.	v__HVSTI{28}.plant.dat	0.36	0.58	0.48
56.	v__FRGRW1{28}.plant.dat	0.06	0.07	0.06
57.	v__T_OPT{28}.plant.dat	22.00	27.34	23.86
58.	v__T_BASE{28}.plant.dat	4.81	6.44	5.62
59.	v__GSI{28}.plant.dat	0.01	0.01	0.01
60.	v__VPDFR{28}.plant.dat	3.46	4.03	3.65
61.	v__FRGMAX{28}.plant.dat	0.62	0.75	0.68
62.	v__WAVP{28}.plant.dat	4.31	5.63	5.19
63.	v__BIOEHI{28}.plant.dat	46.48	61.59	53.43

ters are presented in Table 3. Hydrological fluxes on a year basis for all the basins and districts were then estimated using the validated SWAT model from 2003-2013.

SWAT model Performance evaluation

Model performance during calibration and validation were inspected using two prediction error statistics *viz.* the coefficient of determination (R^2) (Krause *et al.,* 2005) and modified NSE (Nash and Sutcliffe, 1970). The equation for R^2 and NS are given below:

$$R^2 = \left[\frac{\sum_{i=1}^{N}(Oi-\bar{O})(Si-\bar{S})}{\left(\sqrt{\sum_{i=1}^{N}(Oi-\bar{O})}\right)\left(\sqrt{\sum_{i=1}^{N}(Oi-\bar{O})}\right)}\right]^2 \quad ...(1)$$

$$NSE = 1 - \frac{\sum_{i=1}^{N}(Oi-Si)^2}{\sum_{i=1}^{N}(Oi-\bar{O})^2} \quad ...(2)$$

In the above equations Oi represents the value of i^{th} observed data, $\bar{O}$ represents the mean value of the observed data, Si represents the i^{th} simulated value, $\bar{S}$ represents the model simulated mean value and N represents the total number of events, respectively.

3. RESULTS AND DISCUSSION

Calibration and Validation Statistics of SWAT Model

Model performance during calibration and validations was found to be in line with the observed data. The NS values during model calibration ranged from 0.49-0.62 for all the 15 HRUs and the R^2 values during model calibration ranged from 0.86-0.9. Whereas, NS and R^2 values during model validation were $\cong$0.5 and $\geq$ 0.7, respectively. The prediction error statistics of validated SWAT model are presented in Table 4.

NS and R^2 values $\cong$0.5 and $\geq$ 0.7 can be considered as satisfactory for SWAT model using satellite ET-based

Table: 3
Details of the optimized parameters under SWAT calibration

Parameter name	Parameter description
ESCO	Soil evaporation compensation factor.
EPCO	Plant uptake compensation factor.
REVAPMN	Threshold depth of water in the shallow aquifer for "revap" to occur (mm).
SOL_K	Saturated hydraulic conductivity.
SOL_AWC	Available water capacity of the soil layer.
SOL_BD	Moist bulk density.
CN2	SCS runoff curve number f
ALPHA_BF	Base flow alpha factor (days).
CANMX	Maximum canopy storage.
SLSUBBSN	Average slope length.
GW_DELAY	Groundwater delay (days).
GWQMN	Threshold depth of water in the shallow aquifer required for return flow to occur (mm).
GW_REVAP	Groundwater "revap" coefficient.
EVLAI	Leaf area index at which no evaporation occurs from water surface.
SURLAG	Surface runoff lags time.
CH_K2	Effective hydraulic conductivity in main channel alluvium.
ALPHA_BNK	Base flow alpha factor for bank storage.
BLAI	Max leaf area index.
BIO_E	Biomass/Energy Ratio.
HVSTI	Harvest index.
FRGRW1	Fraction of the plant growing season corresponding to the 1st. Point on the optimal leaf area development curve.
T_OPT	Optimal temp for plant growth.
T_BASE	Min temp for plant growth.
GSI	Max stomatal conductance (in drought condition).
VPDFR	Vapour pressure deficit corresponding to the fraction maximum stomatal conductance defined by FRGMAX
FRGMAX	Fraction of maximum stomatal conductance that is achievable at a high vapour pressure deficit.
WAVP	Rate of decline in radiation use efficiency per unit increase in vapour pressure deficit.
BIOEHI	Biomass-energy ratio corresponding to the 2nd. point on the radiation use efficiency curve.
v__	Means the default parameter is replaced by a given value.
r__	Means the existing parameter value is multiplied by (1 + a given value).
7,28,33,42,142	Represents forest-deciduous, winter wheat, rice, wheat grass and irrigated double crops, respectively

Table: 4
Prediction error statistics of validated SWAT model for the study region

HRU number	R^2	NS
ET_248	0.82	0.24
ET_310	0.83	0.4
ET_345	0.8	0.3
ET_360	0.79	0.24
ET_415	0.79	0.23
ET_420	0.81	0.36
ET_430	0.74	0.08
ET_432	0.82	0.38
ET_463	0.76	0.13
ET_535	0.77	0.17
ET_552	0.77	0.29
ET_605	0.72	0.02
ET_608	0.79	0.35
ET_618	0.85	0.54
ET_634	0.77	0.29

calibration and validation of SWAT Model. Odusanya *et al.* (2019) used MODIS-derived ET data to calibrate and validate the SWAT model for different sub-basins in an ungauged watershed in Nigeria. They reported that out of the 53 sub-basins for about 63% of the sub-basins the model NSE values were >0.5 and the average NSE values for SWAT model validation using MODIS derived ET for all sub-basins were 0.45 which was considered acceptable.

Spatial Variability of Hydrologic Fluxes

The average rainfall (RF) for year 2003-13 for Moga, Barnala, Sangrur, Patiala and Ludhiana districts varied from 365.2-1253.4 mm y^{-1}. The percolation loss (PL) varied from 2.01-181.5 mm y^{-1}. The ETact values ranged from 341.5-763.98 mm y^{-1}. The surface runoff (SR) values varied from 20.4-463.2 mm y^{-1}. The water yield (WY) varied from 20.54-464.4 mm y^{-1}. The overall average values of RF, PL, ETact, SRO and WY for the five study districts were found to be 674.2 mm y^{-1}, 52.5 mm y^{-1}, 503.3 mm y^{-1}, 118.2 mm y^{-}

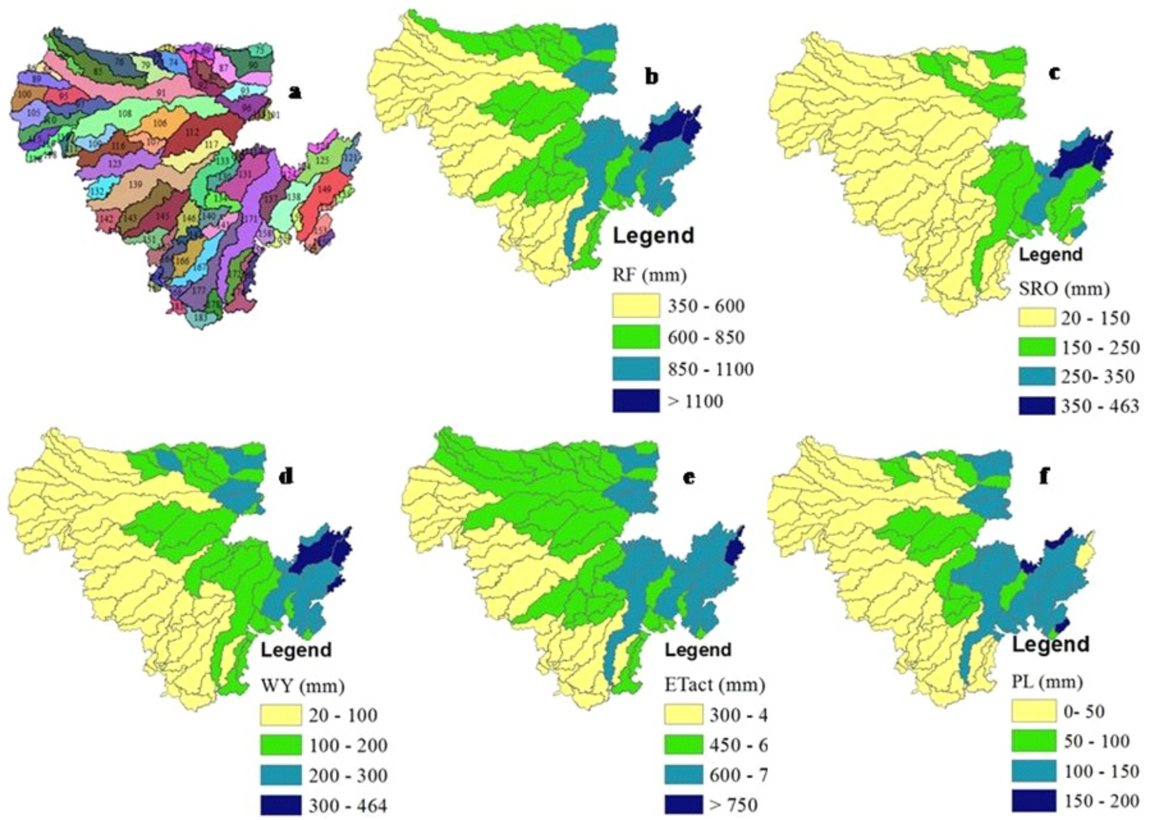

Fig. 4. Map showing a) SWAT generated sub-basins and spatial variability of b) Rainfall, c) Surface runoff, d) Water yield, e) actual evapotranspiration and f) Percolation losses in the study region

^{1}and 120.5 mm y^{-1}. Moreover, the PL, ETact, SRO and WY were found to be 7.8%, 74%, 17.5% and 17%, respectively. Spatial variability of average RF, SRO, ETact, PL and WY in the study region are shown in Fig. 4.

Sub-basin boundaries of any watershed system may or may not match with the district boundaries. Moreover, during delineation of watershed from DEM, the remote point and the outlet of any delineated sub-basin may not be the same as the district boundary. Therefore, in the present study, to estimate district wise hydrological flux variation, sub-basins were clipped to district boundaries and the district wise hydrologic fluxes were estimated. The clipped boundaries of sub-basins within each district boundaries are presented in Fig. 5. It can be observed from Fig. 5 that the delineated area of sub-basins in each district (*viz.,* Barnala, Moga, Sangrur, Patiala, Ludhiana) are distint and the respective polygon features of the sub-basins are uniquely displayed with varying colour. Moroever, the entire area of the district is being covered under different sub-basins as presented in Fig. 5. The RF for year 2003-13 was 462.4 mm y^{-1}, 817.6 mm y^{-1}, 569 mm y^{-1}, 491 mm y^{-1} and 748 mm y^{-1} for Moga, Patiala, Sangrur, Barnala and Ludhiana, respectively. The SWAT estimated average ETact and PL values for these districts were 409.3 mm y^{-1}, 557.5 mm y^{-1}, 454 mm y^{-1}, 425.2 mm y^{-1}, 548 mm y^{-1} and 7.7 mm y^{-1}, 9.5 mm y^{-1}, 5.7 mm y^{-1}, 2.1 mm y^{-1}, 8.8 mm y^{-1}, respectively. The ROsur and WY values for the same period for these study districts were estimated to be 42.8 mm y^{-1}, 180.54 mm y^{-1}, 81.1 mm y^{-1}, 54.5 mm y^{-1}, 132.8 mm y^{-1} and 43.1 mm y^{-1}, 184.2 mm y^{-1}, 82.64 mm y^{-1}, 54.96 mm y^{-1}, 135.7 mm y^{-1}, respectively. Among all the districts, the ETact was observed highest for Moga districts (88.5% of district average RF) followed by Barnala (86.6% of the district average RF), Sangrur (79.7% of district average RF), Ludhiana (73.2 % of district average RF) and Patiala (63.2% of district average RF), respectively. The highest ETact of Moga district may be attributable to the fact that the ground water depletion in Moga district was the highest as compared to other four districts. Such depletion is related to more ground water extraction rate in the district and thus the excess water used would affect the evaporation component contributing to more ETact value compared to other districts. The transpiration component will not vary much, but the evaporation from soil surface due to excess water application would result in the higher ETact value as compared to other districts. The WY values were found highest for Patiala (22% of the district average RF) followed by Ludhiana (18.1% of the district average RF), Sangrur (14.5% of the district average RF), Barnala (11.2% of the district average RF) and Moga (9.32% of the

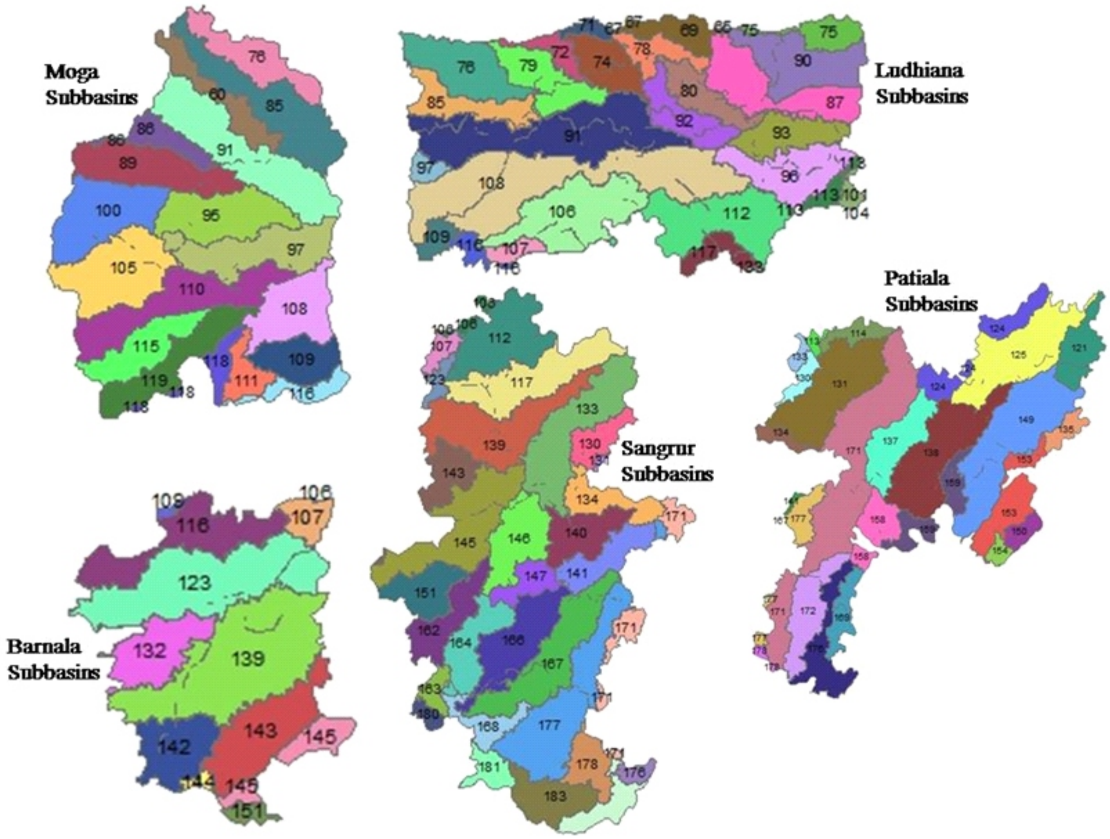

Fig. 5. District wise sub-basin areas for estimation of hydrological fluxes

district average RF). Moreover, the highest PL rate was found for Patiala (9.6 % of the district average RF) followed by Ludhiana (8.8% of the district average RF), Sangrur (5.6% of the district average RF), Barnala (2.1%) and Moga (1.1% of the district average RF), respectively. Results indicated that the Moga, Barnala and Sangrur districts were having the highest rate of ETact values, but, lowest WY and PL values as compared to Ludhiana and Patiala districts. A similar trend in decrease of WY with an increase in ETact values in the Gomti river basin was reported by Abeysingha *et al.,* 2015 using SWAT model.

Trend of Yearly Average RF and Etact

The RF for all the districts was observed to be increasing over time. Trend analysis of rainfall depth and ETact of the study region during 2003 to 2013 was undertaken using linear regression technique. Trend of RF and ETact are shown in Fig's 6 and 7, respectively.

The ETact represents the exchange of water and energy between the soil and atmosphere (Ochoa *et al.,* 2019). The soil moisture content on the other hand is dependent on the amount of precipitation and irrigation water applied. Major cropping system of the five study districts were rice and wheat. The area under major crops in the study districts were 0.57 M ha, 0.52 M ha, 0.46 M ha, 0.35 M ha and 0.22 M ha

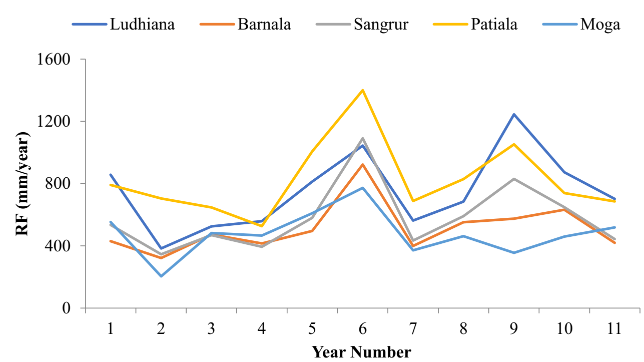

Fig. 6. District wise RF trend during 2003-13

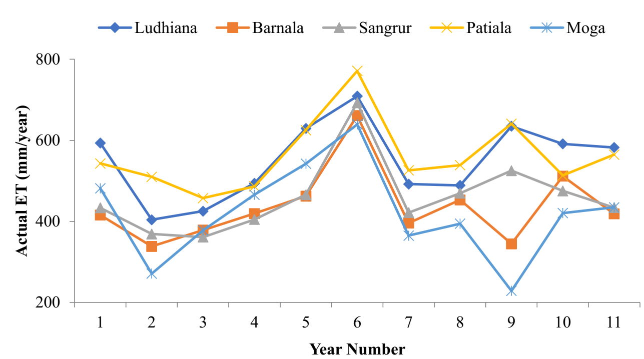

Fig. 7. District wise ETact trend during 2003-13

Table: 5
District wise regression statistics for RF and ETact trends over years

	Regression statistics for rainfall trend	Regression statistics for ETact trend
Barnala	y = 15.17x + 421.2 R^2 = 0.096	y = 5.520x + 403.2 R^2 = 0.041
Moga	y = 2.053x + 464.8 R^2 = 0.002	y = 4.846x + 407.1 R^2 = 0.028
Patiala	y = 18.93x + 464.3 R^2 = 0.083	y = 6.156x + 524.7 R^2 = 0.053
Sangrur	y = 10.11x + 763.3 R^2 = 0.018	y = 9.140x + 404.4 R^2 = 0.111
Ludhiana	y = 30.41x + 567.2 R^2 = 0.162	y = 10.68x + 485.4 R^2 = 0.138

for Sangrur, Ludhiana, Patiala, Moga and Barnala districts, respectively. An increase in cropped area by 1.2% under the rice-wheat cropping system was observed during 2003 to 2013. The effect of increase in area under major cropping system in the study districts were reflected in the increased ETact pertaining to the Central Punjab encompassing these five districts. An increase in ETact indicated an increase in demand of irrigation water to meet the crop water requirements. However, most of the ETact requirements were met from ground water resources of the region. Similar findings pertaining to increase in number of tubewells and corresponding increase in groundwater extraction was reported by Chawla *et al.,* 2010. Results of this study are indicative of more load on groundwater because majority of farmland is under groundwater irrigation as compared to canal irrigation in the region.

4. CONCLUSIONS

SWAT model was successfully calibrated and validated using MODIS ET fractions based ETact data derived through SSEBop model (*ver.* 5.0). Validated SWAT model was used for estimating hydrological fluxes in five districts of central Punjab, India. District wise estimation of hydrological fluxes are generally preferred over sub-basin wise analysis due to its use by the policymakers and planners for chalking out district wise water management activities. Moreover, the district wise plan presented in this study emanated from sub-basin wise plan, in which the SWAT model was calibrated using HRUs leading to sub-basin wise hydrological fluxes estimation and subsequent geo-processing operation such as clipping with the district administrative boundaries. Results indicated that a significant portion of rainfall and groundwater was utilized for meeting the ETact requirements in all districts. Moreover, it was observed that water yield values generated from the sub-basins under Moga, Barnala and Sangrur districts were less as compared to Ludhiana and Patiala districts. Impact of increasing ETact was reflected in excess groundwater draft in all the five study districts during the study period. The protocol developed in this study can be useful pertaining to extraction of AET from open-source satellite data leading to validation of SWAT model. Further, the generated data can be used for estimation of water budgeting parameters leading to judicious agricultural water management at regional scales.

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