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Estimation of Flow for Ungauged Watersheds in Pranhita of Godavari River Basin in India Using SWAT

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Abstract: For sustainable growth with a rational Engineering and Environmental solutions, the long term records of hydrological observation are of immense value. The current paper is an attempt to apply the physically based, spatially distributed SWAT (Soil Water Assessment Tool) to assess its ability to predict flow at watershed scale ungauged locations in Pranhita sub-basin. The test sub-basin belongs to the Godavari basin located in the central part of India, draining an area of 1,09,079 km^2. The SWAT model is tested for streamflow, calibrated at outlet of Wardha, Penganga and Pranhita sub-basins of Pranhita. The spatial heterogeneity in the parameter settings are tested at 16 monitoring gauge locations within the sub-basin, treating them as ungauged sites. The results indicate that SWAT can capture the amount and variability of streamflow acceptably well both at annual and monthly time scale. The model performance at testing sites range between acceptable and good. In general, the results show more than 90% of the stations have annual NSE values greater than 0.5 and about 60% have NSE greater than 0.8. Also, measure for annual R^2 of 0.8 were exceeded by 14 out of 16 stations and 0.9 by 10 out of 16 sites. On similar lines, monthly NSE of 0.5 is exceeded by 95% stations and 0.8 by 56%.

Regression is the most widely used technique for transferring information to ungauged catchment. A Regional Analysis has been made for Pranhita sub-basin. Empirical relations have been developed based on the climate and catchment parameter dataset generated by SWAT. The correlation matrix of six variables viz. precipitation, % cropped area, % forest area, mean temperature, relief, and sub basin area with average natural runoff was developed. This was followed by clustering of sub-basins, which involved Principal Component Analysis (PCA) and K-Means Clustering. After dividing the dataset into clusters, empirical equations for the formed clusters were developed for monsoon months from the dataset of SWAT, that related the dependent variable "monthly discharge" with the climate and watershed attributes.

A comparison of SWAT flow simulated at watershed level in ungauged locations is made with flow series developed from Regional equation of Pranhita for monsoon months. Overall, the SWAT model can satisfactorily predict hydrologic

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budget for the ungauged basins in Pranhita with calibration at basin scale using both the approaches. The Regression based hydrogical response gives a lower NSE as compared to the direct SWAT output. However, the ease of applicability of Empirical equation makes it a viable alternative to adopt for small watersheds, in the absence of other suitable technique.

Key words: Hydrological Budget, sub-basin, ungauged, Godavari, assessment, watershed, Cluster, simulation, prediction

1. Introduction

The long term records of hydrological observation are a prerequisite to the design of water resource structures and a key to solution of environmental problems. The assessment of long term flow series is often faced with inadequate or non-available information records. This calls for a need of Regional studies which involves extrapolation of flow records from gauged to ungauged basin. In view of tremendous spatio-temporal heterogeneity of climatic and landscape properties, this remains fraught with considerable difficulties and uncertainties. Various approaches have been adopted to extrapolate flow records such as relating drainage basin and climate attributes to predict hydrological response, use of measurements by remote sensing, application of process based hydrological models with or without specifying the climate inputs. A number of regional analysis have related watershed attributes to one aspect of response such as flood frequency (NERC, 1975) or to unit hydrograph parameters (Burn and Boorman, 1993). However, for design of storage and irrigation supply structures, long term series of hydrologic response is of interest. This calls for a need to make prediction of basin response with water balance models. The research sought to relate the parameters of monthly water balance model to drainage basin attributes in a region have met with limited success. Vandewiele et al (1995) derived the parameters of a monthly water balance model using kriging and found good results for ungauged catchments. Tung et al (1997) recommended the use of multivariate statistical methods which can account for the correlation structure among the watershed model parameters. The analysis by Fernandez et. al. (2000) showed that the regional relation for watershed model parameters with basin characteristics did not lead to improvement in calibration of watershed at ungauged sites. Merz and Bloschl (2003) showed that the best regionalization method are the use of average parameters of immediate upstream and downstream neighbours and regionalization by kriging. T S. Kokkonel et. al. (2003) investigated the approach to daily streamflow prediction and noted that the relationship between model parameters and physical catchment descriptors can result in a significant decrease in model performance. They further suggested that if a gauged catchment resembles ungauged catchment in a sense of hydrological behaiour, the entire set of parameters from gauged catchment should preferably be adopted instead of deriving quantitative reltionships between catchment descriptors and model parameters. The study by D. A. Post et al (1999) showed that for daily streamflow prediction, the relationship between model parameters and landscape attributes showed mixed results. He concluded that better understanding of hydrological controls are needed to improve prediction. The approach for extrapolation of response information from gauged to ungauged basins using global average and regression based parameters by Gitau et al (2010) reported regionalized parameter sets for the SWAT model can be used for making satisfactory hydrologic response predictions in ungauged watersheds. Another method to assess unavailable flow has been made through measurements by satellite radar altimetry (Sun et al. 2010, 2012). Each of the approaches carry a number of limitations pertaining to inadequacy of the models or estimation methods, inadequate representation of critical processes governing the basin response and incomplete specification relating to properties of basin and climate inputs. The uncertainty gets further compounded due to the impact of human induced changes to the land surface and climate, occurring at the local, regional and global scale. Due to conceptual simplification, the models need to be calibrated to observed hydrological variable to varying degrees (Srinivasan et al. 2010). One approach to address this is to develop a model that under physically based spatial and temporal inputs, uses comprehensiveness in the model’s interrelationship to predict flow for ungauged locations. (Arnold et al. 1998). The method has been adopted satisfactorily in an ungauged coastal basin where calibration and validation for upstream sub-watersheds is followed by extending the parameter settings to ungauged sub-watersheds. (Lee et al. 2012)

The current study focuses on developing a model in SWAT for Pranhita basin of India. SWAT incorporates spatially and physically distributed watershed inputs to simulate a set of comprehensive processes and most of its parameters can be estimated automatically using the GIS interface and meteorological information combined with internal model database. The hypothesis of the study is that, given appropriate spatial input data, SWAT can provide a satisfactory simulation of the water budget at ungauged sites, when calibrated at a basin scale. The model has been calibrated at sub-basin level and simulated output of response at each of the gauging locations in the sub-basin has been compared with measured values for evaluation as ungauged site. Regional study approach has been also discussed in the paper which defines the watershed attributes and hydro-metorological parameters through multi-linear regression. The Empirical relation have been developed for monsoon months June to October. The hydrological response output of SWAT and Regional study have been compared with observed flow and evaluation of the two approaches as a tool for ungauged flow estimation have been evaluated.

Study area description

The Pranhita sub-basin, located in central part of India, belongs to the Godavari basin, comprising of rivers Wainganga, Penganga and Wardha (***Figure 1***) draining an area of 1,09,079 km^2. The highest point of the basin is at 1086 m.a.s.l and the lowest point is located at Tekra gauging station at 95 m.a.s.l. Close to 75% of the watershed area lies below 451m elevation and 50% above 321m. The mean slope is around 0.016. The average daily discharge is 1063 cumec near the outlet with values ranging from 1.1 to 38914 cumec. The average annual rainfall varies from 900mm to 1900mm out of which more than 90% is received during the south-west monsoon from June to October.

SWAT model description

SWAT is a physically based, continuous time model with spatially explicit parameterization (Arnold et al., 1996). The model divides watershed into multiple sub-basins and further sub-divides into Hydrologic Response Units (HRUs) based on land use, soil and slope information . The major components of SWAT include hydrology, weather, erosion, plant growth, nutrients, pesticides, land management, and stream routing. Physical characteristics, such as slope, reach dimensions, and climatic data are considered for each subbasin. For climate, SWAT uses the data from the station nearest to the centroid of each subbasin. Calculated flow, sediment yield, and nutrient loading obtained for each subbasin are then routed through the river system. Channel routing is simulated using the variable storage or Muskingum method. For this study, only SWAT components concerned with runoff simulation is briefly introduced.

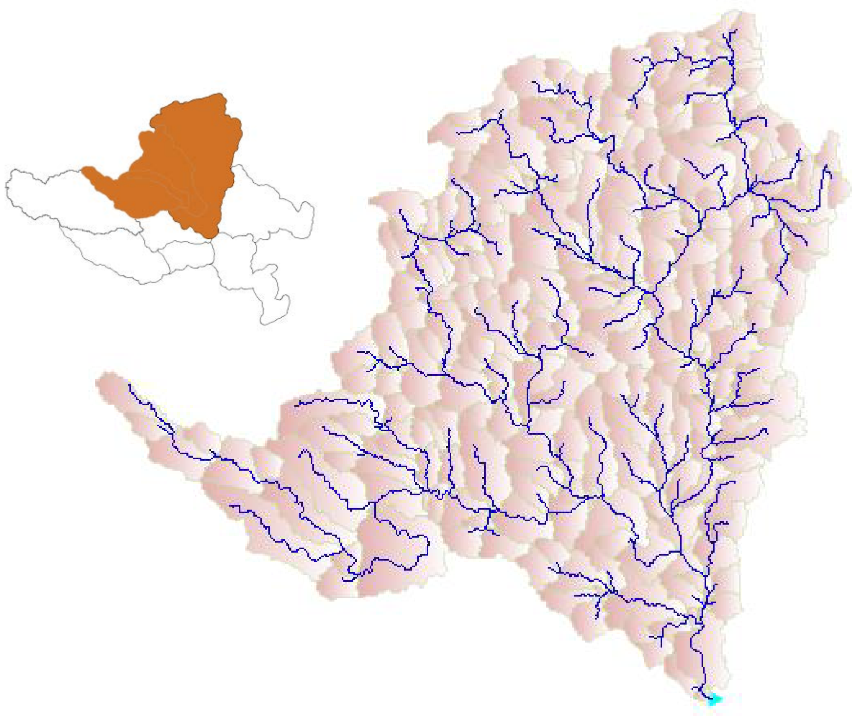

Figure 1: Pranhita Sub basin of Godavari

The local HRU water balance is presented by four storage volumes: snow, soil profile, shallow aquifer, and deep aquifer. Soil profile can be subdivided into multiple layers. Soil water processes include infiltration, evaporation, plant uptake, lateral flow, and percolation to lower layers. The soil percolation component of SWAT uses a water storage capacity technique to predict flow through each soil layer in the root zone. Downward flow occurs when field capacity of a soil layer is exceeded and the layer below is not saturated. Percolation from the bottom of the soil profile recharges the shallow aquifer. Daily average soil temperature is simulated as a function of the maximum and minimum air temperature. If the temperature in a particular layer reaches less than or equal 0 ^{0}C, no percolation is allowed from that layer. Lateral sub-surface flow in the soil profile is calculated simultaneously with percolation. Groundwater flow contribution to total stream flow is simulated by routing a shallow aquifer storage component to the stream (Arnold and Allen, 1996). The model offers three options for estimating potential evapotranspiration (PET) including Hargreaves (Hargreaves and

Samani, 1985) , Priestley-Taylor (Priestley and Taylor, 1972), and Penman-Monteith (Monteith, 1965) method.

It computes evaporation from soil and plants separately. Percolation from the bottom of the soil profile and root zone recharges the shallow unconfined aquifer. Surface runoff from daily rainfall is estimated with a modification of the Soil Conservation Service (SCS) Curve Number (CN) method and Green-Ampt infiltration method. Return flow is simulated by creating a shallow aquifer (Arnold et al.,1998). Runoff is predicted separately for each HRU and routed to obtain the total runoff for the watershed. Hydrologic routines within SWAT account for snowfall and melt, vadose zone processes (i.e. infiltration, evaporation, plant uptake, lateral flow and percolation) and ground water flows. Outflow from a channel is adjusted for transmission losses, evaporation, diversions and return flow.

SWAT model setup

The parameters of watershed were derived using the SWAT Map Window interface, which provides a graphical support and allows the construction of the model input into the digital maps. HRUs are the basic building blocks of SWAT at which all landscape processes are computed. In this study, a total of 268 number of Hydrological units were defined in the Pranhita basin at the threshold drainage area of 250 sq km. As a physically based hydrological model, SWAT requires a great deal of input data in order to derive parameters that control the hydrological processes in a given watershed. Major input dataset include weather, topography, soil, land use/land cover data and management practices. The data used in modeling are :

Digital Elevation dataset (DEMs) at 90m resolution obtained from the NASA Shuttle Radar Topographic Mission (SRTM) website. The elevation dataset has been used for automatic delineation of watershed boundary and channel network to provide watershed configuration and topographic parameter estimation. The main inputs provided by the DEM are channel length (main and tributary routing streams), channel slope and tributary slope by HRU. The basin has medium topographic relief with the elevation in the basin ranging from 1086m to 100m. The average slope of the sub-basin is 1.6%.

The Landuse map was obtained from USGS Global Land Cover Characterisation (GLCC) database (April 1992-March 1993) http://edcsns17.cr.usgs.gov/glcc/glcc.html). Based on the landuse and land cover LULC data, the sub-basin consists of 73% agriculture, 20% pasture, 6% forest (Refer ***Figure 2***) coverage. While the agriculture dominates throughout the area with pasture land distributed in between, the eastern fringes have forest covering. The LULC were developed for 1992-1993 which represents the time of model calibration as not much of changes in landuse have occurred in the intervening period.

The soil map by Food and Agriculture Organisation of the United Nations (FAO,1995) with a spatial resolution of 10km as per AISLUS Classification, was used. The spatial data reveals that the soil of Pranhita sub-basin is predominantly clay with clay loamy soil interspersed throughout the basin.

National Climate Centre (NCC) of Indian Meterological Department (IMD) has developed high resolution long range gridded daily rainfall and temperature dataset for the Indian region. These dataset provide daily precipitation and temperature values at 0.5 and 1 degree interval respectively and give a good information on the spatial and temporal distribution of precipitation and temperature in the study watershed. The spatio-temporal dataset of daily precipitation and temperature (maximum and minimum) were provided using IMD gridded dataset. The aggregated daily precipitation and temperature to the subbasins creates one weather station for each HRU sub-basin using GIS interface, to input into the SWAT model. Wind speed and solar radiation were simulated from the nearest climate station using the weather generator in SWAT. Similarly, evapotranspiration was calculated within the model using Penman-Montieth Method (Montieth, 1965).

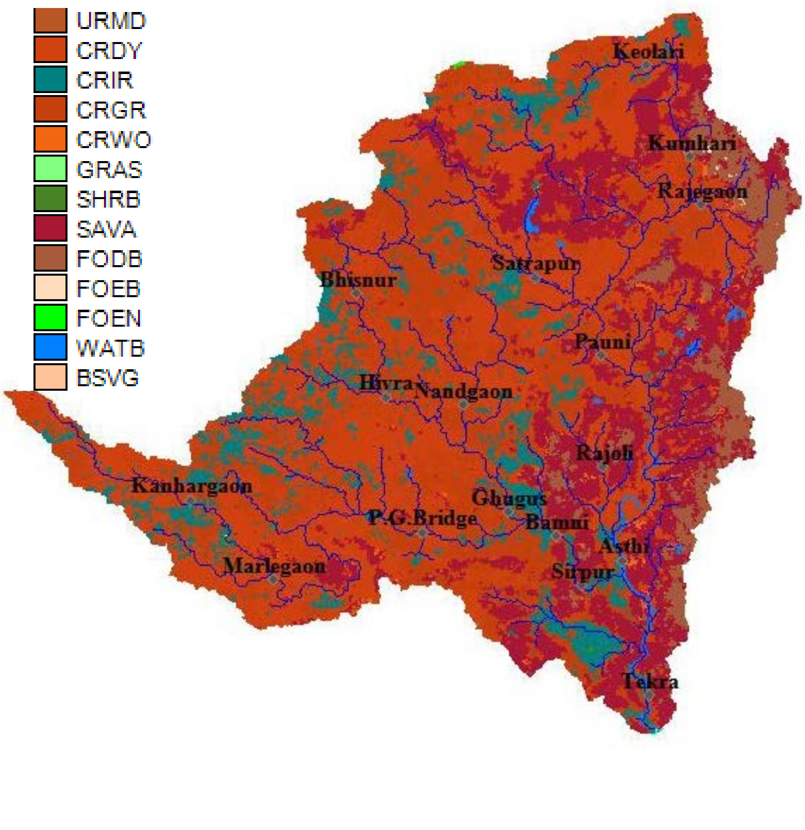

Figure 2: Land Use Cover Map for Pranhita Sub basin

Streamflow

The daily and monthly streamflow observation data for calibration and validation has been obtained from CWC (Central Water Commission) maintained gauging stations. **Figure 2** shows the CWC monitoring gauging locations of streamflow data used in comparing with SWAT outputs. Naturalisation of flow has been done to adjust them for the effects of regulation from several irrigation projects, as the basin has about 12% utilization reported from studies.

Evaluating the performance of SWAT predictions

The model has been calibrated at sub-basins viz. Wardha, Penganga and Pranhita at their outlet. The calibrated values of input parameters were obtained by calibrating SWAT to obtain the closest match of simulated water budget components to observed values for the period 1971-72 to 1982-83, while maximizing the agreement between the observed and predicted total water yield at annual and monthly intervals. The calibration was made from June 1971 to May 1983 over a period of 13 years for which utilization data is available. The flow records within the sub-basins after naturalization, have been used to evaluate the spatial extrapolation capability of SWAT for ungauged flow estimation. The objective of validation at these smaller sub-watersheds is to ensure that the model is accurately simulating the watershed on different spatial scales. The flows were compared on monthly and annual basis. A hydrologic model such as SWAT is said to have good performance when the simulated flow hydrograph at a given location within a watershed is comparable with the corresponding observed hydrograph in terms of volume and peak. Besides visualization plot showing simulated versus observed values, the evaluation coefficients for deterministic predictions include percent bias (PBIAS), coefficient of determination (R^2), and Nash Sutcliffe efficiency (NSE), following statistical guidelines set by Moriasi et al. (2007).

PBIAS measures the average tendency of simulated data to be larger or smaller than the observed counterparts (Gupta et al., 1999). PBIAS values with small magnitude are preferred. Positive values indicate model overestimation bias, and negative values indicate underestimation model bias (Gupta et al., 1999). The R^2 value is equal to the square of Pearson's product moment correlation coefficient (Legates and McCabe, 1999). It represents the proportion of total variance in the observed data that can be explained by the model. R^2 ranges from 0.0 to 1.0. Higher values equate to better model performance. NSE indicates how well the plot of observed versus simulated values fits the 1:1 line. It ranges from $-\infty$ to 1 (Nash and Sutcliffe, 1970), and larger NSE values denote better model performance. Although R^2 values have been used often in the past to compare model results, the recommendations of ASCE (1993) indicate that the Nash-Sutcliff measure is a better representative measure for model goodness of fit. A higher value of R^2 and NSE indicates simulation outcome matches measured values of water budget components more closely.

$$PBIAS = \frac{\sum(Q_m - Q_s)}{\sum(Q_m)} X\ 100$$

$$R^2 = \sigma^2 = \frac{\left[(Q_m - \overline{Q}_m)(Q_s - \overline{Q}_s)^2\right]}{\sum(Q_m - \overline{Q}_m)^2 \sum(Q_s - \overline{Q}_s)^2}$$

$$NSE = 1 - \frac{\sum(Q_m - Q_s)^2}{\sum(Q_m - \overline{Q}_m)^2}$$

Where, Qm = Measured discharge , Qs = Simulated discharge, $\overline{Q_m}$ = Mean of Measured discharge series , $\overline{Q_s}$= Mean of Simulated discharge series, The other symbols have the same meanings as defined in the preceding equation.

2. Results and Discussion

The objective of calibrating SWAT at annual and monthly level for flow at the three gauging stations Tekra, Ghugus and P G Bridge were achieved within measurement error (***Table 2***). The NSE values range from 0.88 to 0.93 on an annual scale and from 0.91 to 0.95 on monthly scale for calibration period. Similarly, R^2 vary from 0.92 to 0.95 and PBIAS values are less than 20% . The validation results are marginally low in some but well within an acceptable range.

Table 2: Performance measure of SWAT model

	C. A.	Monthly				Annual		
	(km2)			R^2	NSE	R^2	NSE	PBIAS
Tekra	108780	Calib	1971-72 to 1982-83	0.95	0.94	0.92	0.88	-10
		Valid	1983-84 to 1992-93	0.97	0.95	0.98	0.89	-16
Ghugus	21429	Calib	1971-72 to 1983-84	0.92	0.91	0.93	0.91	-5
		Valid	1984-85 to 1993-94	0.90	0.87	0.90	0.84	-15
P G Bridge	18441	Calib	1971-72 to 1983-84	0.95	0.95	0.94	0.93	-7
		Valid	1984-85 to 1993-94	0.93	0.92	0.96	0.95	-9

The model output was also compared for dry and wet years. An analysis of wetter than normal years and drier than normal years shows that the model gives better results in wetter years than drier years. For example, the monthly NSE's are 0.94 for the three wet years and 0.58 for the four drier years. A comparison of the monthly observed and simulated streamflow for the wet years with highest NSE and dry years with the worst NSE reveals that the model tended to overpredict streamflow during the monsoon period of the year.

Given the parameter settings derived from calibration, the extrapolation to ungauged sites have been checked at 16 station for the time period 1990-91 to 1999-00. The statistics R^2, NSE and PBIAS compare reasonably well. (refer **Table 3**). With the exception of Bishnur and Hivra of Wardha sub-basin, the model performance obtained from calibrated model range between acceptable and good. In general, the results show more than 90% of the stations have annual NSE values greater than 0.5 and about 60% have NSE greater than 0.8. Also, measure for annual R^2 of 0.8 were exceeded by 14 out of 16 stations and 0.9 by 10 out of 16 sites. On similar lines, monthly NSE of 0.5 is exceeded by 95% stations and 0.8 by 56%.

Table 3: Statistical measure of model output for various sites in Pranhita basin

			Catchment Area	Annual			Monthly	
	Station	Sub-basin	(km^2)	R^2	NSE	PBIAS (%)	R^2	NSE
1	Asthi	Pranhita	50990	0.97	0.92	-8.3	0.94	0.94
2	Bamni	Pranhita	46020	0.95	0.86	-16.8	0.93	0.9
3	Bishnur	Wardha	5000	0.79	0.09	-44	0.71	0.3
4	Ghugus	Wardha	21429	0.98	0.63	-37.4	0.81	0.62
5	Hivra	Wardha	10240	0.89	0.15	-56	0.82	0.59
6	Kanhargaon	Penganaga	3515	0.97	0.94	-7	0.82	0.81
7	Keolari	Pranhita	2970	0.91	0.69	-24.5	0.9	0.85
8	Kumhari	Pranhita	8070	0.97	0.85	-15.7	0.92	0.91
9	Marlegaon	Penganga	7410	0.99	0.57	-41	0.91	0.81
10	Nandgaon	Wardha	4580	0.94	0.33	-38	0.94	0.71
11	Pauni	Pranhita	35520	0.97	0.54	-29.1	0.93	0.73
12	P G Bridge	Penganga	18441	0.97	0.89	-16.7	0.94	0.88
13	Rajegaon	Pranhita	5380	0.71	0.62	-16.9	0.77	0.76
14	Rajoli	Pranhita	1900	0.93	0.72	-15	0.93	0.91
15	Satrapur	Pranhita	11100	0.85	0.71	-16.1	0.81	0.66
16	Sirpur	Pranhita	47500	0.98	0.9	-14.7	0.93	0.91

Regression approach to Regional study

Regression is the most widely used technique for transferring information to ungauged catchment. A Regional Analysis has been made for Pranhita sub-basin by relating climate and catchment attributes of dataset generated by SWAT with hydrological response on a monthly level. A dataset of these parameters have been developed from the calibrated SWAT sub-basin level output. Six dimensions viz. precipitation (mm), percentage cropped area (%CA), percentage forest area (%FA), mean temperature (^{0}C), relief (m), and catchment area (km^2) have been used as clustering variables. Multiple regression analysis was undertaken on the data set of each sub-basin Wardha, Penganga and Wainganga. The correlation matrix of the six variables with average natural runoff was performed to identify the cross correlation among parameters. Data were standardized to transform all the data to have zero mean and unit standard deviation by applying the relation (xi-μ)/σ, where μ and σ are the mean and standard deviation of xi's. Covariance matrix was formed from the data set and Eigen values were calculated. This was followed by arranging the components in order of significance, to eliminate the components of less significance. The standardized data series were multiplied with the chosen eigenvectors to derive principal components.

k-means clustering was adopted to partition the data in which each observation belongs to the cluster with the nearest mean as initial centroid. Each data object pi (1≤ i ≤ n) was assigned to the closest centroids qj (1≤ j ≤ k) using Euclidean distance formula.

$$ED(p,q) = \sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2 + \cdots + \cdots (p_d - q_d)^2} \quad .$$

In K-means clustering algorithm, the objective is to minimise the sum of minimum distance i.e., distances to the nearest cluster centers.

$$\sum_{j=1}^{k} \sum_{i=1}^{n} [\mathrm{x}_{\mathrm{i}}^{\mathrm{j}} - c_j]^2 \ldots \ldots \ldots \ldots \ldots \ldots$$

where , $\mathrm{x}_{\mathrm{i}}^{\mathrm{j}}$ is the data point belonging to the cluster j and cj is the cluster center.

The sub-basins output simulation data set were set into the selected cluster groups. After dividing the dataset into clusters, multi linear regression that relate the dependent variable "monthly discharge" with the independent variables namely, "Precipitation", "Temperature", "Relief", "% Crop Area", "% Forest Area" and "Catchment/ sub basin area" were developed for monsoon months June to October for each cluster.

The form of the equation is expressed as

Q (mm) = C_1 PCP + C_2 PCP^2 + C_3 PCP1 + C_4 PCP2 + C_5 PCP3 + C_6 RL + C_7 (%CA) +C_0

Where,

PCP = Total precipitation during the period/ month (mm); PCP1= Precipitation in the previous month ; PCP2= Precipitation in the 2^{nd} previous month ; PCP3= Precipitation in the 3^{rd} previous month ; %CA = Percentage Cropped area; %FA = Percentage Forest area; RL = Relief i.e. difference between maximum and minimum elevation (m).

Some of the Empirical relations derived to evaluate monthly flow Q (mm) are provided in **Table 4**.

Table 4 : Multipliers and coefficients of Regional Relationship for Sub-basins of Pranhita

Months	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_0
Wardha								
June	-	0.0005	-	-	-	-	-	-6.2871
July	0.5237	-	0.2345	-	-	-	-	-117.238
Aug	0.7462	-	0.0767	-	-	-	-	-106.15
Sept	0.5386	-	0.0382	-	-	-	-	-28.0199
Oct	0.3564	-	0.1023	0.0619	0.0519	-	-	-32.1961
Penganga								
June		0.0005	-	-	-	-0.0309	-	-1.6833
July	0.4797	-	0.2362	-	-	-	-	-109.985
Aug	0.6784	-	0.1236	-	-	-	-	-107.206
Sept	0.5082	-	0.0983	-	-	-	-	-36.9148
Oct	0.351	-	0.1062	0.085	0.0772	-	-	-46.6231
Pranhita								
June	-	0.000675	-	-	-	-	-	-11.94
July	0.646	-	0.3059	-	-	-	-	-166.125
Aug	0.8401	-	-	-	-	-0.0577	-	-97.7935
Sept	0.6427	-	0.0941	-	-	-0.0233	-	-38.706
Oct	0.4048	-	0.1644	-	-	-	-0.2872	22.9502

The flow simulation from Empirical relationship, SWAT output and observed flow for selected stations were compared. **Figure 3** shows the graphical plot of flow for monsoon months for selected stations within the basin. The simulated flow through calibration match the observed values and trends reasonably well. The flow simulated for Rajoli and Keolari by Regression is significantly good while acceptability of Kanhargaon and Satrapur is moderate. Overall The NSE values decrease by 25% in Regression based model than the calibrated model output.

The study validates how well distributed models are able to produce acceptable results using readily available, physically based input parameters for watersheds ranging from small to very large. It is worth noting that on average, the evaluation coefficients are less on a monthly temporal scale than an annual scale, which may be attributable to limited information about the detailed watershed characteristics and utilization pattern. **Figure 4** shows the scatter plots for monsoon stream flows for the period 1990 to 1999 between observed and simulated outputs of both the approaches for comparison. The calibrated flow shows slightly overestimated discharge while regression based flow shows underestimated values at high flow and overestimated values at lower flow at Kanhargaon. Keolari, Rajoli and Satrapur show consistent overestimation in both approaches. The Regression based overestimation is higher for Keolari and is lower for Satrapur and Rajoli.

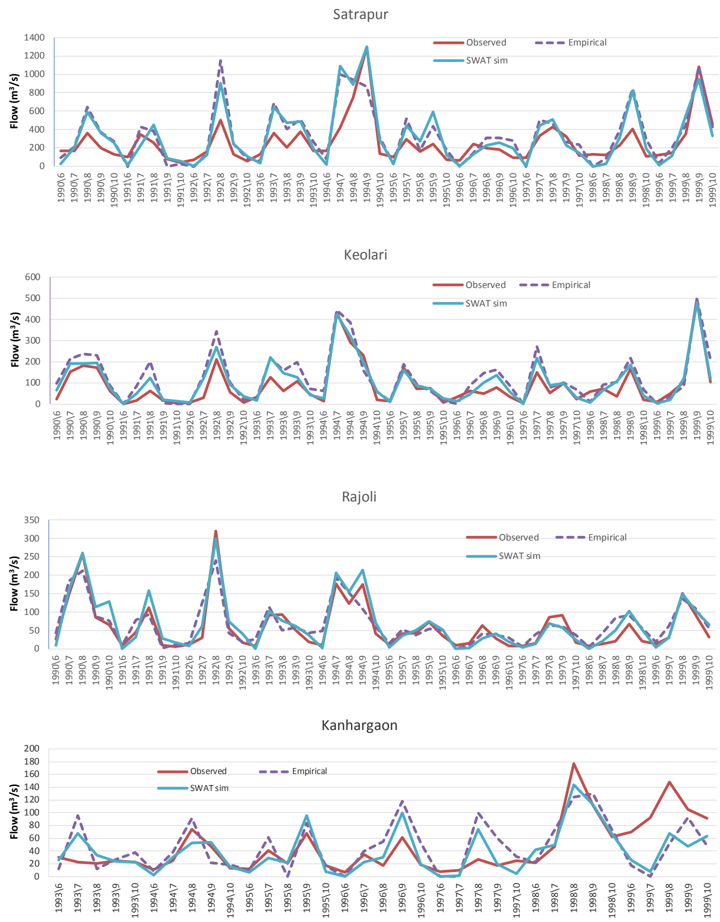

Figure 3: A comparison between observed, calibration based and Empirical relation based streamflow hydrograph for selected stations within test basin for monsoon months

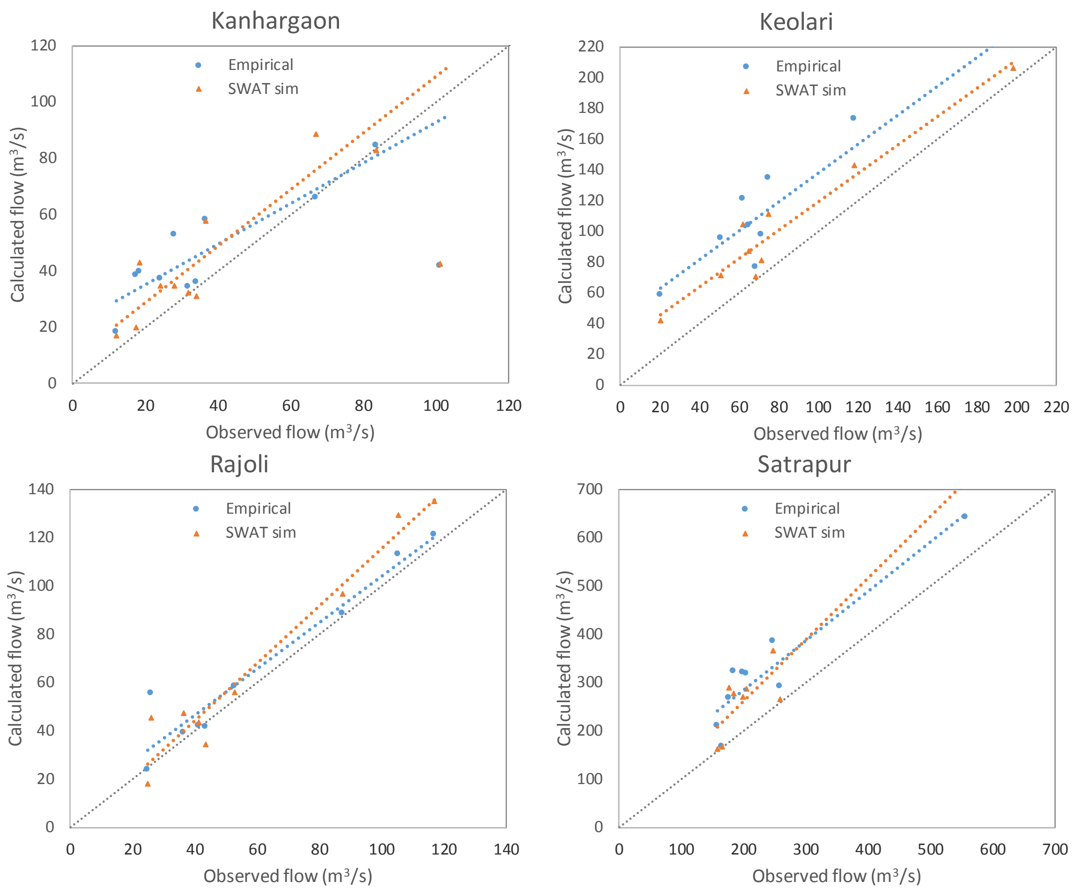

Figure 4: Scatter plot of observed with calibration based and Empirical relation based streamflow for selected stations within test basin

3. Conclusion

The model proposed is a framework which combines spatial and temporal input data of hydrography, terrain, landuse, soil and weather for SWAT in the Pranhita basin. The calibrated SWAT model is tested for streamflow. The model was then validated and the parameter settings were extended to ungauged watersheds.

We used annual and monthly streamflow from 16 monitoring gauges located in the basin to test SWAT and found that SWAT can capture the amount and variability of annual and montly streamflow acceptably well.

The performance statistics of the model range between acceptable and good. In general, the results show more than 90% of the stations have annual NSE values greater than 0.5 and about 60% have NSE greater than 0.8. The low statistics of some stations may be attributed to incomplete information about the utilization details from reservoirs and dams within the watershed basin.

Regional Analysis has been made for Pranhita sub-basin by relating climate and catchment attributes of dataset generated by SWAT with hydrological response on a monthly level. A dataset of these parameters have been developed from the calibrated SWAT sub-basin level output. Six dimensions viz. precipitation (mm), percentage cropped area (%CA), percentage forest area (%FA), mean temperature (in ^{0}C), relief (m), and catchment area (km^2) have been used as clustering variables. The flow simulation from Empirical relationship, SWAT output and observed flow for selected stations were compared. The fitness statistics of Regression derived flow show consistently lower NSE's as compared to SWAT output. Without undermining the ease of applicability of Regression relation for ungaued catchments, it may be worthwhile to conclude that direct SWAT output if calibrated at adequate resolution of hydro-meterollogical records can be a better spatial extrapolation technique for ungauged flow estimation. Overall, the SWAT model can satisfactorily predict hydrologic budget for the ungauged basins in Pranhita with calibration at basin scale. However, the ease of applicability of Empirical equation makes it a viable alternative to adopt for small watersheds. In the absence of better techniques available, Regression based approach can suitably be adopted for ungauged basins.

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