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# Performance of evapotranspiration methods for hydrological simulations using SWAT in a sub-tropical and sub-humid catchment of India

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**ABSTRACT**

Selection of effective methods of evapotranspiration (ET) estimation has become a vital task in hydrological simulations using soil and water assessment tool (SWAT) at watershed scale. These methods are mostly selected based on input data availability and their applicability at regional scale. In this study, three potential evapotranspiration (PET) methods namely, hargreaves method (HA), penman-monteith (PM) method and priestly-taylor (PT) method inbuilt in the SWAT model were evaluated with the available climatic data of Kantamal catchment in Eastern India. The model performance in each case was tested by matching the simulated streamflow with the observed ones. The HA method was found to be the most suitable one with $R^2$, NSE, PBIAS and RMSE values of 0.94, 0.88, -17.0 and 217.6 $m^3s^{-1}$ during calibration period, and 0.87, 0.83, -16.0 and 204. 08 $m^3s^{-1}$ during the validation period, respectively. PM and HA methods demonstrated comparable performance in simulating streamflow, however, the PT method exhibited lower performance compared to other two methods, indicating that it is not recommended for hydrological simulation studies using SWAT under similar agro-climatic conditions.

## 1. INTRODUCTION

Catchment scale management of water resources requires at least the quantitative knowledge of hydrological fluxes where water quality is not an issue. Accurate assessment of these fluxes is the basic need for watershed planning and management (Zhao *et al.,* 2013; Panda *et al.,* 2021a). As the pressure on fresh water sources is increasing day by day, the need of proper management of this precious resource is important for its sustainability and sustainability of mankind on earth surface (Larbi *et al*., 2020). Spatio-temporal assessment and direct measurement of the hydrological process like runoff, infiltration, evapotranspiration (ET), groundwater is quite difficult and sometimes unaffordable (Bizuneh *et al*., 2021; Nasiri *et al*., 2020). Therefore, nowadays with the advancement of computational technology various kind of hydrological models have been developed starting from simplifies empirical black box model to data intensive physically based distributed models (Guug *et al*., 2020; Sahoo *et al*., 2021). In catchment scale hydrological models, different hydrological processes are either simulated using mathematical equations or derived from water balance or energy balance methods. ET is one of the most vital component of natural hydrological cycle and hence, its accurate estimation is very much crucial for physically based hydrological models like SWAT (Padhiary *et al.,* 2018). ET is the movement of water from land based ecosystems to the atmosphere system in the form of water vapor. It constitutes about 50% of the precipitation in humid areas and about 90% of precipitation in arid zones (Zhao *et al.,* 2013). ET is an invisible process and its actual measurement is very difficult. It is the dominant part of crop water requirement. More than 95% of the absorbed water is transpired through stomatal opening in plant leaves (Sentelhas *et al*., 2010; Gemechu *et al*., 2021). Its precise estimation is not only important for water budgeting but also for climate change studies, irrigation scheduling, crop yield modelling, drought monitoring, and planning and management of fresh water resources (Falamarzi *et al.,* 2014; Panda *et al.,* 2021a).

ET includes two processes namely evaporation and transpiration and convert liquid water to water vapor (Allen *et al.,* 1998; Verstraeten *et al.,* 2005). Evaporation occurs from land surface, water bodies, soil moisture, groundwater etc., whereas transpiration occurs from vegetation. PET is the highest rate of ET as per the climatic demand when water is plentiful in the plant root zone and the plant is not subjected to any kind of stress. Estimation of AET is very challenging, time consuming and expensive. Hence, indirect methods are most commonly used for its estimation, even in hydrological models also.

The PET estimation methods are categorized into three major classes based on energy, temperature and mass transfer functions. Energy balance concept is applied for energy based methods. Xu and Singh (2000) in their study compared eight different energy balance methods named after the developers such as Makkink, Turc, Jensen and Haise, McGuinness and Bordne, Priestley and Taylor, Hargreaves, Doorenbos and Abtew. It was concluded that the Makkink, Priestley and Taylor, and Abtew methods outperformed the other methods. Under climatic data scarce condition, many researchers suggested that temperature-based ET methods are more useful than others. Seven different temperature based ET estimation methods were compared by Xu and Singh (2001). They reported that the Blaney-Criddle method (Blaney, 1959), the Hargreaves method (Hargreaves and Samani, 1985) and the Thornthwaite method (Thornthwaite, 1948) performed better under limited data records. The method that is based on mass transfer is the oldest among all. It estimates potential evaporation from free water surface and uses the wind speed and vapor pressure deficit for estimation of ET. It is the first reported method of potential evaporation estimation which was proposed by Dalton in the year 1802 (Zhao *et al*., 2013). Later, Penman (1948) introduced another evaporation method on mass transfer principles that accounts lake evaporation.

The FAO 56 recommended PM method, a combination technique that includes all the three approaches in its formulation. It is the physically-based method widely used for ET estimation in hydrological models (Xie and Wang, 2007; Liu *et al.,* 2009; Buck-Sorlin *et al.,* 2011; Zhang *et al.,* 2010; Liu *et al.,* 2012; Li *et al.,* 2011). Andersson (1992) compared the sensitivity of seven PET methods in HBV model and observed a slight improvement in accuracy of the model simulation by using the temperature based methods. The PM method showed better accuracy than other methods. Sensitivity of 27 PET methods in 308 basins were analyzed by Oudin *et al.* (2005) in 308 basins using four lumped hydrological models. It was reported that the temperature based and energy based methods showed better efficiency than the PM method. Kannan *et al.* (2007) compared the sensitivity of HA method with PM method for runoff simulation using SWAT. They concluded that the temperature based HA method outperformed the PM method.

SWAT, initially developed for the study of hydrological response from ungauged catchments, is a physically based model (Arnold *et al.,* 1998; Samadi *et al.,* 2017). At present, SWAT model is extensively used for simulating water yield, streamflow, soil moisture, evapotranspiration, nutrient yield, sediment yield and crop yield (Zhang *et al.,* 2019; Yesuf *et al.,* 2016; Bhatt *et al.,* 2016; Larbi *et al.,* 2020; Panda *et al.,* 2021b; Tola and Shetty, 2023). The popularity and versatility of the SWAT model have been enhanced in diverse fields of natural resource management due to the creation of the SWAT-calibration and uncertainty procedures (SWAT-CUP) model, which facilitates auto-calibration, sensitivity, and uncertainty analysis. The SWAT model incorporates three PET estimation techniques, namely PM, HA, and PT, to estimate ET (Aouissi *et al*., 2016). SWAT estimates AET using an integrated conversion method that takes into account leaf area index and soil moisture extraction (Zhao *et al*., 2013; Vagheei *et al*., 2023).

The PM method has been recognized as the universally accepted method for PET estimation (Allen *et al.,* 1998; Jabloun and Sahli, 2008; Immerzeel and Droogers, 2008; Sentelhas *et al.,* 2010). It requires daily climatic observations of minimum temperature, maximum temperature, relative humidity, wind speed and solar radiation. These data are generally not available in finer resolution due to lack of recording stations. The other two methods (HA and PT) can also provide acceptable results but need less intensive data than PM method. Under data scarce situation, SWAT uses a weather generator "WXGEN" database for generating an average climatic data for the entire world in absence of climate data records.

Now-a-days, SWAT model is popularly used for agro-hydrological simulation with lots of agricultural application like irrigation scheduling, water productivity optimization, crop yield prediction etc. Hence, selection of ET estimation method with respect to the climatic data availability is crucial for both agricultural and hydrological applications (Aouissi *et al*., 2016). Therefore, in this study a trial has been made to identify the most suitable ET estimation method that produces precise streamflow and catchment water balance and also the spatio-temporal variability in simulated PET in Kantamal catchment of Mahandi river basin of eastern India.

## 2. MATERIALS AND METHODS

### Study Area

This research was conducted within the Kantamal catchment located in the middle Mahanadi basin of India, which is the only significant river system in eastern India flowing through the states of Chhattisgarh and Odisha as shown Fig.1. The catchment's area spans between longitudes 82°02′11″ to 84°18′56″E and latitudes 19°16′7″ to 20° 44′12″N, covering 20,024 km$^2$. It is distributed across eight districts in Odisha, including Kalahandi, Bolangir, Nuapada, Kandhamal, Nabarangpur, Rayagada, Boudh, and Sonepur, and one district in Chhattisgarh, namely Gariabandh. Agriculture is the primary land use in the catchment, occupying over 50% of the area, where rice, pulses, millet, groundnut, sunflower, sugarcane, cotton, and vegetables are the dominant crops. The average annual rainfall in the catchment is 1360 mm, with 1170 mm received during the monsoon season between June and September. The catchment's maximum temperature ranges between 19 to 43°C and minimum temperature ranges between 5 to 32°C in a year. The highest temperatures are typically experienced during the summer months of April and May and the lowest temperatures during the winter months of Dec and Jan.

In this study, effect of selecting different PET methods on the overall water balance of the catchment was studied using three PET estimation methods available in SWAT and best one is recommended for the study area. The detail of the methodology adopted is shown in Fig. 2.

## Data Requirement

Primary data needed to run SWAT model are digital elevation model (DEM), soil, land use and climatic parameters. Different data sets collected from various sources / agencies to run the model are presented in Table 1. Observed streamflow data are obtained for model calibra-

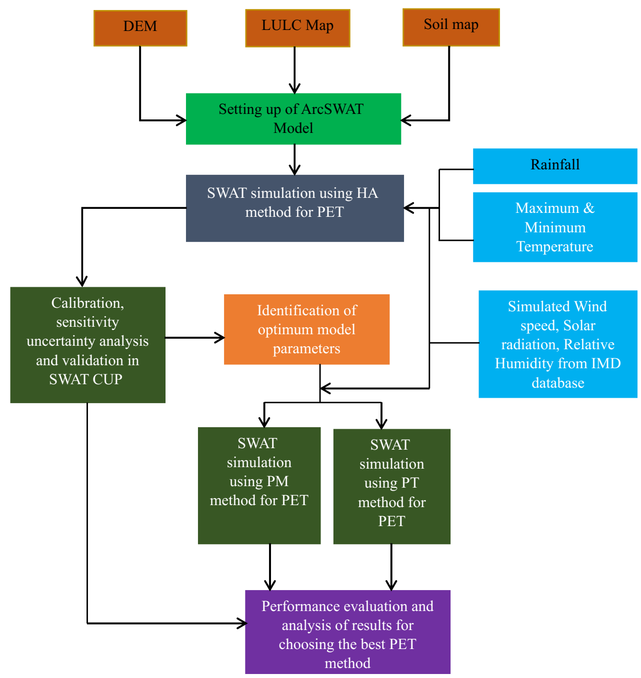


**Fig. 2. Work flow diagram of methodology**

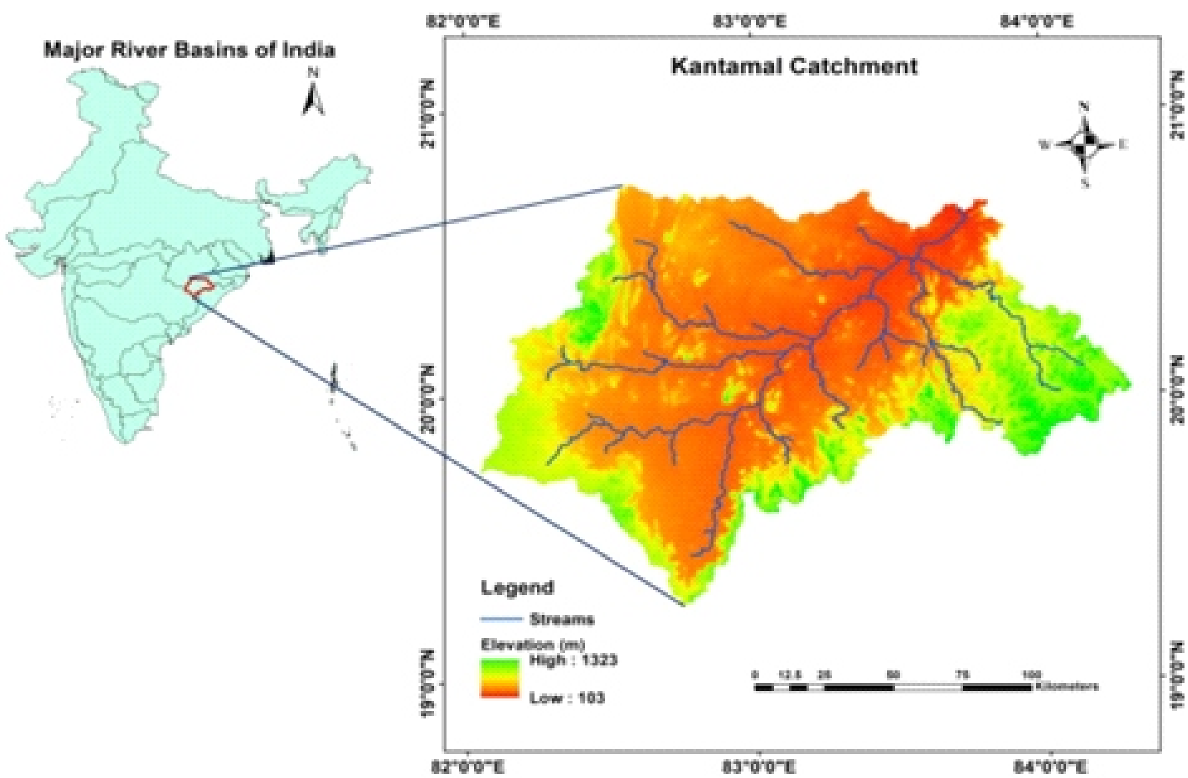


**Fig. 1. Location map of Kantamal catchment**

**Table: 1**
**Sources of input data**

| Data | Source | Year |
|---|---|---|
| Soil | NBSS&LUP (1:50000) (https://www.nbsslup.in/) | 2006 |
| Land use | National Remote Sensing Centre (1:50000) (https://www.nrsc.gov.in/) (ISRO), Hyderabad | 2014-15 |
| Rainfall | Recorded block-wise rainfall data from Special Relief Commissioner, Odisha (https://srcodisha.nic.in/) | 2000-2018 |
| Temperature | 1º×1º gridded minimum and maximum temperature data from India Meteorological Department (IMD), Pune | 2000-2018 |
| Streamflow | Daily discharge data (2000-2018) from Water Resources Information System of India (India-WRIS), CWC (https://indiawris.gov.in/wris) | 2000-2018 |
| DEM | Digital Elevation Model (DEM) from Shuttle Radar Topography Mission (SRTM 30) of USGS (http://srtm.csi.cgiar.org/) | 2005 |

tion and validation. Details of land use pattern and soil types of the catchment are illustrated through Fig. 3 and Fig. 4, respectively.

## Land Use and Soil

It is well-known that land use/land cover (LU/LC) and soil types have a significant impact on the hydrological cycle's runoff, infiltration, percolation and ET processes. For this study, a LU/LC map of 2014-15 at a scale of 1:50000 was obtained from the National Remote Sensing Centre (NRSC), Hyderabad, India. The study area was divided into five major LU/LC, including water bodies, waste land, forest, built-up areas, and agricultural land, as shown in Fig. 2. Water bodies account for only 1.96% of the basin's area. Agricultural land, the dominant land use in the catchment, covers around 50.11% of the study area. The forested land occupies 37.52% of the catchment area and is mostly concentrated in the eastern, southeastern, and western regions, while the built-up areas (1.2%) and waste lands (9.21%) are scattered sporadically across the catchment. Additionally, the soil texture map of the watershed was obtained from ICAR-NBSS&LUP, Kolkata, as shown in Fig. 3. The catchment's soil texture is divided into seven classes, namely clay, loam, clay loam, silty clay, sandy loam, silty clay loam, and sandy clay loam. Clay loam soil covers nearly half (49.9%) of the catchment area, followed by sandy loam soil, which covers 26.5% of the catchment.. Sandy clay loam and sandy clay soil types are spread over 21.1% and 2.5% of the area, respectively. The physical properties of the soil types is presented in Table 2.

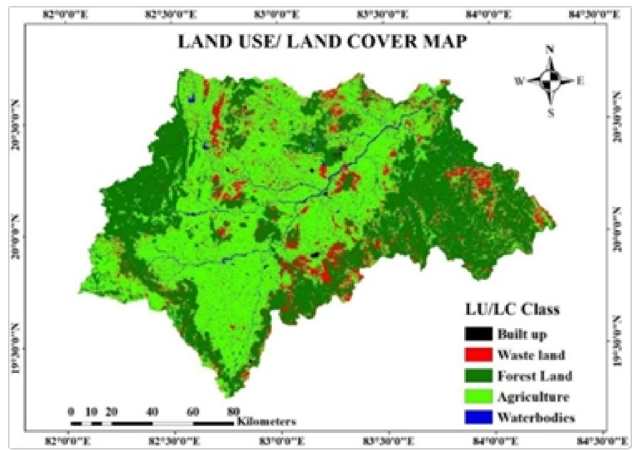


**Fig. 3. Land use map of the study area**

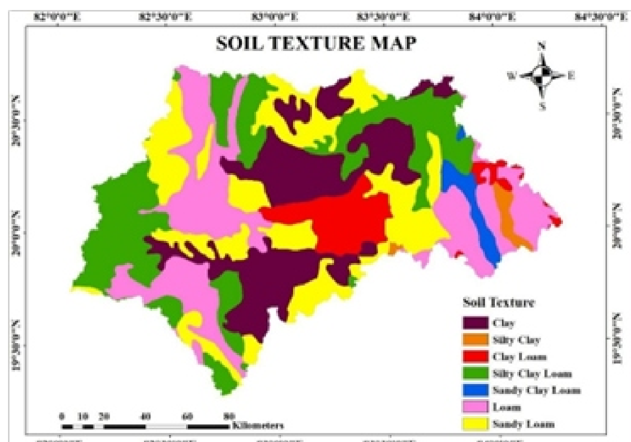


**Fig. 4. Soil map of the study area**

**Table: 2**
**Soil physical properties**

| Soil texture | Soil bulk density (g cm$^{-3}$) | Available water holding capacity (%v) | Soil organic carbon (%) | Clay | Silt | Sand |
|---|---|---|---|---|---|---|
| Clay | 1.32 | 16 | 0.51 | 45.7 | 32.3 | 22 |
| Silty clay | 1.27 | 15 | 0.49 | 42.3 | 47.6 | 10.1 |
| Clay loam | 1.4 | 14 | 0.48 | 33.9 | 28.1 | 38 |
| Silty clay loam | 1.34 | 16 | 0.47 | 32.3 | 49.5 | 18.2 |
| Sandy clay loam | 1.51 | 10 | 0.5 | 22.4 | 9.6 | 68 |
| Loam | 1.42 | 15 | 0.45 | 25.7 | 37.9 | 36.4 |
| Sandy loam | 1.49 | 10 | 0.2 | 17.8 | 20.2 | 62 |

**SWAT Model**

SWAT is a semi-distributed hydrological model. It was developed by the United States Department of Agriculture (USDA) - Agricultural Research Service (Arnold *et al*., 1998). It divides a catchment into sub-watersheds and further to hydrological response units (HRUs). An HRU is the basic unit of hydrology having uniform land use, soil and slope (Arnold *et al.,* 1998; Uniyal *et al*., 2015a, Das *et al*., 2022). The threshold limit for HRUs is an important consideration in SWAT modelling, and it has implications for deciding model accuracy and efficiency. The threshold limit is taken for HRU creation determines the minimum area required for a unique combination of land use, soil, and slope to be considered as a separate HRU. SWAT automatically determines unique combination land use, soil and slope depending upon their classes. Smaller threshold results in finer spatial discretization, allowing for a more detailed representation of the landscape. Subdividing the watershed into areas having unique land use, soil and slope combinations enables the model to reflect differences in ET for various crops and soils. In this study, 10% threshold land use/soil/slope area over sub-basin area was taken to delineate the HRUs. The inputs for SWAT model consist of climatic and soil parameters, topography, and land use and management practices (Neitsch *et al.,* 2011; Padhiary *et al.,* 2019). The model is capable of simulating continuous hydrological events at daily, monthly and annual time steps (Arnold *et al.,* 1998; Neitsch *et al.,* 2011). SWAT can also simulate sediment yield, nutrients outflow and crop yield of a watershed (Neitsch *et al.,* 2011; Panda *et al.,* 2021a). It simulates runoff based on USDA Natural Resources Conservation Services-Curve Number (NRCS-CN) method. ET is estimated by three widely used methods such as FAO 56 PM method (Monteith, 1965; Allen *et al.,* 1998), HA method and PT method 48 (Priestley and Taylor, 1972).

The SWAT model is embedded with variable storage method or Muskingum method for flow routing, Green and Ampt infiltration method for infiltration rate, and kinetic reservoir routing method (Sloan *et al*.,1983) for lateral flow. Volume balance approach developed by Neitsch *et al*. (2011) has been used to estimate recharges to shallow and deep aquifers. The model is capable of simulating the groundwater level of the shallow aquifers in each HRU without any physical datum. Its limitation is it cannot simulate the flow of groundwater between the boundaries of two adjacent HRUs. Two different methods are set in the SWAT model for estimating the surface retention coefficient. In the first method, the surface retention coefficient depends on soil moisture content and in the second method it depends on the cumulative ET. The annual soil loss at HRU scale is estimated by SWAT model using the modified universal soil loss equation (Wischmeier and Smith, 1978). The water balance equation developed by Neitsch *et al*. (2011) for simulating soil water content at desired time step is given in (eq. 1):

$$SM_t = SM_0 + \sum_{i=1}^{t} (R_i - Qs_i - ET_i - S_i - Qg_i) \quad ...(1)$$

Where, $SM_t$ = soil moisture content at the end of the day (mm), $SM_o$ = initial soil moisture content in the beginning of the day (mm), $R_i$ = depth of rainfall during the day (mm), $Qs_i$ = quantity of surface runoff during the day (mm), $ET_a$ = actual ET during the day (mm), $S_i$ = Quantity of water entering the vadose zone from the soil profile during the day (mm), $Qg_i$ = Quantity of return flow during the day (mm); $i$ = index for the day under consideration; and $t$ = time interval in days.

**Watershed Delineation**

The process of catchment delineation in SWAT model involves a systematic partitioning of larger basins into smaller, manageable units for more precise hydrological simulation and analysis. SWAT utilizes digital elevation model (DEM) to delineate watershed and sub-watersheds. The model identifies outlets within the basin, determines flow directions and flow accumulation to delineate watershed boundaries. Further, the sub-watersheds are divided in to HRUs considering uniform land use, soil and slope. In this study, the entire catchment is sub-divided into 15 sub-watersheds and 1563 HRUs.

**SWAT-CUP**

A component model for the calibration, validation and sensitivity analysis of SWAT model output developed by Abbaspour *et al*. (2007) is named as SWAT-CUP. Parameter uncertainty analysis is also well taken by this model. Four calibration algorithms available in this model are ParaSol, SUFI-2, GLUE, and MCMC. Out of them SUFI-2 algorithm has been used in the present study for calibration of stream flow and analysis of sensitivity and uncertainty. The SUFI-2 (Sequential Uncertainty Fitting) algorithm is widely used in the SWAT model for parameter calibration and uncertainty analysis due to its effectiveness in handling the complex, non-linear, and highly parameterized nature of the model. The popularity of SUFI-2 can be justified by its ability to efficiently explore the parameter space and provide reliable estimates of parameter values while accounting for parameter uncertainty (Moriasi *et al*., 2007; Vagheei *et al*., 2023).

The level of significance between the datasets was estimated using *t-test*. The *p-values* have been used to test the significance of the sensitivity. The larger absolute value of *t-test* indicates a parameter to be more sensitive and similarly the lower *p-values* proximity to zero show more significance. The SUFI-2 algorithm accounts both for input and output parameter uncertainty. Uncertainty in input parameters is represented by uniform distribution of data and the uncertainty in output is computed at 95% prediction uncertainty (95PPU). Latin hypercube sampling method calculated at 2.5% and 97.5% prediction limit was used for obtaining the cumulative distribution of the output parameter (Abbaspour *et al*., 2007). Further, the *P-factor* and *R-factor* were used to evaluate the strength of calibration and uncertainty (Khoi and Thom, 2015; Abbaspour *et al*., 2015; Kumarsamy and Belmont, 2018, Das *et al*., 2022, Zhang *et al.,* 2023).

### Evapotranspiration (ET) Methods

ET includes evaporation from the water bodies and soil, and transpiration from the vegetative cover. Thornthwaite (1948) first coined the term PET as a part of climatic classification. Out of several methods developed for estimating PET, three methods namely, HA method, PT method and PM method are embedded in SWAT model. Modellers can choose any of these methods based on availability of climatic input data (Aouissi *et al*., 2016). In many developing countries like India, availability of observed climate data is very scarce at watershed scale. Therefore, gridded climate data derived from the recorded data of climatic stations are mostly used in hydrological modelling with acceptable accuracy. In India, IMD developed 0.25°×0.25° gridded data of rainfall and 1°×1° degree gridded data of maximum and minimum temperature have been considered as the finest resolution climatic data, which is freely available in daily time step.

However, other climatic variables are not abundantly available for regional studies (Panda *et al*., 2021a, Gholami *et al*., 2023). For such situation, the process based hydrological models like SWAT are capable of using an average simulated climatic data to run the model. Maximum and minimum temperature, relative humidity, wind speed and solar radiation are the required climatic data for ET estimation by PM method embedded in SWAT. In data scarce areas, these climatic variables can be simulated from 1°×1° gridded climate data developed by IMD for the entire country and freely available in the official website of SWAT model. Likewise, there is an inbuilt weather generator (WGEN) model in SWAT to generate an approximate climatic data for the entire world, which is used to fill-up the missing values of observed climatic data (Sharpley and Williams, 1990; Aouissi *et al.,* 2016).

### Hargreaves (HA) Method

The HA method was originally developed in Davis, California from eight years of research using lysimeter. It estimates PET using minimum climatic data like maximum and minimum temperatures. The original equation went through several modifications before it was used in SWAT (Hargreaves and Samani, 1985). The modified Hargreaves equation is shown in eq. 2:

$$\lambda E_0 = 0.0023.H_0(T_{max} - T_{min})^{0.5}.(\bar{T}_{av} + 17.8) \qquad ...(2)$$

Where, $\lambda$ = latent heat of vaporization (MJ $kg^{-1}$), $E_0$ = PET (mm $d^{-1}$), $H_0$ = extra-terrestrial radiation (MJ $m^{-2}$ $d^{-1}$), $T_{max}$= maximum ambient temperature for the day under consideration (°C), $T_{min}$= minimum ambient temperature for day under consideration (°C), $T_{min}$ = minimum ambient temperature for day under consideration (°C), and $\bar{T}_{av}$ = mean air temperature for the given day (°C).

### Penman-Monteith (PM) method

The PM equation (eq. 3) combines mechanisms that accounts for the energy required for evaporation. It takes into account the removal of water vapour, soil heat flux, aerodynamic resistance and canopy resistance using physically based mathematical formulations (Monteith 1965; Arnold *et al.,* 1998).

$$\lambda E = \frac{\Delta(H_{net} - G) + \rho_{air} C_p \left[e_z{}^0 - e_z\right]/r_a}{\Delta + \gamma(1 + r_c/r_a)} \qquad ...(3)$$

Where, $\lambda$ = latent heat flux density (MJ $m^{-2}d^{-1}$); E = rate of evaporation $day^{-1}$ (mm $d^{-1}$); $H_{net}$= net radiation (MJ/$m^2$/d); $\Delta$ = slope of the saturation vapour pressure-temperature curve, de/dT (kPa °$C^{-1}$); G = ground heat flux density (MJ $m^{-2}d^{-1}$); $Cp$ = specific heat at constant pressure (MJ $kg^{-1}$ °$C^{-1}$); $\rho_{air}$= air density (kg $m^{-3}$); $e^0_z$= saturation vapour pressure of air at height z (kPa); $e_z$= actual vapour pressure of air at height z (kPa); $r_a$ = aerodynamic resistance (s $m^{-1}$); $\gamma$ = psychrometric constant (kPa °$C^{-1}$); and $r_c$ = plant canopy resistance (s $m^{-1}$).

The PM equation for adequately watered plants under normal atmospheric conditions and assumed logarithmic wind profiles can be written as eq. 4:

$$\lambda E_t = \frac{\Delta(H_{net} - G) + \lambda K_1(0.622.\lambda.\rho_{air}/P).\left[e_z{}^0 - e_z\right]/r_a}{\Delta + \gamma(1 + r_c/r_a)}$$

Where, $\lambda$ = latent heat of vaporization (MJ $kg^{-1}$), ET = maximum transpiration rate (mm $d^{-1}$), $K_1$= a dimensionless coefficient to ensure uniformity in units of the two terms in the numerator, and $P$ = atmospheric pressure (kPa).

### Priestly-Taylor (PT) method

Priestley and Taylor (1972) developed a simplified equation (eq. 5) for estimating evaporation from wet surface by removing the aerodynamic factor and the energy factor was multiplied by a coefficient, $\alpha_{pet}$, whose value is 1.28, when the surrounding is wet or humid. This method is suitable for humid climatic condition but it underestimates PET in arid and semi-arid regions.

$$\lambda E_0 = \alpha_{pet}.\frac{\Delta}{\Delta + \gamma}.(H_{net} - G) \qquad ...(5)$$

### Calibration and Validation

SWAT model calibration and validation has been accomplished using the observed and simulated monthly streamflow data at Kantamal outlet of the catchment. Nineteen years of streamflow data (2001-2018) were used for the simulation. First 3 years data were used for warming up operation of the model. Streamflow records from 2004 to 2012 were used for model calibration. The remaining 6 years data from 2013 to 2018 were used for model validation. The output of SWAT model was used as input to SWAT-CUP for calibration, sensitivity analysis, uncertainty assessment and validation. The objective of the model calibration is to identify the optimal values of the model parameters for best simulation. Global sensitivity analysis was performed to identify the most sensitive parameters. Fifteen different parameters were selected for model calibration, sensitivity and uncertainty analysis as presented in Table 3.

**Performance indicators**

Model performance under different simulation scenarios were evaluated using statistical indicators like nash-sutcliffe efficiency (*NSE*), percentage bias (*PBIAS*), root mean square error (RMSE), coefficient of determination ($R^2$), and *P*- and *R-factor*. These indicators are expressed mathematically through eqs. 6, 7, 8 and 9.

$$R^2 = \frac{[\sum_{i=1}^{n}(S_i - \bar{S})(O_i - \bar{O})]^2}{\sum_{i=1}^{n}(S_i - \bar{S})^2 \sum_{i=1}^{n}(O_i - \bar{O})^2} \quad \text{...(6)}$$

$$NSE = 1 - \frac{\sum_{i=1}^{Nn}(O_i - S_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \quad \text{...(7)}$$

$$PBIAS = \frac{\sum_{i=1}^{n}(O_i - S_i)}{\sum_{i=1}^{n} O_i} \times 100 \quad \text{...(8)}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(S_i - \bar{S})} \quad \text{...(9)}$$

Where, $O_i$ = observed data on $i^{th}$ time period; $S_i$ = predicted / simulated value of $i^{th}$ time period; $\bar{O}$ = mean of observed data; $\bar{S}$ = mean of simulated data, and $n$ = total number of simulation period.

The *P-factor* and the *R-factor* were used to quantify the model parameter uncertainties associated with SWAT simulation. The *P-factor* represents the percentage of observed data bracketed within the 95% prediction uncertainty band (95PPU) of the simulation results. It ranges from 0 to 1. The *R-factor* represents as the ratio between average width of the 95PPU band and the standard deviation of the observed variable and varies from 0 to $\infty$ (Abbaspour *et al.,* 2007; Zhao *et al.,* 2018; Panda *et al.,* 2021a). Larger values of both factors represent better simulation under parameter uncertainty. Mathematical expressions for *P-factor* and *R-factor* are given in eq. 10 and 11, respectively (Abbaspour *et al.,* 2007; Uniyal *et al.,* 2015b).

$$P - factor = \frac{ny_{t_i}}{n} \quad \text{...(10)}$$

Where, $ny_{ti}$ = number of observed values bracketed by 95PPU, and $n$ = total number of observed values.

$$R - factor = \frac{\frac{1}{n}\sum_{t_i=1}^{n}\left(y^{M}_{t_i,97.5\%} - y^{M}_{t_i,2.5\%}\right)}{\sigma_{obs}} \quad \text{...(11)}$$

Where, $y^{M}_{t_i,2.5\%}$ is the lower boundary and $y^{M}_{t_i,97.5\%}$ is the upper boundary of the 95 Uncertainty Band (UB) and $\sigma_{obs}$ is the standard deviation of the observed data.

**Model Simulation**

In the present study, hydrological simulation of Kantamal catchment under Mahanadi river basin has been made using the three embedded ET simulation methods *i.e.,* HA, PM and PT method. Calibration and validation of the model using HA method was carried out with the observed

**Table: 3**
**Calibration parameters used in SUFI-2**

| S.No. | Parameter | Description |
|---|---|---|
| 1 | R_CN2.mgt | SCS runoff curve number |
| 2 | V_ALPHA_BF.gw | Base flow alpha factor (days) |
| 3 | V_GW_DELAY.gw | Groundwater delay (days) |
| 4 | V_GWQMN.gw | Threshold depth of water in the shallow aquifer required for return flow to occur (mm) |
| 5 | V_OV_N.hru | Manning's "n" value for overland flow |
| 6 | V_LAT_TIME.hru | Lateral flow travel time |
| 7 | V_ESCO.hru | Soil evaporation compensation factor |
| 8 | V_EPCO.hru | Plant uptake compensation factor |
| 9 | V_SURLAG.hru | Surface runoff lag coefficient (day) |
| 10 | V_CANMX.hru | Maximum canopy storage |
| 11 | V_RCHRG_DP.gw | Deep aquifer percolation fraction |
| 12 | R_SOL_K (1).sol | Saturated hydraulic conductivity (mm $hr^{-1}$) |
| 13 | R_SOL_AWC(1).sol | Available water capacity of the soil layer r (mm $mm^{-1}$) |
| 14 | R_CH_N2.rte | Manning's "n" value for the main channel |
| 15 | R_CH_K2.rte | Effective hydraulic conductivity in main channel alluvium (mm $hr^{-1}$) |

streamflow records at Kantamal gauging station. Streamflow calibration parameters were then used for model prediction using PM and PT methods. The aim was to screen out the most suitable ET estimation method in SWAT model for water balance and estimation of stream flow precisely for eastern Indian climatic conditions using various statistical and parameter uncertainty indicators like NSE, $R^2$, PBIAS, RMSE, *P-factor and R-factor*. Spatio-temporal variation of PET under different methods was also studied to check its applicability for agricultural water management in different sub watersheds and seasons of the year. The workflow diagram of methodological procedure is shown Fig. 4.

## 3. RESULTS AND DISCUSSION

In evaluating the ET estimation methods with respect to their effect on streamflow simulation using SWAT, the initial model calibration, parameterization, and uncertainty analysis were carried using HA method only. Recorded data of minimum and maximum temperature collected from the catchment were used for estimation of evapotranspiration. The optimal value of the calibrated parameters were used in SWAT for simulating streamflow with PM and PT methods. The main purpose of fixing the calibration parameters is to study the effect of change in PET method on catchment water balance.

### Sensitivity Analysis

Identification of sensitive parameters and their optimal values bears a paramount importance in semi-distributed hydrological models. It involves the ranking of individual input parameters with respect to their influence on the model output. In the present study, SWAT-CUP model with SUFI-2 algorithm was used for auto calibration, parameter sensitivity and uncertainty analysis. A total number of 15 SWAT parameters, presented in Table 3, were selected for this purpose based on previous studies and literature (Winchell *et al.,* 2010; Padhiary *et al*., 2019; Panda *et al*., 2021a). The SWAT-CUP is embedded with the module of global sensitivity analysis in which all the input parameters change simultaneously and the sensitivity is evaluated over the entire range of input parameters.

Sensitivity analysis was executed by 1000 runs of SWAT-CUP model. The results are depicted in Table 4. The indicators like *t-stat* and *p-value* were used for quantification of the sensitivity and assessing the relative importance of each parameter (Abbaspour *et al*., 2015). The highest absolute value of *t-stat* and lowest *p-value* represents the most sensitive parameter. In the present study, SCS-CN value for AMC II ($CN_2$) has been identified as the most sensitive parameter followed by baseflow parameters like ALPHA_BF, GW_DELAY and GWQMN, respectively (Uniyal *et al.,* 2015a; Padhiary *et al.,* 2019). Streamflow from the Kantamal catchment is found to be dependent mostly on curve number, which is governed by surface properties like LULC, soil and land management practices. As the catchment covers a large part of the Mahanadi river basin, the baseflow contribution to streamflow is also dominant and sensitive next to the surface runoff.

### Model calibration, validation and uncertainty analysis

SWAT model was calibrated using the observed streamflow data from 2004 to 2012 with 3 years of warm-up period and validated from 2013 to 2018 as portrayed through Fig's. 5 and 6. Uncertainty analysis was conducted during the process of calibration. A close relationship was witnessed between model calibration and uncertainty analysis. Without uncertainty analysis, calibration is meaningless because it takes care of errors associated with model input data, parameters, conceptualization, structure, mathematical formulation and measured data (Uniyal *et al*., 2015a; Padhiary *et al*., 2019). The SUFI-2 algorithm in SWAT-CUP is provided with stochastic calibration technique. It

**Table: 4**
**Minimum, maximum and fitted value of calibration parameters by SUFI-2**

| Sensitivity rank | Parameter | Minimum | Maximum | Fitted value | t-stat | p-value |
|---|---|---|---|---|---|---|
| 1 | R_CN2.mgt | -0.20 | 0.20 | -0.10 | 3.62 | 0 |
| 2 | V_ALPHA_BF.gw | 0.00 | 1.00 | 0.37 | 3.50 | 0 |
| 3 | V_GW_DELAY.gw | 0.00 | 500.00 | 242.00 | 2.32 | 0.12 |
| 4 | V_GWQMN.gw | 0.00 | 5000.00 | 0.51 | -2.05 | 0.15 |
| 5 | V_OV_N.hru | 0.01 | 30.00 | 20.85 | ?1.57 | 0.18 |
| 6 | V_LAT_TIME.hru | 0.00 | 180.00 | 118.63 | 1.47 | 0.21 |
| 7 | V_ESCO.hru | 0.00 | 1.00 | 0.13 | 1.36 | 0.25 |
| 8 | V_EPCO.hru | 0.00 | 1.00 | 0.22 | -1.11 | 0.31 |
| 9 | V_SURLAG.hru | 0.05 | 24.00 | 12.13 | -0.69 | 0.42 |
| 10 | V_CANMX.hru | 1.00 | 100.00 | 93.18 | ?0.53 | 0.52 |
| 11 | V_RCHRG_DP.gw | 0.00 | 1.00 | 0.57 | ?0.47 | 0.59 |
| 12 | R_SOL_K (1).sol | 0.00 | 2000.00 | 899.96 | 0.35 | 0.62 |
| 13 | R_SOL_AWC(1).sol | 0.23 | 1.06 | 0.35 | 0.18 | 0.75 |
| 14 | R_CH_N2.rte | 0.11 | 0.45 | 0.27 | 0.02 | 0.98 |
| 15 | R_CH_K2.rte | 0.01 | 500.00 | 124.26 | 0.01 | 0.855 |

generates a band of stream flow output (95PPU) taking into account 2.5% and 97.5% levels of the cumulative simulated stream flow generated by changing model parameters within the range using Latin hypercube sampling technique. The model takes care of uncertainties from various sources when most of the observed stream flow data are bracketed within the 95PPU band (Padhiary *et al*., 2019). Uncertainty in stream flow simulation is also measured by *P-factor* and *R-factor*.

The model simulation results with 95PPU band plotted against the observed stream flow data for model calibration and validation periods are portrayed through Fig's. 6 and 7, respectively using Hargreaves ET model. It is observed that most of the measured streamflow data are well bracketed within the 95PPU band, which indicates that the model simulation takes care of uncertainty that arises from various sources of hydrological modelling. However, some irregularities are also observed during the peak flow simulation in the year 2006 and 2008 during the calibration period and in the year 2016 and 2018 during validation period when the observed peak flows are slightly exceeding the 95PPU band. This infers the weakness of the SWAT model while predicting the peak flow. Various researchers claim that the curve number method used in SWAT model for simulating direct runoff under-estimates the peak flow (Uniyal *et al*., 2015a; Padhiary *et al*., 2019; Panda *et al*., 2021a). The values of *P-factor* and *R- factor* were found to be 0.77 and 0.46 during model calibration, and 0.79 and 0.47 during the validation period, respectively. The values of *P-factor* and the *R-factor* are very much within the desired range. Thus, it may be inferred that the overall performance of the model with respect to parameter uncertainty is satisfactory.

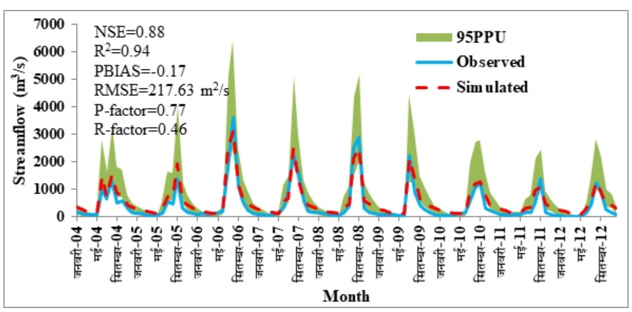


**Fig. 6. Time series plot of simulated vs observed streamflow with 95PPU band during calibration period**

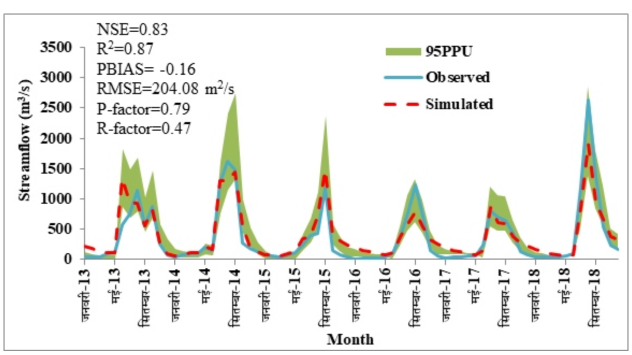


**Fig. 7. Time series plot of simulated vs observed streamflow with 95PPU band during validation period**

**Streamflow Simulation using Alternative PET Estimation Methods**

Streamflow of Kantamal catchment was simulated under three scenarios by changing the PET estimation methods. The HA, PM and PT methods were used under scenario-I, scenario-II and scenario-III, respectively. Simulated streamflow under the three scenarios were compared with the observed streamflow data at Kantamal outlet. The results are presented in Fig's. 8 and 9 for calibration and validation periods, respectively. They depict a better match between the model simulated streamflow under three scenarios with the observed data during the high and low flow periods with minimum irregularities. As stated before, the model simulation is under-predicting streamflow in the year 2006, 2008, 2016 and 2018 under all scenarios. It implies that variation in PET estimation methods has no significant effect on peak flow simulation rather it may be due to the limitation of model formulation to simulate the peak flows. It may be inferred that in low flow situations during non-monsoon periods, the model is slightly over-estimating the streamflow and PET selection methods have negligible influence on controlling the high and low flow simulation in SWAT.

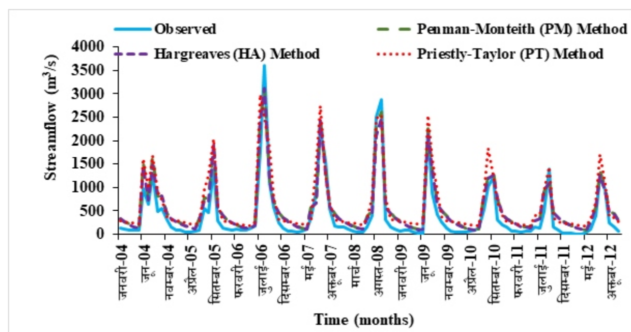


**Fig. 8. Comparison of monthly observed and simulated stream - flow using HA, PM and PT methods during calibration period**

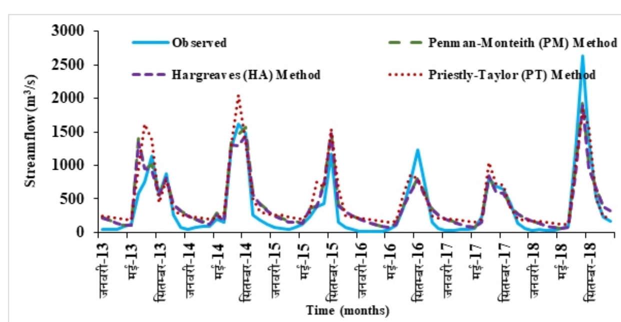


**Fig. 9. Comparison of monthly observed and simulated streamflow using HA, PM and PT methods during validation period**

### Water Balance

Annual water balance simulation of Kantamal catchment has been figured using the check tool of the SWAT model as shown in Table 5. It depicts the highest annual PET (1914.5 mm) under PM method followed by HA (1809.0 mm) and PT (1441.8 mm) method. The PET is over-estimated in PM method and under-estimated in PT method as compared to HA method. The highest PET simulation by PM method may be due to consideration of both temperature and radiation factors and as the study area is not under humid climatic condition, the PT method predicts low PET as compared to HA method. However, annual AET is lower in PM method (538.1 mm) in comparison to HA method (559 mm). This may be due to the fact that the transpiration inbuilt in PM method is more physically based compared to other two methods, where the transpiration is estimated by multiplying a simplified leaf area index (LAI) based factor with PET. PT method predicts the lowest AET (479.5 mm). Similarly, HA and PM methods simulated other components of annual water balance like surface runoff, lateral flow, percolation and groundwater recharge very close to each other. However, PT method overestimated these water balance components as compared to HA and PM methods.

### Performance Evaluation

The statistical tools such as $R^2$, NSE, PBIAS and RMSE were used for performance evaluation of SWAT with respect to streamflow simulation during calibration and validation (Table 6). According to $R^2$ and NSE values, the SWAT model simulates PET very effectively in all PET methods as ascertained from the values of these indices, which are higher than the threshold value of 0.75 (Padhiary *et al*., 2019). Percentage bias (PBIAS) is also below the threshold limit of 20% during calibration and validation periods in both HA and PM methods but exceeds the threshold limit in PT method. RMSE values were found to be 217.63 $m^3s^{-1}$, 223.79 $m^3s^{-1}$ and 319 $m^3s^{-1}$ in HA, PM and PT methods during calibration and 204.08 $m^3s^{-1}$, 200.47 $m^3s^{-1}$ and 228.38 $m^3s^{-1}$ during validation period, respectively. It is observed that RMSE values are also closely estimated in case of HA and PM method, however RMSE is higher in case of PT method. It is further observed from the indices that both HA and PM methods are performing neck to neck when used in SWAT model, where as in case of PT method the values are much deviating.

From the results of model performance, it may be concluded that HA method is the best performing one among the three methods under the condition of limited climatic data with only maximum and minimum temperatures. The finding has a close agreement with the results of Kannan *et al*., 2007 and Aouissi *et al*., 2016 derived on similar aspects. PM method using observed maximum and minimum temperature data with simulated average data of solar radiation, relative humidity, and wind speed also performed very close to HA method. However, PT method is not a good choice for streamflow estimation using SWAT in

Kantamal catchment at the middle reach of Mahanadi river basin, which comes under the eastern Indian river basins prevalent with typical sub-topical and sub-humid climate.

### Spatial Distribution of PET

Spatial distribution of PET was predicted by all the three methods in 15 sub-watersheds of Kantamal catchment as shown in Fig. 10. The lowest predicted value of PET is 1506.97 mm, 1828.01 mm and 1378.44 mm and the highest value of PET is 1917.07 mm, 2064.97 mm and 1486.57 mm in HA, PM and PT methods, respectively. The spatial distribution map indicates a significant pattern of PET distribution among the sub-watersheds of the catchment. In HA method, the sub-watersheds namely, 10, 6, 3 and 2 show higher PET towards north-west part of the catchment whereas, under PM method the sub-watershed 12, 2, 14 and 1 show higher PET than other sub-watersheds. In case of PT method, sub-watersheds with index number 13, 15, 12 and 14 show higher PET and these sub-watersheds are present in cluster at south-west corner of the catchment. As there is a

**Table: 5**
**Water balance components under different methods**

| Water balance components (mm) | PM method | HA method | PT method |
|---|---|---|---|
| PET | 1914.5 | 1809.0 | 1441.8 |
| ET | 538.1 | 559.0 | 479.5 |
| Surface Runoff | 664.6 | 663.7 | 687.9 |
| Groundwater Recharge | 13.4 | 12.4 | 15.0 |

**Table: 6**
**Summary statistics of model performance under different PET methods**

| Indices | Calibration | | | Validation | | |
|---|---|---|---|---|---|---|
| | HA method | PM method | PT method | HA method | PM method | PT method |
| $R^2$ | 0.94 | 0.93 | 0.87 | 0.87 | 0.86 | 0.84 |
| NSE | 0.88 | 0.88 | 0.75 | 0.83 | 0.83 | 0.78 |
| PBIAS | -17.00 | -18.00 | -21.00 | -16.00 | -20.00 | -32.00 |
| RMSE ($m^2s^{-1}$) | 217.63 | 223.79 | 319.22 | 204.08 | 200.47 | 228.38 |

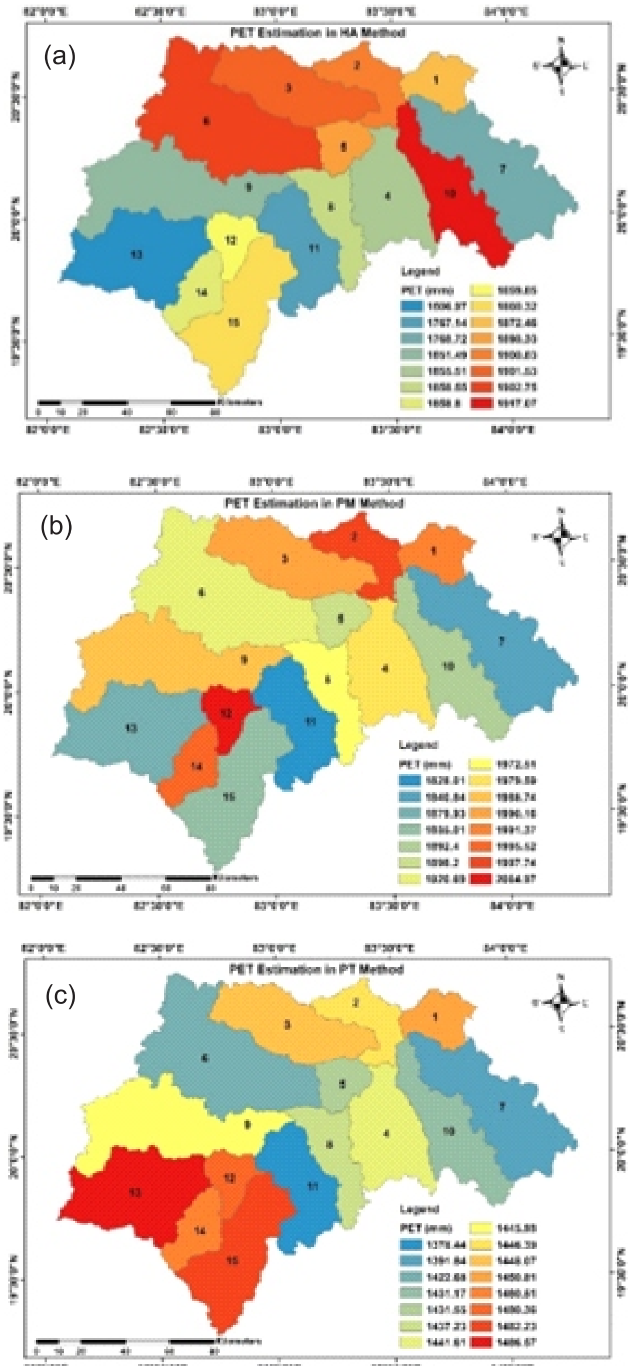


**Fig. 10. Spatial distribution of PET under (a) HA method, (b) PM method, and (c) PT method**

distinct spatial variation in PET under the three methods, therefore, optimal care must be taken while using SWAT model for ET based irrigation planning and crop water management. Validation of ET is therefore recommended for such regional studies to screen out the most suitable PET method. However, non-availability of observed time series ET data is a great constraint in such studies for developing countries like India.

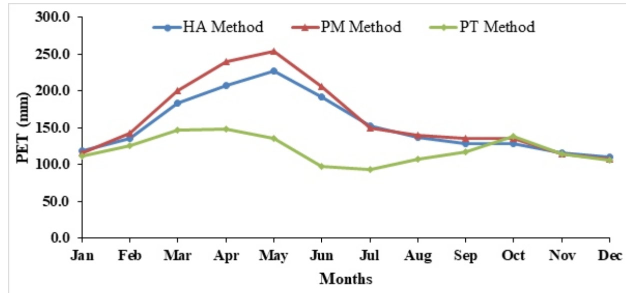


**Fig. 11. Temporal distribution of average PET under different methods**

### Temporal Distribution of PET

The temporal distribution of monthly PET under the three methods is illustrated in Fig. 11. It is observed that PM method predicts the highest monthly PET than other two methods over the years. The HA method shows medium level of PET, lower than the PM method, and PT method predicts the lowest PET among the three methods. Monthly cumulative PET increases in summer months *i.e.,* from March to June. The same pattern is observed in HA and PM methods, while PT method does not follow the temporal pattern of ET in the region. Therefore, PT method is not suitable for PET estimation or ET based crop planning in the study area as well as in other areas having similar climatic conditions.

## 4. CONCLUSIONS

Stream flow of Kantamal catchment has been simulated at monthly time step using three PET estimation methods. In HA method, the maximal and minimal temperatures obtained from IMD gridded data were used whereas, in other two methods the maxima land minimal temperature data in addition to other simulated climatic data from an average climate data base of IMD were used. Statistical indices like $R^2$, NSE values were found to be the highest and PBIAS, RMSE were the lowest in case of HA method. The results depict that temperature based HA method is most effective for streamflow modeling at par with the physically based PM method using simulated climatic data of wind speed, relative humidity and solar radiation. However, the model performance using PT method is little inferior to other two methods. The values of *P- and R-factors* were found to be 0.77 and 0.46 during calibration period and 0.79 and 0.47 during validation period, respectively. The HA method is adjudged as the best PET method as it predicts streamflow more accurately than the other two methods. There is a very negligible difference in streamflow simulation using HA and PM methods and so, it may be concluded that either of the two methods may be used depending upon the data availability. There is significant variation in spatio-temporal behavior of PET under the three methods. Therefore, it is emphasized to undertake utmost care while selecting PET methods for hydrological simulation as well as crop related studies, where ET is a vital component.

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