A catchment scale assessment of water balance components: a case study of Chittar catchment in South India

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Abstract
The detailed analyses of the water balance components (WBCs) of the catchment help assess the available water resources, especially in the arid climate regions for their sustainable management and development. This paper mainly used the Soil and Water Assessment Tool (SWAT) model to analyze the variation in the WBCs considering the change in the Land Use and Land Cover (LULC) and meteorological variables. For this purpose, the model used the inputs of LULC and meteorological variables between 2001 and 2020 at 5 years and daily time intervals, respectively, from the Chittar river catchment. The developed models were calibrated using SWAT-CUP split-up procedure (pre-calibration and post-calibration). The model was found to be good in calibration and validation, yielding the coefficient of determination ($R^2$) of 0.94 and 0.81, respectively. Furthermore, WBCs of the catchment were estimated for the near future (2021–2030) at the monthly and annual scales. For this endeavor, LULC was forecasted for the years 2021 and 2026 using Cellular Automata (CA)-Artificial Neural Network (ANN), and for the same period, meteorological variables were also forecasted using the smoothing moving average method from the historical data.

Keywords Chittar catchment · Water balance components · Water balance model · SWAT · LULC · Cellular automata ANN

Introduction
The water demand for meeting various requirements is increasing worldwide, despite a sharp decline in available potable water (Boretti and Rosa 2019; Mohanavelu et al. 2020). The survey of the world population by the United Nations states that in 2030, about 40% of the Indian population is expected to reside in urban areas (McKinsey Global Institute 2010). Similarly, in a few other developing countries (Brazil, Indonesia, South Africa, etc.), an increasing trend toward urbanization has been recorded mainly during the second half of the twenty-first century. Urbanization and rising population cause mismanagement of water resources, leading to water scarcity and eventually affecting the country’s socioeconomic status (Mishra and Singh 2010). It is also influenced by hydrometeorological phenomena such as uneven rainfall distribution and soil moisture distribution. Consequently, it leads to unstable water resource conditions in developing countries (Goyal et al. 2018). Hence, understanding the hydrological responses on the catchment scale helps better manage water resources, for which developing water balance models is often encouraged. The model requires the catchment characteristics such as the area, shape, LULC, soil, topography, etc. This is primarily to study the response of a catchment to the hydrological processes, mainly in pre-, and post-event of rainfall through water balance models (Liang and Xie 2003). The water balance models have been in use to assess the hydrological responses mainly to simulate the WBCs such as rainfall, evapotranspiration (ET), surface runoff, lateral flow, percolation, and soil water (Lu et al. 2015). Many computer simulation-based codes are available to estimate WBCs, and using them, many theoretical and experimental studies have been conducted in the past (Pandi et al. 2021; Xu and Singh 2003).
The water balance models can be developed at various time scales such as hourly, daily, monthly, seasonally, and yearly. The hourly to daily time scale models are often relatively accurate and most suitable for rainfall-runoff and flood modeling studies. However, to develop such models, the availability of fine-resolution data is scarce in many parts of the world, leaving the models on a monthly scale.

SWM (Stanford Watershed Model) is the first computer-coded physical-based water-balance model developed during 1959–1966 (Crawford and Linsley 1966). Since then, a wide range of modeling approaches has been proposed varying from simple empirical to more data rigorous machine learning-based models and physics-based models. Parida et al. (2006) applied the ANN-based water balance model to forecast the catchment scale runoff coefficient over eastern Botswana. Cheng et al. (2016) used multivariate analysis to map the relationship between input and output of a hydrological system. Kasiviswanathan et al. (2016) developed a data-driven model to predict groundwater levels over the Amaravathi catchment, India. The physics-based models have gained more popularity toward the end of the twentieth century along with the significant progress in the advancement of computational facilities and the availability of high-resolution data. Pandi et al. (2021) have evaluated the performances of empirical, data-driven, physical, and hybrid models. The most commonly used physics-based water balance models are the variable infiltration capacity model (Hurkmans et al. 2008); Wapaba model (Wang et al. 2011); SimHyd (Chiew et al. 2002); Australian water balance model (Boughton, 2004); Soil and Water Assessment Tool (SWAT) (Patil and Ramsankaran 2017; Kundu et al. 2017), and MIKE-SHE coupled MIKE-11 (Loliyana and Patel 2018).

Though several physical-based models have been reported in the literature, the SWAT model being relatively easy to set up and able to explain the catchment behavior through various physics-based model parameters has gained significant interest among researchers (Xu and Singh 1998; Francesconi et al. 2016). It has the capability to define the model to have a lumped response at the hydrological response unit (HRU) and at the same time able to estimate the spatial variability at the sub-catchment level. Please note that an HRU is a fundamental spatial unit having unique land use, soil, and land-management conditions. After abstraction, runoff generated from each HRU is routed to the stream reaches and finally reaches the catchment outlet. Murty et al. (2014) used SWAT to compute WBCs such as runoff, groundwater, and ET over the Ken catchment, India. In general, the selection of water balance models mainly depends on the purpose and availability of the hydrometeorological data having consistent spatiotemporal resolution and a priori knowledge of the initial range of model parameters. Presently high-spatiotemporal resolution meteorological data are not available in most of the developing countries. Many previous studies recommended that the water balance model at the monthly scale is reasonably good in water management studies within the catchment (Pal et al. 2021; Xu and Singh 1998). Xu and Singh (1998) have reviewed different monthly water balance models for their applications and pointed out the data constraints. Marin et al. (2020) reviewed the performance of the SWAT model in small-sized forest catchments (< 1000 km²). They observed that the impacts of future climate greatly influence the surface runoff and land-use scenarios especially on the surface runoff and sediment yield.

The changes in LULC and meteorological variables are triggered majorly by the rising population, urbanization, climate change, and environmental factors (Garg et al. 2017). The most commonly used LULC forecasting software package includes CA-ANN, Dyna-CLUE, IDRISI’s CA-MARKOV, etc. In this study, LULC was forecasted using the CA-ANN model. The CA-ANN model is a simple and widely used software package to forecast LULC (Rahman et al. 2017). Aarthi and Gnanappazham (2018) applied the CA-ANN model to forecast the LULC over Sriperumbudur Taluk, Tamil Nadu, India. They used historical data from 2009, 2013, and 2016 to forecast the urban sprawl and other classes for the year 2020. Cheng et al. (2017) proposed an integrated evaluation-classification-downscaling-based climate projection framework for predicting daily precipitation, minimum and maximum temperature over the Athabasca River basin, Canada. McCabe and Wolock (2011) and Pandžić et al. (2009) used the moving average method to forecast precipitation and temperature to estimate runoff and ET. Akrami et al. (2014) used the smoothing moving average and wavelet transform in short-term precipitation forecasting over the Klang River catchment, Malaysia. The smoothing moving average method is a simple and approximate technique widely used in time series analysis and forecasting of variables of interest (McCabe and Wolock 2011).

This paper used the data collected from the Chittar catchment, Tirunelveli District, Tamilnadu, India, to evaluate WBC trends by considering the LULC and temporal climate changes at the monthly and annual scale. The rationale behind selecting this catchment was to emphasize the importance of effectively managing the monsoon rainfall as it is the major source of water, especially in the state of Tamil Nadu, located in the southern part of India. The average annual rainy day in the state is about 60 days. The annual average rainfall of Tamil Nadu state is 980 mm, out of which about 50–70% of total annual rainfall is lost through the evapotranspiration process (Gosain et al. 2011). Hence, modeling the WBCs is vital for sustainable water management. It may be noted that most of the existing water balance studies over developing countries like India are empirical or data-driven or GIS-based overlay analyses. Although few studies reported the development of water balance models (Kundu et al. 2017), they are mostly based on the selection...
of input and output variables. Further, the impacts of LULC and meteorological variables changes are not incorporated in the model development (Kundu et al. 2017). Few researchers (Kumar et al. 2016; Nithya et al. 2019; Dinagarapandi et al. 2020) delineated groundwater potential zones using remote sensing, GIS, and multi-criteria decision-making techniques over the Chittar catchment. Further, no remarkable reported hydrological model studies in the catchment. Thus, this paper focuses on developing a monthly and annual water balance model to simulate past and near-future period WBCs at a catchment scale and to study the dynamics of WBCs using the SWAT model. The spatiotemporal variations in LULC and meteorological variables are modeled and incorporated in the water balance model.

Methodology

SWAT is a semi-distributed, open-source hydrological model that creates a HRU for estimating WBCs by forcing the meteorological variables. The model can predict future WBCs based on the parameter estimated using historical data, including ET, surface runoff, lateral flow, percolation, soil water, and rainfall. The flowchart describing the methodology of the study is shown in Fig. 1. Model performance is evaluated by the split-up procedure in model calibration and further validated with the calibrated model parameters for the unseen data. Subsequently, the water balance model is applied to predict the future WBCs. The data used in this paper was in the period 2001 to 2030 to analyze the trend in monthly and annual time scale WBCs. HRU is the combination of LULC, soil, and slope. The initial value of soil water content is assigned as a fraction of field capacity, and it is assumed to be constant at the catchment scale. In this study, the initial field capacity has arrived from average annual rainfall with the help of the default functional relationship in SWAT (Arnold et al. 2012; Tripathi et al. 2006). Please note that the initial value for soil water content does not impact steady-state WBCs (Arnold et al. 2012). Though the LULC gradually changes, meteorological variables are highly dynamic in nature. Nonetheless, forecasting both LULC and meteorological variables is important for predicting the future WBCs.

The historical WBCs include the ET, surface runoff, lateral flow, percolation, and soil water for the given rainfall. From these WBCs, accumulated river discharges are routed from elevated regions into the lower region, i.e., pourpoint. Here, the measured discharge at the pourpoint is used to calibrate and validate the model. The 20 years of daily meteorological data (2001–2020) from the Cheranmadevi station was used to develop the SWAT model. The measured discharge at A P Puram gauging station was collected from the Central Water Commission, Government of India (location shown in Fig. 2). The SWAT Calibration Uncertainty Procedures (SWAT-CUP), a standard algorithm tool, was used to calibrate the results of SWAT surface runoff discharge prediction. SWAT-CUP, a user-friendly public domain program and a predefined Sequential Uncertainty Fitting Algorithm-2 (SUFI-2) algorithm developed by Abbaspour et al. (2007) was used in this study. In this algorithm, simulated discharge

Fig. 1 The flowchart describing the proposed methodology

![Flowchart](image_url)
was used to estimate the error matrices during model calibration (Setegn et al. 2010; Chen et al. 2018). Historical LULC data having 5-year intervals were analyzed, and a forecast was made for 2021 and 2026 using the CA-ANN algorithm. Similarly, with the help of historical meteorological data, the near future meteorological data were generated using the smoothing moving average method (Adamowski et al. 2012). Through this procedure, a future water balance model was developed from the forecasted LULC and meteorological variables. Later, the variations in the different WBCs were analyzed on a catchment scale. For demonstrating the influence of time scale, monthly and annual scale data were used to analyze the historical and forecast WBCs. The combined formulae to simulate the WBCs (Neitsch et al. 2011; Lu et al. 2015) are as follows; the Penman–Monteith method (Tripathi et al. 2006) is more accurate and feasible to estimate ET. Modified Soil Conservation Service (SCS) curve number is accepted worldwide to approximate the surface runoff. The kinematic storage model was used to estimate the lateral flow. The methodology of storage routing was to assess the percolation. Finally, soil water content was estimated using the topsoil layer’s wilting point and field capacity (Abbaspour et al. 2007). The variations in the temporal scale at the Chittar catchment were analyzed to understand the WBC distribution.

**Study area**

The Chittar river is one of the tributaries of the Thamirabarani river catchment, as shown in Fig. 2. The catchment area is about 1600 km² and falls in the latitude of 8° 45′N to 9°15′N and longitudes of 77°10′E to 77°50′E. The main river travels around 82 km before joining the Thamirabarani river. It lies in a hot and dry humid climate zone with temperatures varying from 25 to 40 °C. The average annual rainfall of this catchment is about 880 mm. About 50% of annual rainfall is received through the northeast monsoon from October to December, and the southwest monsoon from June to August contributes 30% of annual rainfall (Dinagarapandi et al. 2020). The catchment boundary is derived up to the A P Puram gauging station, as shown in Fig. 2. The catchment area of A P Puram gauging station is about 1300 km². In order to avoid the inconsistency in the modeling, the A P Puram catchment was taken as an area of...
interest (i.e., Chittar catchment), and further analysis was carried out on it.

Summary of the data used

The key input model parameters were LULC, soil, slope, and meteorological forcing variables. The Aster-GDEM was used as input for deriving the topography of the study area. The Aster-GDEM was released with the 60-m spatial resolution on October 17, 2011, jointly by NASA of the USA and METI of Japan. The catchment boundary and slope maps were delineated from Aster-GDEM. The slope affects both runoff and infiltration and thus influences the variation in the WBCs (Dinagara Pandi et al. 2017b). It was found that the catchment has a percentage of slope that varies from 0 to 18%. The cadastral level soil maps prepared by the directorate of natural resource management, Tamil Nadu Agricultural University, Coimbatore, India, were used in this study. The soil database consists of soil texture, soil depth, sand, silt, clay content, etc. It was directly utilized in the model. The map is available on a 1:50,000 scale, having 62 classes over the Chittar catchment.

The LULC maps were delineated through physical interpretation from Landsat imagery in the GIS environment. The 30 m resolutions of Landsat TM, Landsat ETM+, and Landsat 8 OLI were used in this study (Zhang and Yu 2020). Huang et al. 2013 concluded that the increase in LULC features had relatively little influence on simulated monthly WBCs. Accordingly, in this study, LULC was classified as per level 1 of National Remote Sensing Centre (NRSC) LULC Monitoring Division (2011–2012) guidelines. In level 1, built-up land, agricultural land, wasteland, water bodies, and forests were the LULC features. Historical LULC features of 2001, 2006, 2011, and 2016 were analyzed and used in the LULC forecasting (Fig. 3). The databases of LULC, soil, and slope maps were combined into a single format as HRU. The meteorology variables at a daily scale were collected between 2001 and 2020 from the Water Resources Organization, Public Works Department, Government of Tamil Nadu, Chennai, India, for the Cheranmahadevi station. The data include rainfall, maximum temperature, minimum temperature, solar radiation, wind speed, and relative humidity.

Land Use and Land Cover forecasting

The historical LULC maps corresponding to the years 2001, 2006, 2011, and 2016 were prepared as shown in Fig. 3. These data are expected to analyze the transition potential. The analysis of transition potential helps to map the areal changes between the LULC features. The ANN was used to model the transition potential of LULC features (Mas...
et al. 2014). The transition potential trained between 2001 and 2006 was used. The technique cellular automata was used to simulate the future LULC by adopting the transition potential. Finally, CA-ANN was espoused to forecast the LULC of the year 2016. The data accessed for the year 2016 was used to validate the model performance by the multi-resolution budget. The Kappa statistics was used to compare the spatial matching of two datasets (Dinagarapandi et al. 2020). It achieved 87% of correctness from the actual 2016 data. Similarly, CA-ANN algorithms were used to follow the historical trends captured in the LULC data collected in 2011 and 2016 and forecast data of 2021. Further, a similar procedure was repeated to forecast LULC of the year 2026 using the data pertaining to the years 2016 and 2021. This forecasted LULC was imported into the HRU to develop the future water balance model.

Meteorological variables forecasting

The smoothing moving average is a simple time series forecasting method that is preferable to forecast at a daily time scale (Kocsis et al. 2017). It adopts the principle of the cumulative smoothing technique. In this study, historical period daily meteorological variables were taken from 2001 to 2020 and then projected for the periods starting from 2021 to 2030. The cumulative 5-day moving average of meteorological forcing variables from the starting point (January 1, 2001) for smoothing the data from the historical period were prepared. The same procedure was adopted to forecast all other meteorological variables, viz. maximum temperature, minimum temperature, solar radiation, wind speed, and relative humidity. It may be noted that meteorological data are the main forcing variables to understand how water and energy consumption interact with each other to influence the variation in the WBCs.

Results and discussions

Model calibration and validation

The river discharge data pertaining to the periods 2001 to 2010 and 2011 to 2015 were used for model calibration and validation, respectively. According to this time period, corresponding soil, slope, 5-year intervals LULC, and daily meteorological were chosen. The split-up procedure was followed for the model calibration. The model calibration was carried out in two stages in the split-up procedure, i.e., pre-calibration and post-calibration (Abbaspour et al. 2015; Odusanya et al. 2019). The pre-calibration helps to identify the major sensitive parameters and then to further tune in the post-calibration.

The model was simulated to reproduce the monthly river discharge. The model calibration and validation results show a reasonable fit with observed discharge and are plotted in Fig. 4a and b, respectively. However, few simulated peak values could not match the observed peak. Further, various performance indices computed for the model calibration and validation periods are presented in Table 1. The estimated $R^2$ and Nash–Sutcliffe efficiency (NSE) for the calibration period were 0.94 and 0.89, respectively. The validation results were consistent with calibration, and the model produced an $R^2$ of 0.81 and an NSE of 0.76. The percent bias (PBIAS) deviation was within ±3 that supports the reasonable fit of model simulation with observed discharge (Moriasi et al. 2007). Similarly, root mean square error (RMSE) was very consistent across the calibration and validation, yielding a value of 0.33 and 0.49, respectively. Both $R$ factor and $P$ factor were found to be reducing from calibration to validation. The large $P$ factor (near to 1 is satisfactory) was good at 95% of uncertainty (Poméon et al. 2018). The slight reduction of the $P$ factor during the validation period might be due to a mismatch of a few peaks with the observed data. The model performance indices revealed that the SWAT model simulated monthly river discharge values closely match the observed discharge during calibration and validation periods. Hence, the developed SWAT model can simulate the WBCs at the catchment scale.

Land use and land cover

LULC features are the primary source for the SCS curve number and which influence the change in the surface runoff, lateral flow, and percolation (Dinagara Pandi et al. 2017a; Zhang and Yu 2020). This paper analyzed LULC changes with the five features, as shown in Fig. 3. These features were forecasted for the years 2021 and 2026 (Fig. 3). The dynamics of the area contribution of each feature is represented in Fig. 5 for the years 2001, 2006, 2011, 2016, 2021, and 2026. The upper catchment is covered by forest land, about 18% of the total area. The agricultural and forest land jointly covers about 77% of the catchment area. The remaining 23% is covered by wasteland (18%), water bodies (3%), and built-up land (2%), as shown in Fig. 5. The low-lying catchment is distributed with the agricultural land and wasteland for about 74% of the total area. Mostly, LULC changes occurred over these agricultural land and wasteland due to natural or anthropogenic activities. Probably, scanty rainfall in the year results in low soil moisture and reduced agricultural productivity. Built-up and water bodies are quite less covered in this low-lying catchment, with approximately 8% of the total area. The mutual LULC changes occurred between agricultural land, wasteland, built-up land, and water bodies. It was observed that built-up land expanded rapidly by about 47% (22 to 42 km$^2$) from 2001 to 2026.
The increasing population could be the driving force for this conversion. The water bodies were found to be steadily decreasing at the rate of 0.7 km²/year, which declined in surface water availability. The wasteland consisted of 6% of the total area decreased from 2001 to 2026, and alternately, an increase of 3% of agricultural land at the same period was noticed. These conversions directly change the runoff, infiltration, soil moisture, and ET process. The magnitude and
direction of change in these WBCs depend on topography, crop characteristics, period of cultivation, irrigation method, and land management practices. The forest land being the only a feature class, experiences minimal changes from 2001 to 2026. LULC change from 2001 to 2016 causes the agricultural land to turn into a wasteland. Then, forecasting the LULC for the period of 2026, the wasteland was found to be converting into built-up land in the upper low-lying catchment. Please note that the spatiotemporal distribution of agricultural and forest land is essential to determine the ET distribution at the catchment scale.

**Meteorological variables**

The available 20-year daily meteorological data (i.e., 2001 to 2020) and the recent 5-year data (i.e., 2016–2020) were used for validation. The smoothing moving average technique was used to predict future meteorological data. The model validation was carried out using monthly scale rainfall data. The correlation coefficient for the validation period was found to be 0.82. Hence, the model performance can be considered reasonably satisfactory. Using the smoothing moving average technique, the maximum and minimum temperature, solar radiation, wind speed, and relative humidity were also forecasted. Daily minimum temperature and a maximum temperature range from 16 to 32 °C and 24 to 43 °C, respectively. Generally, the maximum temperature is reported from March to May (i.e., summer), and the minimum temperature is reported from December to February (i.e., winter) every year. The contribution of solar radiation has been much higher between 5 and 10 W/m² in the summer months of March to May. Daily average wind speed ranges from 0 to 11.6 km/h, and it mostly lies between 1 and 5 km/h. Maximum wind speed occurs in the months of July and August. The relative humidity ranges from 22.5 to 93%, and it mostly lies between 60 and 90%. These meteorological parameters are the primary controlling variable for the WBC distribution at the catchment scale.

**Monthly WBCs**

Figure 6 shows the simulated catchment scale monthly WBC distribution over the historical period 2001 to 2020 (i.e., 240 months) and forecast period 2021 to 2030 (i.e.,

![Fig. 6 Monthly WBC contribution (in mm) for the period of 2001 to 2030 [the bar graph represents the northeast monsoon period that occurs from October to December]](image-url)
120 months). The trend outliers of monthly WBCs were found to be varying between 0 and 600 mm. The highlighted bar in Fig. 6 represents the northeast monsoon period that occurred from October to December over the catchment. It is generally observed that rainfall, surface runoff, lateral flow, and percolation simultaneously reach a peak during the northeast monsoon period. The soil moisture rapidly raises monsoon onset and attains peak at the end of the monsoon period. The ET attains peaks during non-monsoon months. These results reveal that the onset of northeast monsoon rainfall plays an important role in the WBC trend over the catchment. Overall, through the monthly water balance model, the variations in WBCs mainly due to the changes in LULC and meteorological variables were analyzed.

**Rainfall**

Daily rainfall was forecast using the smoothing moving average technique for the year between 2021 and 2030 using the historical rainfall data (i.e., 2001 to 2020). Rainfall was observed to be highly fluctuating compared to other WBCs. So, rainfall is a more significant component that plays a crucial role. Throughout the 30 years, the trend of rainfall did not show a considerable change (Fig. 6). The monthly rainfall of the post-monsoon period (i.e., January to May) was generally less than 150 mm. Few heavy rainfalls (more than 150 mm) were observed from March to May in 2005, 2008, 2014, 2020, 2025, and 2030. However, such heavy rainfall might have occurred due to the onset of the advancement of the southwest monsoon over the catchment. The rainfall varies between 0 and 50 mm during the pre-monsoon period of June to September every year. In general, monthly maximum rainfall was recorded from October to December onset of the northeast monsoon. The uneven distribution of annual rainfall is expected to cause droughts and floods and further influence agricultural productivity. So, mapping the available water is important for the sustainable development of the catchment.

**Surface runoff**

Surface runoff was found to be varying from 0 to 325 mm (Fig. 6). It was observed that the maximum number of peaks occur during October to December on the set of monsoons. However, few peaks were also observed during the post-monsoon period, such as February 2002, April 2005, March 2008, March 2014, and May 2014. The maximum runoff of 325 mm was observed in December of the year 2005. The surface runoff was zero in 177 months, out of which 69 zero runoff months were observed during the forecast period (i.e., 2021 to 2030). This trend is quite similar to rainfall with a short delay. Thus, likely canal irrigation or injection wells runoff harvesting structures should be constructed within low-lying lands. Surface runoff is impacted by the LULC and meteorological variables in the water balance model, and this component shows the acceleration and impacts of other WBCs.

**Lateral flow**

Lateral flow contribution was found to be minimum among the WBCs. This may be due to the combined effect of flatlands, less natural landscape, and low permeability of topsoil. In the Chittar catchment, lateral flow is slightly high, especially during monsoon. In the non-monsoonal period, less rainfall attains zero lateral flow (Fig. 6). The monthly mean lateral flow is 9.27 mm and 7.76 mm for historical and forecast periods, respectively. It provides a maximum value of 64 mm within 360 months. The maximum number of peaks occurred in November and December. Overall, the lateral flow is the relatively less sensitive parameter over the Chittar catchment at the monthly scale.

**Evapotranspiration**

A strong seasonal trend was found in the ET. All the peaks occurred during pre/post-monsoon periods and were low during the monsoon period (Fig. 6). Thereby, January to March ET was found to be varying in the range from 10 to 123 mm. The maximum ET was observed from April to June (summer) every year. Again, the ET values were found to be reducing to 0 in December from 70 mm in August. The monthly ET is more than 50 mm for 74 months out of the 90 summer months. It was observed that ET has a positive correlation with monthly rainfall trends. This may be due to the increase in rainfall increasing the soil water and subsequently elevating the ET. The ET and soil water are mutually interlinked parameters. The ET resulted in a high correlation with meteorological variables, soil, and LULC.

**Percolation**

Percolation has trends with rainfall, soil water, and surface runoff. A positive trend was observed with rainfall (Fig. 6). The percolation is generally high during a rainy day. A maximum number of zero and near-zero percolation occurs from April to September. It was found that the total sum percolation during historical and forecast periods is 1472 mm and 1542 mm, respectively. The maximum percolation was observed from October to December. The total sum of October to December percolation is about 3397 mm. Percolation rate determines the groundwater susceptibility and its effects. Here, percolation also depends on the soil properties, topography, and LULC.
Soil water

Soil water is gathered from other WBCs. It showed the reflection of gain and loss to the model and retained the left-out water that lies in the soil. So, the trend of soil water had a combination of other WBC trends (Fig. 6). The soil water gradually rises from October and attain maximum in December, and this rise may be due to the monsoon rainfall. After the monsoon period, a declining trend was observed, which might be due to the removal of soil water by ET and percolation. The soil water was found to be varying between 3 and 194 mm with a standard deviation of 53 mm in the historical period and 2–186 mm with a standard deviation of 56 mm in the forecasting period. The soil water is also affected by the soil properties, LULC, and topography. The spatiotemporal distribution of soil water greatly influences the irrigation requirement, groundwater recharge, soil stability, and soil chemistry.

Annual WBCs

Figure 7 shows the simulated annual WBC trend from 2001 to 2030. Rainfall, surface runoff, ET, soil water, and percolation are significant contributors to the annual water balance model. It was observed that rainfall, surface runoff, and ET resulted in maximum variation at the annual scale. The rainfall has a positive correlation with surface runoff, soil water, and percolation. The recorded maximum and minimum rainfalls were 1370 mm, and 400 mm occurs in the years 2008 and 2016, respectively. Specifically, this analysis defines the ideas for sustainable water resources management in the Chittar catchment. The rainfall contributes significantly to ET and surface runoff. The agricultural and forest land jointly covers about 77% of the catchment area, contributing to high ET. The uneven monsoon rainfall increases the surface runoff and decreases the percolation. From Fig. 7, surface runoff can be mainly observed as an inverse trend with ET and a significant positive trend with rainfall. Accordingly, rainfall and surface runoff reach a peak simultaneously and vice versa. This peak surface runoff diverts a considerable volume of water toward the water body, leading to flooding inundation.

Figure 8 shows the annual percentage contribution of different WBCs over the Chittar catchment. Figure 8 shows a maximum ET from 2016 to 2018 with a peak value of 84% (in 2018). This might be due to the severe meteorological drought (due to failure northeast monsoon) that hit over South India during 2016–2018 (Mishra et al. 2021). Further, the model predicts a similar drought scenario with a peak ET of 55% during 2027 and 2028. The ET had a low share of 18% in 2008. This low ET can be interpreted from the downpour of rainfall due to the Nisha cyclone that struck Sri Lanka and South India during 2008. Lateral flow has the lowest share throughout 30 years, with percentages varying from 3.3 (2016) to 12.7 (2021). This might be due to less natural land formation (i.e., forest and wasteland share is about 30%) and increased imperviousness in the catchment. The surface runoff minimum and maximum contributions were 4% and 50% in the years 2016 and 2008, respectively. Typically, surface runoff is directly comparable with rainfall and inverse toward ET. This drift can be expressed in the surface runoff peak because it needs to collect the excess rainfall in overland flow and lateral flow. Then, it entered as the huge volume of water toward the river that led to

![Fig. 7 Annual WBC contribution in mm for the period of 2001 to 2030](image)
flood inundation, soil erosion, landslide, etc. Similarly, the low surface runoff marks a worse drought and increases the dependence on groundwater. The percolation resulted in a positive trend with surface runoff and a negative trend with ET throughout 30 years period. Generally, percolation was found to be less than surface runoff; however, in 2016, 2022, 2028, and 2030 percolation were almost equal to or slightly more than surface runoff (Fig. 8). The high percolation may be due to the impact of continuous heavy rainfall over the catchment. This helps the natural groundwater recharge and reduce flood peaks. The lateral flow contribution is minimal compared to others. But, it did not reach zero. The annual lateral flow share varies from 3 to 13%. The lateral flow was found to be low from 2016 to 2020, and the remaining years did not show much variation. The lateral flow was generally less than percolation due to the relative level surface of the catchment. It can be inferred that the texture and profile of the soil influence the soil water storage and redistribution on an annual scale. Hence, soil water did not show much variation. However, the reported small variability may be in response to the spatiotemporal changes in other WBCs over the catchment.

Conclusions

The land and water resources are ecologically connected at the catchment scale, where the increasing population has given rise to competing and conflicting demands on finite resources. The detailed analyses of the spatiotemporal distribution of WBCs are an important element in the sustainable development of land and water resources at the catchment scale. In this paper, the SWAT model was used to analyze monthly and annual scale WBCs of the Chittar catchment. The historical LULC of 2001, 2006, 2011, and 2016 were prepared for assessing the trend of the WBCs. LULC was forecasted using the CA-ANN model. The model produced a good performance in validation (87% of correlation) and the further used to forecast LULC of 2021 and 2026. The historical daily meteorological data (for the period 2001 to 2020) was used to forecast future meteorological variables for the period 2021 to 2030 using the smoothing moving average technique. The parameters of the water balance model were calibrated using the observed river discharge. Model validation resulted in NS and $R^2$ of 0.76 and 0.81, respectively, from the observed and simulated monthly discharges. The major conclusions drawn from the study are as follows:

1. The agricultural and built-up land was found to be constantly increasing during the three decadal periods. The annual average reduction of water bodies over the catchment is about 0.75 km²/year. The forest land is the only subclass that underwent minimal changes. Both gains in built-up land and loss in the water body lead to an increase in surface runoff and a reduction in lateral flow and percolation.
2. Out of the five WBCs, monthly rainfall shows maximum variation during historical (132 mm) and forecast (98 mm) periods, respectively. The lateral flow shows the least variation among the five WBCs. A similar trend also followed on an annual scale.
3. The monthly ET varies from 0.1 to 124 mm from 2001 to 2030 over the Chittar catchment. The ET is high during January, February, and March every year and low during June, July, August, and September, in response to the supply of water to the soil by rainfall.
4. The annual average surface runoff, lateral flow, percolation, soil water content, and ET are 303.2 mm, 96.3 mm, 144.4 mm, 152.1 mm, and 398 mm, respectively. About 70% of annual rainfall converts into surface runoff and ET. So, rainwater harvesting is necessary to mitigate the effects of drought and flood.
5. The rainfall, surface runoff, and ET are the three major WBC parameters controlling water availability. Overall, the surface runoff, percolation, lateral flow, and soil water positively correlate with rainfall. From the simula-
tion results, it is identified that ET and lateral flow have

delays with rainfall.

The performance of the hydrological model is majorly
controlled by the reliable estimate of the model input para-

meters for which the spatiotemporal resolution of the me-

teorological data plays a key role. As this paper used smooth-
ing moving average technique, the effects of preserving the
characteristics of extreme events might be diluted. Hence,
future studies are suggested to use global circulation models
(GCMs) for forecasting the local meteorological variables
as an additional covariate in order to improve the accuracy.
Further, mapping the spatiotemporal trend of WBCs at sub-
catchment or further smaller spatial unit is suggested for
more accurate planning.

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Declarations

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