A Catchment Scale Assessment of Water Balance Components: A Case Study of Chittar Catchment in South India

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Abstract

Analyzing the Water Balance Components (WBCs) of catchment help in assessing the water resources for their sustainable management and development. This paper used Soil and Water Assessment Tool (SWAT) model mainly to analyze the variation in the WBCs through 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 the year 2001-2020 at five year and daily time interval respectively from the Chittar river catchment. The developed models were evaluated 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 monthly and annual scale. For this endeavour, LULC was forecasted for the year 2021 and 2026 using Cellular Automata (CA)-ANN and for the same period meteorological variables were also forecasted using the smoothing moving average method from the historical data.

1.0 Introduction

The water demand for various purposes is ever increasing worldwide, despite a sharp decline of available potable water worldwide including both surface and groundwater. The survey by the United Nations for the world population states that in 2030, about 40% of the Indian population is expected to reside in urban areas (McKinsey Global Institute, 2010). Similarly, in few other developing countries (Brazil, Indonesia, South Africa etc.), an increasing trend towards urbanization has been recorded mainly during the second half of the 21st century. Urbanization and rising population cause mismanagement of water resources leading to the water scarcity and, eventually affecting socio-economic status of the country (Mishra and Singh, 2010). It also affects by hydro-meteorological phenomena such as uneven distribution of precipitation and soil moisture. Consequently, it leads to unstable water resources condition in the developing countries (Goyal et al. 2018). Hence, understanding the hydrological responses on the catchment scale help better management of water resources, for which developing water balance models are often encouraged. The model requires the catchment characteristics such as the area, shape, Land Use and Land Cover (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 precipitation through water balance models (Liang et al. 2003). Water balance model has been in the use to assess the hydrological responses mainly to simulate the water balance components (WBCs) such as precipitation, evapotranspiration (ET), surface runoff, lateral flow, percolation and soil water (Lu et al. 2015). There are many computer-based codes are available to estimate WBCs and also many theoretical and experimental studies have been conducted in the past. The water balance model can be developed at various time scales: hourly, daily, monthly, seasonally, and yearly. The hourly to daily time scale models are generally accurate and most suitable for rainfall-runoff and flood studies. However, the availability of such a fine resolution data is rare in many parts of the world and thus daily and monthly scale water balance models are mostly preferred.

SWM (Stanford Watershed model) is the first computer coded physical-based water-balanced models developed during 1959-1966 (Crawford and Linsley, 1966). Since then, the wide range of modeling approaches are available varying from simple empirical, more data rigorous machine learning-based models and physically-based models. Parida et al. (2006) applied Artificial Neural Network (ANN) aided water balance model to forecast the catchment scale runoff coefficient over eastern Botswana. Kasiviswanathan et al. (2016) developed data-driven model to predict groundwater level over Amaravathi catchment, India. The physics-based model started evolving from the 19th century with the advancement of computational facility, better understanding of physical processes and availability of high-resolution data (Pandi et al. 2021). Pandi et al. (2021) have reviewed the applications and performances of empirical, data-driven, physical and hybrid models. The most commonly used physical-based water balance models are 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; Swain and Patra, 2019); MIKE-SHE coupled MIKE-11 (Loliyana and Patel, 2018) etc. Xu and Singh, (1998) and Francesconi et al. (2016) reviewed the various applications of the SWAT model. Among several models developed, SWAT is well documented and applied in many countries worldwide. Murty et al. (2014) used SWAT to compute WBCs such as runoff, groundwater and ET over the Ken catchment. In general, selection the water balance models mainly depend on the purpose and availability of the number of input parameters and different hydro-meteorological variables along with their consistent spatiotemporal resolution. Presently high-spatiotemporal resolution meteorological data are not available in most of the developing countries. Many previous studies recommend that the water balance model at the monthly scale is reasonably good in water management studies at the catchment scale (Pal et al. 2021; Xu and Singh, 1998). Xu and Singh, (1998) have reviewed different monthly water balance models for their applications in the field and pointed out the data constraints.

The changes in LULC and meteorological variables are triggered mainly by the rising population, urbanization, climate change and environmental factors (Garg et al. 2017). The most commonly used LULC forecasting software package includes Cellular Automata (CA)-ANN, Dyna-CLUE, IDRISI's CA-MARKOV etc. In this study, LULC were 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 CA-ANN model to forecast the LULC over Sriperumbudur Taluk, Tamilnadu, India. They used historical data from 2009, 2013 and 2016 to forecast the urban sprawl and other classes for the years 2020. 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 forecasting of precipitation over Klang River catchment, Malaysia. The meteorological variables are generally forecasted using the smoothing moving average method.

This paper used the data collected from Chittar catchment, Tirunelveli District, Tamilnadu, India to demonstrate the response of LULC and climate temporal changes in the WBCs. The rationale behind the selection of this catchment was to emphasise the importance of managing monsoon precipitation as it is

the major source of water especially in the state Tamilnadu, located in the southern part of India. The average annual rainy day is about 60 days in the state. The annual average rainfall of Tamilnadu state is 980 mm out of which about 50% - 70% of total annual precipitation is losses through evapotranspiration process (Gosain et al. 2011). Hence, modeling of the WBCs is important for sustainable water management. It may be noted that most of the existing water balance studies over developing country like India are empirical or data driven or GIS based overlay analysis. Despite few studies reported development of water balance models (Swain and Patra, 2019), they are mostly biased input and output variables. Further, the impacts of LULC and meteorological variables changes are not incorporated in the model development (Swain and Patra, 2019). Thus, this paper focuses on developing a monthly and annual water balance model to simulate past and near-future period WBCs at catchment scale and to study the dynamics of water balance and changes occurred in different WBCs using SWAT model. The spatiotemporal variations in LULC and meteorological variables are also modeled and incorporated in the water balance model.

2.0 Methodology

SWAT is a semi-distributed, open source hydrological model functioning by creating Hydrological Response Unit (HRU) and operates 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 precipitation. The flow chart methodology of this 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 collected for the period (2001 to 2030) for analyzing the changes in monthly and annual time scale WBCs. HRU is the combination of LULC, soil, and slope. Though the LULC gradually changes, meteorological variables are highly dynamic in nature. The forecasting of LULC and meteorological variables are important for predicting the future WBCs.

The historical WBCs give simulated include the ET, surface runoff, lateral flow, percolation, and soil water as per the given precipitation. From these WBCs, river discharges routed from elevated regions that accumulated into the lower region at pour point. Here, the measured discharge at the pourpoint is used to calibrate and validate the model. The twenty years daily metrological data (2001-2020) from Cheranmadevi station is used for developing the model in SWAT. The measured discharge at A P Puram gauging station is collected from Central Water Commission, Government of India (refer to the location 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 public domain program, being user-friendly, and a predefined Sequential Uncertainty Fitting Algorithm -2 (SUFI-2) algorithm developed by Abbaspour et al. (2007) is used in this study. In this algorithm, SWAT discharge is used to estimate the error matrices for model calibration and validation (Setegn et al. 2010; Chen et al. 2018). Historical LULC data having five years intervals; are analyzed, and a forecast is made for 2021 and 2026 using the CA-ANN algorithm. Similarly, historical meteorological variables are used to develop the smoothing moving average for simulate the future meteorological data (Adamowski et al. 2012). Thus, a

future water balance model is developed from the forecasted LULC and meteorological variables. Later, WBCs outcomes are analyzed on a catchment scale. For the varied temporal scale, monthly and annual scales are used in both historical and forecast WBCs. The combined formulae to simulate the WBCs (Neitsch et al. 2005; Lu et al. 2015) are as follows; Penman-Monteith method 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 is used to estimate the lateral flow. The methodology of storage routing is to assess the percolation. Finally, soil water content is estimated using the topsoil layer's wetting point and field capacity (Abbaspour et al. 2007). The variations in the temporal scale at the Chittar catchment are analyzed to understand the WBCs distribution.

2.1 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 precipitation of this catchment is about 880 mm. About 50% of annual rainfall is received through the northeast monsoon during October to December and the south-west monsoon from June to August contributes 30% of annual precipitation (Pandi et al. 2020). The catchment boundary is derived upto 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 is taken as an area of interest (i.e., Chittar catchment), and further analysis is carried out only for this portion the catchment.

2.2 Summary of the data used

Major input parameters are LULC, soil, slope, and meteorological variables. The Aster-GDEM is used as input for topography. The Aster-GDEM was released with the 60 m spatial resolution on October 17, 2011, jointly by NASA of the United States and METI of Japan. The catchment boundary and slope maps are delineated from Aster-GDEM. The slope affects both runoff and infiltration, and so affecting WBCs (Dinagara et al. 2017b). The study area considered for this paper; the percentage of slope varies from 0 to 18 %. The cadastral level soil maps prepared by the Directorate of natural resource management, Tamilnadu Agricultural University, Coimbatore, India, were used in this study. The soil database consists of soil texture, soil depth, sand, silt, clay content, etc. and it was directly utilized in the model. The map is available on 1: 50,000 scale, having 62 classes over the Chittar catchment.

The LULC maps are delineated from Landsat imagery in the GIS environment through physical interpretation. The 30 m resolutions of Landsat TM, Landsat ETM+, and Landsat 8 OLI are used in this study (Saravanan et al. 2015; Zhang and Yu, 2020). LULC is 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, waste land, water bodies, and forest are LULC features. Historical LULC features of

2001, 2006, 2011, and 2016 are analyzed and used to investigate the LULC changes (Fig. 3). The databases of LULC, soil, and slope maps are combined into a single format as HRU. The meteorology variables at daily scale are collected between the year 2001 and 2020 from the Water Resources Organization, Public Works Department, Government of Tamilnadu, Chennai, India for the Cheranmadevi station. The data include the precipitation, maximum temperature, minimum temperature, solar radiation, wind speed, and relative humidity.

2.2.1 LULC forecasting

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

2.2.2 Meteorological variables forecasting

The smoothing moving average is one of the simple time series forecasting methods 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 are taken from 2001 to 2020, and the projected for the periods start from 2021 to 2030. Those variables are applied in the cumulative distribution for every five days, smoothing the moving average. The cumulative five-day moving average contributes from the starting point (1-Jan-2001) to attain the smoothing moving average from the historical period. The similar method is adopted to forecasted all other meteorological variables viz. maximum temperature, minimum temperature, solar radiation, wind speed, and relative humidity. Thus, meteorological variables act as the main forcing variable to know how water and energy consumption interact to see the loss and gain of WBCs.

3.0 Results And Discussions

3.1 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 and according to this time period corresponding soil, slope, five-year intervals LULC, daily meteorological were chosen. The split-up procedure was followed for the model

calibration. In the split-up procedure, the model calibration was carried out in two stages 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 further tuned in the post-calibration.

The model was simulated for reproducing the monthly discharge and the results corresponds to model calibration and validation are plotted in Fig. 4a and 4b respectively, which shows a reasonably fit with observed discharge. However, few simulated peak values were not able to match the observed peak. Further, various performance indices computed for the model calibration and validation periods are presented in the Table. 1. The estimated coefficient of determination (R^2) and Nash Sutcliffe Efficiency (NSE) for the calibration period were 0.94 and 0.89, respectively. The validation results were also quite consistent with calibration, and the model produced an R^2 of 0.81 and NSE of 0.76. The percent bias (PBIAS) deviation was within ± 3 that supports the reasonable fit of model simulation with observed discharge (Moriassi 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) are good at 95 % of uncertainty (Poméon et al. 2018). The slight reduction of P factor during the validation period might be due to a mismatch of few peaks with the observed data. The model performance indices revealed that the SWAT model simulated monthly river discharge values were very closely matching the observed discharge both during calibration and validation periods. Hence, the developed SWAT model can be used to simulate the WBCs at catchment scale.

3.2 LULC

LULC features are the primary source for the SCS – Curve Number and which influence the change in the surface runoff, lateral flow and percolation (Saravanan et al. 2015; Dinagara et al. 2017a; Zhang and Yu, 2020). In this paper, LULC changes were interpreted with the five features as shown in Fig. 3. These features were forecasted for the years 2021 and 2026 (Fig. 3). The dynamics of 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 waste land (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 waste land for about 74% of the total area. Mostly, LULC changes occurred over these agricultural land and waste land due to natural or anthropogenic activities. Probably, scanty rainfall in the year results in low soil moisture and also reduced the agricultural productivity. Built-up and water bodies were quite less covered in this low-lying catchment with approximately 8% of the total area. The mutual LULC changes occurred between agricultural land, waste land, built-up land, and water bodies. It is observed that built-up land expanded rapidly by about 47% (22 km² to 42 km²) from 2001 to 2026. The increasing population is the driving force for this conversion. The water bodies are found to be steadily decreasing at the rate of 0.7 km²/year with consequent, which declining in surface water availability. The waste land consisted of 6 % of total area decreased from 2001 to 2026 and alternately an increase of 3 %

of agricultural land at the same period was noticed. These conversions significantly altered the runoff, infiltration, soil moisture, and ET process. The forest land is the only feature class that experienced minimal changes from 2001 to 2026. LULC change from 2001 to 2016 causes the agricultural land to turn into waste land. Then, forecasting the LULC for the period of 2026, the waste land was found to be converting into a built-up land in the upper low-lying catchment. Please note that spatiotemporal distribution of agricultural and forest land is important to determine the ET distribution at the catchment scale.

3.3 Meteorological variables

The available twenty-year daily meteorological data (i.e., 2001 to 2020), the initial fifteen-year data (i.e., 2001-2015) were used for calibration. The remaining five years data, i.e., 2016 to 2020 were used for model validation. The smoothing moving average technique was used to predict future meteorological data. The model validation was carried out at monthly precipitation. The correlation coefficient for the validation period is 0.82. Hence, the model performance is reasonably satisfactory. The maximum daily precipitation is 170 mm occurred in December, 2005. The maximum and minimum temperature, solar radiation, wind speed, and relative humidity were also forecasted using the smoothing moving average technique. Daily minimum temperature and maximum temperature ranges from 16 to 32°C and 24 to 43°C respectively. Generally, the maximum temperature is reported during 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 is much higher between the 5 to 10 W/m² in the summer months of March to May. Daily average wind speed ranges from 0 to 11.6 km/hr, and it mostly lies between 1-5 km/hr. Maximum wind speed occurs in the month of July and August. The relative humidity ranges from 22.5 to 93%, and it mostly lies between 60 to 90%. All these meteorological parameters are the primary controlling variable for the WBCs distribution at the catchment scale.

3.4 Monthly WBCs

Figure 6 shows the simulated catchment scale monthly WBCs distribution over the historical period 2001 to 2020 (i.e., 240 months) and forecast period 2021 to 2030 (i.e., 120 months). The trend outliers of monthly WBCs were found to be varying between 0 mm and 600 mm. Overall through monthly water balance model, the variations in WBCs mainly due to its impact on LULC and meteorological variables changes.

3.4.1 Precipitation

Monthly precipitation was forecasted using the smoothing moving average technique for the year between 2021 and 2030 using the historical precipitation data (i.e., 2001 to 2020). Precipitation was observed to be highly fluctuating compared to other WBCs. So, precipitation is a more significant component that plays a crucial role. Throughout the 30 years, the trend of precipitation did not show a considerable change (Fig. 6). The monthly precipitation of post-monsoon period (i.e., January to May) were generally less than 150 mm. Few heavy precipitations (more than 150 mm) were observed during

March to May in years 2005, 2008, 2014, 2020, 2025, 2030. However, such heavy precipitation might have occurred due to the onset of the advancement of the southwest monsoon over the catchment. The precipitation varies between 0 to 50 mm during the pre-monsoon period of June to September every year. In general, monthly maximum precipitation was recorded during October to December on set of north-east monsoons. The uneven distribution of annual rainfall expects to cause both droughts and floods, which might further influence agricultural productivity. So, the mapping of available water is important for sustainable development over the catchment.

3.4.2 Surface runoff

Surface runoff has varied from 0 to 325 mm (Fig. 6). It was observed that the maximum number of peaks during October to December on the set of monsoons. However, few peaks are also observed during post-monsoon period such as February 2002; April 2005; March 2008; March 2014 and May 2014. The maximum runoff of 325 mm observed in December in the year 2005. The surface runoff is zero in 177 months, out of which 69 zero runoff months were observed during the forecasted period (i.e., 2021 to 2030). This trend is quite similar to the precipitation 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.

3.4.3 Lateral flow

Lateral flow contribution is 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 the monsoon period. In the non-monsoonal period, less precipitation 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 happened in November and December. Overall, the lateral flow is the relatively less sensitive parameter over the Chittar catchment at monthly scale.

3.4.4 Evapotranspiration

The ET shows a seasonal pattern. All the peaks have occurred during pre/post-monsoon periods and low during the monsoon period (Fig. 6). Thereby, January to March ET is varies in the range from 10 to 123 mm. The maximum ET is observed from April to June (Summer) every year. Again, the ET value reduces to range 0 to 70 mm during August to December. The monthly ET is more than 50 mm during 74 months out of 90 summer months. It observed that ET has a positive correlation with annual precipitation patterns. This may be due to an increase in precipitation increases the soil water and subsequently pushes the ET. The ET and soil water are mutually interlinked parameters. The ET is highly correlated with meteorological variables, soil, and LULC.

3.4.5 Percolation

Percolation has trends with precipitation, soil water, and surface runoff. It was observed positive trend with precipitation (Fig. 6). The percolation is generally high during rainy day. A maximum number of zero and near-zero percolation occurs from April to September. The total sum percolation during historical and forecast periods are 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 determined the groundwater susceptibility and its effects. Here, percolation also depending on the soil layer properties, topography and LULC.

3.4.6 Soil water

Soil water is gathered from other WBCs. It showed the reflection of gain and loss to the model. It retained the left-out water that lies in the soil. So, the trend of soil water had a combination of other WBCs 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 decline trend is observed due to removal of soil water by ET and percolation. The soil water varies 3 - 194 mm with a standard deviation 53 mm during historical period and 2 -186 mm with standard deviation 56 mm during forecast period. The soil water is also affected by the soil properties, LULC, and topography of the area. The spatiotemporal distribution of soil water is greatly influencing the irrigation requirement, ground water recharge, soil stability and soil chemistry.

3.5 Annual water balance model

Figure 7 shows the simulated annual WBCs trend during 2001 to 2030. Precipitation, surface runoff, ET, soil water and percolation are major contributors in the annual water balance model. It observes that precipitation, surface runoff and ET showed maximum variation at annual scale. The precipitation has positive correlation with surface runoff and negative correlation with ET. The recorded maximum and minimum precipitations are 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 ET and surface runoff are the two predominant two consumers of precipitations. The agricultural and forest land jointly covers about 77 % of the catchment area that contributes to high ET. The uneven monsoon rainfall increases the surface runoff and decreases the percolation. From Fig. 7, surface runoff is mostly observed as an inverse trend with ET and a significant positive trend with precipitation. As precipitation is one of the major contributing parameters for surface runoff. Accordingly, precipitation and surface runoff reach a peak simultaneously and vice versa. This peak surface runoff diverts a huge volume of water towards the water body that leads to flood inundation.

Figure 8 shows the annual percentage contribution of different WBCs over the Chittar catchment. Figure 8 shows that ET has reported maximum during 2016 to 2018 with peak value of 84% (in 2018). This may come due to the severe metrological drought (due to failure north-east monsoon) hit over south India during 2016 – 2018 (Mishra et al. 2021). A further model predicting 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 share was reported because of a downpour of precipitation due to Nisha cyclone that struck Sri Lanka and South

India. 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 waste land share is about 30%) and increased imperviousness in the catchment. The surface runoff minimum and maximum contributions are 4 % and 50 % in the years 2016 and 2008, respectively. Typically, surface runoff is directly comparable with precipitation and inverse towards ET. This drift is expressed in the surface runoff peak; because it needs to collect the excess precipitation in overland flow and lateral flow. Then, it entered as the huge volume of water towards river body that led to flood inundation, soil erosion, landslide, etc. Similarly, the low surface runoff marking drought worse and increase the dependence on water wells. The percolation has a positive trend with surface runoff and negative trend with ET throughout 30 years period. Generally, percolation is less than surface runoff; however, in 2016, 2022, 2028, and 2030 percolation was almost equal or slightly more than surface runoff (Figure 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 the minimum compared to others. But it does not reach zero. The annual lateral flow share varies from 3 % to 13 %. The lateral flow is low during 2016 to 2020, and the remaining years are not showing much variation. The lateral flow is generally less than percolation due to the relative level surface of the catchment. At annual scale major portion of soil water storage and redistribution are controlled by the texture and structure of soil. Hence, soil water not showing much variation. However, the reported small variability may be in response to the spatiotemporal changes in annual precipitation over the catchment.

4.0 Conclusions

In this paper, SWAT was used as a tool to develop the monthly and annual water balance model for the Chittar catchment. The historical LULC of 2001, 2006, 2011, and 2016 were prepared and analyzed for assessing the changing pattern of the catchment. LULC was forecasted using the CA-ANN model. The model produced the good performance in validation (87 % of correlation) and the further used to forecast LULC of 2021 and 2026. The daily meteorological data for the period 2001 to 2020 was used to forecast future metrological variables by applying the smoothing moving average technique for the period 2021 to 2030. The parameters of water balance model were calibrated using the historical river discharge. The monthly scale WBCs were simulated from the model. Model validation had resulted NS and R^2 of 0.76 of and 0.81 respectively between the observed and simulated discharges. Model was further used to simulate WBCs from the year 2021 to 2030 to analyze the near future variability using the LULC and meteorological variables forecasted by CA-ANN and smoothing moving average method respectively. Some of the major conclusions drawn from the study are as follow:

1. The agricultural and built-up land are constantly increasing during the three decadal periods. The annual average reduction of water bodies over the catchment is about 0.75 sq. km/year. The forest land is the only subclass that underwent minimal changes. Both gain in built-up land and loss in the water body leads to an increase in surface runoff and reduction in lateral flow and percolation.

2. Out of the five WBCs, monthly precipitation shows maximum variation during historical (132 mm) and forecast (98 mm) periods respectively. The lateral flow shows the least variation among the five WBCs. The similar trend followed in annual scale also.
3. The monthly ET varies from 0.1 mm 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 supply of water to the soil, ET decreases rapidly. To limit the ET, selecting appropriate crop and irrigation methods are important for water conservation.
4. The annual average surface runoff, lateral flow, percolation, soil water content, and ET are 303.2 mm, 96.3 mm, 144.4 mm, 152.1mm, and 398 mm, respectively. Surface runoff and ET jointly consume about 65 % of annual precipitation. So, rainwater harvesting is necessary to mitigate the effects of drought and flood.
5. The precipitation, surface runoff, and ET are the three WBCs parameters controlling water availability. Overall the surface runoff, percolation, lateral flow, and soil water have a positive correlation with precipitation. The ET has a negative correlation with precipitation. From the simulation results, it is identified that ET and lateral flow have delays with precipitation.

Declarations

Ethics approval and consent to participate Not applicable

Consent for publication Not applicable

Availability of data and materials The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

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Authors' contributions DP did the modeling part, and wrote the first draft of manuscript. SK performed literature search, conceptualization of work and revision of the manuscript. KSK provided constructive comment to improve the manuscript and editorial comments on the draft report. MK provided supervision and suggestions on the revision of the manuscript. All authors read and approved the final manuscript.

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Tables

Table. 1 Model performance indices for monthly river discharge

Parameter	Calibration	Validation
Coefficient of determination	0.94	0.81
Nash- Sutcliffe	0.89	0.76
P-factor	0.98	0.60
R-factor	1.14	0.77
Percent bias	2.70	1.60
Root Mean Square Error	0.33	0.49

Figures

Figure 1

Figure 2

Location map of Chittar catchment

A) 2001

B) 2016

C) 2021

D) 2026

Forest
 Agricultural land
 Waste land
 Built up land
 Water bodies

Figure 3

Historical and forecasted LULC maps

a) Model calibration during 2001-2010

b) Model validation during 2011-2015

Figure 4

Monthly observed and simulated discharge at A P Puram gauging station

Figure 5

Areal contribution of LULC features in sq km

Figure 6

Chittar catchment scale monthly WBCs contribution (in mm)* *Highlighted bar in the figure describes the north east monsoon period that occur between the September to December every year

Figure 7

Annual WBCs and its moving trends

Figure 8

Annual percentage contribution of WBCs