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Assessing the necessity of water transfer using SWAT modelling

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ABSTRACT

Assessment of water resources potential through hydrological modelling is an essential work in managing hydrological extremes. This study focuses on assessing net water availability in the Left Bank Catchments of the Cauvery River Basin, Tamil Nadu, using the Soil Water Assessment Tool and Water Budgeting Method for the period from 2001 to 2020. The estimated average runoff volume obtained post calibration of the model is 2704 $Mm^{3,}$ with average total water demand 9620 Mm^3 per year, in which 74 % (about 2.6 times of average runoff) belongs to the irrigation water demand. Hence, a large quantity of water is required to minimize the deficit, and that can be achieved only by diverting flood water from the Cauvery River (at the downstream side of Mettur dam) through a canal combined with modern irrigation practices. Since the flood release alone is said to be diverted, it will not affect the regular flow in the river, and it will not disturb the current water transfer practices, and the food production will become sustainable in this area.

1. Introduction

The development, utilization, and conservation of water are vital for water resources planning [1]. Deficit of water arises due to rapid population growth & land use changes, combined with higher living standards challenge water security [2]. Rainfall is the primary water source, which is affected by spatial and temporal variations, orographic effects, and monsoons [3]. In India, the diverse topography and monsoonal systems cause uneven rainfall, which leads to floods and droughts, resulting in flood devastation in one part and water scarcity in the other. Further, failure of monsoon or reduced rainfall during the non-monsoon period leads to lean or no flow in the rivers [4]. Nowadays, water scarcity imposes significant challenges in rivers, and hence, comprehensive water management strategies become necessary [5]

With water demand rising sharply, India requires all of its surface runoff within the next two decades to meet urban and agricultural needs [6], and hence, conservation of the available water is crucial [7]. It is indeed for the development of the agricultural sector and to ensure food security [8,9]. To address this challenge, a proposal is made for river interlinking projects aimed at diverting water from surplus basins to deficit regions, ensuring adequate supply for its growing population [10]. The classic idea of Interlinking rivers, proposed by Sir Arthur Cotton (1919) and later refined by K.L. Rao (1970), seeks to transfer surplus water to deficit areas. During 1980, about 30 river linking projects were proposed in the National Perspective Plan (NPP) [11]. The National Water Development Agency (NWDA), established in 1982, studies inter- and intra-river links to transfer water from surplus to deficit regions and reduce imbalances [12]. Intra-Basin Water Transfer (IBWT) addresses scarcity by diverting water within a basin [13]which requires intense planning and coordinated efforts for execution

Accurate surface runoff estimation using hydrologic models that mathematically simulate real-world conditions is essential for planning and designing hydraulic structures [14]. Numerous models estimate surface runoff, among which HEC-HMS and SWAT are the most widely used, and they are open-source, globally tested, and well-documented models. SWAT is a sophisticated distributed model, effectively evaluates water availability across diverse and complex river basins [15]. Unlike many models, SWAT simulates crucial water balance parameters such as runoff, groundwater flow, evapotranspiration, and infiltration [16]. SWAT can be used for simulating water availability, water allocation strategies for irrigated agricultural systems [17,18]. It is used in decision-making for water transfer studies for the effective reduction of

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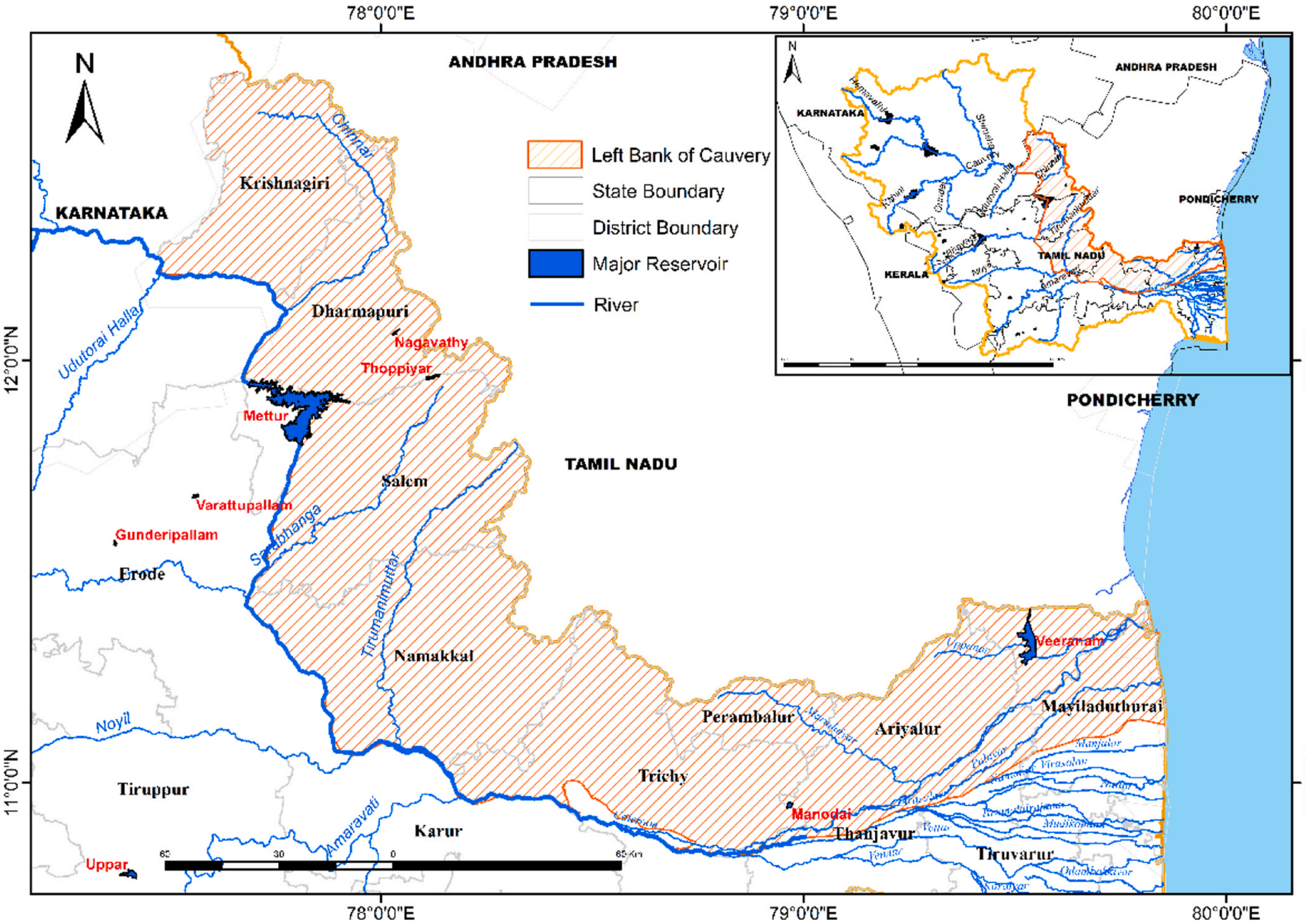

Fig. 1. Index map of the Left Bank of Cauvery (LBC) River Basin.

agricultural water shortages [19].

SWAT integrates with GIS platforms like Arc-SWAT and QSWAT for detailed spatial analysis and visualization. It subdivides basins into smaller sub-basins and computes Hydrologic Response Units (HRUs), which enhances model accuracy and supports basin-scale water resource assessment [20,21]. SWAT incorporates spatial variability in land use, topography, and soils to identify surplus and deficit zones. Its performance is enhanced through calibration tools such as SWAT-CUP, R-SWAT, and SWAT+ Toolbox. The R-SWAT is an open-source GUI in R, enables visualization, calibration, sensitivity analysis, and uncertainty assessment of the SWAT model [22]. All the above things make it exceptionally capable for IBWT feasibility assessments.

Most existing water transfer schemes emphasize inter-basin transfers, where surplus water is diverted from donor basins to deficit basins through extensive canal and reservoir networks [23]. Particularly, studies on projects such as the Ken–Betwa Link and the National River Linking Project have employed hydrological models such as SWAT and rainfall–runoff analysis to quantify water surpluses [24]. However, these studies generally assess donor and recipient basins separately, often overlooking persistent local water scarcity within the donor basin itself [25,26]. Consequently, unresolved intra-basin deficits can persist, undermining both the effectiveness and equity of such schemes. To address this critical gap, the present study undertakes a novel and comprehensive evaluation of water availability within the donor basin before considering external transfers. By applying the SWAT model and employing detailed water budgeting techniques at the sub-catchment scale, this research rigorously assesses net water availability, demand, and deficit. This work not only advances scientific understanding of basin-level water management but also underscores the necessity of meeting intra-basin water demands as a prerequisite for any sustainable and equitable water transfer strategy.

2. Study area description

The Cauvery River originates at the Talakaveri of Karnataka at an altitude of 1341 m [27]. It runs for about 800 km through Karnataka, Kerala, Tamil Nadu, and Puducherry, making it the eighth-longest river in India, and it drains into the Bay of Bengal. The Cauvery River Basin, also known as the Rice Bowl of India, spreads over 81.1×10^3 km^2, out of which 42.23 % lies in the State of Karnataka, 54.04 % in the State of Tamil Nadu, 3.53 % in the State of Kerala, and 0.19 % in Union Territory of Pondicherry. The basin exhibits a dendritic to sub-dendritic drainage pattern and is categorized as an eighth-order drainage system. Major tributaries joining the river are Harangi, Hemavati, Shimsha, Arkavati, Lakshman Tirtha, Kabbani, Suvarnavati, Bhavani, Noyil, and Amaravati. Totally 96 dams are constructed within the basin, with the main purpose to serve for irrigation within the basin. The Cauvery River basin experiences a tropical climate. The basin receives a major part of the rainfall during the South West Monsoon on its western side, and the eastern side of the basin receives rain in the North East Monsoon due to depressions in the Bay of Bengal [28]. The variation of annual average rainfall in the basin is found between 597 mm to 1167 mm. This study has been performed for the areas in the Left Bank Catchments (LBC) of the River Cauvery (Fig. 1) within the Tamil Nadu region. The LBC consists of five minor tributaries, namely, Chinnar, Sarabhanga, Thirmanimuttar, Marudhaiyar, and Uppanar.

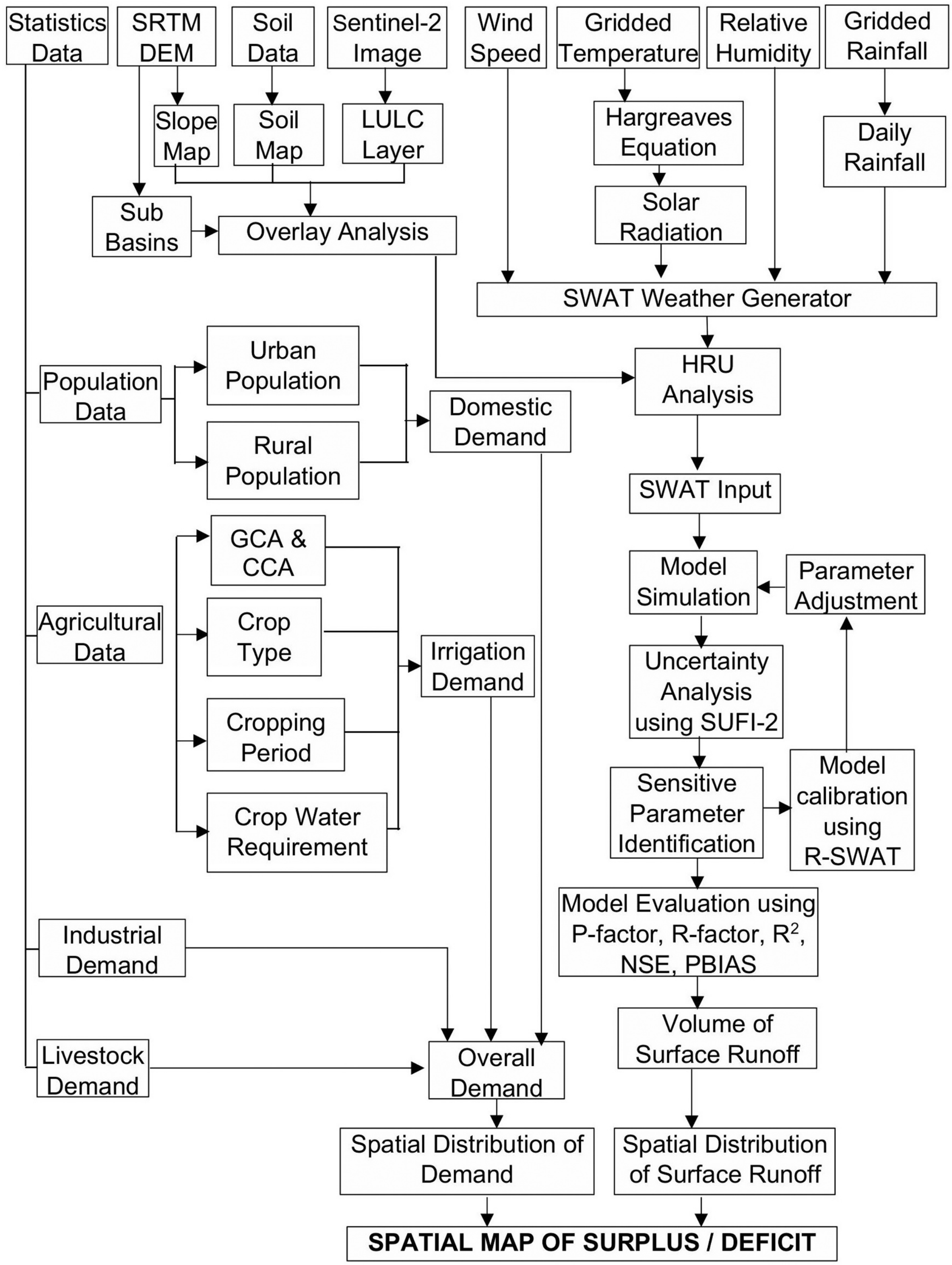

Fig. 2. Methodology flow chart.

3. Methodology

The study mainly focuses on identifying the subbasin that requires water using the SWAT modelling and the water budgeting method. The SWAT model runs on the basis of the elevation profile, hydrometeorological data, land use pattern, and soil profile. The Digital Elevation Model (DEM) data is used to develop the elevation, slope, and drainage network, which becomes the input for the hydrological modelling. Remote Sensing-based classified soil and Land Use and Land Cover (LULC) patterns are also given as input, which influences the response of the SWAT model. The hydrometeorological parameters, such as rainfall, air temperature (minimum and maximum), wind speed, relative humidity, and solar radiation, will be imported to the hydrological model.

The meteorological parameters and the various thematic layers are used to generate the Hydrological Response Units (HRU). Then the model simulation is carried out and its performance is assessed using dotty plots and graphs. If the model exhibits poor performance, then the model is again calibrated and re-simulated till the performance matches

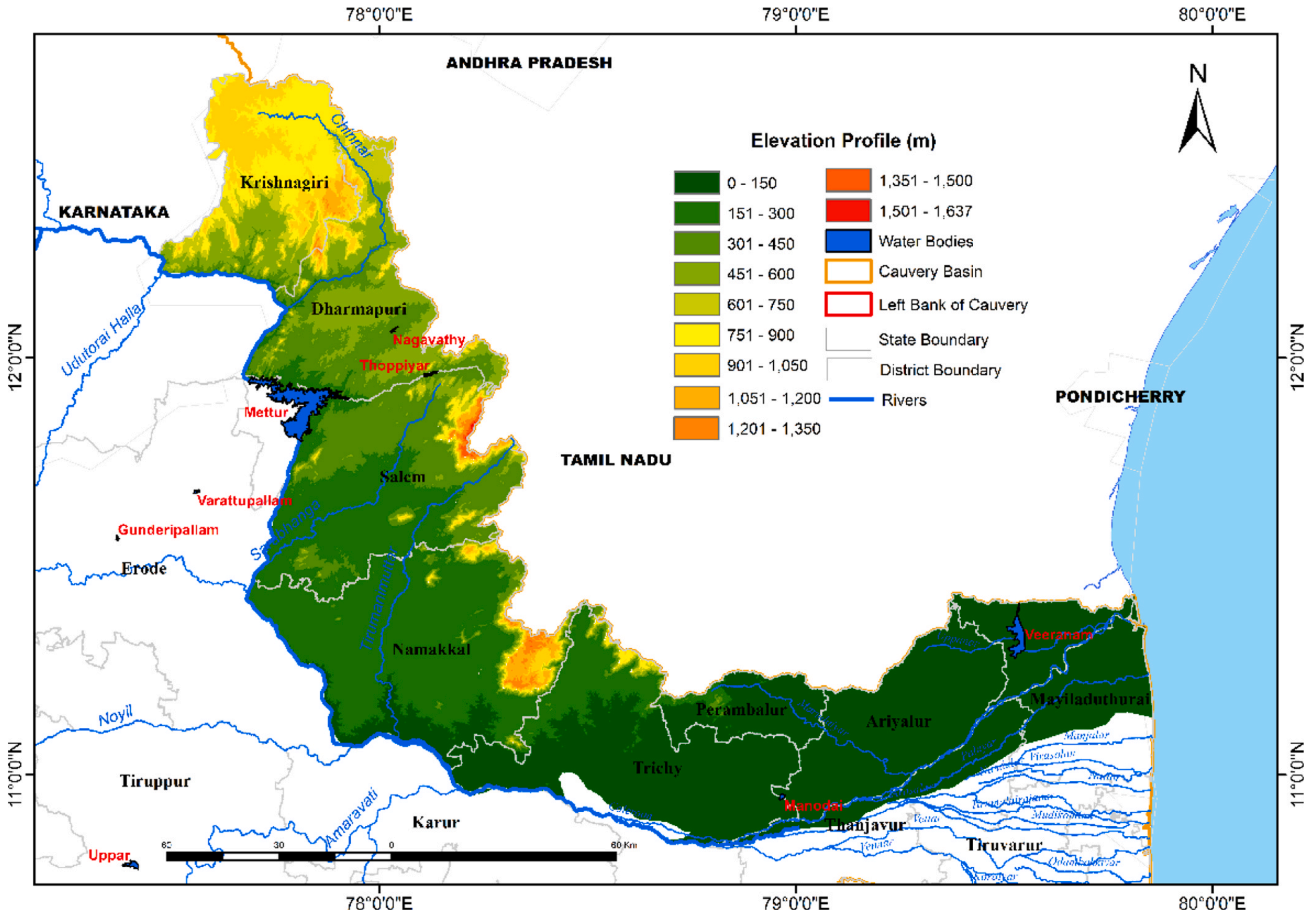

Fig. 3. Elevation Profile map of LBC.

the optimal value. After calibration of the model, the runoff volume generated, and then water budgeting at the catchment level is carried out. This provides the information regarding surplus and deficit zones within the basin. Based on the results, the possible mitigation measures for the deficit areas are suggested. The overall methodology to assess the necessity of water transfer within the basin using SWAT modelling is shown in Fig. 2.

3.1. Hydrologic conceptual modelling by SWAT

In the SWAT model, the watershed delineation, identification of Hydrological Response Unit (HRU), and entry of hydrologic parameters as input tables are done at the model initialization phase [29]. The estimation of runoff depth is done by adopting the Soil Conservation Service method [30]. The amount of surface runoff generated at the catchment scale is calculated by using the water balance equation, which is given by:

$$Q_{surf} = SW_0 + \sum_{i=0}^{n} (R_{day} - SW_t - E_a - w_{seep} - Q_{gw}) \quad (1)$$

SW_t is the final soil water content (mm),
SW_0 is the initial soil water content on day i (mm),
R_{day} is the amount of precipitation on day i (mm),
Q_{surf} is the amount of surface runoff on day i (mm),
E_a is the amount of evapotranspiration (ET) on day i (mm),
W_{seep} is the amount of water entering the vadose zone from the soil profile on day I (mm),
Q_{gw} is the amount of return flow on day i (mm).

Systematic adjustment of parameters and multiple iterations are done for calibration of the model until optimal matching of simulated and observed streamflow is obtained. This iterative procedure allowed for refinement of parameter values to improve the model accuracy. Further, the performance of the calibration is evaluated using statistical indices such as the Nash-Sutcliffe Efficiency (NSE), Percent Bias (PBIAS), and the Coefficient of Determination (R^2). The uncertainty analysis for model output is carried out by considering the P factor (% of observed data that comes under the 95 %age Prediction Uncertainty (95PPU) range) & the R factor (the indication of the width of the uncertainty range with respect to the standard deviation of the observed data). Then the runoff volume generated from each sub-basin, also known as available water, is estimated.

3.2. Assessment of water demand & net available water

The water demand for various sectors (irrigation, domestic, industrial, and livestock) is assessed at the sub-basin scale. The irrigation water requirement is calculated based on the type of crop, cropping period, and cropping area. Three categories of crops, such as major crops (paddy, cotton, maize, etc.), major millets (cholam, cumbu, ragi, etc.), and annual crops (sugarcane and banana), are used to calculate the irrigation demand. For drinking water demand, the population forecast is done for 2050 AD using the past census data [31] by taking per capita demand as 200 lpcd and 70 lpcd for urban and rural populations. The industrial water demand is taken as 100 % of the urban water demand and 172 % of the rural water requirement. 50 % of the rural drinking water requirement and the entire livestock demand are assumed to be met through groundwater [32]. Hence, 100 % of urban water demand, 50 % of rural water requirements, and 100 % of industrial water needs are met with the surface water potential. After calculating the surface

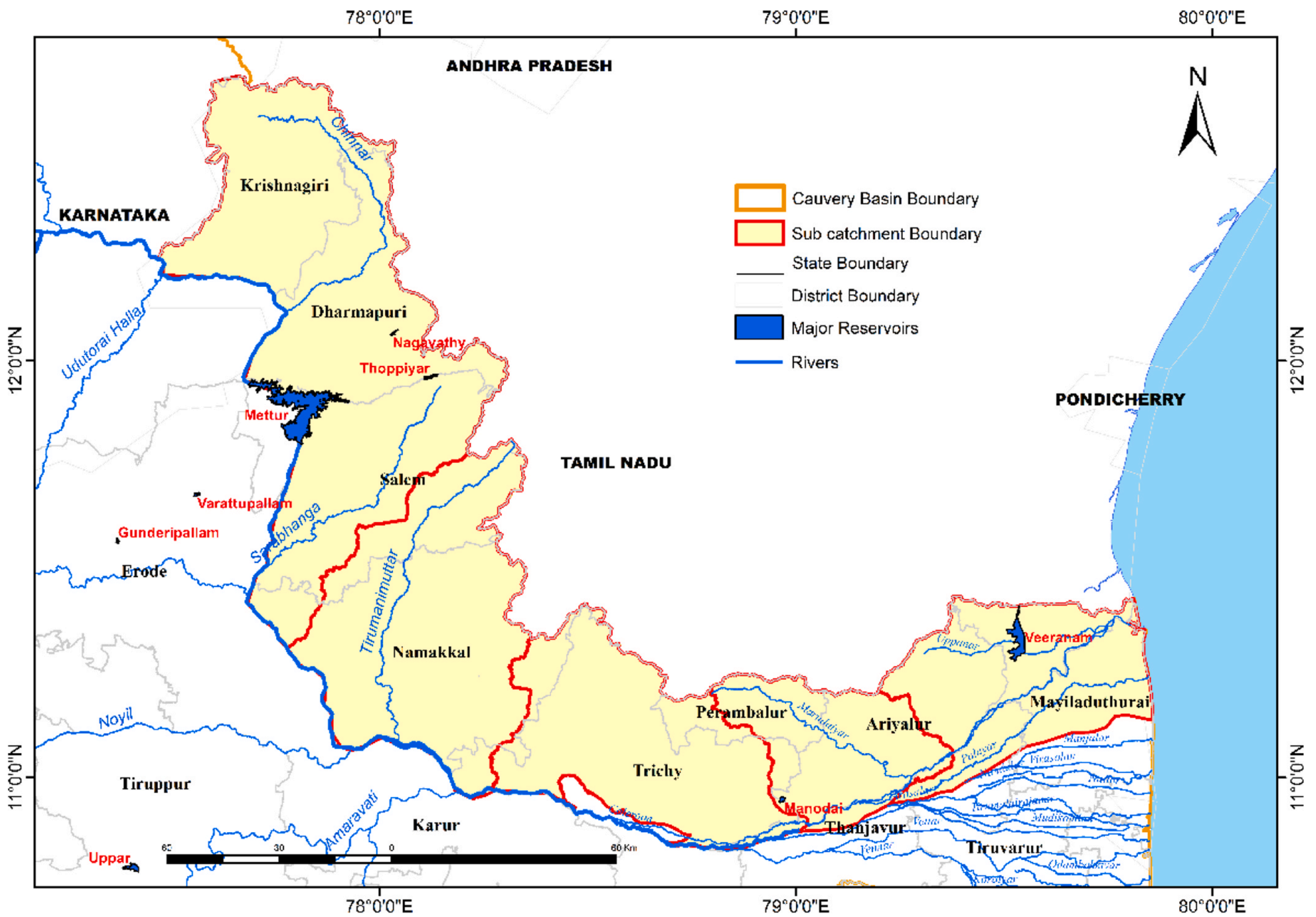

Fig. 4. Left Bank Catchments of Cauvery, Tamil Nadu.

water availability and demand, the spatial distribution of the net available, total water requirement, and the water deficit is found and converted into corresponding maps.

4. Results and discussions

The elevation profile (Fig. 3) of the study area is derived from the SRTM DEM obtained from the United States Geological Survey (USGS) with a spatial resolution of 30 m. Before modelling, the DEM is preprocessed by reprojecting into a consistent coordinate system suitable for hydrologic analysis and clipping to the watershed extent. This preprocessing ensured the creation of accurate sub-basin delineations and hydrologic response units. The catchments have been delineated based on the elevation profile (Fig. 4). The elevation varies from 2500 m to less than 5 m. The LULC classes have been found using the Sentinel 2 Imagery data at 10 m resolution (Fig. 5). The LULC pattern is dominated by agricultural lands (55.78 %), followed by forests (19.11 %), built-up area (13.51 %), rangeland (8.85 %), water (2.27 %), bare ground (0.33 %), and flooded vegetation (0.15 %). The FAO-UNESCO global soil data [33] is used to derive the soil map (Fig. 6). The study area mostly comprises soil types like sandy loam, loam, clay loam, and clay. The catchment-wise agricultural soil classification is also found using the Agritech portal of GoTN, and given in Table 1, from which it is clear that the non-calcareous red and black soils dominate the western and central regions, while alluvial, red loamy, and saline coastal soils are found in the eastern delta regions.

The meteorological datasets, such as rainfall and temperature, have been obtained from a gridded dataset of the India Meteorological Department with a spatial resolution of 25 km and 100 km, respectively. The average rainfall of the study area is found to be 926.2 mm, and the average maximum and minimum temperatures are 34.31°C and 17.15°C, respectively. No additional bias correction is applied to the IMD climatic data since it is derived from a dense network of observations using established spatial interpolation techniques, which already minimizes bias at the gridding stage. The gridding process ensures close alignment with observed station statistics, making further corrections insignificant. This approach is commonly adopted for high-quality observational grids in hydrological modelling [34]. The solar radiation is derived from air temperature by applying the Hargreaves equation [35], which is fed into the SWAT model. Once all the data inputs are given, the model simulation is performed. The HRUs are constructed using unique combinations of dominant land use, soil, and slope classes, resulting in 138 HRUs in total. Each HRU represents the most prevalent land use, soil, and slope within each subbasin, following standard practice for hydrological modelling [36].

4.1. Parameter sensitivity analysis in the SWAT model

The beginning of the simulation process is done after the development of HRU. The initial model results are used to identify the sensitive parameters based on the dotty plots (Fig. 7). The existence of a well-defined trend in parameter sensitivity analysis indicates that the parameter has a strong influence on model outputs, making it highly sensitive and crucial for calibration [37].

The dotty plot results show that CH_N2, CH_K2, and GW_DELAY are the most sensitive parameters for this study. CH_N2 (effective hydraulic conductivity in main channel alluvium) directly controls the rate at which water can move through the streambed material. A higher CH_N2

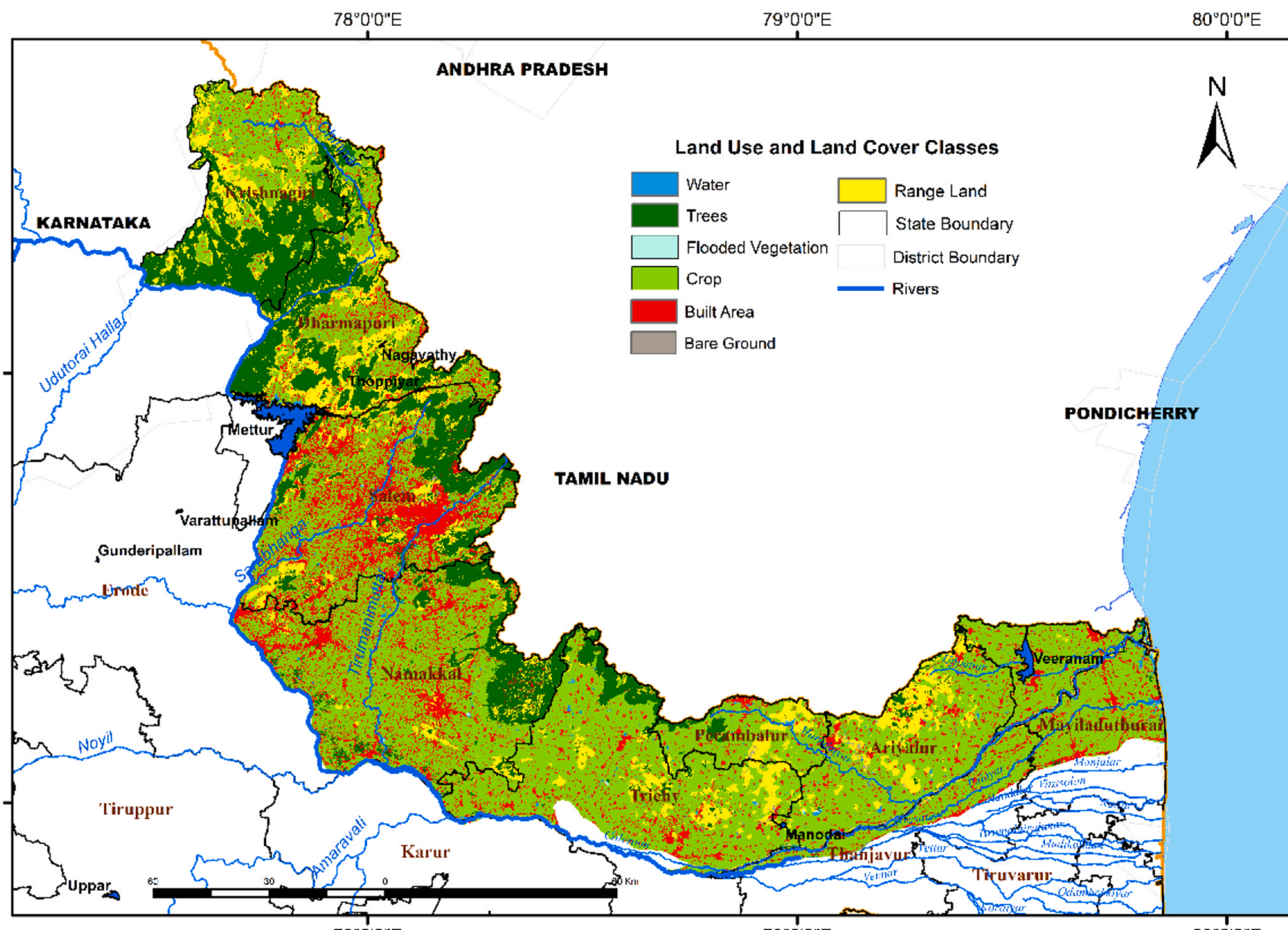

Fig. 5. Land Use Land Cover map of LBC.

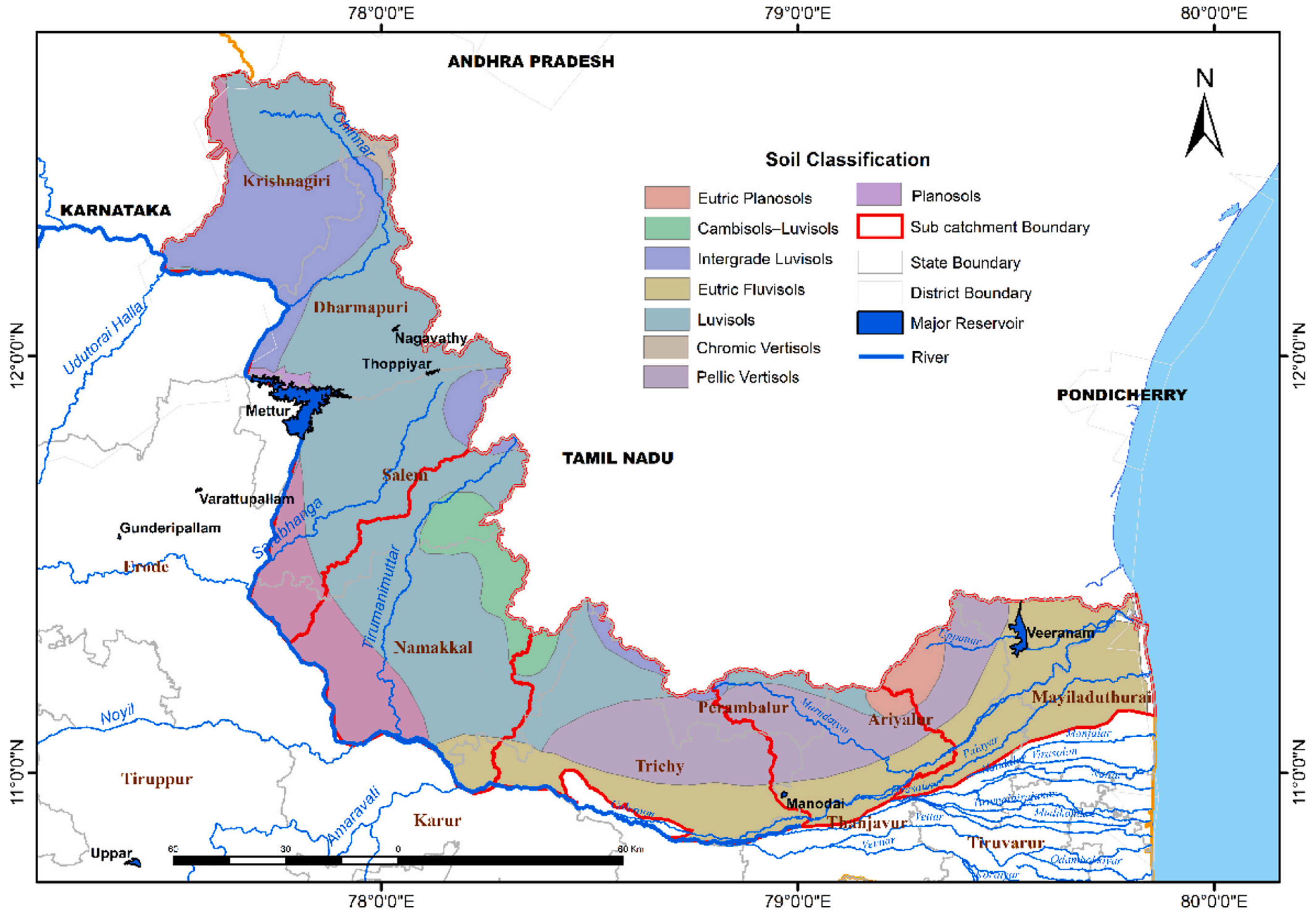

Fig. 6. Soil classification map of LBC.

Table 1
Agricultural soil classes in LBC, Cauvery River Basin (Agritech Portal).

Catchments	Districts Covered	Soil Type
Catchment 1	Krishnagiri, Dharmapuri	Non-Calcareous Red, Non-Calcareous Brown, Calcareous Black
Catchment 2	Namakkal	Non-Calcareous Red, Non-Calcareous Brown, Calcareous Black, Red Loamy, Black
Catchment 3	Trichy	Red Loamy (New Delta), Alluvium (Old Delta)
Catchment 4	Perambalur, Ariyalur	Red Loamy, Black, Red Loamy (New Delta), Alluvium (Old Delta)
Catchment 5	Cuddalore, Mayiladuthurai	Red Sandy Loam, Clay Loam, Saline Coastal Alluvium, Red Loamy (New Delta), Alluvium (Old Delta)

leads to increased transmission losses from the channel, reducing surface runoff and streamflow, and vice versa. CH_K2 (Manning's 'n' value for the main channel) determines the roughness of the main channel, affecting flow velocity. Higher CH_K2 values represent rougher channels, slowing down water movement and increasing travel time, which can delay and flatten the hydrograph peaks. GW_DELAY (groundwater delay in days) controls the lag between water percolating into the shallow aquifer and its appearance as baseflow in the stream. A longer GW_DELAY means a delayed baseflow response, affecting the low-flow periods and the persistence of flow during dry spells.

4.1.1. Uncertainty analysis

Out of 20 years, three years (2004–2006) are taken as a warm-up period for the model. A total of 50 simulations were done by altering the most sensitive parameter values until a match between simulated and observed flow at the Musiri gauging station occurred. The SUFI-2 algorithm is used to check the uncertainty of the model, which is represented by a shaded region of the curve (defined as the 95 PPU in Fig. 8). The goodness-of-fit and efficiency of the model are tested using R^2, NSE, and PBIAS (Table 2). Since the study area is a large basin, more variation of parameters and insufficient data availability at the micro level contribute towards the uncertainty of the model, which is reflected in the statistical analysis of the model output.

The various components of the water balance (precipitation [PREC], surface runoff [SURQ], groundwater contribution [GWQ], evapotranspiration [ET], lateral flow [LATQ], and water yield [WYLD]) obtained as model output are plotted (Fig. 9). The decadal rainfall variation during 2001–2010 and 2011–2020 is found to be 935 mm and 880 mm, respectively. The result shows that the rainfall is following a decreasing trend in the last decade. The evapotranspiration (ET) and water yield (WYLD) exhibit significant fluctuations, peaking around 2011–2013, indicating a response to precipitation dynamics. No significant variation of lateral flow (LATQ) over the entire period. Whereas the groundwater contribution (GWQ) and surface runoff (SURQ) display varying trends, with GWQ showing a gradual increase and SURQ fluctuating over the study period. The multiyear mean of these parameters was found to be REC (mm) = 1297.06 mm, SURQ = 291.18 mm, LATQ = 56.47 mm, GWQ = 302.94 mm, ET = 548.82 mm, and WYLD = 568.82 mm.

The SWAT model simulation revealed a heterogeneity in surface runoff across 138 sub-watersheds, ranging from 0 mm to 730.99 mm. It is found that 39.9 % of sub-basins with low runoff (50–100 mm), while 8.0 % exhibited very high runoff (>300 mm). Mass balance analysis shows that the model performance shows a deficit of −159.9 mm (17 %)

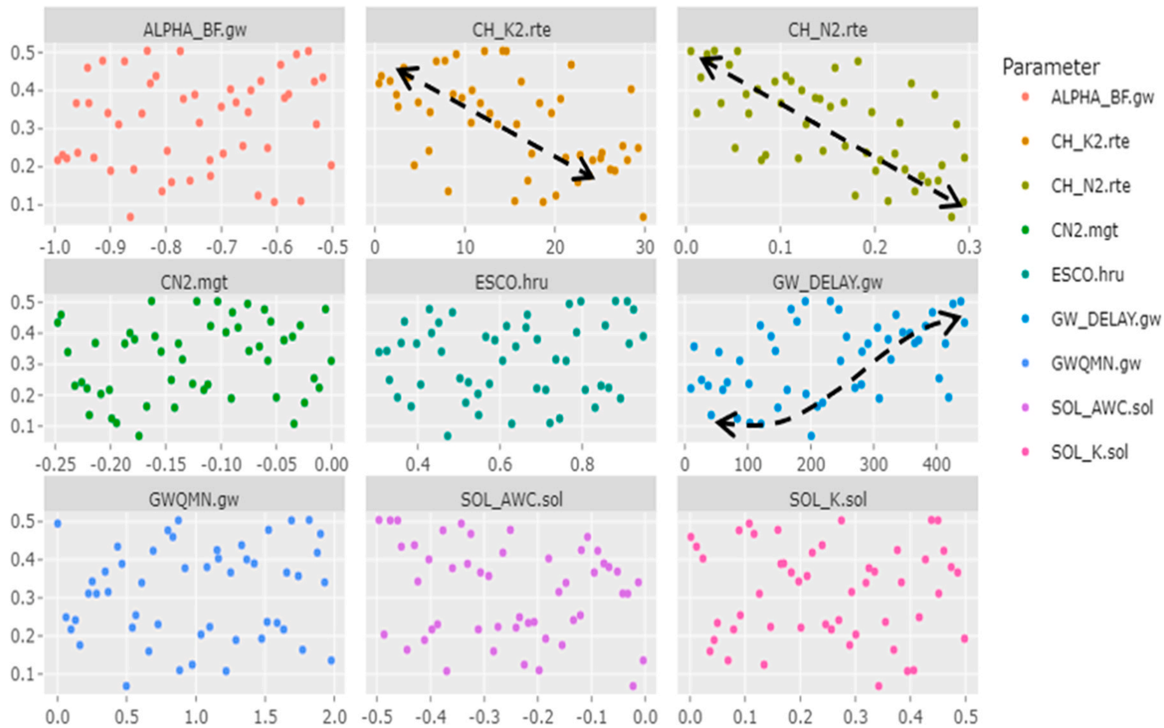

Fig. 7. Dotty Plots for Parameter Sensitivity Analysis.

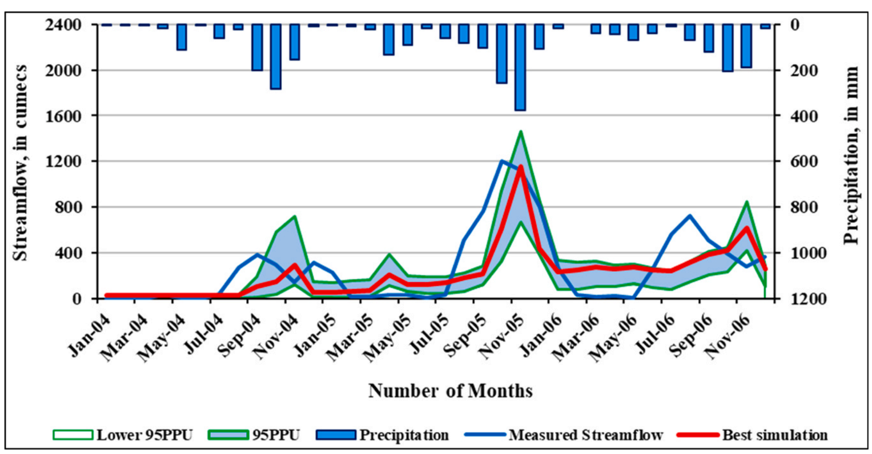

Fig. 8. Graphical Model Evaluation from the SUFI-2 calibration technique.

Table 2
Evaluation of the SWAT model calibration performance every month.

Calibration Method: SUFI-2	Constituent: Streamflow, a calibration variable.				
	Evaluation statistics				
No. of simulations: 50 (Singh et. al., 2023)	**P-factor** 50 %	**R-factor** 0.89	**R^2** 0.51	**NSE** 50.2 %	**PBIAS** 3.6 %

compared to the inflow precipitation (926.2 mm). This range of error is found to be common when compared to previous studies on SWAT models, and it is acceptable for large, complex, or data-limited basins. [38]. The performance metrics of the SWAT model with an R^2 in the range of 0.50 are considered for monthly SWAT simulations based on the experiences from the previous studies [39], where the model balances its reliability against the integral uncertainties. Continental scale applications in Europe similarly adopted moderate R^2 thresholds (0.50–0.60) alongside narrow uncertainty envelopes (P-factor > 0.60, R-factor < 1.5) to maintain model generality across diverse hydrologic settings [40]. For Indian basins with sparse meteorological networks [41] achieved $R^2 = 0.51$ and NSE = 0.50, underscoring that these “good-enough” statistics reliably capture essential hydrologic behaviours despite data limitations.

4.2. Estimated surface runoff volume

The study concerning with estimation of runoff volume generated over the LBC is presented in Table 3. The estimated depth of surface runoff over the left bank catchments of the Cauvery Basin shows a significant variation in runoff generated (Fig. 10). A decreasing trend of the depth of surface runoff exists as the catchments move away from the coast. The average depth of runoff generated from catchment 5 is very high and very low at catchment 1, since the former is very near the coast and the latter is located far away. Even though catchment 1 is spread

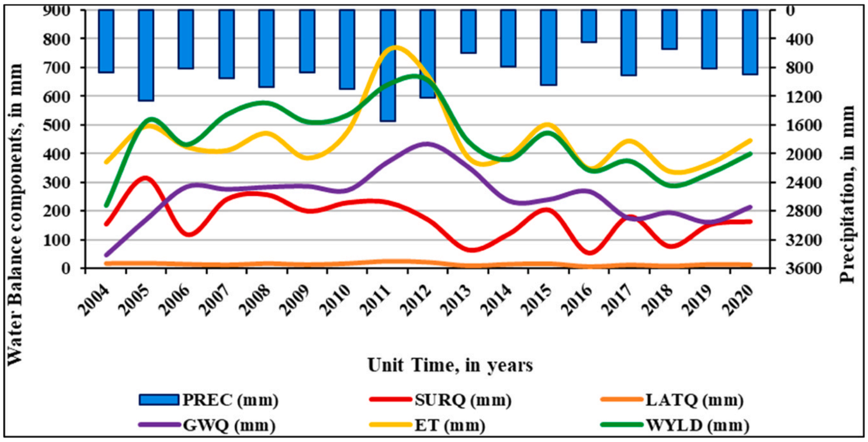

Fig. 9. Time series plot for simulated hydrologic cycle elements.

Table 3
Estimated Runoff Volume in Left Bank Catchments.

Catchments	Catchment Area (km^2)	Avg. Depth of Runoff (mm)	Runoff Volume (Mm^3)
Catchment 1	6376.77	94.44	602.23
Catchment 2	4826.18	106.31	513.05
Catchment 3	3015.88	108.68	327.75
Catchment 4	1648.39	280.59	462.52
Catchment 5	2103.88	379.73	798.91
Total runoff volume in LBC of the Cauvery River			**2704.47**

over a larger area (6376.77 km^2), it contributes about 22.27 % of the total runoff volume. In contrast, Catchment 5, with a smaller area of 2103.88 km^2, generates the highest runoff volume at 798.91 Mm^3 , accounting for 29.53 % of the total. This may be due to the presence of the locations near the coastal region, where intense rainfall events are common due to the tropical depression created during the northeast monsoon. The catchments 3 and 4 contribute only 12.12 % and 17.10 % to the total runoff, despite covering 16.78 % and 9.17 % of the total area under study, due to the poor rainfall distribution over the area, which reduces surface runoff generation.

4.3. Assessment of water demand

The irrigation water requirement is grouped under three categories for each catchment. For this, the district-wise data on area under each crop is obtained from statistical data [42] and converted into the catchment level. Similarly, the domestic water requirement of urban and rural areas is calculated separately for 2050 by projecting the 2011 census data. The catchment-wise industrial water need is also calculated as per the NWDA. The total water demand of all the catchments within the study area is presented in Table 4. The estimated total water demand for the study area is about 9620.88 Mm^3, comprising irrigation, domestic, and industrial needs. Among these, irrigation water demand is dominant, accounting for approximately 74 % (7084.56 Mm^3) of the total. The results (Fig. 11) show that Catchment 5 has the highest water demand in the agricultural sector since it covers the Cauvery delta region, where extensive agriculture is practiced. The catchments 3 and 4 have the least irrigation water requirement due to fewer agricultural practices in that area. This area receives less rainfall compared to other parts of the basin, since both are located far away from the delta & coast. The maximum domestic water demand (urban and rural) is estimated for catchments 1 & 2, which is mainly due to the urbanized industrial areas of the Krishnagiri and Dharmapuri districts of Tamil Nadu. Whereas catchment 5 falls under major agricultural areas and shows a lesser domestic water demand.

4.4. Net available water at LBC

The net available water at LBC is calculated by subtracting the water demand from the surface runoff volume generated (Table 5). The estimation of net available water for the LBC of the Cauvery River basin reveals that a severe deficit occurs across all five catchments (Fig. 12), with deficits varying around 70 %. This indicates that a substantial portion of the water demand in each catchment remains unmet by the locally generated surface runoff. Catchment 3, which consists of regions like Trichy and Perambalur, faces the highest stress, meeting only about 22.5 % of its total requirement. Even the catchment with the highest runoff (Catchment 5) suffers a deficit of 67.52 %. Overall, the LBC of the Cauvery River basin can meet only around 28 % of its total water requirement through surface runoff resulting from the rainfall. Based on the net water availability, the overall water deficit is about 6916.415 Mm^3, which is about 71.89 % of total demand.

This water deficit directly affects the water availability for agricultural activity, and hence, the cropping area will get reduced automatically, causing reduced food production. This is evident from the other studies that there is a deterioration of the production of crops due to a reduction in irrigation water availability in the Cauvery irrigation system, which causes the farmers to grow only once a year. A decline in irrigation productivity at the Cauvery delta system is reported in the CARDS Report [43], by means of calculating the total productivity factor index during the study period, 1976–2005. From another study, the rice production in the study area is not sufficient for the state of Tamil Nadu, where rice is a staple food for the people, which leads to food insecurity [44]. The rainfall deficit and delayed surface water irrigation results in crop failure due to crop stress [45].

4.5. Strategies for effective water management

Left Bank Catchments (LBC) of the Cauvery River Basin have a critical imbalance between irrigation water demands and locally produced runoff supplies. The estimated total water demand from irrigation in the LBC amounts to 9297 Mm^3 , but basin-runoff annually produced amounts to only 2704 Mm^3 . This significant deficiency categorically makes the LBC a water-stressed region. This situation needs to be overcome through structural and managerial amendments with the goal of equitable water allocation and sustainable farming in the fertile area. The cultivable area of the LBC is approximately 9884 km^2, but coverage with irrigation is exceedingly uneven. As per the statistics data of the

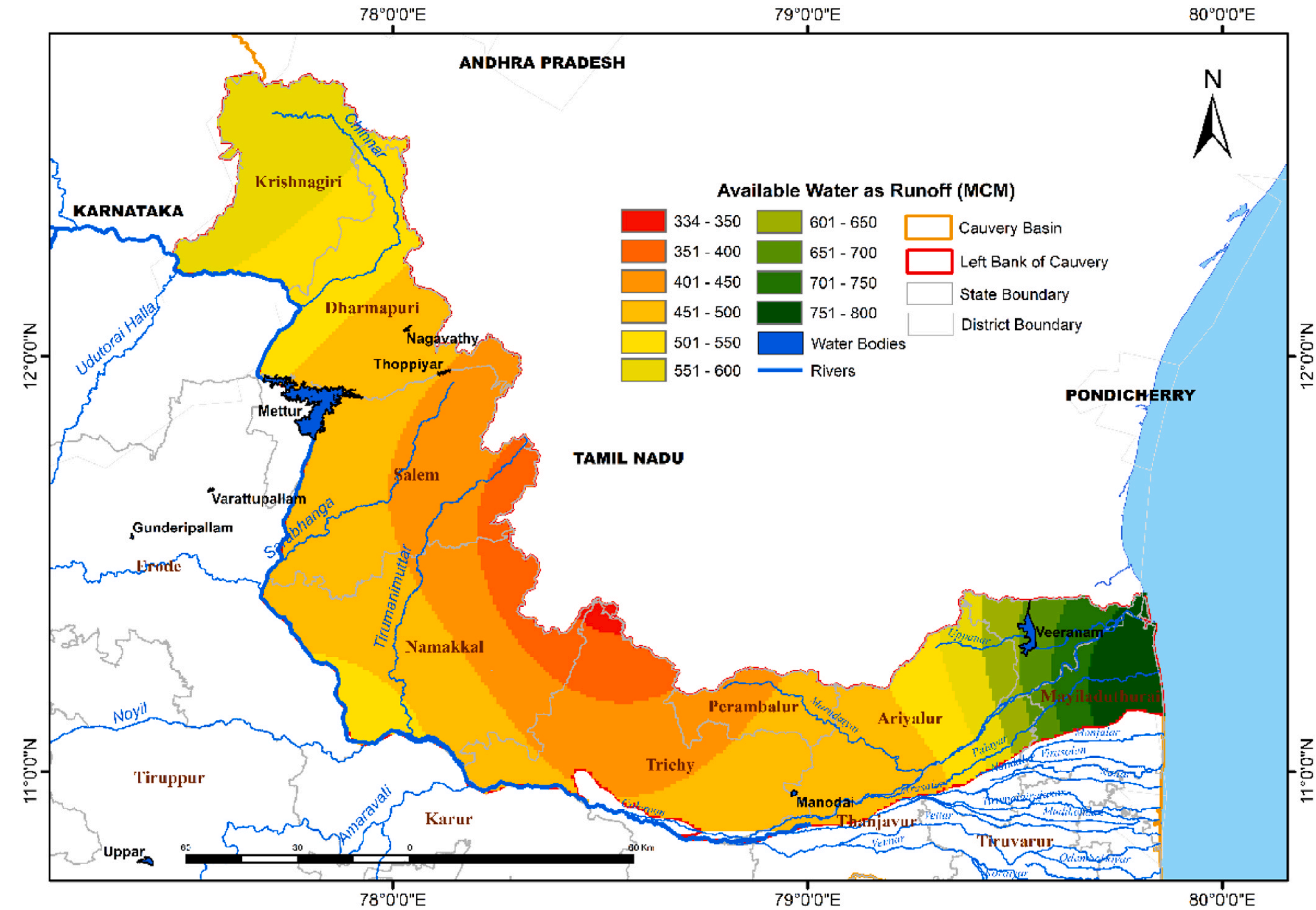

Fig. 10. Variation in Surface Runoff Volume at the LBC.

Table 4
Estimation of Water Requirement.

Catchments	Catchment Area (km^2)	Irrigation Water Requirement (Mm^3)			Domestic Water Requirement (Mm^3)		Industrial Water Requirement (Mm^3)	Total Water Demand (Mm^3)
		Major Crop	Millets	Annual Crops	Urban	Rural		
Catchment 1	6376.77	1456.77	526.41	145.56	23.53	34.54	46.305	2233.115
Catchment 2	4826.18	717.34	729.17	309.54	19.87	29.19	39.125	1844.235
Catchment 3	3015.88	1062.42	229.36	103.92	13.96	20.5	27.480	1457.640
Catchment 4	1648.39	1517.09	15.99	68.08	5.72	8.41	11.270	1626.560
Catchment 5	2103.88	2330.94	7.74	76.89	9.85	14.49	19.415	2459.325
Total	**17971.10**	**7084.56**	**1508.70**	**703.99**	**72.93**	**107.10**	**143.595**	**9620.875**

Government of Tamil Nadu, only1.4 % of the area is covered with traditional tank-based systems, while 16 % is covered with canal-based irrigation. More than half of the cultivable area (51.1 %) is covered with groundwater and well-based irrigation, which constitutes an unsustainably high level of dependence on the extraction of the aquifers. Alarmingly, 31.2 % of the cultivable area is rainfed with sole dependence on rainfall. Cropping in these areas is consequently highly sensitive to fluctuations in the climate, particularly during lean monsoons. These indicate the necessity to establish an efficient water resource management scheme to transform rainfed lands into irrigated, productive agriculture.

The possible ways to overcome this situation is the application of precision irrigation coupled with innovative methods, and water transfers from surplus areas. Precision irrigation technologies such as drip and sprinkler irrigation have been found to reduce water utilization by up to 30 % compared with classical flood-based irrigation technologies [46] If applied across 50 % of the total area of cropping, the potential irrigation requirement could go down from 9297 Mm^3 to 6508 Mm^3 . However, the demand still exceeds the volume of available runoff. Furthermore, widespread utilization of precision technologies implies high initial outlays on capital, technical labour, and regular maintenance, all of which limit the feasibility of pursuing the above approach individually in the LBC.

Against these constraints, water transfer from surplus areas becomes a more viable and sustainable alternative. Recent Hydrological data indicate that discharges in rivers and inflows to reservoirs in India over the past few years were greater compared to the average [47]. Furthermore, according to the Central Water Commission's National

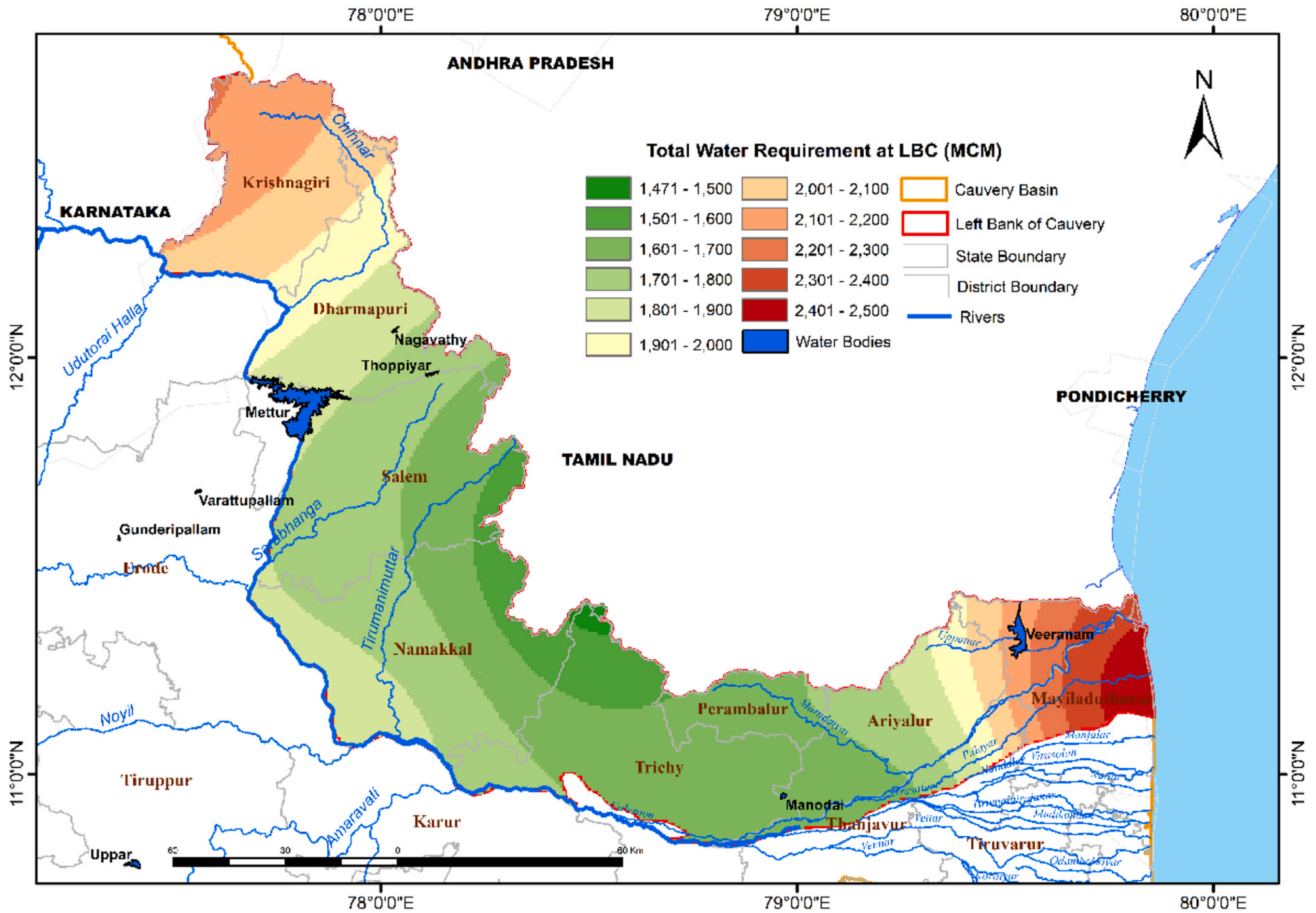

Fig. 11. Variation of water requirement at the LBC.

Table 5
Net Available Water in LBC of Cauvery River Basin, Tamil Nadu.

Catchments	Runoff Generated (Mm^3)	Total Water Requirement (Mm^3)	Net Available Water (Mm^3)	% Deficit
Catchment 1	602.23	2233.115	−1630.885	−73.03 %
Catchment 2	513.05	1844.235	−1331.185	−72.20 %
Catchment 3	327.75	1457.640	−1129.890	−77.52 %
Catchment 4	462.52	1626.560	−1164.040	−71.56 %
Catchment 5	798.91	2459.325	−1660.415	−67.52 %
Total	**2704.46**	**9620.875**	**−6916.415**	**−71.89 %**

Water Mission, the Mettur Dam has an outflow during flooding every three years or so. These infrequent high flows currently pass unnoticed to the downstream reaches and ultimately drain into the sea. Since the water-deficit areas of the LBC are found within the Cauvery basin, downstream of the Mettur Dam, these areas can be converted into agriculturally richer areas by diverting the water only during the high flows and the Mettur dam surpluses, through an artificial canal system as an Intra Basin Water Transfer (IBWT) scheme.

Since the water diversion plan must be executed only during the flood release from the Mettur Dam, which occurs only for a few days in a year, this will not affect the utilization from the upstream to the tail end of the Cauvery River. This assures equitable sharing across the entire basin while simultaneously enhancing agricultural resilience across the LBC. In addition, while coupled with precision irrigation in command regions receiving IBWT, water use efficiency too would be encouraged to the fullest. Reduced water use per hectare in such areas would also facilitate greater command area expansions, enhancing the dividends from diversion even more. This integrated solution, capturing the supply-augmentation potential of IBWT during flood seasons and the demand-side efficiency of precision irrigation, constitutes a synergistic solution for LBC. It allows more area of cultivability to shift from rainfed to reliable irrigation, stabilizing yields, and securing food in this critical farm belt region. Since water transfer from surplus to deficit areas is crucial, it is proven that it alleviates water scarcity and enhances agricultural productivity. It also plays a significant role in improving water security and supporting sustainable socio-economic development by mitigating drought and flood impacts [48], [49]. The adoption of IBWT in LBC, in particular, is likely to reduce irrigation deficits considerably, boost cropping intensity, and achieve sustainable agriculture in Tamil Nadu's fertile farming plains, also known as the Rice Bowl of India.

5. Conclusions

The study quantified the water availability and irrigation demand in the Left Bank Catchments (LBC) of the Cauvery River Basin using the SWAT model and a water budgeting approach. The analysis revealed pronounced spatial variations in runoff, with annual depths ranging from 94 mm in the upper catchments to 379 mm near the coast. The basin's total runoff (2704 Mm^3) meets only about 28 % of the irrigation demand (9297 Mm^3), confirming a critical water deficit that threatens agricultural sustainability. To address this imbalance, two complementary strategies were evaluated. Precision irrigation can reduce water demand by nearly 30 %, enhancing field-level efficiency, but its large-scale adoption is limited by economic and technical constraints.

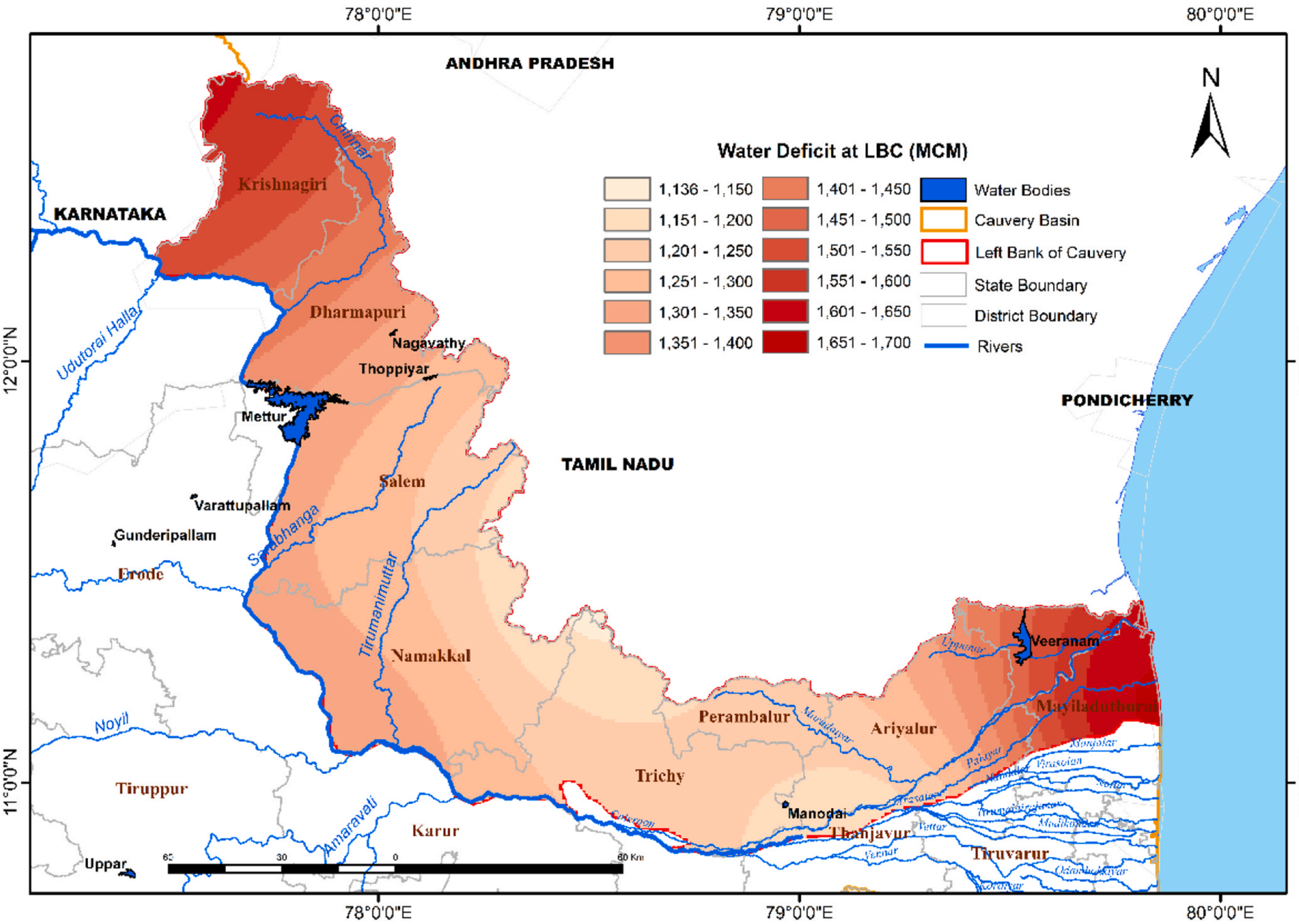

Fig. 12. Distribution of net available water at the LBC.

Alternatively, intra-basin water transfer (IBWT) of surplus floodwaters from the Mettur Dam offers a feasible means to augment supplies during high-flow periods without affecting downstream users. An integrated approach that combines IBWT with precision irrigation is therefore recommended to stabilize agricultural productivity, reduce groundwater dependence, and improve overall water use efficiency in the LBC. Future studies should emphasize detailed canal alignment design, socio-economic viability, and environmental assessments to ensure the sustainable implementation of this strategy.

Author declarations

Not applicable.

Code availability

Not applicable.

CRediT authorship contribution statement

Vijay Aravinth Radhika Panchabikesan: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Sudharsanan Rajagopalan:** Writing – review & editing. **Ravikumar Govindasamy:** Supervision. **Kailasanathan Balamurugan:** Literature Survey, Methodology, and Formal analysis.

Consent for publication

Not applicable.

Consent to participate

Not applicable.

Ethics approval/declarations

Not applicable.

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Declaration of Competing Interest

All authors declare no competing financial or personal interests that could inappropriately influence or bias the content of this manuscript.

Data availability

Data will be made available on request.

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