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Enhancing hydrologic modelling through the representation of traditional rainwater harvesting systems: A case study of water tanks in South India

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Abstract

Water tanks as traditional rainwater harvesting systems for agriculture are widely distributed in South India. They have a strong impact on hydrological processes, affecting streamflow in rivers as well as evapotranspiration. This study aims at an accurate representation of water harvesting systems in a hydrologic model to improve model performance and assessment of the catchment water balance. To this end, spatio-temporal variations of water bodies between the years 2016 and 2018 and the months of January and May 2017 were derived from Sentinel-2 satellite data to parameterize the water tanks (reservoir) parameters in the Soil and Water Assessment Tool (SWAT+) model of the Adyar basin, Chennai, India. Approximately 16% of the basin is covered by water tanks. The initial model performance was evaluated for two model setups, with and without water tanks. The best model run was selected with a multi-metric approach comparing observed and modelled monthly streamflow for 5000 model runs. The final model evaluation was carried out by comparing estimated water body areas by the model and remote sensing observations for January to May 2017. The results showed that representing water tanks in the hydrologic model led to an improvement in the representation of the seasonal variations of streamflow for the whole simulation period (2004–2018). The model performance was classified as good and very good for the calibration (2004–2011) and validation (2012–2018) periods as NSE varies between 0.67 and 0.85, KGE varies between 0.65 and 0.72, PBIAS varies between −24.1 and −23.6, and RSR varies between 0.57 and 0.39. The best fit was shown for the high and middle flow segments of the hydrograph where the coefficient of determination (R^2) ranges from 0.81 to 0.97 and 0.75 to 0.81, respectively. The monthly variation of water body areas in 2017 estimated by the hydrologic model was consistent with changes observed in remote sensing surveys. In summary, the water tank parametrization using remote sensing techniques enhanced the hydrologic model's efficiency and applicability for future studies.

KEYWORDS
hydrologic model, Indian water tank, remote sensing, reservoir, SWAT+, water harvesting

1 | INTRODUCTION

The Indian summer and winter monsoons result in strong wet and dry seasons. These specific climate conditions have led to the development of water storage and diversions structures for better management of water resources (Jain & Kumar, 2014). Therefore, rivers in India have been substantially influenced by anthropogenic activities over the past centuries. According to Shah and Kumar (2008), more than 4635 large dams with high storage volumes have been constructed in India. Alongside this, traditional water tanks with relatively small storage capacities have been introduced in South India, mainly for water management and irrigation of agricultural fields. The spatial density of small reservoirs in Indian basins is around 4.2 reservoirs per km^2 (Rabelo et al., 2021). Although the primary purpose of water tanks is irrigation, they also contribute to groundwater recharge, flood control, and minimization of sediment yields (Berg et al., 2016; Mamede et al., 2018). Although the connections between water tanks might be broken during the non-monsoon periods, the dead storage of water behind the tanks contributes to the functioning of ecosystems (e.g., fish habitat) as reported by Ariza-Montobbio et al. (2007). In Sri Lanka, water tanks systems date back to ancient times (since the 5th century BC) and nowadays expanded throughout the whole country to provide a reliable source of clean water and irrigation water, reducing the risk of flooding and mitigating the impact of droughts (Bebermeier et al., 2023; Mahatantila et al., 2008; Saase et al., 2020; Schütt et al., 2013). The tanks are traditional retention storages that are usually made by damming intermittent streams using crescent-shaped earthen bunds in a cascaded or isolated manner (Massuel et al., 2014; Palanisami, 2022). They are constructed as rainwater harvesting structures to store rainwater during the monsoon (rainy) season and release it during the non-monsoon (dry) season (Singh et al., 2014). The tanks are either fed by a channel that connects the tank to a river in the rainy season or they are fed by rainwater. Depending on the land topography, tanks have different depths and sizes. The available water in the tank defines how many of the downstream fields can be irrigated, for example, after sufficient monsoon rainfall all fields may be irrigated, whereas, after a weak monsoon, irrigation water may only be sufficient to irrigate one or two fields close to the tank. Hence, these tanks have a strong effect on crop growth, evapotranspiration, lateral flow, river runoff, and generally on hydrological processes. Water use leads to limited or no water flow in the rivers in the dry season. So far, tanks are widely neglected in catchment modelling studies, which may be explained by missing spatially distributed information. Hence, a precise knowledge of tank water irrigation systems and their spatial distributions is essential to understand hydrological processes in South India. Quantification of the hydrological properties of Indian water tanks (estimating water storage and storage variation) through field surveys is effortful and prohibitive as both surface water area and bathymetry are required.

Challenges that hydrologists have been facing in data-scarce regions (e.g., India) due to limited or incomplete observations can be partly compensated using satellite images (Machiwal et al., 2011). Remote sensing techniques are increasingly useful tools to monitor and characterize changes on the earth, particularly in the field of hydrology (Thakur et al., 2017). An increasing number of satellites with different products and purposes are used for observing natural phenomena (i.e., precipitation, evapotranspiration, soil moisture, snow properties, water storage and water volume changes, land surface temperature, river width, etc.) that provide a valuable contribution to hydrological predictions and modelling (Lettenmaier et al., 2015). Deriving statistical and hydrological properties of reservoirs and lakes (e.g., surface water areas, water volume and storage) from satellite images is possible these days (Gao, 2015; Gao et al., 2012). Estimation of surface water extent can be achieved using optical sensors, such as Landsat (Zhai et al., 2015), Synthetic Aperture Radar (SAR) sensors, RADARSAT (Hong et al., 2015), and the Moderate-Resolution Imaging Spectroradiometer (MODIS) (Khandelwal et al., 2017; Ling et al., 2020). As a primary advantage, Landsat has a higher spatial resolution (30 m), but it is susceptible to cloud cover contamination and has a low frequency of observations (16 days) in comparison to MODIS with coarse resolution and daily coverage (Li et al., 2016).

Hydrologic models can better represent hydrological processes within the catchment with the help of large-scale spatially distributed data provided by remote sensing techniques (Xu et al., 2014). The Soil and Water Assessment Tool (SWAT, Arnold et al., 2012) is a hydrologic model that has often benefited from hydrologic remote-sensing products (Kundu et al., 2017; Parajuli et al., 2018; Patil & Ramsankaran, 2017; Wagner et al., 2012). Moreover, the model has the capability of adequately representing hydrological processes considering reservoir and hydro-infrastructure parameters (Abouabdillah et al., 2014; Mahmoodi et al., 2020). It has been recently restructured by Bieger et al. (2017) (SWAT+) to provide more flexibility to model catchment specific details. Decision tables embedded in the SWAT+ model allow for rule sets and their corresponding operations (Arnold et al., 2018). With the list of conditions considered in the decision tables, the model can efficiently represent complex, rule–based management such as volume and timing of reservoir releases (Arnold et al., 2018; Chawanda et al., 2020). This study aims at (i) investigating the capabilities of the SWAT+ model to represent dense networks of South Indian water harvesting systems (water tanks) with the help of remote sensing data, and (ii) evaluating the influence of water harvesting systems implementation on streamflow simulations.

2 | MATERIALS AND METHODS

2.1 | Study area

The Adyar river basin is located in the northern part of the state of Tamil Nadu, India. The Adyar River with a length of 42.5 km mainly originates from a group of shallow and deep water tanks in the Kancheepuram district (Ramachandran et al., 2019). The study area is the upper Adyar river basin upstream of Chembarambakkam reservoir (226 km^2, Figure 1). The area experiences a tropical wet and dry climate with a strong influence of the winter monsoon (Anandharuban & Elango, 2021). According to the long-term precipitation data

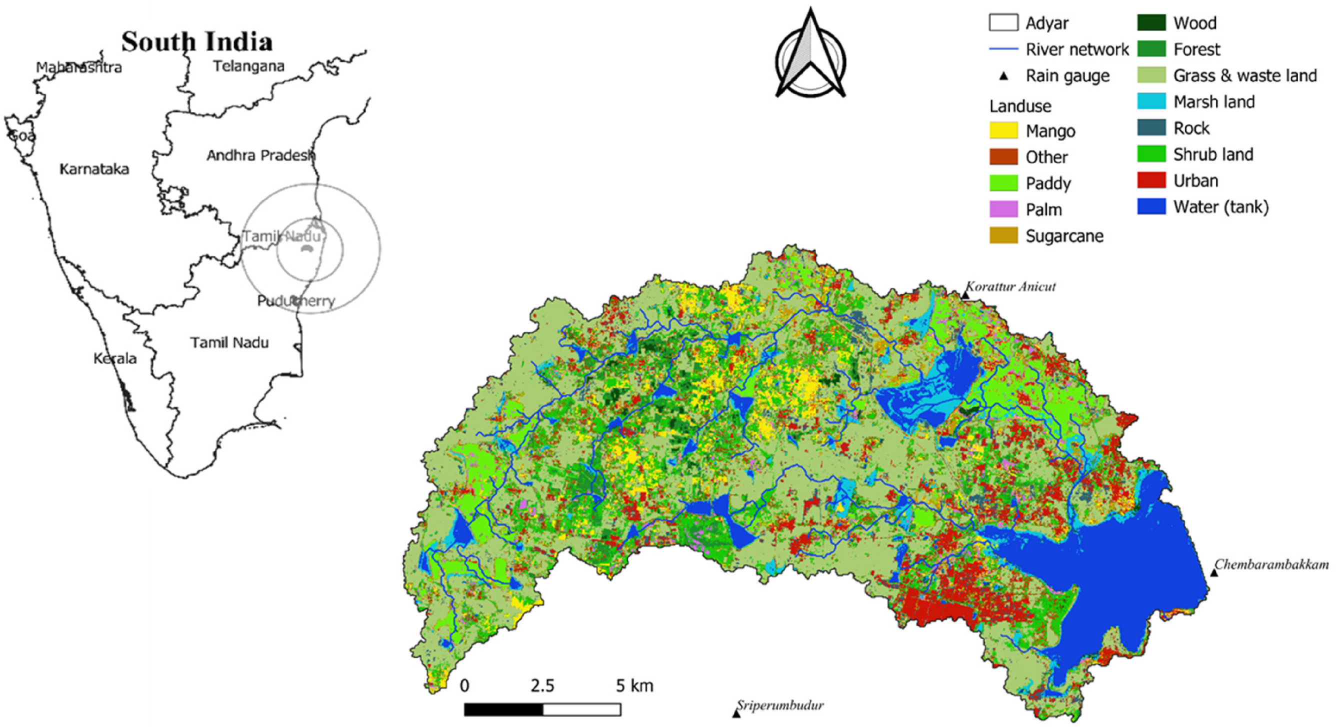


FIGURE 1 Location, stream network, water areas (tanks) and land use (Steinhausen et al., 2018) in the Adyar river basin upstream of the Chembarambakkam reservoir.

(2000–2020) available for the basin, the average annual precipitation over the upper Adyar basin is 1259 mm which is mostly received during the Indian winter monsoon (north-east monsoon). The water level in the Adyar river rapidly increases during the rainy seasons from October to December (winter monsoon) and amplifies the risk of flooding in the surrounding areas (Suriya & Mudgal, 2012). The annual mean temperature for the years 2000 to 2019 is 28.3°C. The month of May with a monthly mean temperature of 39.4°C is the hottest month and January with 16.6°C is the coldest month in the year. The upper Adyar basin covers an area of 225 km^2 and is characterized by broad floodplains and slightly sloping uplands. Elevations range from 24 to 94 m above MSL. Alluvium soil with a sandy-loam and loamy sand textures are the dominant soils which is classified into soil hydrologic groups C and D with low infiltration rates and a high runoff potential (Tigabu et al., 2023; Venugopal et al., 2009). The percentages of grassland, agricultural land, water bodies and herbaceous wetland, and urban areas were 35.5%, 20%, 16.4%, and 8.3% in 2015/16, respectively (Steinhausen et al., 2018, Figure 1). The dominating agricultural crops are rice and sugarcane with 31.5% and 16% of the total agricultural lands, respectively (Steinhausen et al., 2018).

2.2 | Water tanks

Water tanks as low-cost water-harvesting techniques have a historical footprint in water management and supply for sustainable crop production (Palanisami, 2006; Palanisami et al., 2010; Singh et al., 2020). Indian water tank systems have gained greater importance in the last decades as the extreme precipitation events and drought severity and frequency have shown statistically significant increasing trends in India (Goswami et al., 2006; Mallya et al., 2016; Mukherjee et al., 2018). There are more than 39 000 tanks in the state of Tamil Nadu and around 28 tanks in the upper Adyar basin (Figure 1). One of the largest tanks in terms of size and storage capacity is the Chembarambakkam tank with a volume of 103.21 mm^3 (Anandharuban & Elango, 2021). The water of the Chembarambakkam tank is mainly used as a municipal drinking water supply and for irrigation. Increasing demands for drinking water in Chennai city due to rapid population growth and urban expansion in the area (State of environment report of Chennai Metropolitan Area, 2013) pronouncedly decreased the amount of water used for irrigation in recent years. The Chembarambakkam tank can supply 0.01–0.5 mm^3 of water per day to 0.1–5 million people conditional on water availability (Anandharuban & Elango, 2021).

2.3 | Remote sensing data

To provide accurate information on the exact locations and the spatiotemporal variations in surface water areas of tanks between 2016 and 2020 in the upper Adyar basin, multi-spectral satellite data were collected from the United States Geological Survey (USGS). This information is required to configure the hydrologic model (SWAT+). A single Sentinel-2 scene with a resolution of 10 meters (cloud cover: 0%–0.2%) completely encompassed the study area. For the annual comparison (2016–2020), we collected cloud-free images from the same month or season (January–May) to ensure consistency. This focused on the non-monsoon season to assess water management during dry periods. Monthly tank water areas were derived from image scenes taken between January and May 2017. Monthly variations in water areas were utilized to assess the model's performance. To analyse the data, we used 40–46 ground truth polygons for water and 165 ground truth polygons for other land cover types (including agriculture, forest, grassland, urban, marshland, and rock). Google Earth images provided the ground truth polygons, and high-resolution Sentinel-2 images were used for classification. The ground truth polygons were randomly split into training and test data sets. Land use classification was performed using the Random Forest classifier (Breiman, 2001) with the randomForest package by Liaw and Wiener (2002) in R (R Core Team 2022). The classification results were evaluated using the test data, employing a confusion matrix to assess user and producer accuracy for each land use type. The user accuracy expresses the quality of the land use classification from the user perspective and the producer accuracy expresses the quality from the producer perspective (Story & Congalton, 1986).

2.4 | SWAT+ setups

SWAT+ (Bieger et al., 2017), a restructured version of the Soil and Water Assessment Tool (SWAT), is employed to represent the Adyar basin and its water tanks. The model is based on an SRTM (shuttle radar topography mission) digital elevation model (Jarvis et al., 2008) used to derive slope bands (<3%, ≥3% and <5%, ≥5% and <8%, ≥8% and <15%, and ≥15%) based on the FAO classification (FAO, 2020), soil data from Tamil Nadu Agricultural University (TNAU, 2018), land use map containing 13 classes (Steinhausen et al., 2018). These spatial inputs were used to set up a SWAT+ model with 121 sub-basins and 1514 hydrologic response units (HRUs). The landscape was divided into upland areas and floodplains, which were implemented in the model. Daily precipitation data from three rain gauge stations (Figure 1, Korattur Anicut, Sriperumbudur, and Chembarambakkam) and the gridded daily minimum and maximum temperature data with the resolution of 0.5 by 0.5° (Indian Meteorological Department, 2018) were used. The Hargraves equation was employed to estimate potential evapotranspiration. Variable storage routing method was chosen for channel routing. Streamflow data of the Adyar river upstream of the Chembarambakkam reservoir for the years 2004 to 2018 were provided by the Tamil Nadu State Water Resources Department (TWRD 2020) were used to evaluate the model performance.

The water tanks were considered as reservoirs and were added to the basin. In SWAT+ model, reservoirs are placed on all channels generated within the basin to facilitate interactions with other reservoirs and the surrounding landscapes. To analyse any possible improvement in streamflow estimation by the SWAT+ model, two models (with and without water tanks) were set up and their outputs i.e. streamflow were compared before calibration.

2.5 | Modelling water tanks

For representing water tanks in the hydrologic model, the available reservoir module in SWAT was used. Since water tanks are a traditional water harvesting system, they are implemented as operational from the first year of model simulation (2000). The area of each tank was derived from the remote sensing data (Supplementary Material, Table S1). All water bodies with an area of at least 2 ha were considered as water tanks in the model, adding up to 25 water tanks (Supplementary Material, Table S1). Due to the lack of bathymetry data, a depth of half, one and five meters were used to calculate the capacity of small, medium and large reservoirs respectively (Supplementary Material, Table S1). We used the same parameters for the emergency spillway as for the principal spillway (Supplementary Material, Table S1).

As compared to previous versions of SWAT, SWAT+ is more flexible with regard to watershed configuration and spatial connections (Bieger et al., 2017). It represents water bodies as objects allowing for connectivity and interactions with the surrounding catchment and river system (van Griensven et al., 2018). Decision tables in SWAT+ allow for modelling rivers and reservoirs with unique conditions and operation rules (Arnold et al., 2018).

The decision table used to represent water tanks is shown in Table 1. Reservoir volume (vol) and time of year (jday) are used as the conditional variable (var) in the decision table. Limit variable (lim_var), principal spillway volume (pvol) limit operator (lim_op), and limit constant (lim_const) are used for determining condition limits for the reservoir volume. The limit constant for day of year (jday) is set to 151 to approximate the ending of the main irrigation period in the Adyar basin. During the dry season, water release is allowed regardless of the water level in the tanks (alt2), whereas during the rest of the year water is only released if the reservoir volume is higher than or equal to pvol (alt1). In the action corresponding the alt2, 'days' option has been used to allow for reservoir release over a period of 9 months (273 days) if the volume is below principal spillway.

2.6 | Model calibration and validation

The model with the implemented water tanks was calibrated with the available streamflow data. The hydrologic parameters used for model calibration were based on a previous study (Tigabu et al., 2023) and manual sensitivity analysis (Table 2). A set of 5000 parameter combinations were generated by applying Latin Hypercube Sampling (LHS) from the R package FME and the model was run 5000 times with these different parameter sets. The overall performance of the model was evaluated using different performance metrics (Nash-Sutcliffe efficiency coefficient: NSE, Nash & Sutcliffe, 1970; percent bias: PBIAS, Gupta et al., 1999; Kling–Gupta efficiency: KGE, Gupta et al.

TABLE 1 Decision table used in SWAT+ model.

Conditions						Condition alternatives			
var	*obj*	*obj_num*	*lim_var*	*lim_op*	*lim_const*	*alt1*	*alt2*		
vol	res	0	pvol	*	1.000	>	<=		
jday	res	0	null	–	151	–	<		
Actions							**Action entries**		
act_typ	*obj*	*obj_num*	*name*	*option*	*const*	*const2*	*fp*	*outcome*	
release	res	0	over_principal	dyrt	1.000	0.000	pvol	y	n
release	res	0	below_principal	days	273.000	0.000	null	n	y

TABLE 2 Hydrologic parameters selected for calibration of the hydrologic model of the Adyar basin.

Parameter	Description	Unit	Range (max, min)	Type
CN2	Curve number	–	−10, 10	abschg
RCHRG_DP	Deep aquifer percolation fraction	–	0.05, 5	absval
SOL_AWC	Available water capacity	mm H_2O/mm soil	0.1, 0.4	abschg
ESCO	Soil evaporation compensation factor	–	0, 1	absval
SOIL_K	Hydraulic connectivity	mm/h	0.5, 1	absval
REVAP_CO	Evaporation rate from shallow aquifer	mm	0.02, 0.7	absval
SURLAG	Surface runoff lag coefficient	day	0.3, 5	absval
CH_N1	Manning's roughness coefficients	–	0, 5	absval
EPCO	Plant uptake compensation factor	mm	0, 1	absval
ALPHA_BF	Base flow alpha factor	per day	0, 1	absval

[2009]; the ratio of standard deviation: RSR, Moriasi et al., 2007) as each performance metric focuses on different characteristics of the hydrograph (Guse et al., 2019). Each of the stated metrics was calculated by comparing modelled streamflow to the available data from the Adyar Basin on a monthly time scale for the calibration (2004–2011) and validation (2012–2018) periods. These years were chosen for calibration and validation due to similar climate conditions for both periods (mean and maximum annual precipitation are 1434 mm and 2087 mm, respectively, for the calibration period and 1175 mm and 2426 mm, respectively, for the validation period). The potential impact of the chosen years from the remote sensing survey (2016–2019) on the model outputs was assessed by evaluating the model's performance during that period. To inspect the model performance on different segments of the hydrograph, the coefficient of determination: R^2 was adopted.

To evaluate the representation of water tanks in the model in addition to streamflow, the seasonal variations of water tank areas (water spread areas) from the model were compared to remote sensing derived areas for 2017.

3 | RESULTS

The surface water areas derived for the post-winter monsoon season (Jan-Mar) in the years 2016–2020 are shown in Figure 2. The user and producer accuracies of water are 87%–90% and 76%–90% for the upper Adyar basin, respectively. Moreover, based on the available cloud-less image data in 2017, water areas of the upper Adyar basin were classified monthly from January to May 2017 and achieved high user (88%–99%) and producer accuracies (85%–100%) for the water class. In these 5 years, the tank surface water area of upper Adyar basin was the largest in 2018 (27.9 km^2), followed by 2016 (26.8 km^2), and the smallest in 2019 (8.7 km^2). Large tanks shrank in surface water area extent and some small tanks in the western part dried out in 2017 and 2019. A large number of tanks were in an extremely dry state during the post-monsoon season in 2019 (Figure 2). Even the largest tanks were only partly filled with water in 2019 in the southeastern part of the upper Adyar basin. The strong dynamics can be related to the strength of the previous monsoon, as 2018 was an extremely dry year explaining the small surface water areas in 2019, and in November and December 2015 a strong winter monsoon led to flooding all over Chennai, explaining the large surface water areas in 2016.

The surface water areas of tanks declined during the post winter monsoon months of 2017 (Figure 6). Overall, the surface water area reduced from 11% to 7% of the upper Adyar basin. The Chembarambakkam tank as the major tank was analysed in more detail with regard to storage changes (Figure 3). The water area decreased significantly from the shallow shore to the deeper centre.

Assuming all tanks were at full capacity in the 2016 image following the exceptionally wet winter monsoon of 2015, we calculated the

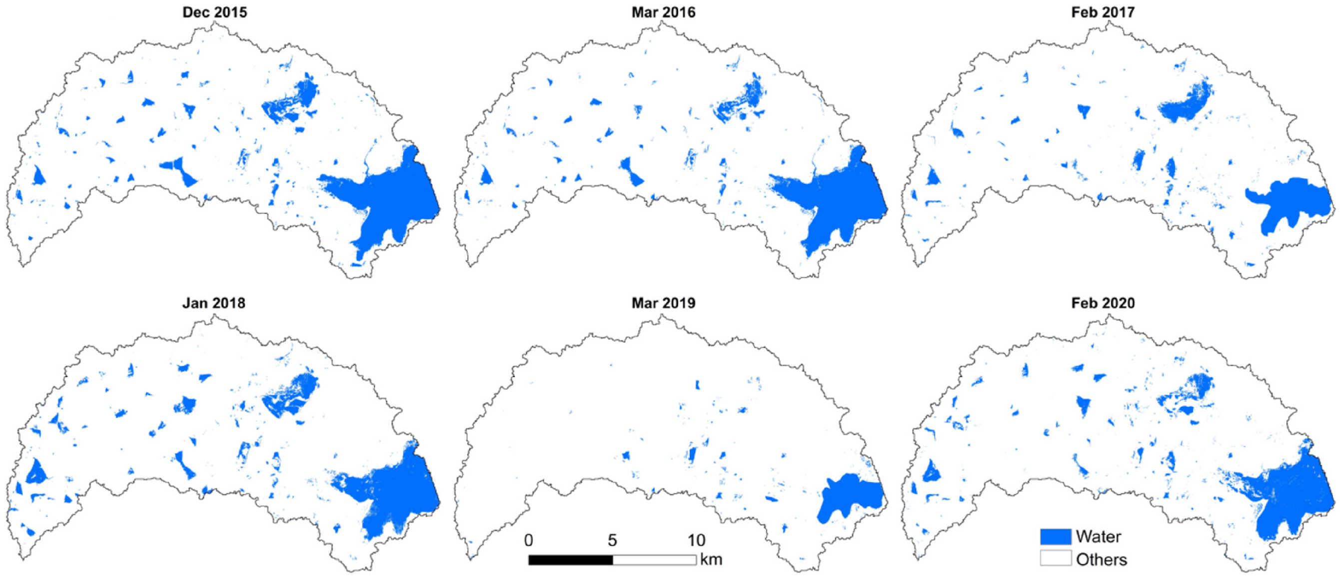


FIGURE 2 Spatial distribution of water areas in the Adyar basin between 2015 (Steinhausen et al., 2018) and 2020.

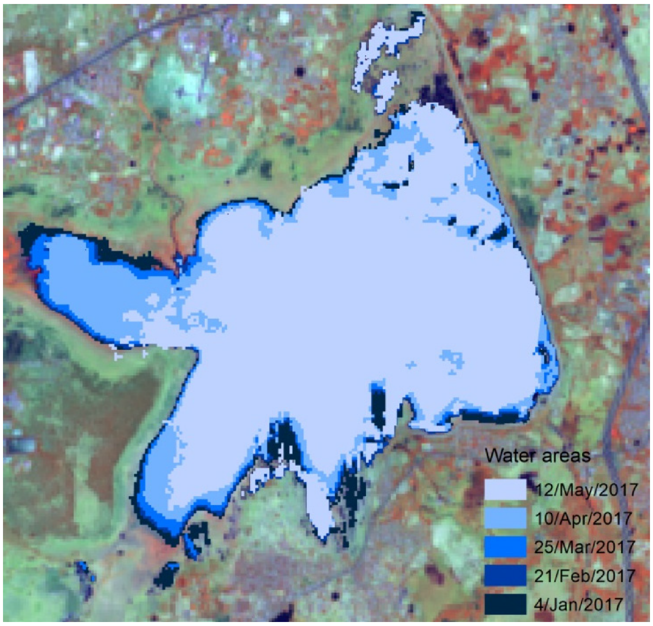


FIGURE 3 Changing spatial distribution of surface water areas of the Chembarambakkam tank between January and May 2017.

percentages of surface water areas for all other images during the non-monsoon season of 2017. The results indicated a reduction of approximately 20% in the surface water areas of the tanks from January to May. As an example Figure 3, illustrated the water depletion in the Chembarambakkam tank during the non-monsoon season of 2017.

The collected information on water tanks was used to parametrize the hydrologic model. Stream flow was simulated with two uncalibrated model setups (with and without water tanks) for the period of 2000–2018 and compared in Figure 4. A higher consistency was revealed between observations and simulated streamflow by the model with water tanks (Pearson correlation coefficient is 0.78) in comparison with the model without water tanks (Pearson correlation coefficient is 0.62).

Among the 5000 model runs, according to the calculated performance measures, the values of parameters that resulted in the best streamflow simulation were identified (Table 3). The evaluation of the model performance for the selected parameter values is given in Table 4. According to Moriasi et al. (2007), for the calibration period, the model performance is classified as good based on RSR which is 0.57, and NSE (0.67). In the validation period, the NSE value tends to be slightly higher and the RSR slightly lower indicating an improved performance. Overall, the model performance is good in the calibration and good to very good validation periods. The KGE shows that the model has a better performance in the validation period with a value of 0.72 compared to the calibration period with a KGE value of 0.65. The assumption of a better model performance for the period of satellite observations is underlined by the best KGE, NSE, PBIAS, and RSR values. A good representation of hydrologic characteristics of the upper Adyar basin using the calibrated model is also confirmed by the flow duration curves. All segments of the flow duration curve (FDC segments: very low, low, middle, high and very high flows) are adequately represented for the calibration, validation, and the remote sensing periods (Figure 5). The very high flow segment of the hydrograph is represented well, yet slightly underestimated for the validation ($R^2 = 0.82$, RMSE $= 8.78$), remote sensing surveys periods ($R^2 = 0.77$, RMSE $= 10.14$), and the calibration period ($R^2 = 0.67$, RMSE $= 7.44$). Higher agreement between observed and modelled high flows for the calibration period ($R^2 = 0.97$, RMSE $= 1.07$) in comparison to the validation ($R^2 = 0.81$, RMSE $= 1.98$) and remote sensing periods ($R^2 = 0.84$, RMSE $= 1.73$) are observed. Middle flows are equally well represented in all periods ($R^2 = 0.75$–0.81, RMSE $= 0.9$–

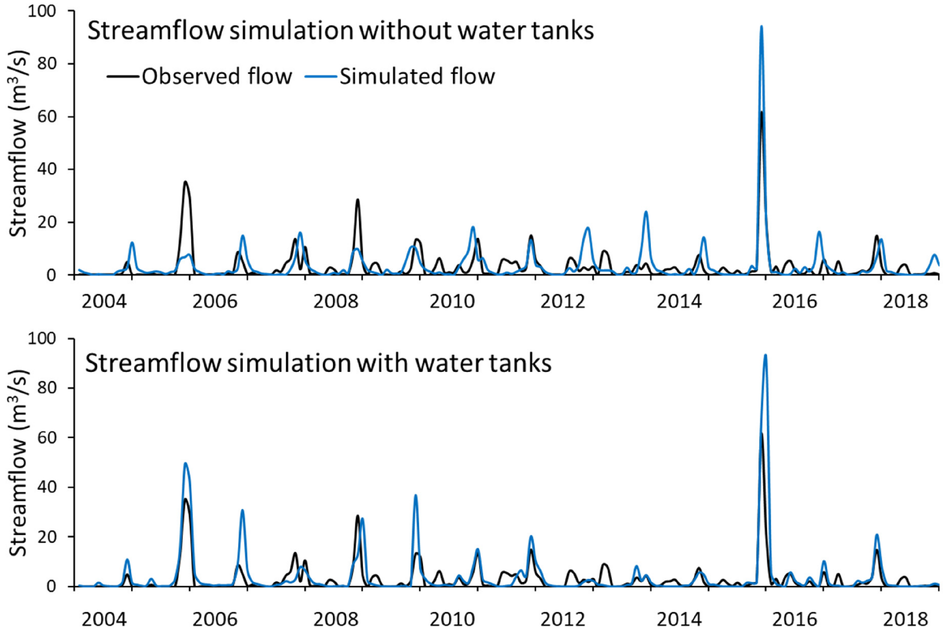


FIGURE 4 Monthly streamflow simulated by the uncalibrated model with and without water tanks.

TABLE 3 Specific values for hydrologic parameters, leading to best model simulation.

Hydrologic parameters									
CN2	SOL_AWC	RCHRG_DP	ESCO	SOIL_K	REVAP_CO	SURLAG	CH_N1	EPCO	ALPHA_BF
7.06	0.11	0.46	0.05	0.55	0.2	3.65	2.98	0.14	0.58

TABLE 4 Model performance metrics on different time periods on a monthly time step.

	Time period	KGE	NSE	PBIAS %	RSR
Calibration period	2004–2011	0.65	0.67	−24.1	0.57
Validation period	2012–2018	0.72	0.85	−23.6	0.39
Remote sensing survey period	2015–2018	0.87	0.9	−12.2	0.31

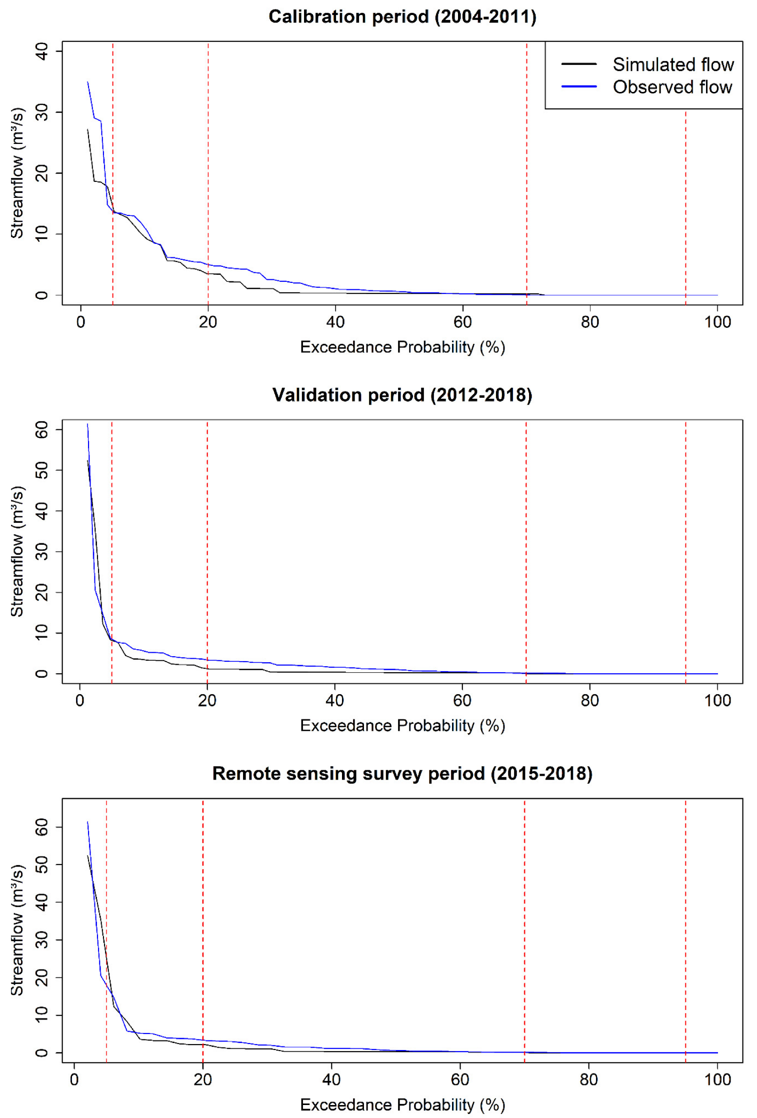
1.24). The RMSE indicates good agreement between observed and simulated low flows in the calibration and validation periods (RMSE = 0.06) and the remote sensing periods (RMSE = 0.05). The calculation of R^2 is not feasible for low and very low segments due to the presence of certain zero values.

The water body area estimated by the hydrologic model between the months of January 2017 to May 2017 shows a constant decrease (Figure 6). This is in agreement with the remote sensing-based changes in the water area, although the changes between January and March were slightly lower in satellite image observations ($R^2 = 0.88$). The remote sensing data indicates a smaller area of water between January and March and larger area of water bodies than the hydrologic model estimations between April and May.

4 | DISCUSSION

The depletion and refilling of water tanks during both the non-monsoon and monsoon seasons analysed through a remote sensing approach, align with the observations made by Vanthof and Kelly (2018). According to their findings, water levels in the tanks peak after monsoon rains and gradually decrease throughout the non-monsoon season due to water discharge. The variations in tank storage on a monthly basis can also be attributed to factors such as irrigation needs based on crop water requirements, household usage (e.g., drinking water supply for Chennai city from the Chembarambakkam tank), and potential evapotranspiration. As previously discussed by Purnadurga et al. (2019), evapotranspiration tends to increase over the course of a year, with a notable rise in temperatures, especially in May—the warmest month of the year.

A higher consistency was revealed between observations and simulated streamflow by the model with water tanks in comparison with the model without water tanks. In general, the water tank implementation improved the timing of the modelled streamflow. Without tanks, peak flows occurred at the wrong time (e.g., autumns of 2015 and 2016). The model with more details on water tanks better represented the peak flows specifically for the last 4 years of the simulation period (2015–2018). This is probably due to the customization of the reservoir's hydrologic parameters and the general rules in the decision table based on the information obtained from the remote sensing data

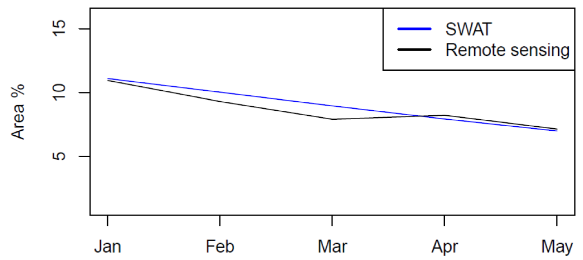


		Very high flow	High flow	Middle flow	Low flow	Very low flow
Calibration period	R^2	0.67	0.97	0.75	0.5	-
	RMSE	7.44	1.07	1.2	0.06	-
Validation period	R^2	0.82	0.81	0.76	-	-
	RMSE	8.78	1.98	1.24	0.06	-
Remote sensing period	R^2	0.77	0.84	0.81	0.35	-
	RMSE	10.14	1.73	0.9	0.05	-

FIGURE 5 Flow duration curve of the monthly streamflow for the calibration, validation and remote sensing periods. The calculation of R^2 is not feasible for low and very low segments due to the presence of certain zero values.

for the same period of time. Improvement in model estimations of flood maps and inundated areas as a result of using satellite data (rainfall) as an input for the model was also reported by Khan et al. (2010). Khaki et al. (2020) stated that higher improvement in hydrologic model quality can be achieved by assimilating multiple satellite products simultaneously. Therefore, long-term remote sensing-based monitoring of water tanks is recommended for better model performance. The suggestion for long-term remote sensing-based monitoring of water tanks can also be substantiated by the model's excellence during the satellite observation period, highlighted by superior KGE, NSE, Percent Bias (PBIAS), and RSR values. This recommendation is particularly pertinent in regions with limited data, where our approach excels without relying on management data.

An examination of the representation of hydrologic characteristics in the upper Adyar basin using calibrated models reveals valuable insights through flow duration curves. However, nuances emerge in



	January	February	March	April	May
Remote sensing	10.95	9.30	7.91	8.22	7.15
SWAT+ model	11.1	10.03	8.96	7.93	7

FIGURE 6 Variations of total water body areas between January and May 2017 estimated by the SWAT+ model and remote sensing.

representing very high flow segments of the hydrograph, which are slightly underestimated during validation, remote sensing surveys, and the calibration period. Notably, the calibration period exhibits higher agreement between observed and modelled high flows compared to the validation and remote sensing periods. This is in agreement with findings by Rabelo et al. (2022), in which implementing a series of reservoirs in a hydrologic model has greater impacts on the very high and high flow segments of the FDC. Overall improvement in the model performance due to reservoir implementation is confirmed by previous studies. For example, Chawanda et al. (2020) show that including reservoir operations has a positive impact on hydrologic model performance in the Orange, Limpopo and Save river basins of Southern Africa. They discussed that improvement in the model performance was limited to basins with sufficient management data. Our remote sensing-based approach, however, does not rely on management data and is therefore particularly suitable for data-scarce regions. In addition, middle flows maintain consistent representation across all periods, highlighting the stability of the model.

Furthermore, our hydrologic model's water body area estimations reveal a consistent decrease between January and May 2017. A parallel observation in remote sensing-based changes corroborates this trend, with minor discrepancies possibly attributed to the omission of small water bodies, a rough estimation of the water bodies' depth, and the lack of bathymetry data in the hydrologic model. Our study adopts a multi-variable approach, as proposed by Krysanova et al. (2018) and Dembélé et al. (2020), to enhance the representation of water fluxes in the model and particularly represent water tanks. This targeted analysis ensured that our model accurately captured the dynamics of water storage and release from these tanks, contributing to a more realistic simulation of water fluxes in the system.

5 | CONCLUSIONS

South Indian water tanks as a cascading system have a strong impact on flow regimes by changing the magnitude and timing of streamflow. Therefore, they need to be represented realistically in hydrologic models. In this study, a remote sensing approach is applied to parameterize water tanks in SWAT+, controlling their operations and management. The remote sensing parameter-identification strategy leads to a higher model simulation accuracy both in timing and magnitude of streamflow. Although water tank implementation based on remote sensing surveys improved the overall model performance for the whole simulation period, this improvement is more pronounced for the years of the remote sensing observations. Hence, more satellite observations may further enhance the efficiency of the simple remote sensing reservoir parameterization approach to model streamflow. Moreover, the successful representation of water tanks in a hydrologic model will allow investigation of how these systems may be optimized to cope with a changing climate.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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