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Village-Level Assessment of Potential Surface Water Storage Using an Integrated Water Balance Approach in the Ippala Vagu Watershed, India

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Abstract: The management of watersheds requires the planning of surface water resources. For hydrological analysis, runoff estimation is essential. This study aimed to estimate the village-level potential surface water storage by integrating the water balance components, including surface runoff, groundwater recharge, and effective rainfall. Surface runoff was estimated using the Soil Conservation Service Curve Number (SCS-CN), groundwater recharge was estimated by the Rainfall Infiltration Factor (RIF), and effective rainfall was estimated by Food and Agriculture Organization/ Agricultural Water Management Group (FAO/AGLW) approaches. Using rainfall data, water balance calculations were performed for the 18 villages within the Ippala Vagu Watershed to evaluate potential surface water storage. In total, 18 villages recorded an annual rainfall volume of 430.50 million cubic meters (MCM), of which 138.24 MCM (32.11%) was estimated as effective rainfall. Surface runoff constituted 71.57 MCM (16.62%), while groundwater recharge was estimated at 68.88 MCM (16.00%). The potential surface water storage amounted to 151.82 MCM, representing 35.27% of the annual precipitation volume. The current storage capacity was merely 73.67 MCM, constituting 48.52% of the potential surface water storage. These findings indicate considerable potential for improving the utilization of available surface water resources within the watershed. Accordingly, increasing water harvesting and storage facilities, especially in villages with high potential surface water storage, is recommended.

Keywords: Surface Runoff, Effective Rainfall, Potential Surface Water Storage, Geographic Information System, SCS-CN Method, Rainfall Infiltration Factor.

1 Introduction

The evaluation of surface water availability is a crucial phase for watershed management in rural areas. Measuring surface runoff is critical to understanding water balance components [1]. Watershed size, land use/land cover (LULC), surface slope, soil type, and hydro-metrological factors all affect the rainfall-runoff process [2]. Accurate rainfall-runoff prediction can support watershed management and reduce the impacts of floods and droughts on water resources [3]. Watershed modeling requires precise rainfall-runoff simulations for irrigation water management and water resources planning [4]. Managing and organizing water resources necessitates a comprehensive collection of historical flow data. Runoff estimation in ungauged or inadequately gauged catchments remains a significant challenge in developing countries such as India because establishing and maintaining stream-gauging networks for small and medium rivers is often costly [5]. Because not all watersheds in India can be measured, an indirect method for assessing runoff is required [6].

The SCS–CN method has gained broad acceptance and has been extensively applied in hydrological studies across India mainly because of its simplicity and effectiveness. Hydrological models provide a simplified representation of the hydrological system within a watershed. The objective of these models is to elucidate how a watershed responds to hydrological processes driven by specific inputs [7]. Rainfall-runoff modeling uses known precipitation data to estimate unknown runoff data. Several methods are available for modeling rainfall–runoff processes. For runoff estimation, the SCS-CN method, which is based on curve number (CN), is a straightforward and simple approach [8].

Increasing computer power and wider availability of spatial data allow accurate predictions of runoff. The possibility of fast integration of diverse kinds of data in a Geographic Information System (GIS) has led to a considerable expansion in its application in the hydrological field [9]. The need for water balance studies at the village level within the watershed arises from the growing demand for water and the uneven distribution of rainfall throughout the year. Only a limited proportion of available surface water is effectively utilized in many rural watersheds. In many watersheds, a considerable portion of seasonal runoff cannot be effectively stored because of inadequate water harvesting and storage infrastructure. Consequently, water scarcity continues to affect many regions despite the availability of seasonal runoff. Therefore, expanding water storage infrastructure is important for improving the utilization of available surface water resources. In villages, people mainly depend on agriculture, which is one of the largest water-demand sectors. Effective village-level planning of water resources is essential to enhance potential surface water storage and reduce existing and future water shortages.

Accordingly, the objective of this study was to estimate village-level water balance components, including effective rainfall, surface runoff, groundwater recharge, and potential surface water storage, for the 18 villages in the Ippala Vagu Watershed using an integrated water balance approach. The estimated potential surface water storage was further compared with the existing storage capacity to identify opportunities for improving village-level water resource planning.

2 Literature Review

Rainfall–runoff estimation has been an active area of hydrological research for several decades because it directly supports flood assessment, irrigation planning, groundwater development, and watershed management. Numerous empirical, conceptual, and physically based models have been proposed to estimate runoff under different physiographic and climatic conditions. The selection of a suitable model generally depends on the availability of hydrological observations, watershed characteristics, and the purpose of the study.

Among empirical approaches, the SCS-CN, now referred to as the Natural Resources Conservation Service - Curve Number (NRCS-CN) method, remains one of the most frequently applied techniques because it requires relatively limited input data while providing reliable runoff estimates for a wide range of watersheds. Verma et al. reviewed the evolution of the NRCS-CN model. They observed that its simplicity, adaptability, and compatibility with GIS and remote sensing have contributed to its widespread use in runoff estimation, flood studies, agricultural water management, and watershed planning [1]. Their review also noted that the increasing availability of digital spatial datasets has substantially improved the estimation of Curve Number values and other hydrological parameters required for runoff computation.

The usefulness of GIS in runoff estimation has been demonstrated in several watershed investigations. Satheeshkumar et al. applied the SCS-CN method in combination with GIS for runoff estimation in the Pappiredipatti watershed of Tamil Nadu. They showed that watershed characteristics such as land use, geomorphology, and soil conditions strongly influence runoff generation [10]. Kumari et al. reached similar conclusions while analyzing the Umiam catchment in Meghalaya, where variations in land use and rainfall were reflected in changes in runoff between different years [11]. Both studies emphasized that spatial datasets improve the representation of watershed characteristics and support planning of suitable water conservation measures.

Although the conventional SCS-CN method has been widely accepted, researchers have continued to refine the model for local watershed conditions. Viji et al. evaluated a modified SCS-CN approach together with the Green-Ampt infiltration model. They found that both approaches produced acceptable runoff estimates, with the modified SCS-CN method giving comparatively lower runoff values for the selected watershed [12]. Afrasiabikia et al. later demonstrated that local calibration of the Curve Number and the initial abstraction coefficient improved runoff prediction in semi-arid environments [13]. These studies indicate that empirical runoff models often benefit from regional calibration before they are applied to specific watersheds.

Physically based hydrological models remain important where detailed hydrological observations are available. Hamdan et al. developed a HEC-HMS model for the Al-Adhaim River catchment [5], while Fanta and Feyissa applied the same model in the Gilgel Gibe watershed of Ethiopia [2]. Both investigations reported satisfactory agreement between simulated and observed runoff after calibration. Similar observations were reported by Ranjan and Singh, who successfully simulated runoff at daily, monthly, and seasonal time scales [14]. These studies confirm the capability of physically based models for detailed hydrological simulation. However, they also depend on extensive input data and calibration procedures that may not always be feasible in ungauged watersheds.

In recent years, machine learning techniques have also been introduced for rainfall–runoff prediction. Chiang et al. compared Support Vector Regression with the HEC-HMS model and reported improved predictive performance using the data-driven approach [4]. Zhao et al. combined the SWAT model with Long Short-Term Memory (LSTM) networks and Bayesian Model Averaging to improve runoff simulation under varying hydrological conditions [3]. These methods have shown encouraging results, but they generally require large datasets and considerable computational effort, which may limit their practical use for routine watershed assessment in many data-scarce regions.

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Runoff estimation alone does not provide sufficient information for watershed planning unless it is linked with water availability and storage assessment. M. Abraham and R. A. Mathew evaluated runoff and water demand in a tank watershed of Tamil Nadu [15]. They reported that the available runoff exceeded the existing water demand, suggesting opportunities for rainwater harvesting and improved utilization of available water resources. Their study illustrated how hydrological analysis can support decisions related to storage infrastructure and watershed development rather than serving only as an exercise in runoff estimation.

The reviewed studies indicate that SCS-CN, GIS-based analysis, and other hydrological models are effective for runoff estimation. However, most investigations have concentrated on runoff prediction or model evaluation at the watershed scale. Although numerous studies have estimated runoff using empirical and physically based models, relatively few have combined effective rainfall, runoff, groundwater recharge, and potential surface water storage within a single village-level water balance assessment. The present study addresses this aspect by integrating these hydrological components for the eighteen villages of the Ippala Vagu Watershed and examining the adequacy of the existing storage capacity to support decentralized water resource planning.

3 Methodology

The overall methodology integrates effective rainfall estimation, runoff estimation, groundwater recharge estimation, and water balance analysis to quantify potential surface water storage at the village level. The water balance equation relates the inflow, outflow, and change in water storage within the selected study area.

$$\text{Inflow} - \text{Outflow} = \text{Change in Storage}$$

In the study area, the total inflow to the system is precipitation (P), and the total outflow is runoff. The change in total water storage (ΔS) in a selected area can be divided into surface water storage (ΔSS), groundwater recharge from rainfall (ΔSG), and moisture storage in soil pores (ΔSM). A water balance analysis was conducted to assess the spatial variance of hydrological components in the selected villages within the Ippala Vagu Watershed region. Potential surface water storage was estimated using the relationship:

$$\text{Potential Surface Water Storage} = \text{Precipitation} - \text{Runoff} - \text{Effective Rainfall} - \text{Groundwater Recharge}$$

The quantity of water available for surface storage was evaluated using a simple water balance method. In this method, total precipitation was the main source of water in the system. Effective rainfall denotes the share of precipitation retained within the crop root zone, whereas runoff and groundwater recharge account for water leaving the surface system. Subtracting effective rainfall, runoff, and groundwater recharge from total precipitation yielded the remaining water, which was considered the potential surface water storage in the study area. The following sections describe the methodologies used to estimate effective rainfall, surface runoff, and groundwater recharge through deep percolation.

3.1. Effective Rainfall

The FAO/AGLW method was used to evaluate effective rainfall, and it relates monthly rainfall to effective rainfall. Effective rainfall provides a practical approximation of the rainfall that is available for crop use after accounting for losses such as runoff, groundwater recharge, and potential surface water storage. The empirical equations used in the FAO/AGLW method are given below.

$$P_{eff} = 0.6 \times P - \frac{10}{3} \quad for\ P \leq \frac{70}{3}\ mm \tag{1}$$

$$P_{eff} = 0.8 \times P - \frac{24}{3} \quad for\ P > \frac{70}{3}\ mm \tag{2}$$

where, P_{eff} is the effective rainfall (mm), and P is the monthly rainfall (mm).

3.2. Surface Runoff

Surface runoff was estimated using the SCS-CN method. A Digital Elevation Model (DEM) was processed in ArcGIS software to delineate the watershed boundary. LULC and soil maps were integrated to assign curve number values based on land cover classes and hydrologic soil groups. These CN values were used in the SCS-CN runoff model to estimate direct surface runoff from daily rainfall, and this model output provided runoff depth.

3.2.1. SCS-CN Method

The SCS–CN method, introduced by the Soil Conservation Service of the United States in 1969, is a widely used conceptual hydrological model for estimating direct runoff generated from daily rainfall depth. This method provides a straightforward, reliable, and consistent approach for runoff assessment [16][17][8]. This method is derived from the water balance equation and evaluates rainfall over a specified time interval. In the SCS–CN method, rainfall depth is given by.

$$P = I_a + F + Q \tag{3}$$

where, P is the rainfall depth (mm), I_a is the initial abstraction (mm), F is the cumulative infiltration or actual retention (mm), Q is the direct runoff depth (mm). Two other concepts are also used in this method. Eq. (4) is based on the initial concept, where S denotes the maximum potential water retention capacity of the soil. This relationship forms the basis for estimating runoff from a given rainfall event.

$$\frac{Q}{(P - I_a)} = \frac{F}{S} \tag{4}$$

where, S is the potential maximum retention after runoff begins (mm). Eq. (5) represents the second concept.

$$I_a = \lambda S \tag{5}$$

where, λ is the initial abstraction coefficient. Combining the above concepts,

$$Q = \frac{(P - \lambda S)^2}{P + (1 - \lambda)S} \quad for\ P > \lambda S \tag{6}$$

$$Q = 0 \quad for\ P \leq \lambda S \tag{7}$$

$$S = \frac{25400}{CN} - 254 \tag{8}$$

where, CN is the Curve Number. This CN is determined from LULC, soil type, hydrologic condition, and AMC. Values of 'λ' vary in the range $0.1 \leq \lambda \leq 0.4$. For Indian conditions, λ generally range from 0.1 to 0.3. For this study, $\lambda = 0.2$ was considered.

3.2.2. Land Use and Land Cover

LULC provides important information on the spatial distribution of land cover, which is required for Curve Number assignment. Accurate LULC classification supports evaluating the CN values for surface runoff estimation.

3.2.3. Hydrologic Soil Group

Hydrologic Soil Group (HSG) classifies the soils according to their runoff potential and infiltration capacity. The classification is based on soil texture, permeability, and drainage characteristics and is commonly divided into four groups (A, B, C, and D). Table 1 shows the Hydrologic Soil Groups. Hydrologic Soil Group data are widely used in hydrological studies, particularly for runoff estimation.

Table 1. Soil texture mapping to hydrologic soil group [18]

Hydrologic Soil Group	Soil Textures	Runoff Potential	Infiltration Rate
Group A	Sand, Loamy Sand, Sandy Loam	Low	High
Group B	Loam, Silt Loam, Silt	Moderate Low	Moderate
Group C	Sandy Clay Loam	Moderate High	Low
Group D	Clay Loam, Silty Clay Loam, Sandy Clay, Silty Clay, Clay	High	Very Low

3.2.4. Antecedent Moisture Condition (AMC)

AMC describes the soil moisture status before a rainfall occurrence, and it affects the soil's rate of infiltration and, subsequently, the quantity of surface runoff produced. Dry soils allow greater infiltration and produce less runoff, whereas wet or saturated soils reduce infiltration and increase runoff.

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The SCS-CN approach categorizes AMC into three types, namely AMC-I (dry), AMC-II (average), and AMC-III (wet). These conditions are determined from the total rainfall received during the five days preceding a storm, with threshold values varying between the growing and dormant seasons. AMC types and corresponding rainfall details are given in Table 2. Considering AMC conditions improves the accuracy of runoff estimation by accounting for variations in antecedent soil moisture.

Table 2. AMC for determining the value of CN [11][19]

AMC Type	**Total Rainfall in previous 5 days**	
	Dormant Season	***Growing Season***
I	Less than 13 mm	Less than 36 mm
II	13 to 28 mm	36 to 53 mm
III	More than 28 mm	More than 53 mm

3.2.5. Runoff Curve Number

In the SCS–CN method, the CN is the primary parameter used to evaluate surface runoff from rainfall. It reflects the runoff potential of a watershed based on LULC and HSG. Lower CN values represent stronger infiltration and water storage capacity and hence less runoff, whereas higher CN values represent lower infiltration and higher runoff potential. Therefore, selecting suitable CN values is critical for accurate runoff estimation.

Table 3. Runoff Curve Numbers [CN_{II}] for Hydrologic Soil Cover Complexes [under AMC-II Conditions] [19]

S. No.	**Land use**	**Runoff Curve Numbers for Hydrologic Soil Group**			
		A	***B***	***C***	***D***
1.	Water	98	98	98	98
2.	Trees	41	55	69	73
3.	Flooded vegetation	95	95	95	95
4.	Crops	59	69	76	79
5.	Built Area	77	86	91	93
6.	Bare ground	71	80	85	88
7.	Rangeland	68	79	86	89

To determine the CN, the study area was first divided into several LULC cover categories and HSG. The weighted contribution (Area × CN) was calculated by multiplying the area of each land use class within each soil group by its standard CN value as specified by Table 3. After that, the weighted products for each land use class were added together and divided by the watershed's total area. This area-weighted averaging approach provided a representative CN-II for the study area. CN-I and CN-III are calculated using Eqs. 9 and 10, respectively.

$$\mathrm{CN_{II}} = \frac{\Sigma(\mathrm{N_i} \times \mathrm{A_i})}{\mathrm{A}} \tag{9}$$

where, $\mathrm{CN_{II}}$ is the weighted Curve Number under AMC-II conditions, $\mathrm{N_i}$ is the Curve Number corresponding to the i^{th} land use-soil combination, $\mathrm{A_i}$ is its area, and A is the total watershed area. The conversion of $\mathrm{CN_{II}}$ to the remaining two AMC states can be performed via the following correlation equations.

$$\text{For AMC} - \text{I}, CN_I \;= \frac{CN_{II}}{2.281 - 0.01281 CN_{II}} \tag{10}$$

$$\text{For AMC} - \text{III}, CN_{III} = \frac{CN_{II}}{0.427 + 0.00573 CN_{II}} \tag{11}$$

where, CN_I, CN_{II}, and CN_{III} represent the Curve Numbers corresponding to AMC-I, AMC-II, and AMC-III conditions, respectively.

3.3. Ground Water Recharge

In situations where sufficient groundwater level data are unavailable, groundwater recharge can be evaluated using the RIF method. This method is an empirical technique used to estimate groundwater recharge resulting from rainfall. In this approach, groundwater recharge is determined by the following expression.

$$R = F \times A \times P \tag{12}$$

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where R is the groundwater recharge volume, F is the rainfall infiltration factor, A is the study area, and P is the seasonal rainfall. This approach incorporates a monsoon and non-monsoon rainfall infiltration factor. The recharge contribution from the non-monsoon season is nil if it is less than 10% of the total yearly rainfall. According to the recommendations of the Groundwater Resource Estimation Committee (2015), the rainfall infiltration factor for alluvial regions varies based on geographical location. A value of 22% is suggested for the Indo-Gangetic plains and inland alluvial areas, 16% for the East Coast alluvial regions, and 10% for the West Coast alluvial regions. The study area falls under the East Coast Alluvial Region; therefore, a rainfall infiltration factor of 16% was adopted for this study [20].

3.4. Study Area

The Ippala Vagu Watershed is located in Andhra Pradesh, India, and spans portions of the NTR and Eluru districts. The Ippala Vagu watershed encompasses a total of 18 villages distributed across four administrative mandals. Of these, eight villages fall under Vissannapet Mandal (16°56′23.28″ N, 80°46′58.08″ E), while seven villages are located in A. Konduru Mandal (17°02′52.08″ N, 80°05′53.52″ E). One village belongs to Reddigudem Mandal. These three mandals are administratively part of the NTR District. The remaining two villages are situated in Chatrai Mandal, which lies within Eluru District. Both NTR and Eluru districts are located in the state of Andhra Pradesh, India.

3.5. Data

Rainfall data used in this study were obtained from the Andhra Pradesh State Development Planning Society (APSDPS), Planning Department, Vijayawada, Andhra Pradesh. The CartoSAT DEM used in this study was acquired from the Bhuvan Geoportal. This high-resolution elevation dataset was derived from stereo imagery captured by the Cartosat-1 satellite mission developed by the Indian Space Research Organization. The LULC data used in this study were obtained from the ESRI Global Land Cover dataset, developed by Impact Observatory in collaboration with ESRI [21]. The dataset is derived from 10 m resolution ESA Sentinel-2 Level-2A imagery and provides annual global LULC maps. Soil data for this study were obtained from the Digital Soil Map of the World (DSMW) available through the FAO Soils Portal. The DSMW is a digital version of the FAO–UNESCO Soil Map of the World, providing standardized global soil information in a GIS-compatible format. The dataset was integrated into the GIS environment to support soil characterization and hydrological analysis. The existing storage capacity data were obtained from the Andhra Pradesh Water Resources Information and Management System (APWRIMS) portal [22].

4 Results and Discussion

The rainfall–runoff model estimates runoff using known precipitation data. Among the available methods, the SCS–CN method is widely used for runoff estimation. It describes the watershed hydrological response based on HSG, LULC, and AMC. Fig. 1 illustrates the flow accumulation map of the Ippala Vagu Watershed. The flow accumulation map helps identify stream networks and watershed drainage patterns. These outputs are useful for watershed development activities.

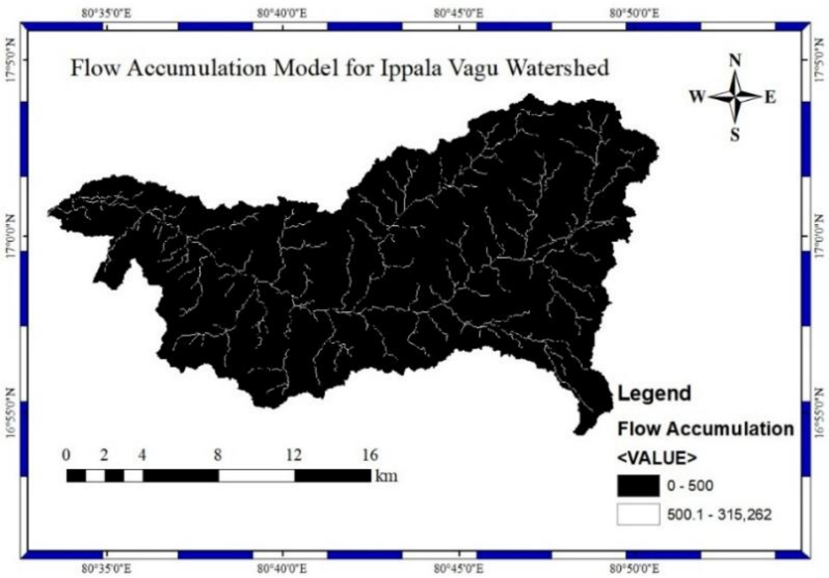

Fig. 1. The flow accumulation map for the Ippala Vagu Watershed.

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4.1. Land Use and Land Cover

Fig. 2 shows the LULC distribution of the study area. The study region covers 286,498,900 m² in total. Agriculture dominates the region with 227,632,800 m² of Cropland as the major land use class. The built-up area of 18,972,100 m² includes communities and infrastructural development. Tree cover and range land make up natural vegetation, occupying 17,455,200 and 15,877,900 m², respectively. Water bodies occupy 6,493,500 m², but flooded vegetation covers just 64,400 m². The smallest land use category is bare ground, covering only 3,000 m². Cropland is the most common land use, followed by built-up areas, tree cover, rangeland, and water bodies. A tiny portion of the land is occupied by flooded vegetation and bare ground. The LULC classes provide the basis for assessing CN values to estimate the runoff.

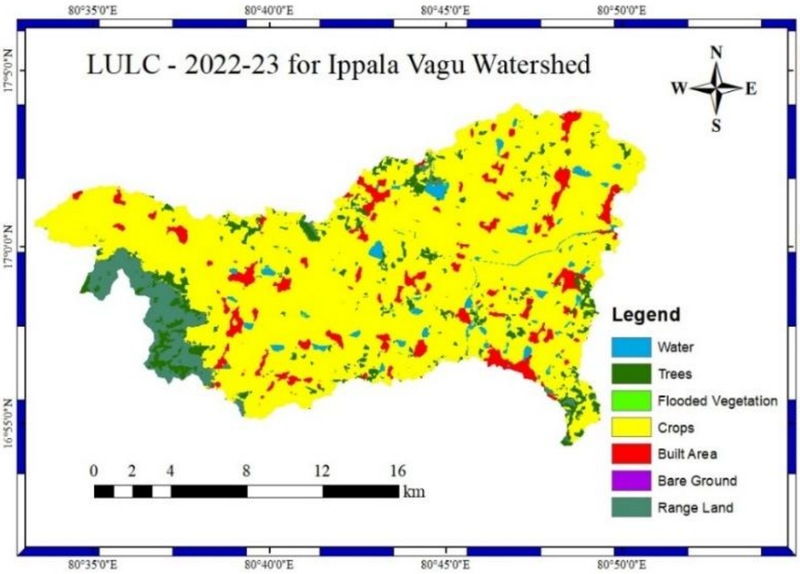

Fig. 2. Land Use Land Cover Map for Ippala Vagu Watershed (2022-23)

4.2. Hydrologic Soil Group

Fig. 3 displays the soil texture distribution of the Ippala Vagu Watershed. Sandy clay loam (HSG C) dominates the study area, accounting for 80.10% of its total area, while loam (HSG B) accounts for 19.90%. Group C soils exhibit high runoff potential because of their low infiltration capacity, whereas Group B soils allow moderate infiltration and generate relatively less runoff.

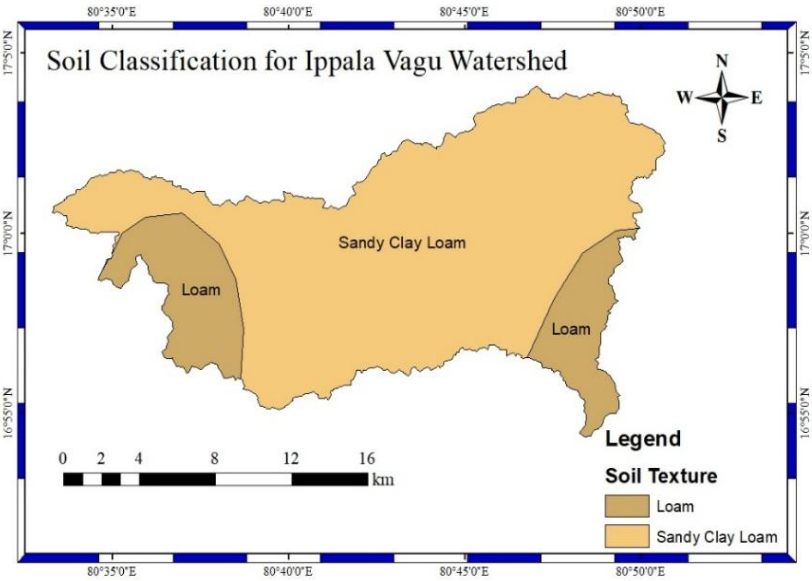

Fig. 3. Soil Classification for Ippala Vagu Watershed

4.3. Curve Number

The CN was analyzed considering the LULC and soil type, which are the elements controlling the infiltration and runoff behavior of the watershed. CN-I (64.22) demonstrates high infiltration and low runoff potential, CN-II (80.37) represents intermediate runoff conditions, and CN-III (90.55) signifies low infiltration and high runoff potential. The CN values increase, indicating a shift from permeable conditions to places producing greater surface runoff.

4.4. Rainfall–Runoff

Fig. 4 compares the monthly rainfall and runoff of the Ippala Vagu watershed region from June to May (2022-23). The results indicate that the rainfall is highly seasonal. The rainfall during the study period was 60 mm in June and peaked in July at about 345 mm. Rainfall is still high in August (around 300 mm) and September (around 205 mm), and then gradually decreases to 160 mm in October. Rainfall in November and December fell sharply to less than 30 mm, and almost no rainfall is recorded in January and February. A slight increase was seen in March, April and May.

The greatest runoff occurs in July (about 100 mm) and August (around 90 mm), with the months of heaviest rainfall. Runoff drops sharply in September and October, and is small in the dry months of November to February. A slight increase in rainfall during March and May resulted in a corresponding increase in runoff. The graph indicates a clear positive relationship between rainfall and runoff. Months of high rainfall cause greater runoff, whereas months of low rainfall cause little or no runoff.

M. Abraham and R. A. Mathew concluded that the annual precipitation for the watershed ranged from 575.7 mm (2002–03) to 3608.0 mm (2005–06) [15]. The runoff, as calculated by the NRCS model, ranged from 94.95 mm to 2324.34 mm, with the associated percentages varying from 16.49% to 64.42% for Tank Watershed in Tamil Nadu. In the present study, 16.62% of the total rainfall was converted into runoff. The results of the present study were compared with those reported by M. Abraham and R. A. Mathew. The SCS-CN method is based on Curve Number values, which directly influence runoff estimation. The Curve Number values adopted for the Ippala Vagu Watershed are lower than those of the tank watershed in Tamil Nadu, resulting in comparatively lower runoff estimates in the present study.

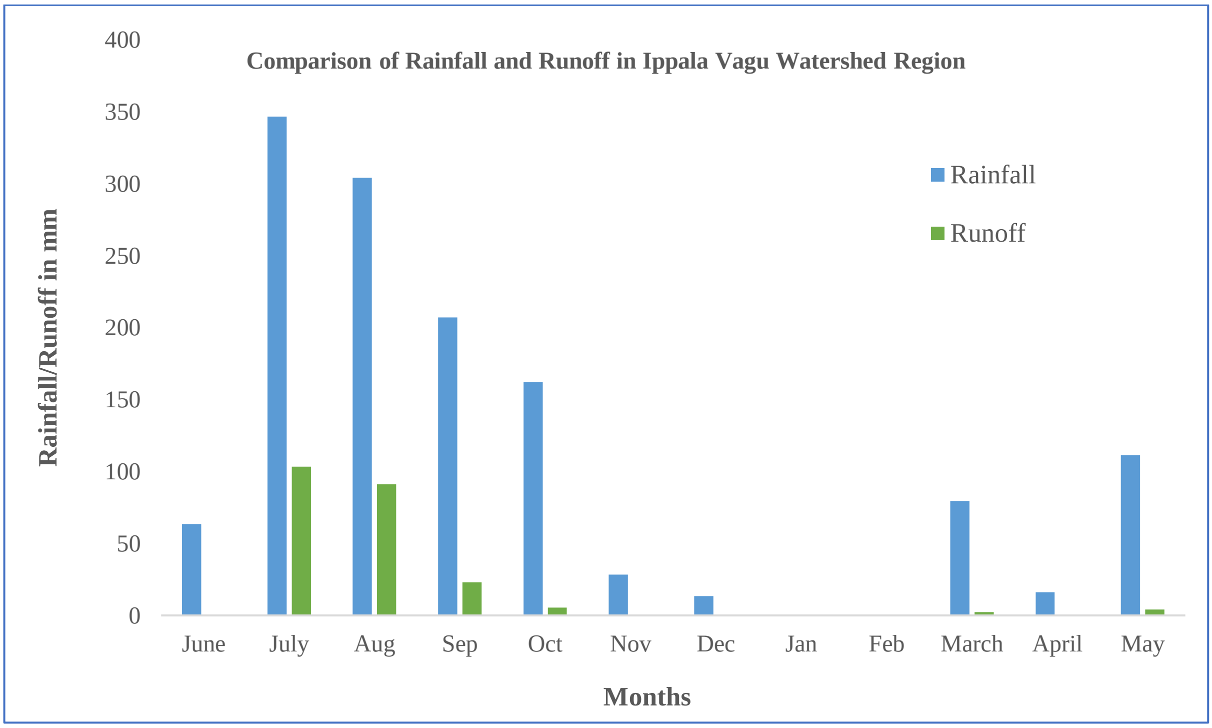

Fig. 4. Comparison of rainfall and runoff in Ippala Vagu Watershed Region

Fig. 5 presents the village-wise water balance components of Ippala Vagu Watershed for the year 2022-23, comprising the volume of rainfall, effective rainfall, runoff, groundwater recharge, and potential surface water storage. The volume of each water balance component for each village was estimated by multiplying the village area by the corresponding average water depth. Total rainfall received in the 18 villages of the Ippala Vagu watershed was 430.50 MCM, and effective rainfall was 138.24 MCM. The estimated runoff and groundwater recharge were 71.57 MCM and 68.88 MCM, respectively. Total potential surface water storage was 151.82 MCM.

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The estimated water balance components varied considerably among the villages. Putrela recorded the highest rainfall volume (53.61 MCM), followed by Vissannapet (38.13 million m³), Koduru (38.39 MCM), Chanubanda (37.21 MCM), and Chandrupatla (33.70 MCM). These villages also generated relatively high runoff and groundwater recharge due to greater rainfall inputs. In terms of potential surface water storage, Koduru had the highest value (18.86 MCM), closely followed by Chandrupatla (18.03 MCM), Vissannapet (15.45 MCM), Putrela (14.75 MCM), and Chanubanda (11.78 MCM). At the other end of the spectrum, Kummarakuntla recorded the lowest rainfall volume (4.06 MCM) and the least potential surface water storage (0.80 MCM), indicating limited water resource availability. Similarly, Krishnarao Palem, Repudi, Gollamandala, and Kambampadu showed comparatively lower potential surface water storage, suggesting the need for improved water conservation and storage measures.

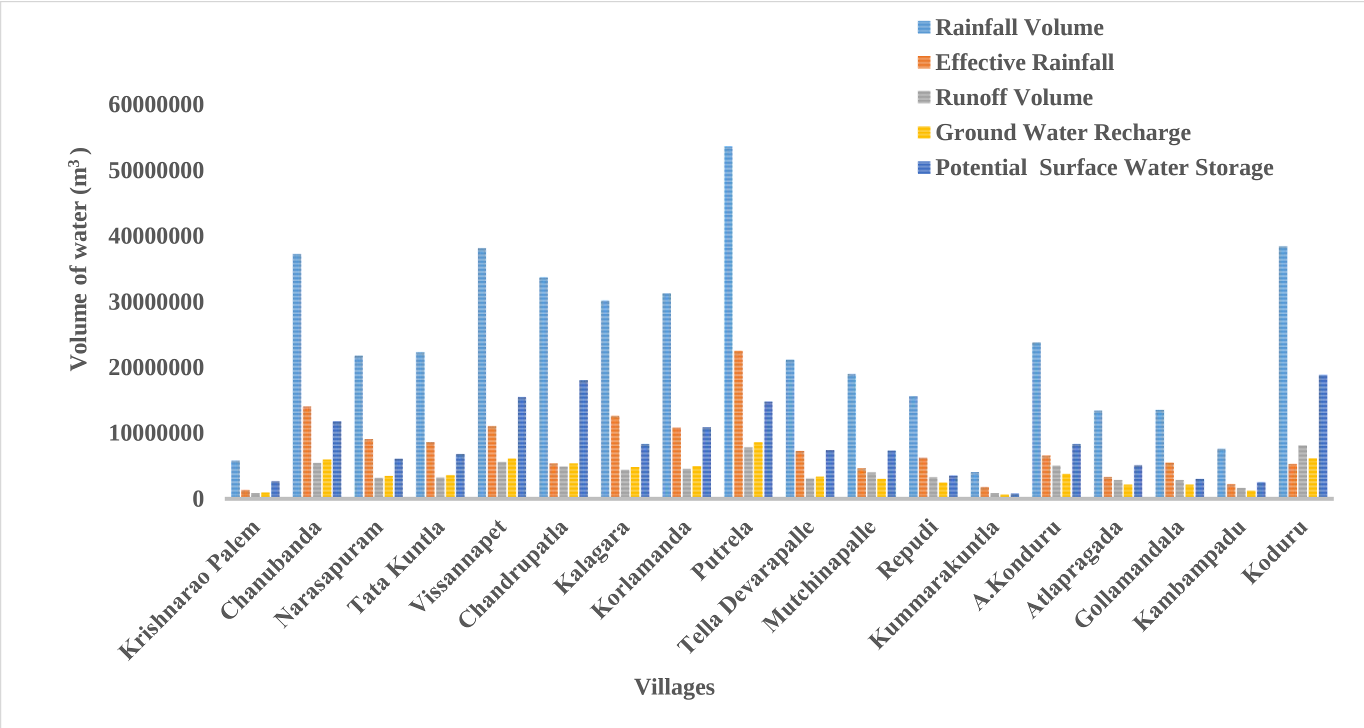

Fig. 5. Village-wise Comparison of water Balance components in the Ippala Vagu Watershed

Fig. 6 shows both potential surface water storage and existing storage Capacity in the villages of the Ippala Vagu Watershed.

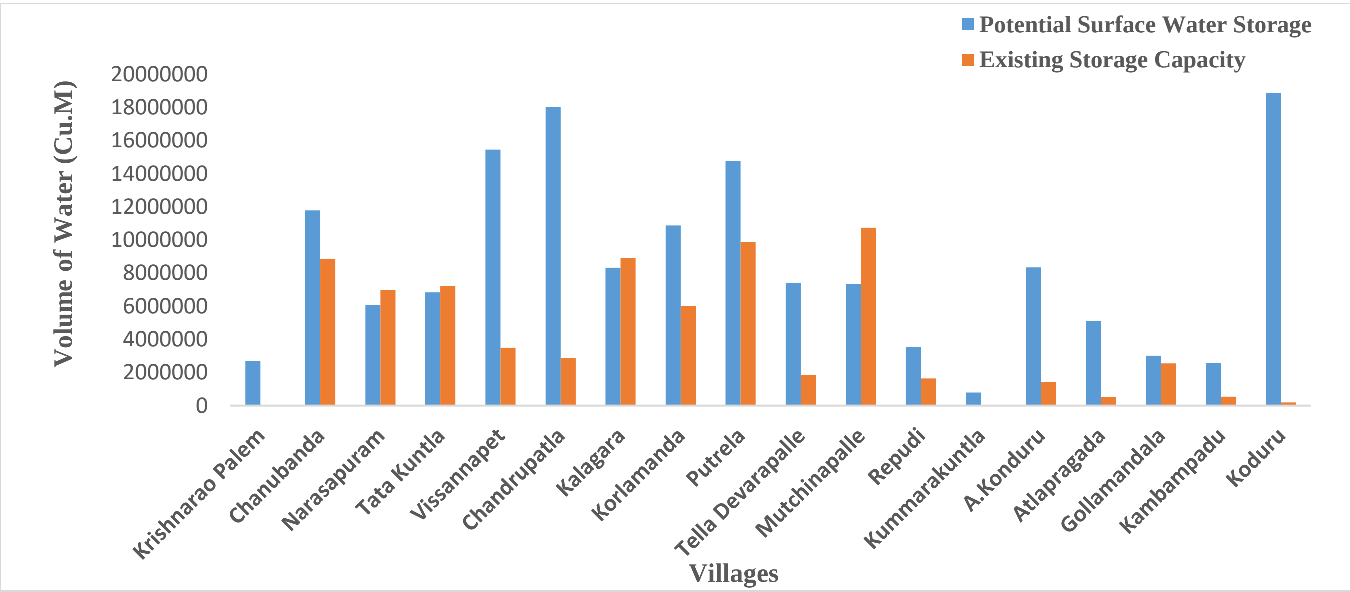

Fig. 6. Comparison of potential surface water storage and existing storage Capacity in the villages of the Ippala Vagu Watershed

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An examination of potential surface water storage and current storage capacity across the 18 villages shows a significant difference. The current storage capacity is only 73.67 MCM, or roughly 48.5% of the 151.82 MCM of surface water that is available based on estimation. This suggests that a significant proportion of the estimated potential surface water storage remains unutilized because of inadequate storage infrastructure. While Koduru, Chandrupatla, Vissannapet, and Atlapragada have great surface water potential but limited storage, villages like Krishnarao Palem and Kummarakuntla have no storage capacity although having surface water available. Conversely, villages such as Narasapuram, Tata Kuntla, Kalagara, and Mutchinapalle exhibit storage capacities that are equivalent to or surpass their potential surface water storage, showing good implementation of water conservation planning. The analysis highlights the need to enhance water storage infrastructure, particularly in villages with high potential surface water storage and limited existing storage capacity, to reduce runoff losses, improve groundwater recharge, and enhance irrigation potential. The analysis indicates that the existing storage infrastructure captures less than half of the estimated potential surface water storage. The identified storage deficit varies considerably among villages, indicating the need for location-specific water harvesting and storage interventions. These findings can support village-level planning for sustainable watershed management.

5 Practical Implications for Watershed Management

Runoff estimation is often used as the primary indicator for watershed assessment; however, effective planning requires consideration of other hydrological components that influence water availability. By combining effective rainfall, runoff, groundwater recharge, and potential surface water storage within a single water balance assessment, the present study offers a more comprehensive basis for identifying locations where additional water harvesting measures may be most beneficial. Similar observations were reported by M. Abraham and R. A. Mathew [15], who emphasized the value of linking runoff estimation with water demand and storage planning, while Verma et al. [1] highlighted the advantages of integrating hydrological analysis with GIS for watershed management.

The village-wise assessment clearly shows that water availability is not uniform across the watershed. Koduru, Chandrupatla, Vissannapet, Putrela, and Chanubanda recorded comparatively higher potential surface water storage than the remaining villages, whereas the available storage infrastructure in several of these locations is relatively limited. This mismatch suggests that future watershed interventions may be more effective if priority is given to villages where storage potential is high but existing storage capacity is comparatively low. Similar use of spatial runoff assessment for identifying suitable watershed interventions has been reported by Satheeshkumar et al. [10] and Kumari et al. [11].

Another notable outcome of the study is the difference between the estimated potential surface water storage and the existing storage capacity. The available storage represents only about 48.5% of the estimated potential, indicating that a substantial proportion of seasonal runoff cannot presently be retained for later use. Increasing the capacity of village tanks, check dams, farm ponds, and percolation tanks in suitable locations could improve the utilization of available runoff while also increasing opportunities for groundwater recharge. Comparable observations regarding the importance of runoff-based planning for water harvesting have also been presented by M. Abraham and R. A. Mathew [15].

Agriculture occupies the largest share of land within the watershed and consequently remains the principal consumer of available water resources. Improving village-level storage infrastructure would increase the reliability of irrigation supplies during periods of limited rainfall and reduce dependence on groundwater wherever surface water can be retained more effectively. Since the proposed assessment relies primarily on rainfall, land use, soil, and elevation datasets that are commonly available for many regions, the same approach can also be adopted for other ungauged or data-scarce watersheds with similar physiographic characteristics. The applicability of integrating GIS with empirical hydrological methods for regional water resource planning has likewise been discussed by Verma et al. [1] and Kumari et al. [11].

The proposed assessment enables identification of villages where additional water harvesting and storage interventions are likely to produce the greatest benefit. Such information can assist engineers and local planning agencies in prioritizing watershed development activities according to the spatial distribution of water availability and existing storage infrastructure.

5.1. Limitations of the Study

The present assessment was carried out using established empirical methods together with available rainfall records and geospatial datasets. Consequently, the estimated runoff, groundwater recharge, and potential surface water storage depend on the assumptions associated with the adopted SCS-CN, FAO/AGLW, and RIF methods. In addition, the runoff estimates were not validated against observed streamflow measurements because such records were unavailable for the watershed. Availability of long-term observed hydrological data would facilitate further evaluation of the estimated water balance components.

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6 Conclusion

The study was conducted in the 18 villages of the Ippala Vagu watershed. Village-wise analysis was carried out for rainfall, effective rainfall, runoff, groundwater recharge, potential surface water storage, and storage capacity. The village-level results were subsequently aggregated to evaluate the overall hydrological characteristics and water resource potential of the watershed. The Ippala Vagu Watershed received an annual rainfall volume of 430.50 million m³, of which 138.24 million m³ (32.11%) was estimated as effective rainfall. The estimated surface runoff was 71.57 million m³ (16.62%), while groundwater recharge was estimated at 68.88 million m³ (16.00%). The estimated potential surface water storage was 151.82 million m³, representing 35.27% of the total rainfall volume and indicating considerable potential for water resource development within the watershed. The findings suggest that increasing water harvesting and storage structures, particularly in areas with high runoff and limited storage capacity, could improve water conservation, enhance groundwater recharge, strengthen irrigation potential, and support sustainable watershed management. The methodology adopted in this study can also be applied to similar ungauged watersheds for preliminary assessment of surface water resources and identification of priority locations for future storage development.

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ETHICS STATEMENT

This study did not involve human or animal subjects and, therefore, did not require ethical approval.

STATEMENT OF CONFLICT OF INTERESTS

The authors declare no conflicts of interest related to this study.

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