

Hydrological assessment of the Gundlakamma sub-basin through SWAT modeling: integration of land use land cover (LULC) and climate changes

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ABSTRACT

Gundlakamma sub-basin faces challenges with increasing water demand and climate change impacts, requiring innovative solutions for sustainable water management. The study was conducted to improve the long-term utilization of water resources in Andhra Pradesh. To accomplish this, the study attempts to estimate LULC change detection and its impact on water resources by analyzing the performance of the soil and water assessment tool (SWAT) model. From 2005 to 2021, the amount of cropland decreased while built-up land increased, indicating urban growth. The SWAT model identifies hydrological processes and assesses the temporal and spatial distribution of water resources in the watershed. Statistical parameters results reveal that a good match was found between actual and modeled flows with Nash–Sutcliffe efficiency (NSE) and coefficient of determination (R^2) greater than 0.75 for both calibration and validation periods. The area has average annual precipitation, surface runoff, water yield, and actual evapotranspiration of 949.96, 215.6, 469.24, and 429.15 mm, respectively. The SWAT model's fascinating outcomes demonstrate that it could be a promising decision support tool for predicting water balance and water yield in other watersheds of Andhra Pradesh for sustainable water management of water resources where water quality and quantity are critical issues.

Key words: Andhra Pradesh, Gundlakamma sub-basin, LULC changes, SWAT model, water balance, water resource

HIGHLIGHTS

- The present study attempts to estimate LULC change detection and its impact on water resources by analyzing the performance SWAT model.
- Land cover changes are influenced by human activities, environmental changes, and land-use decisions.
- The SWAT model's fascinating outcomes demonstrate that it could be a promising decision-support tool for predicting water balance and water yield in other watersheds of Andhra Pradesh.

1. INTRODUCTION

Water resource management is a critical issue in many parts of the world, particularly in countries dealing with rising populations, industrialization, and the negative effects of climate change. Anthropogenic activities are changing the properties of watersheds, notably land cover, which has an impact on the complex biogeochemical processes at work in these settings. The effective and integrated management of water resources in the face of changing land-use and climatic circumstances has arisen as a major problem for many communities, both now and in the near future (Simonovic 2002). Licite *et al.* (2022) advocate a shift in nutrient-rich organic soil management in agriculture toward targeted, research-based climate change mitigation practices. This approach aligns with national and international climate change mitigation targets, particularly in the pursuit of climate neutrality goals. Faye (2022) suggests that drying trends already affect socioecological systems, leading to reduced agricultural yields and land salinization. To mitigate the impact of future drought the necessity of concerted efforts through water conservation measures is suggested, including effective water management policies and climate-smart agricultural practices.

Changes in the physical, biological, and chemical characteristics of land and soil brought on by anthropogenic activity are the main cause of land degradation (Brimoh & Vlek 2004; Korkanc *et al.* 2008; Emadodin *et al.* 2009; Yao *et al.* 2010).

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LULC changes can be used as indicators of ecological stress and can affect air pollution by modifying the interaction between the Earth's surface and the atmosphere (Sun *et al.* 2016). Notably, Landsat satellite remote sensing data, known for their high spectral, geographical, and temporal resolutions, are critical for a variety of mapping and planning projects (Sadidy *et al.* 2009).

Hydrologic models distributed throughout space provide an effective tool for understanding the impact of land-use and climatic factors on stream hydrology and surface water availability (Haverkamp *et al.* 2005). Such models, which are frequently used at the watershed size, include the Hydrologic Simulation Programme Fortran (Holtan & Lopez 1971; HSPF 2001) and the SWAT model (Arnold *et al.* 1998). The SWAT model has been regularly utilized to examine the effects of LULC changes on surface water resources worldwide (Rathjens *et al.* 2015; Zhang *et al.* 2017; Gashaw *et al.* 2018; Abbaszadeh *et al.* 2023) and in India (Kushwaha & Jain 2013; Nagraj *et al.* 2018; Bera & Maiti 2021).

Water balance modeling is an important technique in water resource management since it allows for the simulation of a region's water balance, including precipitation, evapotranspiration (ET), water withdrawal, and the identification of surplus and deficit areas. The SWAT model gives a complete knowledge of watershed behavior over space and time by integrating meteorological data, soil parameters, vegetation characteristics, and land-use dynamics. This model proves invaluable in the face of escalating environmental challenges and the growing demands on water resources, serving as a critical tool for researchers and stakeholders navigating the intricacies of sustainable watershed management.

Wang *et al.* (2019) reviewed the SWAT model, confirming its effective simulation of long-term hydrological processes. However, consistent with previous studies, accuracy declines with shorter time steps, particularly in daily runoff simulations. Despite this, the SWAT model shows promise for improvement to enhance water cycle simulation, aid water resources scheduling decisions, and support effective water resources management.

Hari *et al.* (2019) carried out a study on the simulation of water resources in the Gundlakamma sub-basin, and it was found that the maximum and minimum reservoir outflow in 2010 were 28.94 and 171.03 m³/s, respectively. The average annual surface runoff and actual ET were reported as 210.67 and 404.20 mm, respectively. These values varied with land use and land cover (LULC) patterns. The peak reservoir outflow occurred in October, which was attributed to the increased urbanization, causing higher surface runoff and reduced infiltration in the sub-basin.

Hari *et al.* (2020) used the SWAT model to investigate how changes in land-use cover affect water resource availability in the Gundlakamma sub-basin. Statistical parameters of the SWAT model such as NSE and R^2 values were 0.79 and 0.87 during calibration, and 0.65 and 0.72 during validation, respectively. The simulated and observed values of reservoir outflow showed a good degree of agreement during both the calibration and validation phases.

Human activities have a significant impact on water resources in the Gundlakamma watershed, which is mostly driven by shifting land use. Water quality and quantity changes in the watershed are intimately linked to changes in land-use practices, particularly the increased entry of chemicals into streams from agricultural and urban sources. Due to increasing population, industrialization, and the impending shadow of climate change, the Gundlakamma sub-basin, a critical water supply for surrounding areas, faces complex management difficulties. Geo-informatics emerges as a powerful tool in this context, providing insights into water resource optimization. The area under study is experiencing drought conditions. However, the utilization of the SWAT model in estimating the available water resources in the area has not been thoroughly explored. Despite the importance of this, there has been a lack of in-depth simulation research conducted on the Gundlakamma watershed. The authors of this study have attempted, for the first time, to conduct a comprehensive study of the water resources available in the Gundlakamma sub-basin using the SWAT model.

As a result, a robust SWAT simulation of water quantity has the potential to offer insight into the implications of land-use changes in this region, especially given the significant urban development that is occurring. The main objective of the present study encompasses evaluating the impact of LULC changes on water resources, simulating streamflow, and water balance components to gauge the water resource status, and projecting annual water quantities under diverse urban land-use change scenarios. This study, crucial in managing natural resources for sustainable watershed development, identifies aquifer recharge and saturated hydraulic conductivity as key parameters for simulating water yield. The results of the present findings indicate that climate change poses a threat to water resources, emphasizing the need for future research to assess its impact on impervious land use and overall water quantity. The outcomes of this research could lead to the use of SWAT and other methods that impacted agricultural watersheds within Andhra Pradesh. Ultimately, the findings have the power to assess the applicability of such tools under varying watershed conditions and data availability for water resource management purposes.

2. MATERIALS AND METHODS

2.1. Study area

The Gundlakamma sub-basin rises in the Kurnool region, close to Istkagundam. It is situated between latitudes $15^{\circ} 50' 59.166''$ to $15^{\circ} 29' 27.166''$ N and longitudes $79^{\circ} 38' 7.794''$ to $80^{\circ} 11' 24.858''$ E (Figure 1) and has an elevation of around 600 m from the eastern Nallamala Hills. The area between the Krishna and Pennar sub-basins covers 24,669 km², with 41 watersheds, 15 of which belong to the Gundlakamma sub-basins. The study focused on an area of 8,494 km². The

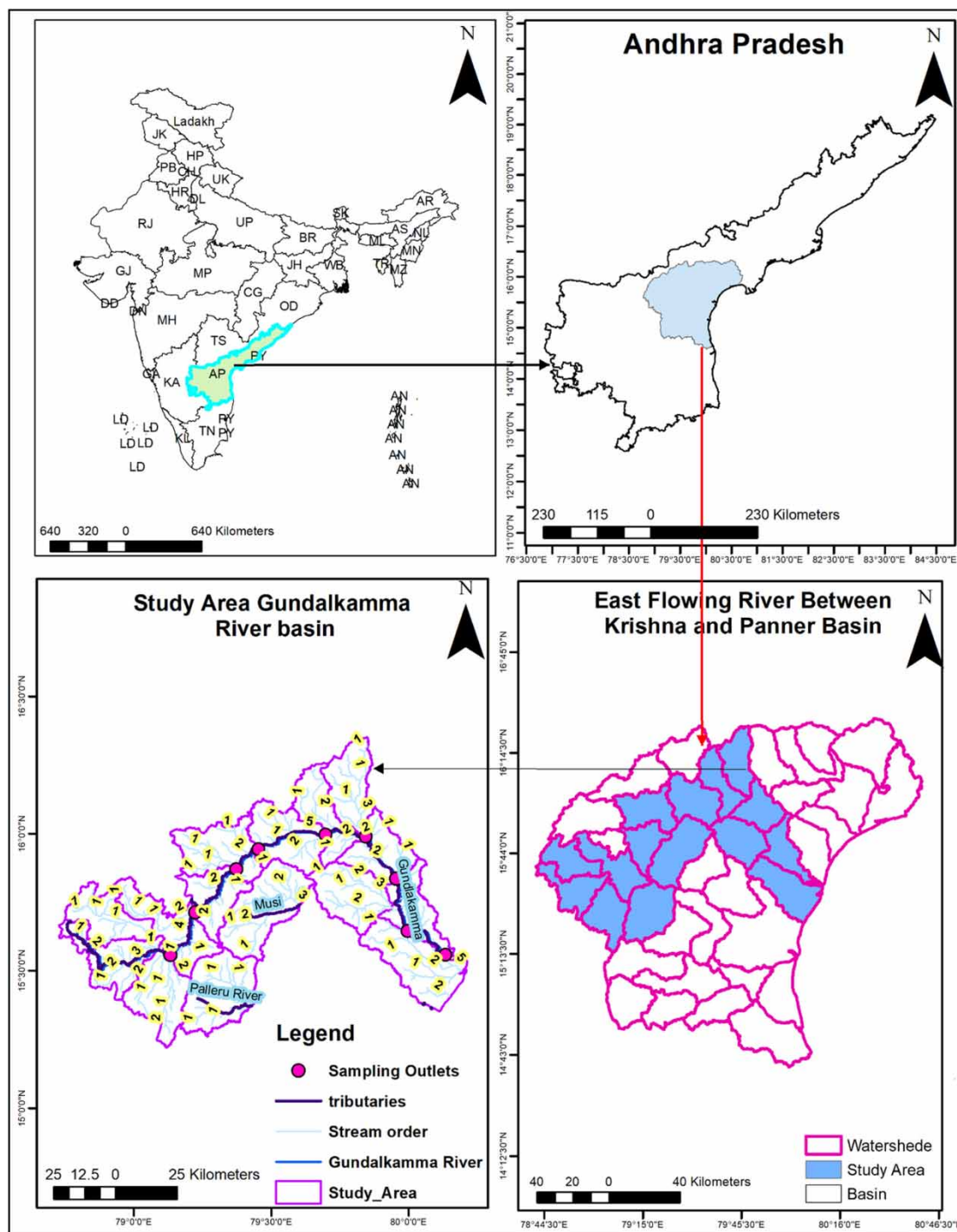


Figure 1 | Study area location map of Gundlakamma sub-basin, Kurnool region Andhra Pradesh.

Gundlakamma sub-basin faces challenges with increasing water demand and climate change impacts, requiring innovative solutions for sustainable water management. According to the [Census of India \(2011\)](#), the sub-basin formed by the east-flowing rivers between Krishna and Pennar covers four districts: Prakasam, Kurnool, Guntur, and Nellore, with a total population of 227,528.

2.2. Geomorphology

The physical landscape and hydrology of the Gundlakamma sub-basin are shaped by its geomorphology. The sub-basin has varying elevations, including hills, mountains, valleys, and plains, which affect water flow patterns, drainage networks, and erosion processes. Understanding the distribution of slopes is crucial for assessing soil erosion and sedimentation processes in the area. The geomorphology of the area is given in [Figure 2](#).

The geomorphological history of the Gundlakamma sub-basin can provide valuable insights into its geological past, hydrological behavior, and susceptibility to environmental processes. Human activities like deforestation, urbanization, and agriculture can significantly alter the natural geomorphology of a region, affecting erosion rates, sediment transport, and overall landscape stability. The knowledge of these factors is crucial for effective water resource management, land-use planning, and environmental conservation within the sub-basin.

2.3. Climate and rainfall

The city has a mildly tropical atmosphere with an average high temperature of 47 °C in May and a low temperature of 14 °C in January. The monsoon season starts in the second week of June, with heavy rainfall in July and August. By the end of

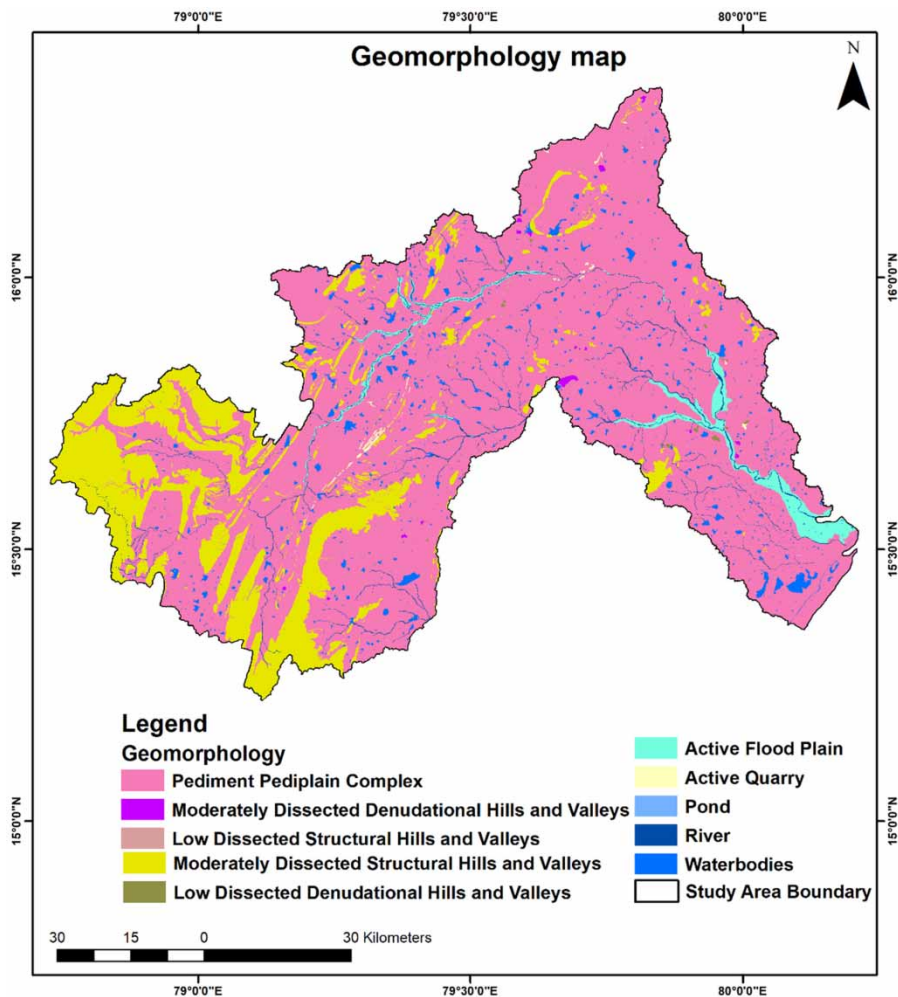


Figure 2 | Geomorphology map of the area.

September, the monsoon retreats, and around 88% of rainfall occurs from June to September. Excess water is available for deep percolation into groundwater during the monsoon.

Mann & Gupta (2022) worked on temporal trends of rainfall and temperature and found that local factors, including mountain summit characteristics, relief, and apexes, significantly influence rainfall. Variations in both rainfall and temperature arise from internal epochal variability and broader climatic factors. Recent changes are attributed to global warming and anthropogenic factors like rapid urbanization, altering rainfall, and temperature patterns.

Rainfall data from 2002 to 2019 in the Gundlakamma sub-basin were collected and statistically analyzed (www.indiaawris.gov.in). The result reveals an average annual rainfall of 930 mm, with a standard deviation of 208 mm and a coefficient of variation of 22.2% (Table 1). The highest rainfall was recorded in 1990 and reached its lowest in 2018. The result of rainfall analysis identifies six drought periods over 33 years, as annual rainfall dips below a 10% reduction from the normal rainfall of 853 mm (Figure 3). The data suggest that droughts occur in the area every 5 years.

2.4. Drainage map

Stream order categorizes streams based on hierarchical position within a drainage network. Drainage data reveal the stream length distribution by order, with larger and more significant streams forming from the convergence of smaller streams. This information is essential to comprehend the overall structure and characteristics of a river system or watershed. The stream orders 1, 2, 3, 4, and 5 have a total length of 960, 548, 231, 107, and 136 km, respectively (Figure 4). The Gundlakamma sub-basin has a particular drainage pattern that determines how water is distributed across its landscape, featuring valleys, ridges, plateaus, hills, and possibly even erosional or depositional landforms caused by water flow and sediment transport. The sub-basin comprises the Palleru River, Musi, and Utlavagu River tributaries, which contribute to the Gundlakamma River.

2.5. Digital elevation model and slope

A digital elevation model (DEM) is a digital representation of the ground surface topography. The topographic data used for DEM were taken from the USGS website in the form of SRTM. The SRTM DEM was clipped to retrieve elevation data within the vector polygon boundary file of the area (Figure 5). DEM processing and slope calculations were performed using ArcGIS 10.7. The altitude varies from 2 to 921 m above mean sea level (AMSL). In general, the western part of the area shows higher elevations with steep slopes. The lower elevation of the area is observed in the eastern part of the area with a gentle slope. The general flow of the basin is from west to east.

Slope refers to the steepness of the terrain in a specified area and is measured in degrees to indicate how much the elevation changes over a given horizontal distance. The slope of the area ranges from 2° to 15° (Figure 6). Different slope classes in degrees of the area are presented in Table 2. The majority of the area, about 83.7%, has a slope range of less than 2°. The steepness of slopes affects the speed of water runoff, erosion rates, and sediment deposition. In areas with steeper slopes, erosion might be more significant, leading to sediment transport downstream.

2.6. Soil map

In the study area, soil characteristics are distributed allowing for an understanding of soil types, erosion levels, productivity, slopes, and textures present in the region. Soil data were collected from www.indiaawris.gov.in and soil characteristics of the area are presented in Table 3.

The majority of the area shows moderate erosion, followed by none to slight, severe, and very severe erosion. About 68.5% of the area has deep/moderately deep depth of more than 50 centimeters, while shallow, very shallow, and extremely shallow soil depth is present in the remaining area. About 45.2% of the total area has highly productive soil, while 25.2 and 24.9% of the soil exhibit low and moderate productivity, respectively. In terms of slope, the area has a gentle slope of 3–8° for 41.4% of the area and is nearly level (0–1°) for 42.1% of the total area. Soil texture of the area is characterized by clay, loamy clay, sandy clay, silty clay, and sandy clay for about 70.9% of the total area, while loam, silt loam, silt, and sandy loam make up 20.2% of the total area.

2.7. Land use land cover mapping

A land use land cover (LULC) map was created for the years 2005, 2010 and 2021 by acquiring remote sensing data such as Landsat SRTM data (<https://earthexplorer.usgs.gov>) and Sentinel 2 (<https://www.esa-landlab.com/apps>). These data were geo-referenced, digitized, and systematically classified to accurately depict the various types of LULC classes in a given area.

Table 1 | Statistical analysis of annual rainfall of Gundlakamma sub-basin

Year	Actual rainfall (mm) X	Normal rainfall (mm) Y	Departure (X/Y) – 1	Cumulative Dep.	X – Y	(X – Y) ²
1990	1,265	853	0.48	–0.05	411.91	16,9670
1991	1,111	853	0.30	0.25	258.07	66,600
1992	774	853	–0.09	0.16	–78.11	6,101
1993	945	853	0.11	0.27	92.33	8,525
1994	973	853	0.14	0.41	120.57	14,537
1995	954	853	0.12	0.53	101.20	10,241
1996	1,140	853	0.34	0.87	287.85	82,858
1997	1,146	853	0.34	1.21	293.36	86,060
1998	1,040	853	0.22	1.43	187.23	35,055
1999	647	853	–0.24	1.19	–205.18	42,099
2000	1,082	853	0.27	1.46	229.33	52,592
2001	910	853	0.07	1.53	57.22	3,274
2002	659	853	–0.23	1.30	–193.74	37,535
2003	793	853	–0.07	1.23	–60.09	3,611
2004	855	853	0.00	1.23	2.63	7
2005	1,030	853	0.21	1.44	177.56	31,528
2006	1,107	853	0.30	1.74	254.68	64,862
2007	1,114	853	0.31	2.05	261.77	68,524
2008	1,099	853	0.29	2.33	246.26	60,644
2009	808	853	–0.05	2.28	–44.65	1,994
2010	950	853	0.47	2.75	397.41	157,935
2011	661	853	–0.23	2.52	–192.00	36,864
2012	961	853	0.13	2.65	108.36	11,742
2013	1,029	853	0.21	2.86	176.11	31,015
2014	589	853	–0.31	2.55	–263.20	69,274
2015	798	853	–0.06	2.48	–54.38	2,957
2016	685	853	–0.20	2.29	–167.29	27,986
2017	752	853	–0.12	2.17	–101.00	10,201
2018	521	853	–0.39	1.78	–331.11	109,634
2019	866	853	0.02	1.80	12.99	169
2020	1,086	853	0.27	2.07	233.90	54,709
2021	1,005	853	0.18	2.25	152.61	23,290
2022	1,020	853	0.20	2.45	167.83	28,167
Minimum						521
Maximum						1,265
Average						930
Standard deviation						206.7
Coefficient of variation						22.2%

The process often combines remote sensing data, Geographic Information System (GIS), and field validation. ArcGIS 10.7 was used to resample image 2005 and Shuttle Radar Topography Mission (SRTM) elevation data into 10 m grid cells. Additional datasets include a topographic map, road network, rivers, water bodies, and specified areas. Landsat pictures were obtained without distortion. All processed datasets used WGS 1984 and UTM Zone 44 P as spatial references. Imagery

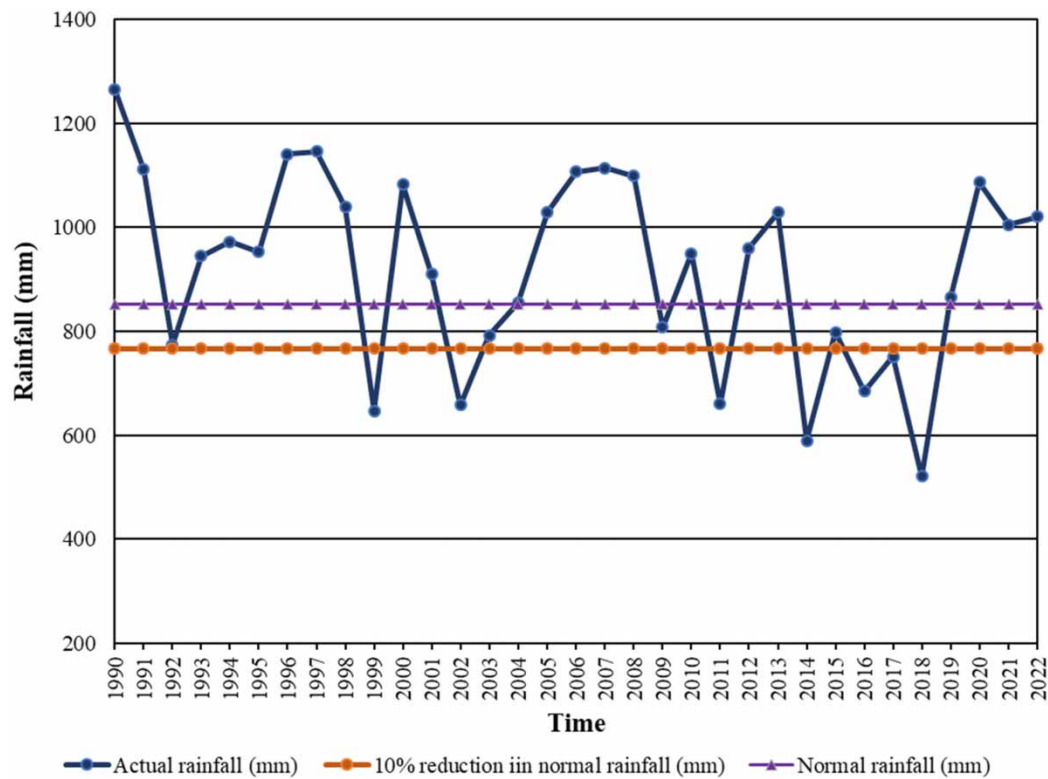


Figure 3 | A comparison of annual rainfall with a 10% reduction in normal rainfall.

was preprocessed by removing distortions, atmospheric effects, and applying radiometric corrections. Techniques like histogram equalization, contrast modification, and band combination were employed to identify LULC classes based on their spectral traits and patterns for improved visual interpretation. Supervised classification used methods like support vector machines (SVM) or random forests to classify each pixel into distinct LULC classes. Relevant labels were assigned based on actual data or field experience and gather real-world information by conducting field research or using high-resolution images for verification. In the present study, LANDSAT satellite images from 2005, 2015, and 2021 were used, with a decade gap between each image.

2.8. SWAT model

To resemble both the quality and quantity of water resources of a river basin, a SWAT was developed by the USDA Agricultural Research Service in 1990. It foresees how land use and management decisions will affect water supplies (Arnold *et al.* 1998). SWAT is a hydrological and water quality model that routes water, sediments, and nutrients from sub-watersheds to mainstream watersheds. It forecasts how changing land use and management circumstances will affect water, sediment, and chemical yields in distinct basins over time.

The SWAT models the hydrological cycle using the water balance equation (Equation (1)) (Neitsch *et al.* 2005).

$$SW_t = SW_o + \sum_{i=1}^t (R_{\text{day}} + Q_{\text{surf}} - E_a - W_{\text{seep}} - Q_{\text{gw}}) \quad (1)$$

Water yield, hydrological response units (HRUs), and entering the principle channel during a time step, are critical parameters for sustainable water resource management. The following equation is used to evaluate water yield within a watershed (Arnold *et al.* 2011).

$$W_{\text{yld}} = Q_{\text{surf}} + Q_{\text{gw}} + Q_{\text{lat}} - T_{\text{los}} \quad (2)$$

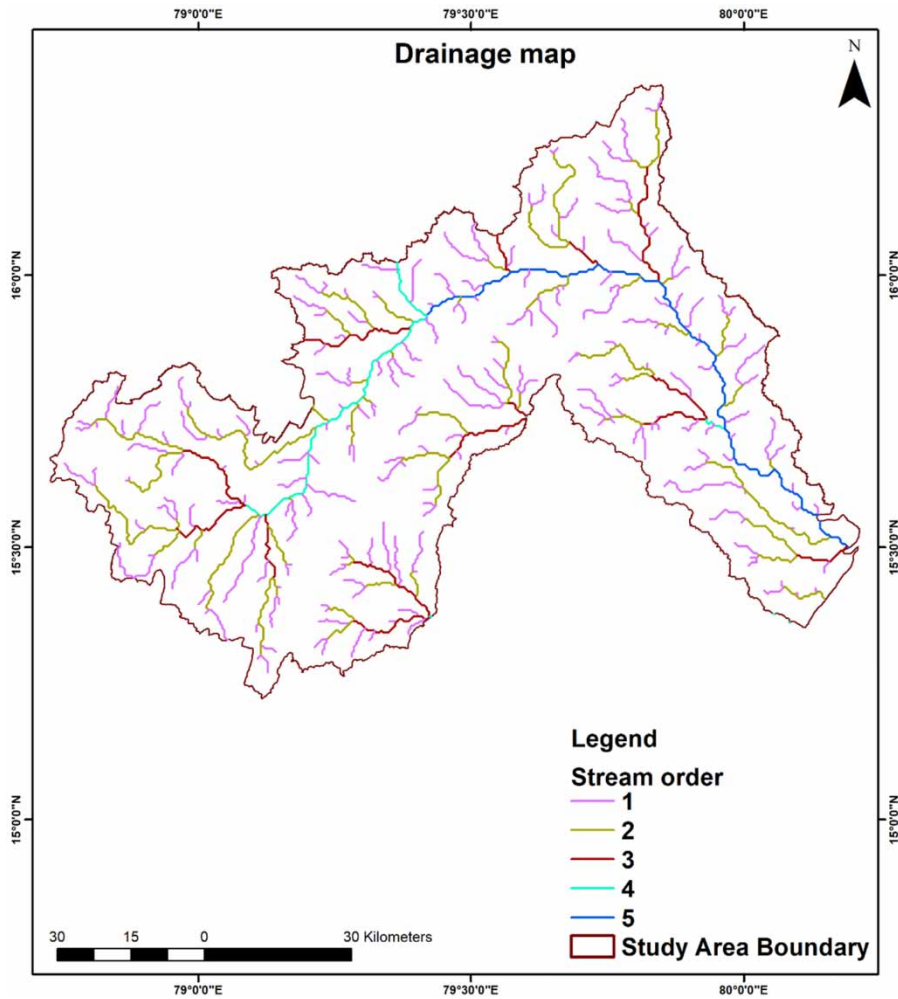


Figure 4 | Stream ordering of the study area.

For the estimation of the surface runoff equation, the following equation can be used

$$Q_{\text{surf}} = \frac{(R_{\text{day}} + 0.2S)^2}{(R_{\text{day}} + 0.8S)} \quad (3)$$

The retention parameter S was determined by the following equation

$$S = 25.4 \left(\frac{100}{\text{CN}} - 10 \right) \quad (4)$$

The prediction of lateral flow was measured by the following equation

$$Q_{\text{lat}} = 0.024 \frac{(2SSC \sin \alpha)}{\theta_d L} \quad (5)$$

The base flow was estimated by the following equation

$$Q_{\text{gfw}} = Q_{\text{gfw-1}} e^{(-\alpha_{\text{gw}} \Delta t)} + Q_{\text{rchrg}} (1 - e^{(-\alpha_{\text{gw}} \Delta t)}) \quad (6)$$

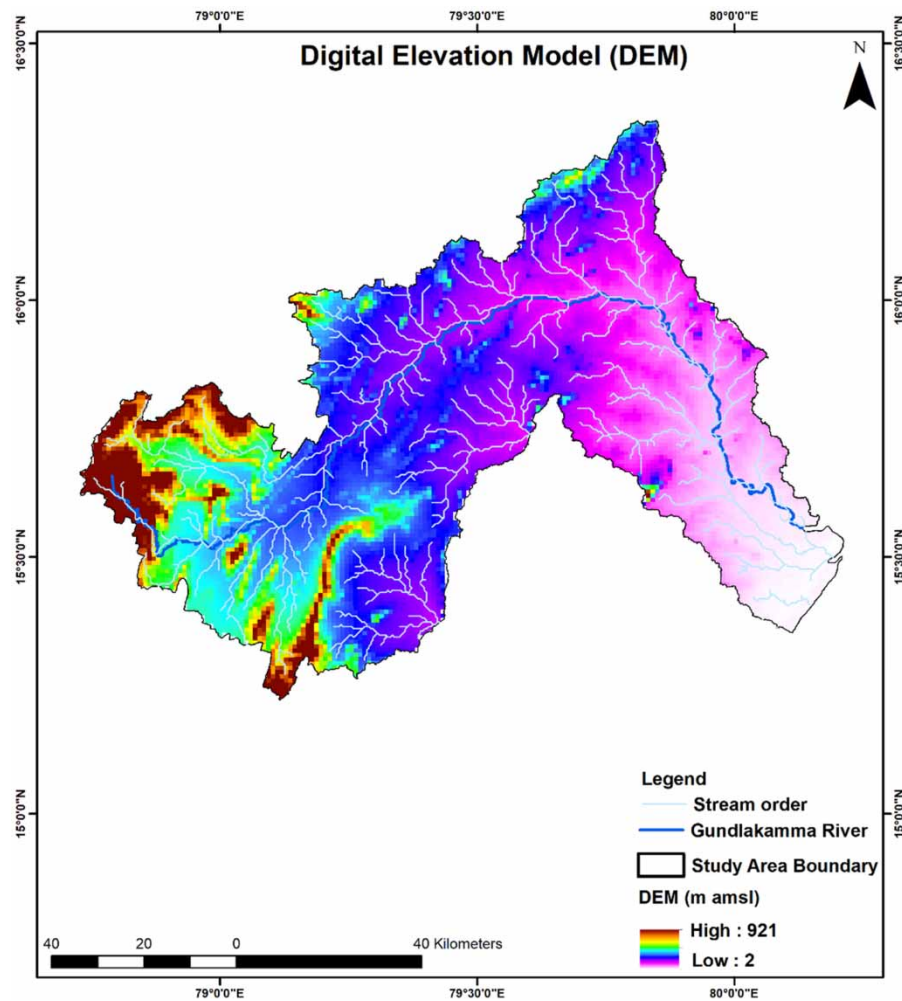


Figure 5 | DEM of the area.

Table 4 displays the notation and terminology used in the aforementioned equations.

2.8.1. Data input

The primary channel network of the sub-basin is where the impoundments are known as Gundlakamma reservoirs. They are loaded from all upstream sub-basins, and the SWAT model can be used to simulate inflow, outflow, and sedimentation. For the SWAT model, LULC, soil, IMD gridded weather, and DEM data were taken from <https://swat.tamu.edu/data/india-dataset/>. The Kandula Obula Reddy Gundlakamma Reservoir Project was built on the Gundlakamma River near Chinnamallavaram Village in Maddipadu Mandal, Prakasam District, Andhra Pradesh. Mean monthly reservoir outflow data were collected from the Office of Chief Engineer, Ongole and Prakasam district from 1 January 2010 to 31 December 2022. Before running the SWAT executables for model calibration and validation, we ensure that all necessary files for simulating SWAT have been prepared and appropriate weather sources have been selected. The Arc-SWAT requires basic ArcGIS 10.7 compatible maps including DEM elevation slope maps, LULC maps for 2005, 2010, and 2015, geomorphology, and drainage network ordering of streamline. The interface requires access to ArcGIS-compatible raster and vector datasets, as well as database files including watershed data, in order to construct a SWAT dataset. Daily rainfall data for the study area were available for 33 years (1990–2022).

2.8.2. Calibration and validation of the SWAT model

The simulation ran for a total of 13 years from 2010 to 2022 from the outlets of the Gundlakamma sub-basin (Figure 1). The calibration phase for the SWAT simulation was 2010–2017, while the validation period was 2018–2022 sub-watersheds.

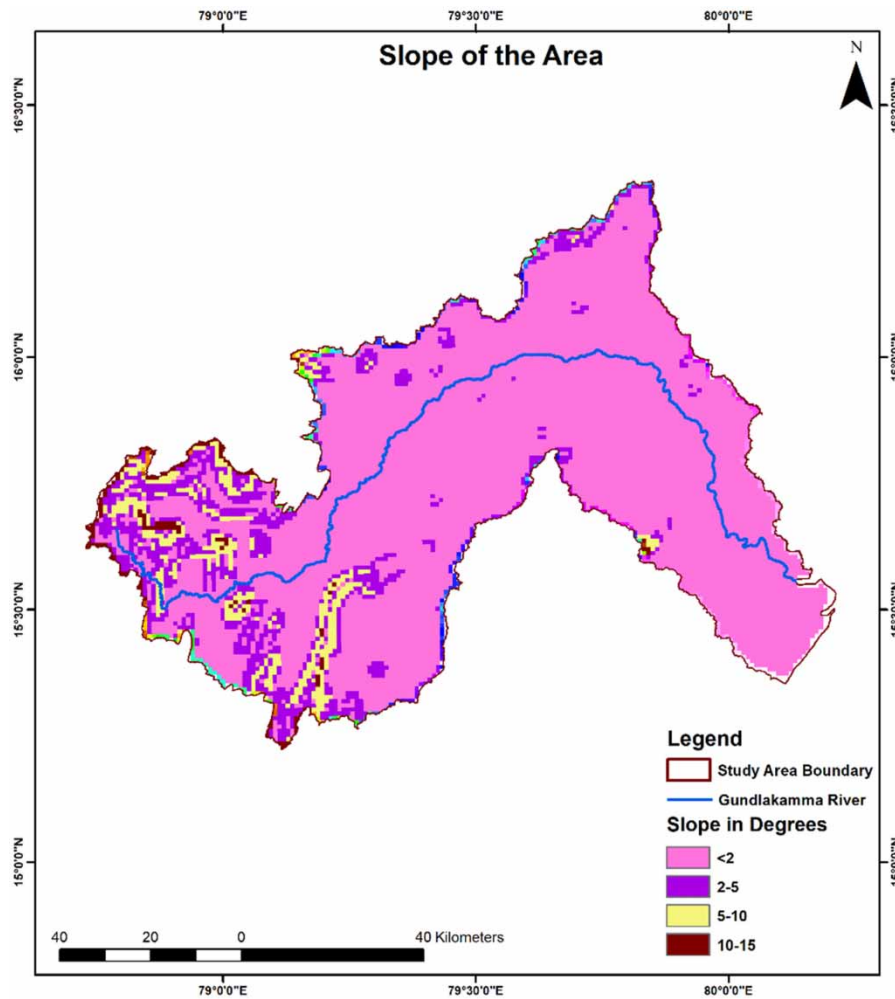


Figure 6 | Slope of the area in degrees.

Table 2 | Different slope classes in degrees of area

Slope (degree)	Area	
	in sq. km	in percentage (%)
<2	6,600	83.7
2–5	870	11.04
5–10	381	4.8
10–15	35	0.44

Parameter adjustment was performed only during the calibration period, while the validation process involved executing the model using the previously calibrated input parameters for different time periods. The water balance and streamflow were calibrated for average monthly conditions, followed by the calibration of several SWAT hydrologic parameters. The SWAT Calibration Uncertainty Program (SWAT-CUP) is an interface that connects with SWAT models to undertake sensitivity analysis, calibration, validation, and uncertainty analysis in hydrological models. It is a combination of algorithms including sequential uncertainty fitting 2 (SUFI-2), particle swarm optimization (PSO), generalized likelihood uncertainty estimation (GLUE), solution parameters (ParaSol), and Mark Chain Monte Carlo (MCMC), and assess the adequacy of SWAT

Table 3 | Soil characteristics of the study area (source: www.indiawris.gov.in)

Soil characteristics	Area	
	in sq. km	in percentage (%)
Soil depth		
Deep/moderately deep (depth >50 cm)	5,815.4	68.5
Extremely shallow (<10 cm)	56.7	0.7
Shallow (25–50 cm)	2,102.0	24.8
Very shallow (10–25 cm)	516.1	6.1
Soil erosion		
Moderate	3,822.0	45.0
None to slight, slight	2,869.7	33.8
Severe	1,741.9	20.5
Very severe, gullied	56.7	0.7
Soil productivity		
Highly productive	3,841.5	45.2
Low productive	2,137.4	25.2
Moderately low productive	339.5	4.0
Moderately productive	2,115.1	24.9
Soil slope		
Gently sloping (3–8%)	3,510.8	41.4
Moderately sloping (8–15%)	1,349.9	15.9
Moderately steep sloping (15–30%)	56.7	0.7
Nearly leveled (0–1%) and very gently sloping (1–3%)	3,573.0	42.1
Soil texture		
Clay, loamy clay, sandy clay, silty clay, sandy clay	6,020.6	70.9
Loam, silt loam, silt, sandy loam	1,717.3	20.2
Loamy sand, sand	695.7	8.2
Rocky, other non-soil categories (built-up, water body)	56.7	0.7

calibration using coefficient of determination (R^2) and NSE. The R^2 number measures the correlation between observed and simulated values, while the NSE value evaluates model performance by measuring the agreement between measured and simulated values. A model's prediction is deemed acceptable if both R^2 and NSE are greater than 0.5 for NSE (Moriassi *et al.* 2007).

3. RESULTS AND DISCUSSION

3.1. LULC change detection

Deforestation, biodiversity loss, and desertification are all caused by the degradation of LULC. The study assessed the LULC deterioration in the study area from 2005 to 2021 using remote sensing indices and LULC change detection. The focus was on natural vegetation changes, urban expansion, soil deterioration due to industrial operations, and surface water body degradation. The major seven LULC classes were identified (Table 5). A study was carried out by Hari *et al.* (2020) and Kesanapalli *et al.* (2018) on the change of LULC patterns in the Gundlakamma sub-basin, and their studies reported a significant increase in urbanization over time.

The LULC maps for 2005, 2015, and 2021 are shown in Figures 7(a)–7(c), respectively. Pie diagrams showing the LULC classification in sq.km of 2005, 2015, and 2021 are given in Figures 8(a)–8(c). The dominant area was covered by the crop land followed by the deciduous needleleaf, mixed forest, built-up land, and water body in 2021.

Table 4 | Notation and terminology used in the above equations

Notation	Terminology
SW_t	Final soil water content (mm)
SW_o	Initial soil water content (mm) in day i
T	Time in days
R_{day}	Precipitation (mm) in day i
Q_{surf}	Surface runoff (mm) in day i or rainfall excess
E_a	Amount of ET (mm) in day i
W_{seep}	Water entering the vadose zone from the soil profile (mm) on day i
Q_{gw}	Groundwater discharge in day i or groundwater contribution to streamflow (mm)
W_{yld}	Water yield (mm)
CN	Soil curve number
Q_{lat}	Lateral flow (mm/day)
θ_d	Drainable porosity
T_{loss}	Transmission losses (mm)
S	Retention parameter (mm)
SC	Hydraulic conductivity (mm/h)
L	Flow length
A	Slope of the land

Table 5 | Change detection in major LULC classes from 2005 to 2021

Land-use land cover classification	2005		2015		2021	
	Area		Area		Area	
	Sq. km	% of convergence	Sq. km	% of convergence	Sq. km	% of convergence
Cropland	4,799.7	56.9	5,246.4	62.2	5,303.8	62.9
Built-up land	51.2	0.6	249.1	3.0	289.1	3.4
Deciduous broadleaf forest	2,202.8	26.1	2,442.4	30.1	2,063.7	24.5
Mixed forest	622.1	7.4	330.7	3.9	608.4	7.2
Barren land	53.8	0.6	2.8	0.03	12.4	0.15
Fallow land	301.3	3.6	4.0	0.05	1.5	0.02
Water bodies	407.7	4.8	163.2	0.7	160.0	1.9
Total	8,438	100	8,438	100	8,438	100

A bar diagram showing the change detection in LULC from 2005 to 2021 is given in [Figure 9](#). Cropland refers to land used for growing crops, while built-up land includes areas developed for urban use, such as residential, commercial, and industrial zones. From 2005 to 2021, the amount of cropland and built-up land increased, indicating urban growth and development. Deciduous needleleaf forests are mostly composed of trees with needlelike leaves that lose their leaves seasonally. From 2015 to 2021, the area of this forest type has significantly decreased due to various factors such as deforestation, urbanization, agricultural practices, changes in vegetation composition, and environmental changes in the area. Mixed forests are a combination of different tree species, including deciduous and coniferous trees. The area of mixed forests has decreased over time due to deforestation, land conversion, and natural disturbances. Barren land refers to areas with sparse or no vegetation. The decrease in its coverage from 2005 to 2021 could be due to changes in land use, reclamation efforts, or natural vegetation regrowth. Fallow land is agricultural land left unplanted for an extended time. The area of fallow land has decreased from 301 km² in 2005 to 1.5 km² in 2021, indicating changes in agricultural practices. This result is supported by the increase in

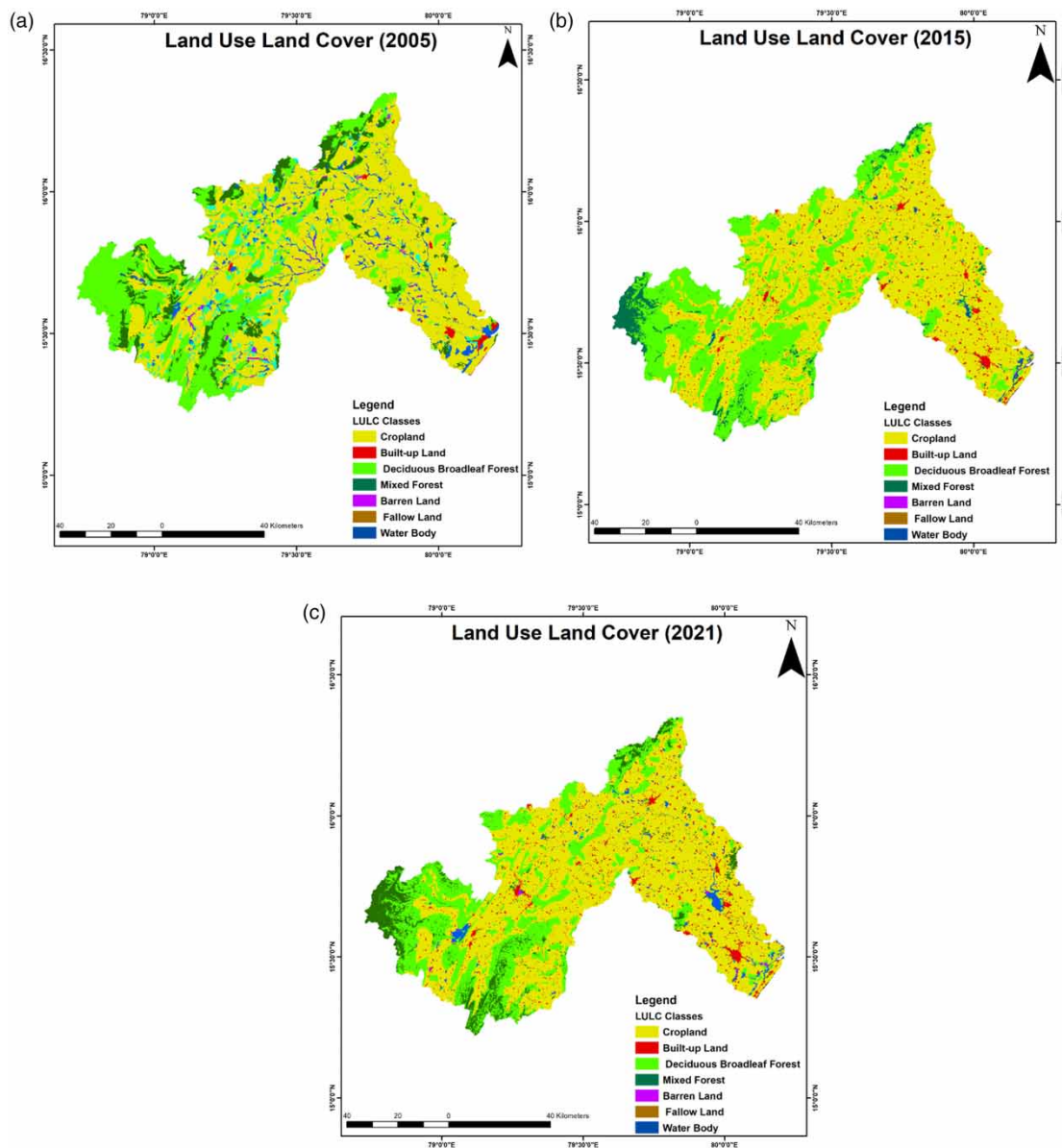


Figure 7 | (a) LULC classification of the area 2005, (b) LULC classification of the area 2015, and (c) LULC classification of the area 2021.

agricultural areas over time. Water bodies, both natural and man-made, like lakes, rivers, and reservoirs, have decreased from 407.7 km² in 2005 to 160 km² in 2021, possibly due to climate change, water management, and human activities. Land cover changes are influenced by human activities, environmental changes, and land-use decisions, resulting in changes in different categories over time in the studied region. The region has seen significant economic growth and an increase in mining activity, which, combined with population growth and industrialization, has put significant strain on the environment.

A similar study was conducted by [Kesanapalli et al. \(2018\)](#) on land use/land cover (LU/LC) pattern and it reported five major land-use classes such as agricultural land followed by forest, barren land, built-up land, and water bodies for the Gundlakamma sub-basin.

3.2. SWAT model

3.2.1. Model calibration and validation

A SWAT model was set up using the dataset of the Gundlakamma sub-basin to simulate total water yield from 2010 to 2022. The model was calibrated using reservoir outflow data. Four years of discharges (2010–2014) were used for calibration, with

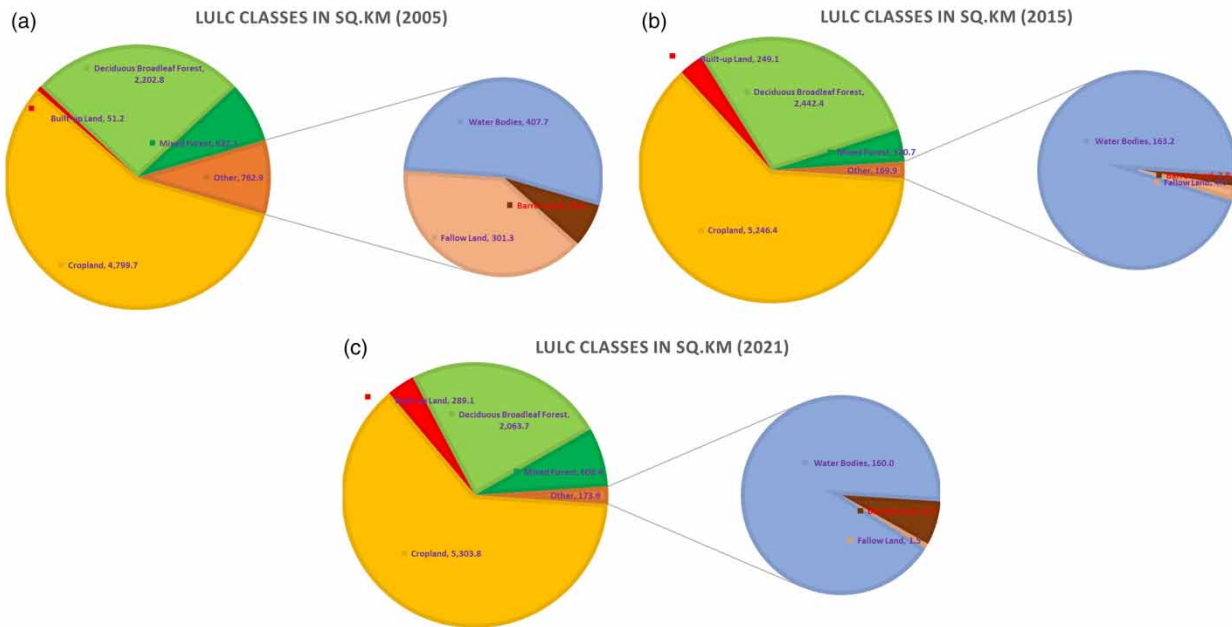


Figure 8 | (a) Pie diagram showing the LULC classification in sq.km of 2005, (b) Pie diagram showing the LULC classification in sq.km of 2015, and (c) Pie diagram showing the LULC classification in sq.km of 2021.

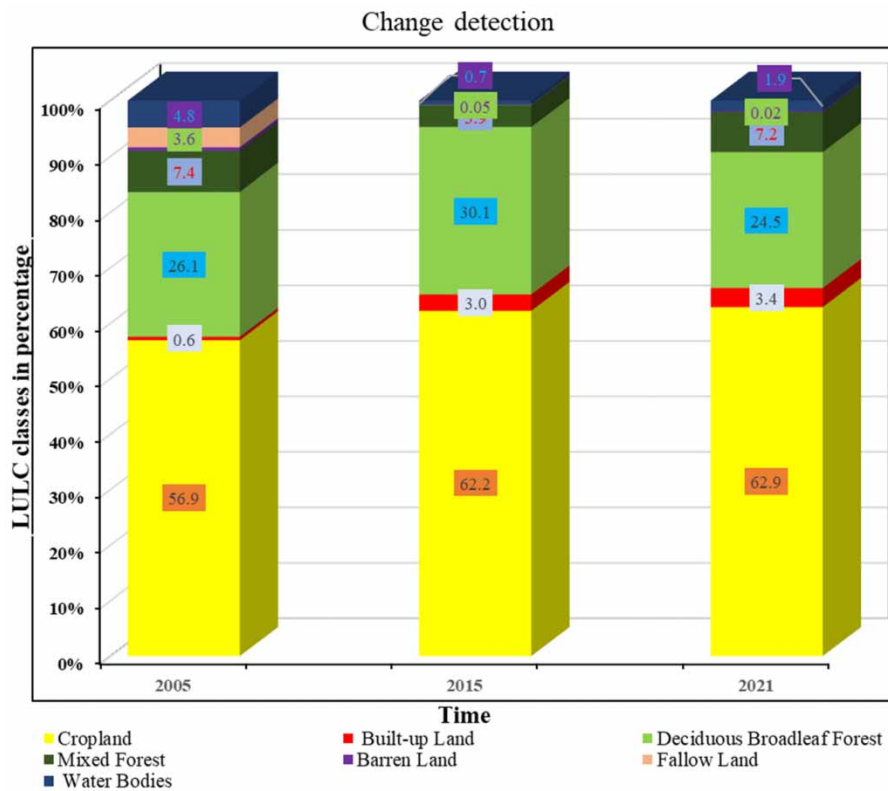


Figure 9 | Bar diagram showing the change detection in LULC from 2005 to 2021.

the first 8 years (2010–2017) for model warm-up. In calibration, both manual and auto-calibration techniques were employed in adjusting parameters to align with observed data. Auto-calibration, utilizing SWAT-CUP with the SUFI-2 algorithm, iteratively refined parameters to enhance the model's alignment with observed values. After the calibration process, model

validation (2018–2022) involved testing the calibrated model by comparing its predictions against field observations, the subset of data not utilized during calibration. This evaluation was conducted without altering any input parameter values.

Figure 10 shows monthly comparisons of measured and simulated streamflow during calibration and validation periods. A comparison of simulated and observed monthly discharges of calibration periods and validation period is shown in Figure 11. The model has a strong predictive capability with R^2 values of 0.81 and 0.790, and NSE values of 0.795 and 0.785 for calibration and validation periods, respectively (Table 6). These results confirm that the SWAT model performed well in this sub-basin, meeting the statistical model efficiency criteria of $R^2 > 0.6$ and $NSE > 0.5$ (Moriassi *et al.* 2007).

The SWAT model estimates important water balance components including water yield, soil water content, and actual ET of the sub-basin for efficient water management and planning. The LULC map has been prepared for 2005, 2015, and 2022, with details presented in Table 5. Land-use changes affect water yield and availability in the sub-basin. Average annual basin values of different components of water balance are presented in Table 7.

Guug *et al.* (2020) applied the SWAT hydrological model to assess water availability, revealing a crucial understanding of catchment water, especially surface runoff and percolation tank dynamics. The study emphasized the significance of percolation tanks, indicating that the shallow aquifer holds extractable water with low input costs during dry seasons. Additionally, findings suggested the potential capture of significant surface runoff through well-designed water harvesting structures like dams and ponds for dry-season irrigation and various purposes.

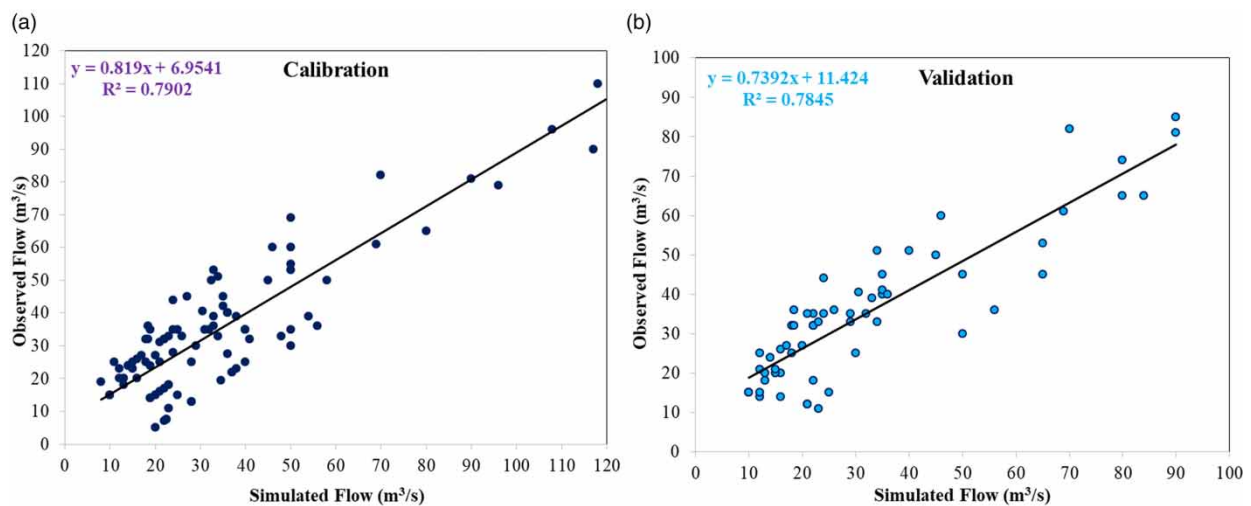


Figure 10 | (a) Monthly discharges simulated and observed during calibration periods; (b) monthly discharges simulated and observed during validation periods.

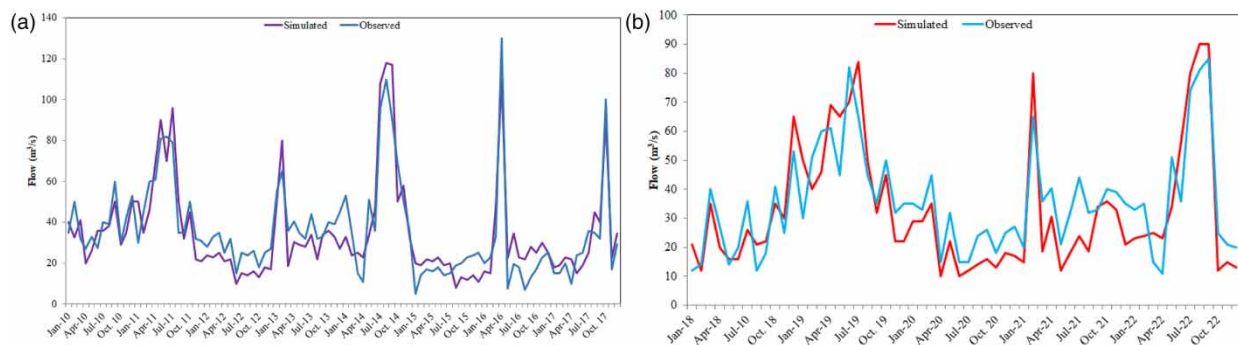


Figure 11 | (a) A comparison of simulated and observed monthly discharges of calibration periods; (b) a comparison of simulated and observed monthly discharges of validation periods.

Table 6 | R^2 and NSE values of SWAT simulated versus observed calibration and validation

Statistical parameters	Monthly calibration (2010–2017)	Monthly validation (2018–2022)
NSE	0.795	0.81
R^2	0.785	0.790

Table 7 | Average annual basin values of different components of water balance

Parameters	Years	
	2010	2021
Precipitation	950	1,005.2
Surface runoff	215.6	232.95
Lateral flow through soil	7.85	8.78
Groundwater (shallow aquifer)	49.5	50.6
Deep aquifer recharge	170	178.9
Actual evapotranspiration	429.5	435.67

Table 8 | Average monthly basin values of different components of water balance

Year	Months	Rainfall (mm)	Surface runoff (mm)	Water yield	Actual ET (mm)
2010	Jan	5.99	1.75	29.5	27.7
	Feb	0	0	26.5	28.7
	Mar	1.43	0.5	27.14	18.1
	Apr	10.46	7.95	26.6	15.75
	May	70	15.1	33.9	28
	Jun	113.52	29.5	53.6	47.9
	Jul	95	17.5	37.1	37
	Aug	150	32.3	45.2	43
	Sep	166.29	35.5	46.9	45
	Oct	180.27	42.5	70.5	68
	Nov	85	17.5	37.1	41
	Dec	72	15.5	35.2	29
	Total	949.96	215.6	469.24	429.15
2021	Jan	7.68	3	30.1	28.95
	Feb	14.92	4.2	30.5	29.95
	Mar	0	0	27.5	28.5
	Apr	17.78	4.5	30.9	30.12
	May	52.95	16.35	35.15	32.5
	Jun	46.73	15.5	35.9	32.8
	Jul	150.85	37.5	54.5	38.25
	Aug	138.06	35.2	52.5	44.25
	Sep	113.91	31.5	48.15	41.25
	Oct	96.82	25.2	39.5	36.5
	Nov	347.46	55.5	65.5	62.5
	Dec	18.04	4.5	30.4	30.1
	Total	1,005.2	232.95	480.6	435.67

The average monthly values of water balance components of 2010 and 2021 are presented in Table 8. Hydrological parameters such as percolation, surface flow, and groundwater contribution to flow indicate a relationship with precipitation. The actual ET values were estimated based on climatic data, available water content in the root zone, and soil properties.

In 2010, the average annual precipitation, surface runoff, water yield, and actual ET were 949.96, 215.6, 469.24, and 429.15 mm, respectively. The maximum surface runoff contribution to flow was 42.5 mm in October, coinciding with the highest rainfall of 180.27 mm. Hydrological parameters such as percolation, surface flow, and groundwater contribution to flow showed a good relationship with precipitation. ET rates are highest from April to August due to vegetation and high temperatures. The hydrological process was quantified for each year in the study area to determine the water balance contribution to the overall annual average.

The analysis involved examining 10 input parameters using the SUFI-2 algorithm and SWAT_CUP to determine their sensitivities. In the Gundlakamma sub-basin, three input parameters in the SWAT model were found to be the most sensitive. These parameters include delay time (GW_Delay.gw) for aquifer recharge (days), saturated hydraulic conductivity (SOL_K.sol) in millimeters per hour, and available water capacity (SOL_AWC.sol). These findings align with Wang *et al.*'s (2019) observations, highlighting the potential of the SWAT model to improve the water cycle simulation, assist in water resource scheduling decisions, and support effective water resource management. A similar observation was reported by Hari *et al.* (2019) and Hari *et al.* (2020) in the Gundlakamma sub-basin.

This work is comprehensive but not exhaustive, offering valuable insights for future researchers, particularly in groundwater flow and solute transport modeling. Further research is needed in the region on soil geochemistry and its connection with groundwater, as well as stable O and H isotope studies, to identify the recharge zones, and establish their relationship with hydrogeochemical parameters. The present study encompasses evaluating the impact of LULC changes on water resources by utilizing the SWAT model. The SWAT model faces limitations, particularly in the reliability of stream-flow simulation outcomes, which may not be adopted directly in decision-making processes. To address these challenges, there is a compelling need to develop a comprehensive SWAT-Paddy module.

4. CONCLUSIONS

The hydrological analysis confirmed that Kurnools basin has low relief and an elongated shape. The dendritic drainage network indicates uniform texture and lack of structural control, aiding the understanding of topographical parameters such as bedrock properties and permeability. The result of rainfall analysis identifies six drought periods over 33 years, as annual rainfall dips below a 10% reduction from the normal rainfall and the study area is facing the drought conditions in the area every 5 years. The slope is crucial in determining penetration and runoff. Infiltration is negatively correlated with slope. Gentle slopes have higher permeability and less runoff, while steep slopes have lower permeability and more runoff. GIS, remote sensing data, and digital elevation models can effectively analyze topographical parameters such as bedrock properties and surface runoff to better understand land formation, drainage management, and groundwater potential in watershed planning and management. Based on LULC, the dominant area was covered by cropland followed by the deciduous needleleaf, mixed forest, built-up land, and water bodies in 2021. Between 2005 and 2021, there was a reduction in cropland and a simultaneous increase in built-up land, signaling urban expansion. Land-use changes affect water yield and availability in the sub-basin. Land cover changes are influenced by human activities, environmental changes, and land-use decisions, resulting in changes in different categories over time in the studied region. The region has seen significant economic growth and an increase in mining activity, which, combined with population growth and industrialization, has put significant strain on the environment. In calibration, both manual and auto-calibration techniques were employed in adjusting parameters to align with observed data. The model has a strong predictive capability with R^2 values of 0.81 and 0.790, and NSE values of 0.795 and 0.785 for calibration and validation periods, respectively. The Gundlakamma sub-basin had average annual precipitation, surface runoff, water yield, and actual ET was 949.96, 215., 469.24, and 429.15 mm, respectively. The maximum surface runoff contribution to flow was 42.5 mm in October, coinciding with the highest rainfall of 180.27 mm. Hydrological parameters such as percolation, surface flow, and groundwater contribution to flow showed a good relationship with precipitation. ET rates are highest from April to August due to vegetation and high temperatures. The hydrological process was quantified for each year in the study area to determine the water balance contribution to the overall annual average. In the Gundlakamma sub-basin, three input parameters in the SWAT model were found to be the most sensitive, including delay time for aquifer recharge (days), saturated hydraulic conductivity in millimeters per hour, and available water capacity (SOL_AWC.sol). This study is crucial in managing natural resources for sustainable watershed development and identifies aquifer recharge and saturated hydraulic conductivity as key parameters for simulating water yield. The results of the present findings indicate that climate change poses a threat to water resources, emphasizing the need for future research to assess its

impact on impervious land use and overall water quantity. The outcomes of this research could lead to the use of SWAT and other methods that impacted agricultural watersheds within Andhra Pradesh.

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SOURCES

1. www.indiawris.gov.in
2. <https://earthexplorer.usgs.gov>
3. <https://www.arcgis.com/apps>
4. <https://swat.tamu.edu/data/india-dataset/>.

STATEMENTS AND DECLARATIONS

The submitted work is original and has not been published elsewhere in any form or language.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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