Original Research Article

Runoff Dynamics and Soil Erosion Assessment using a SWAT Model at Upper Cauvery River Basin

Abstract

The increasing availability of geospatial datasets on watershed characteristics and hydro-meteorological variables emphasises the importance of integrated hydrological models for effective catchment management. Climatic and physiographic determinants such as topography, land use, soil properties, and anthropogenic interventions substantially influence a catchment's hydrological equilibrium. The SWAT model was used to elucidate rainfall-runoff dynamics in the Upper Cauvery River Basin, Karnataka, India (36,682 km²), applying the SCS Curve Number (CN) method for runoff estimation. Runoff was estimated for 2012–2021 using rainfall data from the Indian Meteorological Department (IMD), soil data from the FAO, and land use/land cover and slope datasets.Soil erosion, exacerbated by intensified agricultural practices, was evaluated using the Revised Universal Soil Loss Equation (RUSLE) model integrated with Geographic Information Systems (GIS). The SWAT model results showed that runoff accounted for 15-20% of the total precipitation, with an annual soil loss of 2027.95 tons. The predominance of agricultural land use, covering 66.29% of the basin, significantly contributed to high runoff, whereas the forested areas (26.48%) demonstrated a low runoff potential. About 38% of the basin exhibited a very low soil loss risk, while 11% was classified as high risk and 9% as very high risk. The SWAT model is recognized for its robustness, and this research aims to leverage its capabilities to validate its effectiveness in estimating runoff and erosion, providing crucial insights for advancing sustainable catchment resource management.

Keywords: Hydrological modeling, SWAT model, Rainfall-runoff estimation, Soil erosion, Watershed management.

1. Introduction

The Indian subcontinent has transitioned into a water-stressed region, with per capita water availability sharply declining from a surplus of 5,410 m³ in 1951 to just 1,614 m³ in 2011, despite its population surging to 1.2 billion (Gupta *et al.*, 2019a). Concurrently, the intensification of soil erosion, predominantly driven by hydrological forces, represents a profound threat to environmental quality, agricultural productivity, and global food security (Pimentel *et al.*, 1995; Lal, 2001; Morgan, 2005). The socio-economic and ecological ramifications of soil erosion are particularly catastrophic in developing nations, where vast population segments intrinsically depend on agriculture and land-based resources for sustenance (Erenstein, 1999). Several forces, including hydric and aeolian processes, gravity, flora, and fauna, act as catalysts of soil degradation (Zachar, 1982; Blanco & Lal, 2008). Moreover, tillage practices exacerbate this degradation by displacing soil from elevated to lower slopes, particularly in topographically complex terrains.

Key determinants of surface runoff and soil erosion encompass rainfall intensity, soil erodibility, slope length and gradient, land use/land cover (LULC), and land management practices (Wischmeier & Smith, 1978; Hurni, 1993; Morgan, 2005; Debolini *et al.,* 2013). Furthermore, socio-economic and institutional factors significantly influence surface runoff and soil erosion by shaping land use and management decisions made by farmers. These factors include population pressure, poverty, limited access to agricultural inputs and credit, and the absence of robust land tenure policies (Tefera *et al.,* 2002). Historically, unsustainable land use practices and inadequate investments in sustainable management have contributed to the degradation of arable land across many regions (Zachar, 1982; Blaikie, 1985; Tamene & Vlek, 2008; Debolini *et al.*, 2013). Consequently, soil erosion imposes both local and downstream socio-economic and environmental costs (Zema *et al*., 2012). On-site impacts include the loss of fertile topsoil, nutrient depletion, and reduced agricultural productivity. Simultaneously, off-site effects, though less immediately apparent, can lead to sedimentation, heightened flood risks, and reduced efficiency in hydropower generation and irrigation systems (Hurni *et al.*, 2008; Borrelli *et al.*, 2013; Haregeweyn *et al.,* 2013).

Hydrology, as a cornerstone of environmental science, is critical to sustainability and human well-being. It involves the study of water's distribution, movement, and interactions within the Earth's systems, encompassing its physical and chemical properties and relationships with ecosystems (Ray, 1975). Central to hydrology is the water cycle, which describes the continuous movement of water through different stages and environments. Surface runoff, where water flows over land into rivers and lakes, is essential to this cycle, linking precipitation events to water bodies (Gupta *et al*., 2019a; Gupta *et al*., 2016; Perlman, 2016). It plays a vital role in modulating water flow into stream systems and returning excess precipitation to the oceans, thereby maintaining the hydrological balance. However, rapid urbanization and industrialization have increasingly disrupted this balance, exacerbating challenges such as flooding, erosion, and water scarcity (Sharma *et al*., 2022). As a result, the study and management of runoff have become critical in addressing contemporary water-related issues.

Rainfall-runoff modeling has become indispensable for understanding and managing water resources in diverse regions (Abuhay *et al*., 2023; Gholami *et al*., 2022). These models provide critical insights into catchment hydrological responses to precipitation events by simulating the transformation of rainfall into runoff and subsequent flow through watersheds. Such models are essential for forecasting water availability and mitigating water-related hazards like floods and droughts (Tasdighi *et al*., 2018). Accurate runoff predictions are vital for designing flood control infrastructure, water supply systems, and reservoir management strategies, as well as for assessing the impacts of land use changes, climate variability, and human activities on water resources (Kijowska-Strugała & Bochenek, 2023; Santos *et al*., 2023).

Among the numerous hydrological models available, the Soil and Water Assessment Tool (SWAT) stands out for its robust and versatile capabilities. SWAT is a semi-distributed, physically based model that operates continuously over time while maintaining computational efficiency (Krysanova & Srinivasan, 2015). It requires detailed input data such as climate variables, soil characteristics, topography, and vegetation types to simulate hydrological processes accurately (Al-Kakey *et al*., 2023; Arnold *et al*., 1998). Additionally, SWAT-CUP (Calibration and Uncertainty Procedures) has evolved into a comprehensive tool capable of evaluating the impacts of a variety of chemical and water-related processes, making it highly valuable for simulation and analysis (Fan & Shibata, 2015; Gassman *et al*., 2007; Rahman *et al*., 2013).

The versatility of the SWAT model is further demonstrated by its extensive application across continents, where it addresses critical research needs in hydrology, sediment transport, pollutant dynamics, and scenario analysis (Gassman *et al*., 2014). Researchers have widely used SWAT to investigate water budgets, soil erosion, hydrological processes, and pollutant transport, and it plays a crucial role in assessing the effects of water management practices and land use/land cover (LULC) changes on various environmental factors (Woznicki *et al*., 2016). However, despite its strengths, SWAT presents certain challenges due to its inherent complexity and the vast temporal and spatial datasets it requires. The model's numerous parameters and intricate interrelationships make calibration and validation challenging and time-consuming (Abbaspour *et al*., 2007a, b; Baker & Miller, 2013; Rezaeianzadeh *et al*., 2013; Tokar & Markus, 2000).

Based on these insights, our study aims to comprehensively evaluate SWAT-Based Rainfall-Runoff and Soil Erosion Modeling in the Upper Cauvery River Basin.

2. Description of study area

The Cauvery River, the fourth largest in Southern India, originates at Talakaveri in the Brahmagiri hill range of the Western Ghats, Coorg District, Karnataka (Fig. 1). It stretches 800 km to the Bay of Bengal. It covers a catchment area of 81,155 sq. km, shared by Karnataka, Tamil Nadu, Kerala, and Puducherry. The river spans 381 km in Karnataka and 357 km in Tamil Nadu, with its water cycle driven by the southwest monsoon in Karnataka and the northeast monsoon in Tamil Nadu, receiving an average annual rainfall of 1,000 mm. Temperatures range from 18°C to 44°C. The river supports extensive irrigated agriculture, hydroelectric power plants, and industries, contributing to livelihoods and Karnataka's food production. Rich in biodiversity, the Cauvery Basin is a popular tourist destination known for its forests, wildlife sanctuaries, national parks, ancient temples, and cultural heritage.

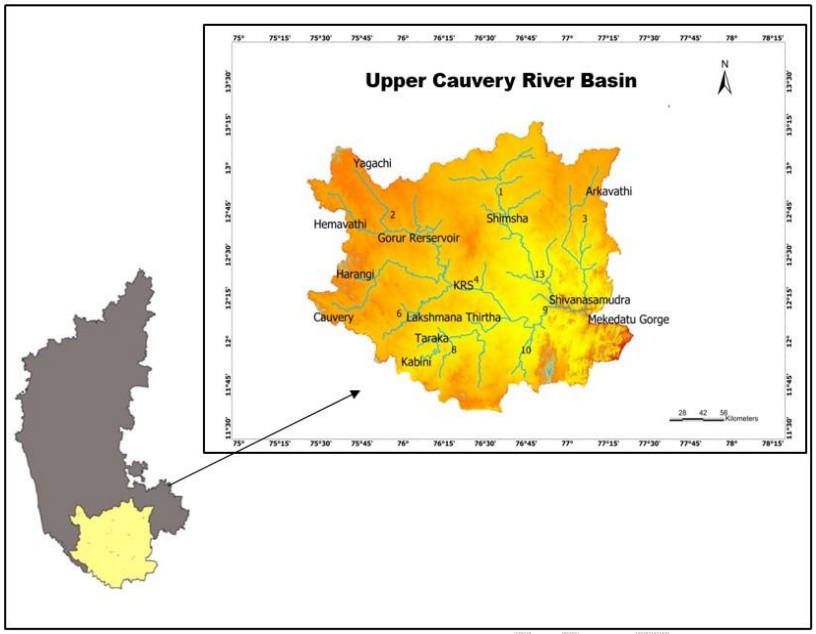

Fig 1: Study area Upper Cauvery River basin

3. Materials and methods

3.1 Input data

The SWAT hydrological model used in this study relies on various input data, including topographical, climatic, land use, and soil data, sourced from multiple databases. Topographical data were obtained from the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM), which served as the basis for watershed delineation. This DEM data generated sub-watershed configurations, stream networks, slope, and slope lengths, utilizing the QGIS interface for SWAT (Fig 2a). Soil data were sourced from the FAO Soil Classification system, revealing seven distinct soil classes, with Silty Clay Loam being the dominant texture (Fig 2b). The FAO classification detailed soil properties, including physical characteristics like texture and structure, chemical properties like phosphorus content, electrical conductivity, cation exchange capacity, and biological attributes like organic matter and organic carbon. Land Use and Land Cover (LULC) data were acquired from the Bhuvan portal, identifying 13 different land use categories, with the major ones being Deciduous Forest, Plantations, and Fallow Land (Figure 2c). This data was essential for assessing the impact of land use on hydrological processes in the study area. Climatic data covering the period from 2012 to 2021, including rainfall, temperature, and wind velocity, were provided by the Indian Meteorological Department (IMD). These climatic variables were crucial for simulating the hydrological response of the watershed under different conditions. A summary of all input data and their sources is provided in Table 1, which supports the SWAT model's application for evaluating runoff and soil erosion processes in the watershed.

Table. 01: Input Data and its sources:

Sl.no	Data set	Source
1	SRTM DEM	Landsat 8 (30m resolution)
2	Soil Map	FAO soil classification
3	LULC	LULC classification by Bhuvan portal
4	Meteorological data	Indian Meteorological Department (IMD)

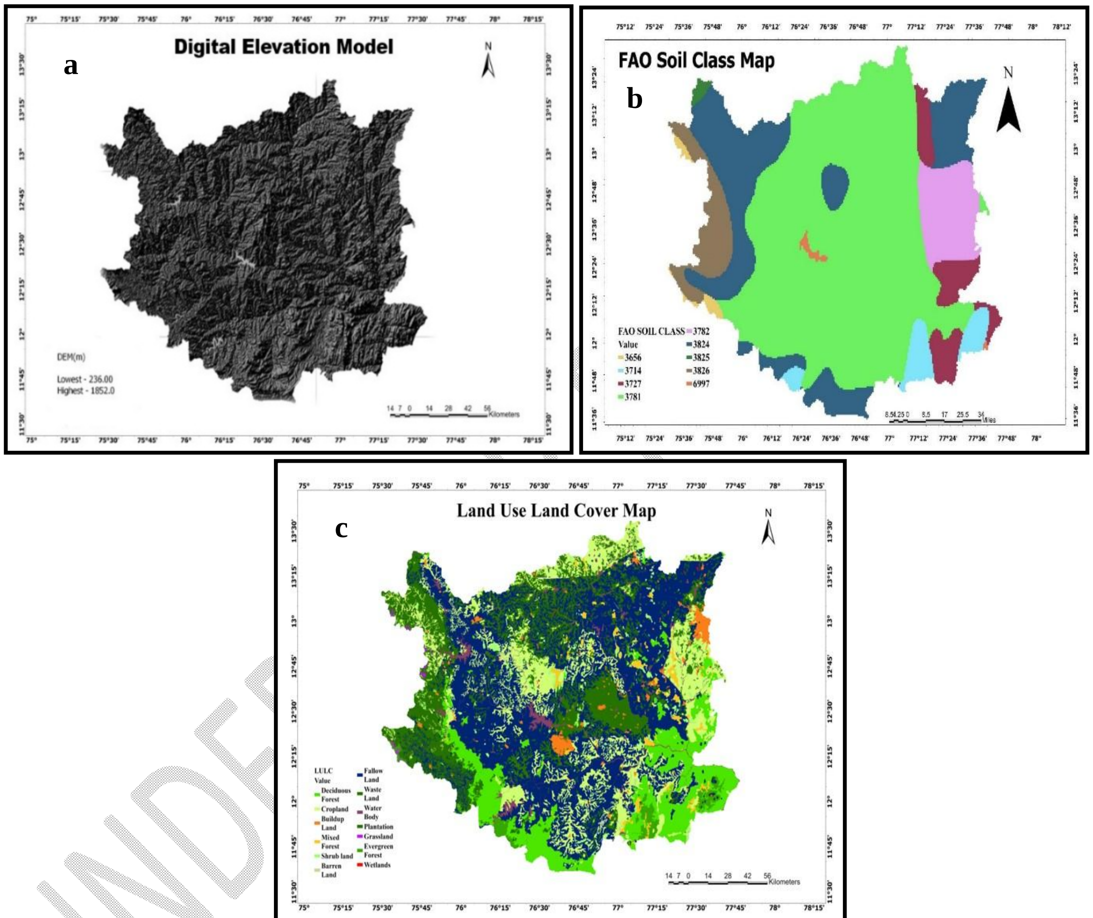

Figure 2: a) Digital elevation model b) Soil classes c) LULC map of the Cauvery River basin

Table 2: Soil classification with their textural classes:

Sl no.	FAO Soil Class	Soil Composition (%)			Textural Class	OC (Kg C/m^2)	OM (%)
		Sand	Silt	Clay			
1	3714	47	29	24	Sandy Loam	0.7	2.35
2	3727	35	43	22	Silty Clay Loam	1.37	1.25
3	3781	35	42	23	Silty Clay Loam	1.26	2.35
4	3824	32	43	25	Silty Clay Loam	0.7	2.167
5	3825	38	39	23	Loam	1.95	1.204
6	6997	41	37	22	Loam	1.45	3.334

3.2 Methodology

The SWAT hydrological model, developed by the USDA Agricultural Research Service (ARS), is a process-based and computationally efficient tool that utilizes spatially distributed inputs, including topography, land use, soil, and climate data, to predict the yields of water, sediment, nutrients, pesticides, and bacteria. In this study, SWAT was employed to simulate the impacts of land management on water, sediment, and agricultural chemical outputs. It is a semi-distributed, continuous-time model specifically designed for long-term river basin simulations.

For this study, land use data were sourced from the LULC classification on the Bhuvan portal, while soil data was obtained from the FAO soil classification. Topographic data were derived from the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) which has a 30m resolution. These DEM data was used to configure sub-watersheds, delineate stream networks, and calculate slope and slope lengths using QGIS and the QSWAT plugin. The model can be initiated by searching for QSWAT in the plugin toolbar and following its three-step process to set up and run simulations. The methodology for this process is summarized in Fig 3.

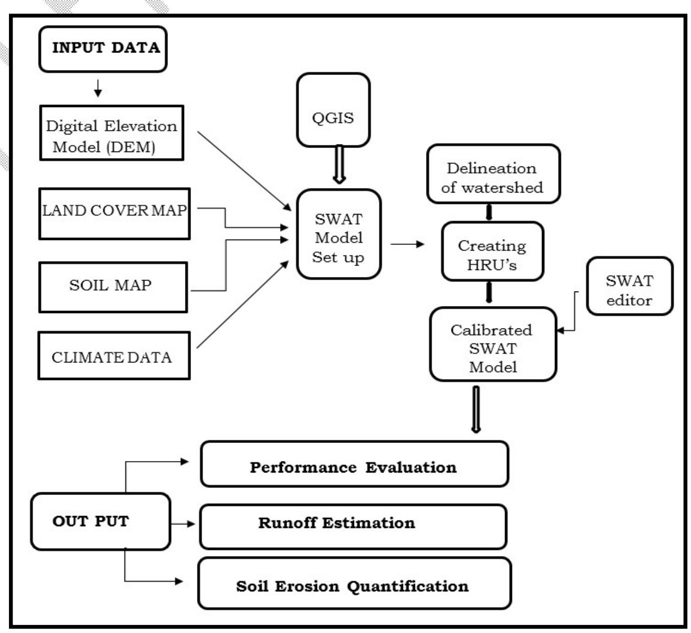

Fig 3. Overview of methodology

3.2.1 Runoff estimation using SCS CN

The SCS curve number method is a simple, widely used, and efficient method for determining the approximate amount of runoff from rainfall events in a particular area. Although the method is designed for a single storm event, it can be scaled to find average annual runoff values. The parameters requirements for this method are very low, the amount of rainfall, and the curve number. The curve number is based on the area's hydrologic soil group, land use, treatment, and hydrologic condition. In hydrological modeling, runoff estimation is the most important parameter. SWAT-based Soil Conservation Service Curve Number (SCS-CN), USDA method is used to predict runoff in 34 HRUs of 13 sub-basins (Fig. 4). This SCS model computes direct runoff through an empirical equation requiring rainfall, soil class, and land use land cover data. Curve number (CN) is a computed variable that is based on the Antecedent Moisture condition (AMC), LULC, and soil data.

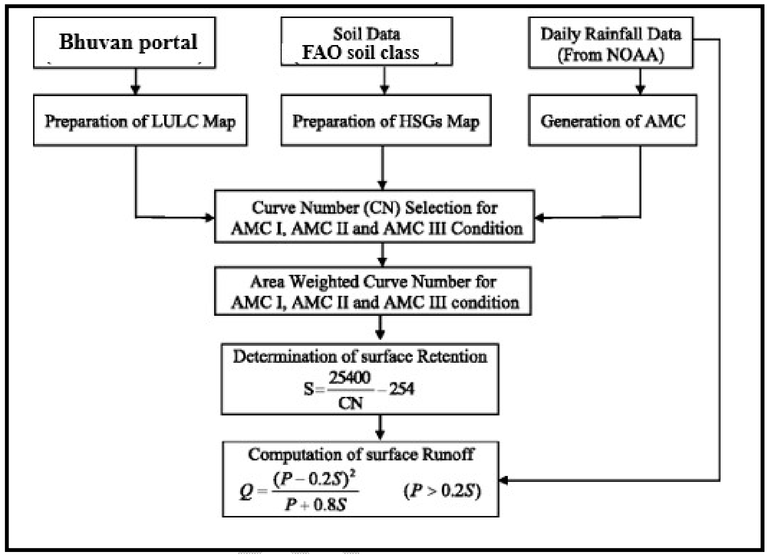

Fig 4. Workflow of SCS CN method of runoff estimation

3.2.2 Soil erosion estimation using the RUSLE model

The estimation of soil erosion for the upper Cauvery Basin in southwestern India was carried out using the Revised Universal Soil Loss Equation (RUSLE) model integrated with GIS (Figure 5). The basin, covering a drainage area of 36,682 km², was analyzed using remote sensing data, and erosion probability zones were determined through GIS. The RUSLE model computes the average annual soil erosion using the equation:

$$\mathbf{A = R \times K \times LS \times C \times P}$$

Here, A represents soil loss per unit area, R is the rainfall-runoff erosivity factor, K is the soil erodibility factor, LS accounts for slope length and steepness, C represents the cover management factor, and P denotes the support practice factor. Rainfall erosivity (R) refers to the kinetic energy and impact of rainfall on erosion, measuring the intensity of rain that causes sheet and rill erosion. Soil erodibility (K) quantifies the vulnerability of soil to detachment and erosion from raindrops and runoff. The C factor relates to crop and management practices affecting vegetation cover, while the LS factor accounts for the impact of slope length and gradient on soil loss. The P factor reflects the efficiency of land management practices like contouring and terracing in reducing erosion. The study's process involved utilizing topographic maps, satellite imagery, and Digital Elevation Model (DEM) data to derive key terrain parameters such as slope and flow direction. These factors were combined with soil data to calculate soil erodibility, while rainfall data were sourced to estimate the rainfall erosivity factor. The land use/land cover (LULC) data, integrated into the model, determined the crop management factor.

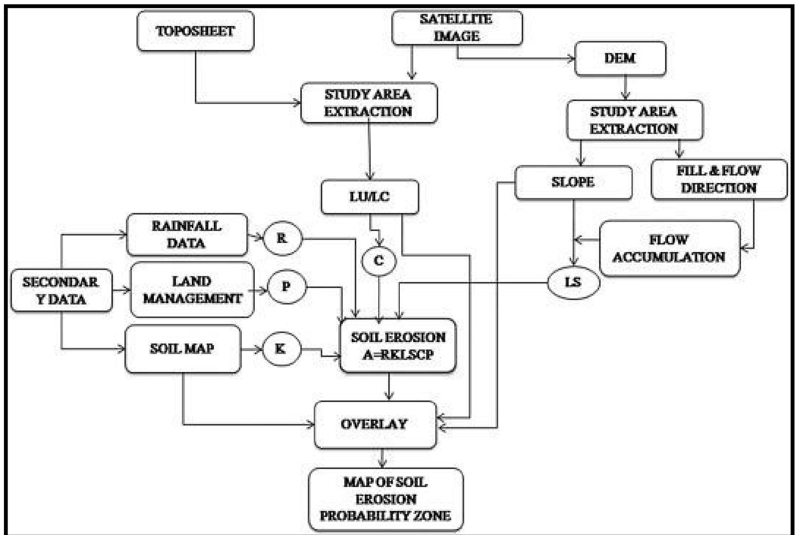

Figure 5. Workflow for estimation of Soil erosion

The RUSLE model was applied to generate soil loss maps, indicating erosion-prone areas. The soil erosion risk was classified based on the calculated soil loss values, producing a potential soil loss map for the upper Cauvery Basin. This comprehensive assessment highlights zones vulnerable to soil erosion, enabling effective land management and conservation practices to mitigate erosion risks.

4. Results and Discussion

This study carried out model simulations over 10 years, from January 1, 2012, to December 31, 2021. The SWAT model was rigorously calibrated to ensure precision, yielding high-accuracy outputs. Runoff estimation was conducted using the Curve Number method embedded within the SWAT model.

4.1 Delineation of Watershed and Flood Plain

This study conducted a comprehensive watershed analysis to facilitate effective water resource management and conservation. The watershed, defined as an area draining water from higher elevations to a common outlet, was divided into 13 sub-basins and 17 channels, including second-order streams. Elevation and flow direction were used to identify point sources, while reservoirs were identified based on depressions and flow accumulation patterns. Influenced by topographic factors, sediment yield in the floodplain represents the sediment transported from upstream and deposited along river courses. This yield is typically quantified either by volume (e.g., acre-feet) or normalized per unit area of the basin. The study computed sediment yield over multiple years, presenting the results as an annual average.

4.2 Hydrologic Response Unit (HRU's)

The hydrologic response unit (HRU) is the smallest spatial unit of the model, and the standard HRU definition approach lumps all similar land uses, soils, and slopes within a subbasin based upon user-defined thresholds. This standard method provides an efficient way to discretize large watersheds where simulation at the field scale may not be computationally feasible. These are the basic conceptual units in the SWAT model. It is the amalgamation of land use, soil, slope, and landscape where all these layers are overlaid. Multiple HRU's are created with a 10% threshold limit of land use, soil, and slope. A total of 34 HRUs are generated for 7 soil classes and 13 land use classes.

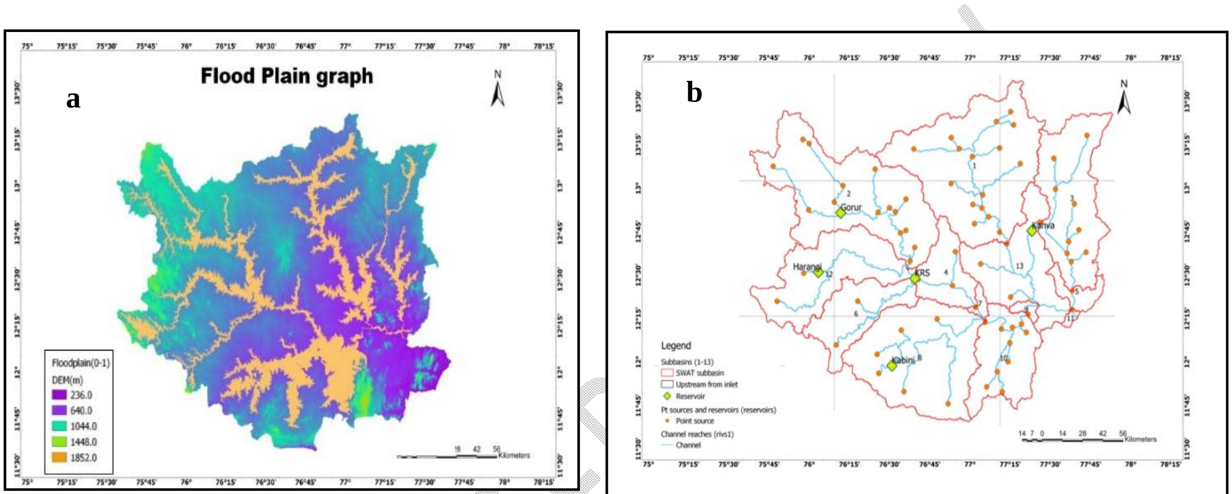

Figure 6: a) Flood plain map, b) Delineated channels and sub-basins

4.3Runoff Estimation using SCS CN method

Runoff estimation was carried out using the Soil Conservation Service (SCS) Curve Number (CN) method, developed by the USDA. This approach was applied to 34 Hydrologic Response Units (HRUs) across 13 sub-basins, relying on rainfall, soil class, and land use/land cover (LULC) data to compute direct runoff. The method classifies soils into four Hydrological Soil Groups (HSGs), which range from Group A (high infiltration, low runoff potential) to Group D (low infiltration, high runoff potential) (Table 3).

4.3.1 Weighted Curve Number (WCN) for each land use class

The Weighted Curve Number (WCN) was computed by assigning CN values to specific land use classes and soil groups. The CN values ranged from 72 for certain agricultural soils to 91 for built-up areas and water bodies (Table 4). The calculated WCN for the study area was 88.25, indicating a high potential for runoff, particularly in areas with impervious soils and urban development. Agriculture, which dominates 62.29% of the land area, significantly influences the region's runoff potential.

Table 03. USDA HSG soil classification

HSG	Types of Soil	Soil Texture	Runoff Potential	Minimum Rate of Infiltration (mm/hr)	Water transmission Rate (in/hr)
A	Deep well-drained soils	Sandy, sandy loam	Low	7.62-12.38	High rate (0.3)
B	Moderately deep with fine to coarse texture	Silt loam or loam	Moderate	4.89-7.06	Moderate rate (0.15-0.28)
C	Moderately fine to fine textures	Sandy clay loam	Moderate	1.87-4.89	Low rate (0.05-0.15)
D	Soil with a permanent high-water table	Clay loam, silty clay loam, silty clay, clay	High	0-1.27	Very low rate (0-0.05)

4.3.2 Runoff quantification

Table 04: WCN calculation table

Land Use	HSG	CN	Area (%)	% of Area*CN	WCN
Agriculture	C	88	62.29	5481.52	88.25
	D	91		5668.39	
	A	72		4484	
Built up	C	88	5.38	473.44	
	D	91		489.58	
	B	82		441.16	
Wasteland	C	88	3.84	2330.24	
	A	82		314.88	
Forest	C	88	26.48	2330.24	
	D	91		2409.68	
Waterbodies	D	91	4.85	441.35	
Others	B	82	1.65	135.3	
	C	88		145.2	
	D	91		150.15	

The analysis of rainfall and runoff data from 2012 to 2021, utilizing the Soil Conservation Service (SCS) Curve Number (CN) method, reveals significant fluctuations in average annual rainfall, peaking above 1000 mm in 2014, 2018, and 2019. Despite these peaks, average annual runoff consistently remained lower, never exceeding 500 mm. The SCS CN method indicates that soil type and land management practices significantly affect runoff generation, with areas classified under hydrologic soil group (HSG) D exhibiting higher runoff potential compared to HSG A.

The analysis demonstrates a correlation between increased rainfall and runoff, particularly in 2014, 2017, and 2018; however, the substantial disparity between rainfall and runoff suggests that a significant portion of rainfall is absorbed or lost to evaporation and infiltration. Runoff percentages consistently remained below 50% of total rainfall, highlighting inefficiencies in runoff generation, potentially due to soil absorption capacity and impervious surfaces in urban areas. With a high weighted curve number (WCN) of 88.25, the study area shows significant runoff potential, necessitating effective water management strategies to optimize resource capture and minimize losses. This integrated approach emphasizes the critical role of land use, soil characteristics, and hydrological dynamics in shaping runoff behavior, underscoring the need for targeted management practices in response to increasing rainfall variability and climate change impacts.

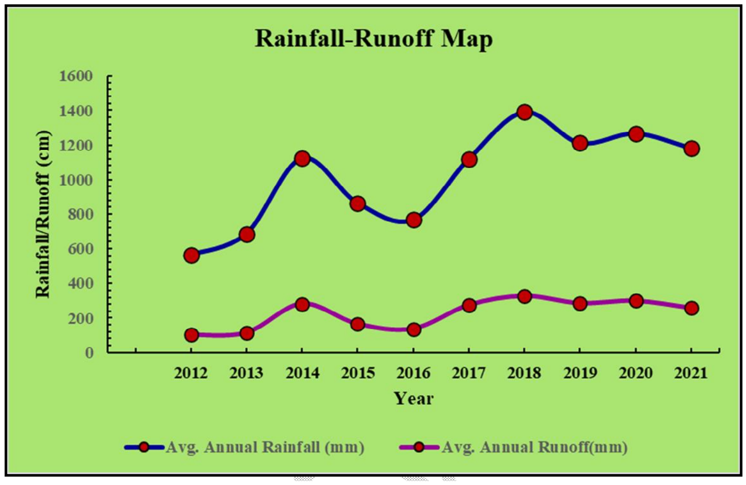

Figure 7. Runoff- Rainfall graph from 2012-2021

4.3.3 Rainfall-runoff correlation

The relationship between potential runoff and rainfall at a specific temporal scale demonstrates a strong positive correlation, evidenced by a correlation coefficient (R-value) of 0.967. This high R-value suggests a nearly perfect linear association, indicating that increases in annual rainfall correspond to proportional increases in annual runoff.

An R^2 value approaching +1 signifies a robust linear relationship, with positive values confirming the direct correlation between these variables. Figure 8 presents the scatter plot of average annual rainfall against runoff, showcasing the data points alongside the best-fit line. This further substantiates the rainfall-runoff relationship within the Cauvery basin.

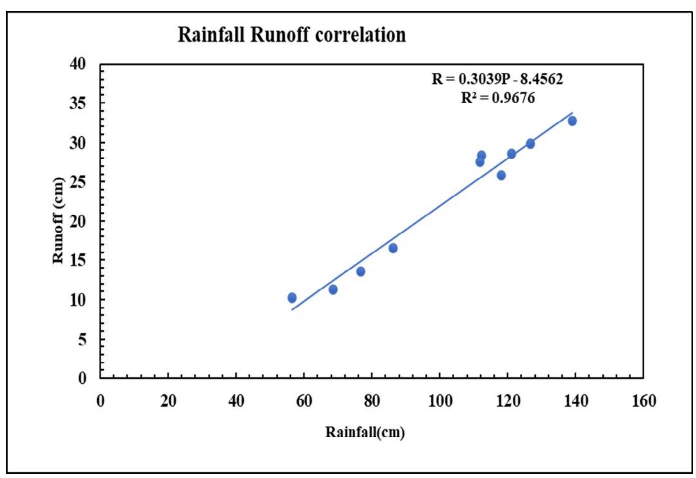

Figure. 8 Rainfall- Runoff corelation

The analysis indicates a commendable correlation, affirming the direct dependency between these two hydrological parameters. Moreover, daily correlation coefficients for rainfall and runoff spanning from 2012 to 2021 consistently reflect this positive linear trend, as illustrated in Figure 7. This reinforces the findings of a significant relationship between rainfall and subsequent runoff, emphasizing the importance of understanding this interaction for effective watershed management.

4.3.4 Runoff Risk Zone Mapping;

The Runoff Risk Zone Map, developed from a decade of daily rainfall data, land use/land cover (LULC) evaluations, and soil classifications, illustrates runoff vulnerability across the basin. The analysis reveals that 66.29% of the basin is classified under High runoff risk, with 21.34 and 55.89 mm/ha/yr rates predominantly associated with agricultural lands. This highlights the elevated susceptibility of cultivated areas to surface runoff, exacerbated by soil properties and intensive agricultural practices.

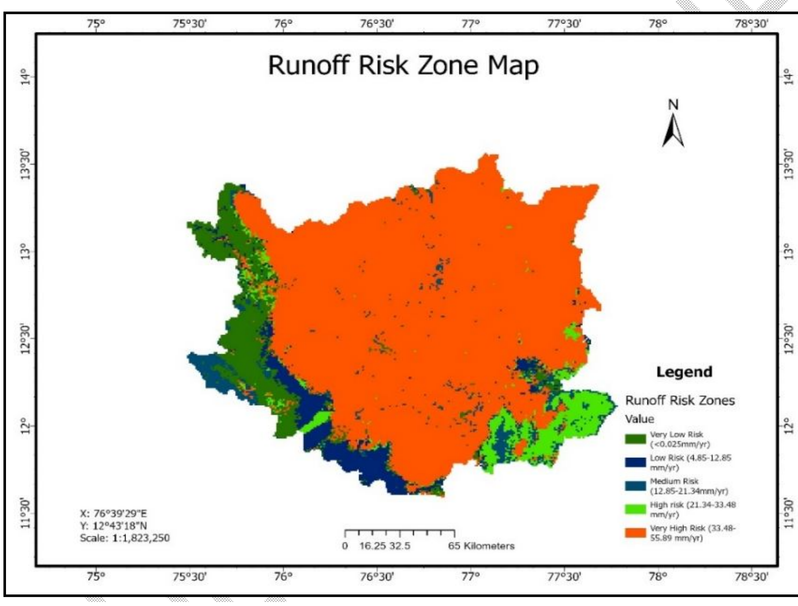

Figure 9. Runoff risk zone mapping of upper Cauvery River basin

In contrast, fallow and barren lands demonstrate the greatest vulnerability, classified as Very High runoff risk, with runoff values reaching up to 55.89 mm/ha/yr due to the lack of vegetation, which exposes the soil to runoff and increases erosion risk. Conversely, 26.48% of the basin, primarily forested areas, is categorized as Very Low-risk, exhibiting runoff values of less than 0.025 mm/ha/yr. Forest ecosystems effectively mitigate runoff through dense vegetation and robust root systems that enhance water absorption. Shrublands and mixed forests fall within the Low-risk category, with runoff values between 4.85 and 12.50 mm/ha/yr, offering moderate protection against runoff. Grasslands and wastelands are designated as Medium-risk, with runoff values ranging from 12.85 to 21.34 mm/ha/yr, reflecting reduced infiltration and vegetation cover. The Runoff Risk Map delineates the runoff risk gradient across the basin, underscoring the pivotal role of land cover in influencing runoff potential. Agricultural areas are particularly susceptible, while forests act as natural buffers, necessitating targeted land management strategies to mitigate surface runoff impacts in high-risk zone.

Table 05. Runoff risk zone classification of the Cauvery River basin

Sl No.	Runoff Risk	Runoff value	Major land use
1	Very Low	<0.025mm/ha/yr.	Forest and Plantation
2	Low	4.85- 12.50 mm/ha/yr.	Shrubland and mixed forest
3	Medium	12.85-21.34 mm/ha/yr.	Grassland and wasteland
4	High	21.34 – 33.48 mm/ha/yr.	Agricultural lands
5	Very High	33.48-55.89 mm/ha/yr.	Follow and barren land

4.4 Soil Erosion quantification;

Soil Erosion can be defined as a method of detachment, transportation of surface soil particles from their origin, and deposition at some other area. Based on the Rainfall erosivity factor, soil erodability factor, slope length and steepness factor, crop management, and support factor we generated the potential soil loss (t/ha/yr.) (fig.10).

The analysis of soil loss risk indicates that 38% of the total area, equivalent to 13,939.16 km^2, falls under the Very Low-risk category, with a soil loss value of less than 0.75 t/ha/yr, resulting in an annual soil loss of 104.54 t/ha/yr. The Low-risk category, covering 24% of the area or 8,803.68 km^2, experiences soil loss between 0.75 and 4.5 t/ha/yr, leading to an annual soil loss of 281.69 t/ha/yr. The Moderate risk category affects 18% of the area, or 6,602.7 km^2, with soil loss values between 4.5 and 8.4 t/ha/yr, contributing 448.9 t/ha/yr to the total annual loss. Meanwhile, 11% of the area, corresponding to 4,035.02 km^2, falls under the High-risk category, with soil loss values between 8.4 and 13.6 t/ha/yr, resulting in 532.62 t/ha/yr of soil loss. Finally, the Very High-risk category accounts for 9% of the total area, or 3,301.38 km^2, with soil loss ranging from 13.6 to 21.4 t/ha/yr, contributing the highest annual soil loss of 660.2 t/ha/yr. Overall, the total annual soil loss across the entire region amounts to 2027.95 t/ha/yr (table 06).

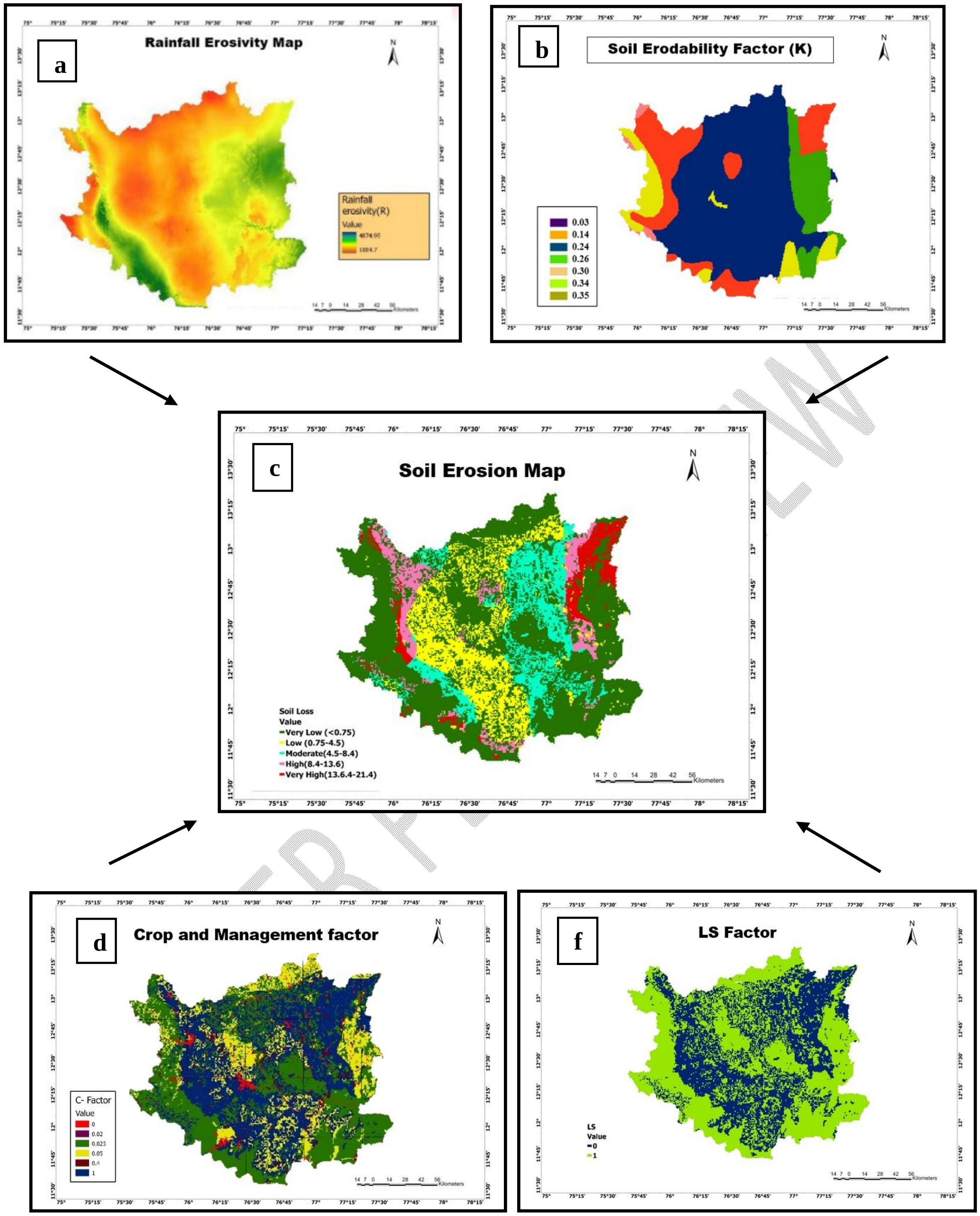

Figure 10. a) Rainfall erosivity map, b) Soil erodibility map, c) Soil erosion map, d) Crop and management factor map, f) Slop length and steepness map

Table 06. Soil erosion quantification using the RUSLE Model

Sl.no	Soil Loss Risk	Soil loss value (t/ha/yr.)	Area (%)	Area (km^2)	Annual Soil Loss (t/ha/yr.)
1	Very Low	<0.75	38	13,939.16	104.54
2	Low	0.75-4.5	24	8,803.68	281.69
3	Moderate	4.5-8.4	18	6602.7	448.9
4	High	8.4-13.6	11	4035.02	532.62
5	Very High	13.6-21.4	9	3301.38	660.2
Total			100	36,682	**2027.95**

5. Conclusion

Hydrological modeling is crucial for water resource planning, design, and decision-making. SWAT, a its robust, comprehensive, and systematic rainfall-runoff model, addresses the challenge of managing natural resources amid environmental changes. Applied to the Cauvery River basin, SWAT was used to simulate runoff from 1st January 2012 to 31st December 2021 using the SCS-CN method. Soil erosion was estimated using the Revised Universal Soil Loss Equation (RUSLE), integrated with ArcGIS Pro. The results indicate 15-18% runoff and a total soil loss of 2027.95 t/ha/yr. Runoff from agricultural and fallow lands contributed significantly (33.48-55.89 mm/ha/yr), requiring management interventions. Soil erosion was highest in cropland and wasteland (13.6-21.4 t/ha/yr), emphasizing the need for agroforestry, reduced chemical fertilizers, and minimal tillage to mitigate erosion. Sedimentation in the lower catchment and reduced reservoir capacity further highlight the need for integrated soil and water management. The SWAT model showed a strong correlation between simulated and observed data, with satisfactory runoff and soil loss estimate results.

Disclaimer (Artificial intelligence)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

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