IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

WATERSHED MANAGEMENT OF STUDY AREA IN SANGLI DISTRICT: A GIS-BASED HYDROLOGICAL ASSESSMENT

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Abstract: Patterns of land use and land cover (LULC) reflect the combined influence of natural processes and human activities. Accurate mapping of these patterns is critical for environmental planning, watershed management, and sustainable land resource development. This study focuses on the KR-36 sub-watershed of the Agrani River basin, covering an area of approximately 348 km². Using remote sensing datasets and GIS-based classification techniques, the region was categorized into six major LULC classes: agricultural cropland, built-up areas, fallow land, vegetation, water bodies, and barren land. Satellite imagery was processed using supervised and unsupervised classification methods, supported by field verification to ensure classification accuracy. The results indicate that agricultural land dominates the region (36.18%), followed by fallow land (30.65%) and vegetation cover (17.10%). The study demonstrates that integrated RS–GIS approaches provide reliable, cost-effective tools for analyzing spatial patterns and supporting informed land-use planning decisions.

***Index Terms* -** Remote Sensing, GIS, Land Use and Land Cover, Sub-Watershed, Agrani River Basin.

I. Introduction

Land use and land cover (LULC) are shaped by climatic conditions, ecological processes, and socioeconomic activities that evolve over time. Monitoring these changes is essential for understanding environmental dynamics and planning for sustainable land management. Remote sensing offers synoptic, multi-temporal, and spatially consistent data that enable scientists to observe changes in vegetation, water bodies, agricultural land, and settlement growth at local and regional scales. GIS further enhances this capability by integrating spatial datasets, performing spatial analysis, and generating thematic maps efficiently.

LULC classification supports decision-making in agriculture, hydrology, forestry, disaster management, and urban development. By combining field-survey data with satellite imagery, researchers can produce highly accurate LULC maps, enabling the assessment of land degradation, deforestation, urban expansion, and agricultural productivity. The present study applies RS–GIS techniques to classify LULC in the KR-36 sub-watershed of the Agrani River basin and to demonstrate how modern geospatial tools facilitate precise land-resource mapping for planning and sustainable development.

II. OBJECTIVE

The objective of this study is to produce a detailed and accurate LULC map for selected villages in the KR-36 sub-watershed of the Agrani River basin using remote sensing techniques integrated with GIS-based analysis.

III. LITERATURE REVIEW

In the last five years, the combined use of remote sensing (RS) and geographic information systems (GIS) has become the standard approach for regional land-use/land-cover (LULC) mapping and watershed planning. National-scale datasets and improved satellite products have increased the temporal and spatial resolution available to practitioners: for example, the National Remote Sensing Centre's recent annual LULC atlas provides consistent, near-annual LULC layers at ~56 m resolution that are directly usable for basin- and watershed-scale analysis and change detection. (NRSC 2024).

Methodologically, supervised classification complemented by field-based validation remains a robust baseline for LULC mapping. Studies published during 2020–2024 continue to rely on hybrid workflows that combine unsupervised clustering to detect spectral classes, followed by supervised classification using well-distributed ground truth samples and post-classification smoothing to reduce "salt-and-pepper" effects (see examples and workflows in recent applied studies). Such hybrid approaches improve classification accuracy in heterogeneous agricultural landscapes where seasonal fallow and mixed cropping complicate spectral separability.

Beyond basic classification, there has been a marked shift toward integrating morphometric and drainage analyses (derived from DEMs) with LULC products to inform hydrological decision-making. High-resolution DEMs (SRTM 12.5 m, ALOS, and commercial sources where available) are now routinely used to generate slope, aspect, drainage density, stream order, and catchment delineations. These morphometric indicators are essential for distinguishing runoff-generating areas from recharge-favorable zones and for siting decentralized structures such as percolation tanks, check dams, and farm ponds. Recent field-validated studies show that coupling DEM-derived indices with LULC yields better prioritization of intervention sites than using LULC or DEM metrics alone. (Baghel, S. et.al.2023)

A major trend from 2020–2024 is the widespread adoption of Multi-Criteria Decision Analysis (MCDA) — frequently implemented as Analytical Hierarchy Process (AHP) or weighted overlay — to delineate Groundwater Recharge Potential Zones (GWRPZ) and to prioritize sites for artificial recharge. These methods systematically integrate multiple thematic layers (rainfall, slope, soil, lithology, LULC, drainage density, lineaments) with expert-driven weightings; when calibrated with local observation points, MCDA/AHP maps show high correspondence with known recharge occurrences and have been used successfully in several Maharashtra and pan-India case studies. The AHP+GIS workflow has become a de facto standard for planners preparing schedules for rainwater harvesting and recharge interventions. (Singh, S. K., & Noori, A. R. 2022).

Accuracy, transferability, and objective weighting remain active research topics. Several recent papers (2021–2024) compared AHP against objective machine-learning and data-driven approaches (e.g., logistic regression, random forest) and found that while AHP is interpretable and operationally simple, machine-learning models often provide superior predictive performance when adequate training/validation data exist. Hybrid workflows that use ML to derive weights or to validate AHP outputs are emerging as best practice for regions where in-situ hydrogeological data are available. Where in-situ data are limited, MCDA/AHP remains a defensible approach for local authorities because of its transparency and ease of stakeholder involvement. (Jerin Joe, et.al. 2025)

Recent applied work also emphasizes quantitative planning — not just mapping. Case studies in India have translated runoff and recharge estimates into explicit infrastructure lists (number and type of farm ponds, percolation tanks, check dams), storage capacities, and benefit–cost indications. For instance, in medium-sized catchments, researchers have used catchment water budgets (rainfall, ET, recharge, runoff) to size interventions that together can capture a very high fraction of annual runoff and measurably raise post-monsoon groundwater levels when regularly maintained. These operational studies provide a bridge between geospatial analysis and implementable watershed plans. (Baghel, S. et.al.2023)

On the LULC front, multi-temporal change detection (e.g., 2010–2020, 2015–2023) is increasingly used to quantify cropland expansion/contraction, fallow dynamics, and urban encroachment — metrics that directly affect hydrological response and recharge potential. Studies show that increases in built-up area and loss of vegetative cover typically correspond with increased runoff and reduced infiltration, underscoring the need to combine LULC change analysis with recharge planning. The NRSC annual LULC products and other multi-temporal datasets have been instrumental in enabling such integrated assessments at basin scale. (NRSC 2024).

Finally, operational guidance emerging between 2020 and 2024 emphasizes integrated, community-centred implementation: GIS outputs are most effective when translated into locally feasible interventions, accompanied by maintenance plans, participatory governance, and cost estimates. Recent reviews argue that technical suitability maps must be coupled to socioeconomic assessments and institutional arrangements to achieve long-term impact. This integrated perspective aligns closely with contemporary watershed programs across India that blend geospatial planning with livelihood and governance measures. (Dapke, P. P. et.al. 2024)

Over the last five years, remote sensing (RS) and geographic information systems (GIS) have advanced from supporting tools to the methodological backbone of watershed assessment and land-use/land-cover (LULC) mapping. Improvements in freely available satellite data (Sentinel-2, high-resolution LISS sensors, and continued use of Landsat archives) combined with faster processing pipelines and cloud computing make multi-temporal LULC mapping at sub-watershed scales both practical and cost-effective (e.g., comparative Sentinel/Landsat studies). These datasets enable practitioners to observe seasonal and inter-annual land-cover dynamics that directly influence runoff–recharge relationships and the siting of conservation structures. (Abida, K., & Barbouchi, M. 2022).

Traditional supervised classification remains widely used because of its interpretability and ease of linking spectral classes to ground truth. However, 2020–2024 literature shows an increasing preference for hybrid workflows that combine unsupervised clustering to reveal spectral groupings, followed by supervised classification (with field-verified training samples) and post-classification smoothing to reduce noise in fragmented agricultural landscapes. More importantly, machine-learning (ML) classifiers — particularly Random Forest (RF) and Support Vector Machines (SVM) — have become standard for improving per-class accuracies in heterogeneous rural environments. Comparative reviews and applied studies across climatic zones have repeatedly found RF to perform robustly across different morphoclimatic contexts, often outperforming decision-tree and maximum-likelihood classifiers when sufficient training samples are available. For semi-arid agricultural catchments, hybrid ML + post-processing workflows deliver both higher overall accuracy and more stable class boundaries than single-method approaches. (Talukdar, S. et.al. 2020).

Digital Elevation Models (DEMs) are now routinely used not only to derive slope and aspect but to compute a comprehensive suite of morphometric indices (stream order, drainage density, bifurcation ratio, relief ratios, elongation, form factor, etc.). Recent reviews (2023–2024) emphasize that morphometric parameters are highly predictive of runoff generation and sediment transport and, when combined with LULC, markedly improve the prioritization of sub-watersheds for conservation measures. The literature also documents better decision outcomes when morphometric indicators are synthesized using PCA or weighted-sum models before being used in prioritization schemes, reducing redundancy and increasing the stability of priority rankings. These developments support using DEM-based morphometrics as a primary input for siting check dams, CCTs (continuous contour trenches), and recharge structures.

Between 2020 and 2024, Multi-Criteria Decision Analysis (MCDA) — especially the Analytical Hierarchy Process (AHP) — remained the most commonly used operational approach for delineating Groundwater Recharge Potential Zones (GWRPZ). AHP’s appeal lies in transparency and stakeholder-friendly weight elicitation across layers such as slope, land use, soil type, drainage density, lineaments, and rainfall. Numerous regional case studies from India and neighbouring countries demonstrate successful application of AHP+GIS for recharge planning and for creating implementable maps for local agencies. However, comparative studies over the period have also shown that data-driven ML models (logistic regression, RF, XGBoost) can outperform AHP when adequate, spatially distributed ground truth (well yields, post-monsoon groundwater levels) is available — because ML can learn non-linear interactions and implicit weights from the data. Best practice emerging in the literature is a hybrid approach: use AHP for initial, transparent weighting and stakeholder buy-in, and supplement (or validate) results with ML to refine spatial predictions where training data permit. This hybrid paradigm preserves operational transparency while leveraging predictive analytics. (Singh, S. K., & Noori, A. R. 2022).

Recent applied studies (2020–2024) emphasize not only mapping suitability but translating water balances into a concrete list of structures: number and type of farm ponds, check dams, percolation tanks, and urban rainwater harvesting units — with storage capacities and cost estimates. These studies combine RS-driven runoff estimates (Inglis or empirical curve methods adjusted for local CN values), evapotranspiration (ET) approximations, and recharge fractions derived from specific yield estimates to compute implementable storage portfolios. Where implemented, these plans show measurable improvements in post-monsoon groundwater levels and reductions in tanker dependence. The operational framing—from suitability map → water budget → infrastructure list—makes RS–GIS outputs directly actionable for Gram Panchayats and watershed programs. (Chandaniha et al., 2025)

The 2020–2024 corpus highlights the necessity of rigorous accuracy assessment (confusion matrices, Kappa, per-class producer/user accuracies) and transparent reporting of training/validation protocols. Transferability (applying models across neighboring watersheds) is achievable but requires careful recalibration of weights or retraining of models because LULC spectral signatures and hydrogeological responses vary with crop calendars, soil moisture regimes, and geology. Researchers advocate multi-temporal validation and reporting of uncertainty bounds (e.g., ensemble ML approaches) for robust planning. (Abida, K., & Barbouchi, M. 2022).

The period saw rapid uptake of Sentinel-2 (10 m) for LULC and Sentinel-1 SAR for moisture/texture information; combined optical+SAR workflows improve classification under cloudy or phenologically dynamic conditions. The use of cloud platforms (Google Earth Engine, AWS) enabled analysts to run continental or national-scale mosaics and multi-temporal composites quickly — a crucial advantage for repeated watershed assessments and change detection. These technological shifts lower the barrier to high-frequency monitoring and enable near-real-time decision support for emergency interventions. (Abida, K., & Barbouchi, M. 2022).

Literature from 2020–2024 consistently argues that technically sound maps must be integrated into governance frameworks and community programs to produce impact. Key implementation challenges include local capacity for construction and maintenance, funding cycles that are short-term, and the need for participatory monitoring to ensure structures are kept functional. Studies recommend coupling technical prioritization with participatory appraisal and cost–benefit screening to ensure long-term sustainability. The consensus is that purely technical suitability maps have limited value unless translated into implementable project designs, budgets, and institutional responsibilities.

Despite advances, gaps remain. First, there is a shortage of well-distributed, long-term in-situ groundwater observations to train and validate ML-based recharge models across many Indian watersheds. Second, objective, transferable weighting strategies for MCDA remain an open problem — particularly when stakeholder preferences conflict. Third, there is a need for standardized workflows and reproducible code that link LULC change detection, morphometrics, runoff estimation, and structure-sizing in a single pipeline. Finally, there is growing interest in coupling socio-economic layers (livelihood vulnerability, willingness to maintain structures) with biophysical suitability maps to optimize investments. Research from 2020–2024 indicates that addressing these gaps will make RS–GIS watershed planning more predictive, equitable, and implementable.

The state of the art from 2020–2024 supports the methodological choices in the Gorewadi plan: (a) integrate DEM-derived morphometrics with LULC for robust prioritization; (b) adopt an MCDA (AHP) framework for transparent stakeholder-driven weighting while using ML methods to validate or refine suitability maps where ground data permit; (c) convert runoff and recharge estimates into a concrete infrastructure portfolio with storage and cost estimates; and (d) embed technical maps within a participatory implementation plan to secure maintenance and governance. These alignments position the Gorewadi project within current best practice and increase its chances for measurable hydrological and socio-economic benefits.

IV. STUDY AREA

The study was conducted in the Agrani River basin, which forms part of the Krishna River system. The river originates near the Western Ghats in a rain-shadow zone at an elevation of approximately 885 m and flows through Sangli district (Maharashtra) and Belagavi district (Karnataka) before joining the Krishna River at Hulga Bali at an elevation of 549 m. The basin lies between 16°39'24" N to 17°19'25" N latitude and 74°40'16" E to 75°13'20" E longitude. This study focuses on selected villages within the KR-36 sub-watershed, illustrated in Fig. 1. The basin exhibits semi-arid climatic conditions, seasonal streams, and predominantly agricultural land use.

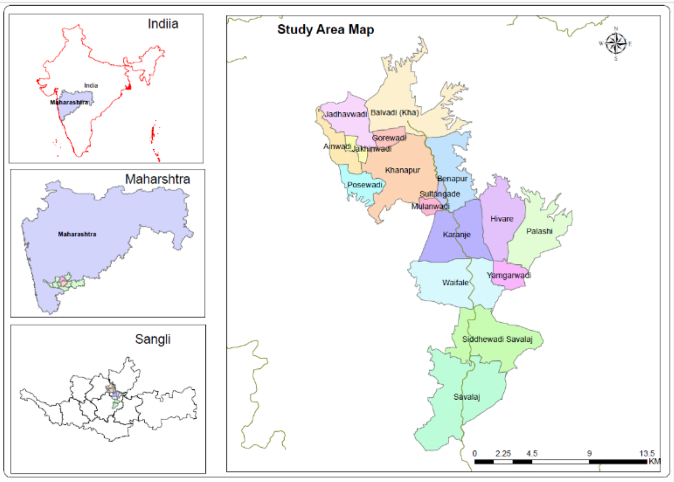

Figure 1 Study area villages

V. MATERIALS AND METHODS

5.1 Satellite Data

Geo-coded False Colour Composite (FCC) imagery from IRS-P6 LISS-IV (2023) was the primary dataset for LULC classification. The imagery corresponds to Path 102 and Row combinations covering the Wardha River watershed and its sub-watersheds. These high-resolution datasets provide detailed spectral information suitable for land cover discrimination.

5.2 Methodology

The methodology employed in this study includes:

- Pre-processing of satellite imagery
- Layer stacking and image rectification
- Unsupervised classification to identify initial spectral clusters
- Supervised classification using field-verified training samples
- Accuracy assessment with ground truth points
- Generation of final LULC maps in ArcGIS

Key classification features included tone, texture, shape, size, and contextual association. ERDAS Imagine software was used for image rectification, subsetting, and classification, whereas ArcGIS was used to generate LULC maps and calculate areal statistics. A workflow diagram summarizing the methodology is shown in Figure 2.

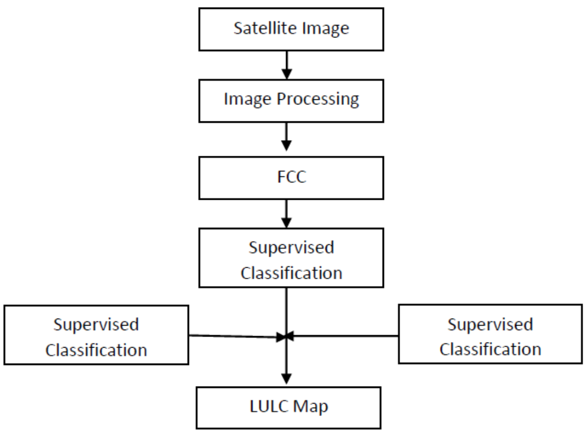

Fig. 2 Workflow Diagram Result and Discussion Land Use and Land Cover

VI. RESULTS AND DISCUSSION

Agricultural cropland accounts for the highest proportion of land (36.18%), reflecting the agrarian economic base of the region. Fallow land (30.65%) indicates seasonal cropping patterns and reliance on monsoon rainfall. Built-up land occupies 6.41% and represents both rural and semi-urban settlements. Water bodies cover less than 1%, highlighting the scarcity of surface water resources. Fig. 3 illustrates the classified LULC map.

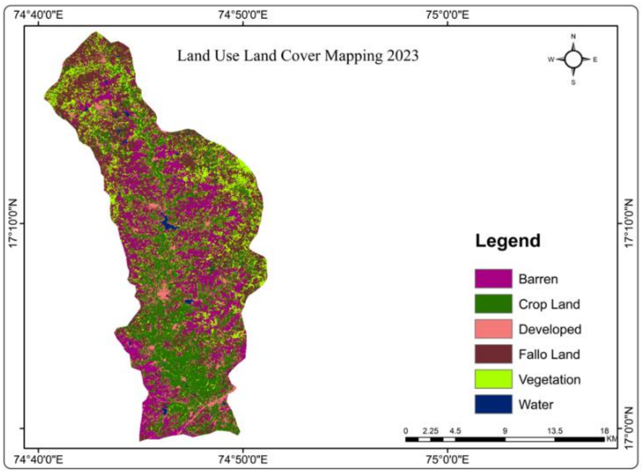

Figure 3 Land Use and Land Cover

LULC analysis revealed considerable variability in land resource distribution across the study region. Based on the classified maps, the sub-watershed consists of six major LULC categories: cropland, fallow land, vegetation, built-up areas, barren land, and water bodies. The spatial distribution indicates dominance of agricultural usage, followed by fallow land and vegetation cover. A summary of the LULC classes is given in Table 1 and Fig.4.

Table 1. Summary of LULC Classification

LULC Category	**Area (km²)**	**Percentage (%)**
Barren Land	30.64	8.75
Crop Land (Agriculture)	126.68	36.18
Built-up Area	22.44	6.41
Fallow Land	107.33	30.65
Vegetation	59.86	17.10
Water Bodies	3.18	0.91
Total	**350.13**	**100.00**

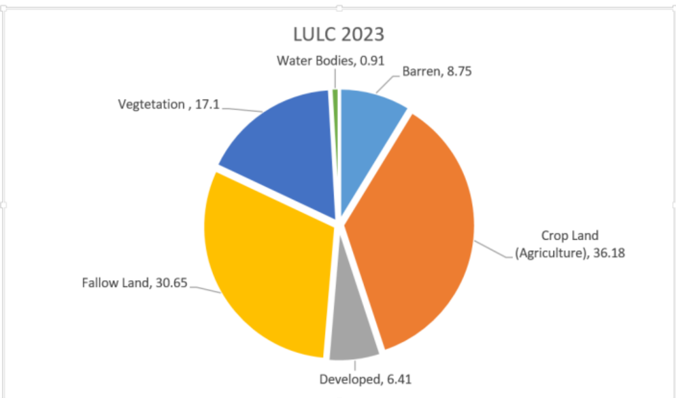

Figure 4 Land Use and Land Cover classification of 2023

VII. CONCLUSION

Effective land resource management requires accurate and up-to-date information on LULC patterns. The integrated use of remote sensing and GIS in this study enabled the generation of detailed LULC maps for the KR-36 sub-watershed of the Agrani River basin. The results indicate that cropland is the dominant land use, whereas water bodies and barren land occupy minimal areas. RS–GIS techniques provide a robust, reliable, and economical means for monitoring land surface dynamics and guide sustainable land-use planning. Future studies can incorporate multi-temporal datasets to assess long-term land-cover change and its environmental impacts.

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