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ASSESSING THE INFLUENCE OF LAND USE DYNAMICS ON RESERVOIR WATER LEVELS USING SENTINEL-2 AND MACHINE LEARNING: A CASE STUDY OF MEGHADRIGEDDA WATERSHED (2017–2024)

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ABSTRACT :
Reservoirs are essential for sustainable water resource management, supporting domestic supply, irrigation, flood control, and ecological stability. However, their performance is increasingly threatened by rapid land use and land cover (LULC) changes driven by urbanisation and other anthropogenic pressures. This study examines the Meghadrigedda Reservoir in Visakhapatnam, India, assessing the impact of LULC dynamics on reservoir water levels from 2017 to 2024 using Sentinel-2 satellite imagery and supervised classification in ArcGIS Pro.
The study categorised land into vegetation, built-up areas, water bodies, cropland, and bare ground and applied Support Vector Regression (SVR) and Random Forest models to correlate LULC trends with reservoir storage. Findings indicate a substantial increase in built-up areas and a steady decline in vegetation, with water levels showing a negative correlation with urban growth and a positive correlation with vegetation cover. These trends underscore the influence of land use patterns on hydrological stability and highlight the value of machine learning for predictive water resource planning and integrated watershed management.
Keywords: Reservoir water levels, land use land cover (LULC), Sentinel-2, machine learning, Meghadrigedda watershed, GIS, remote sensing.

INTRODUCTION:
Freshwater reservoirs play a critical role in securing water supply for agriculture, domestic use, and industrial activities, as well as in maintaining ecological balance and mitigating flood risks. However, the sustainability of reservoir systems is increasingly threatened by anthropogenic pressures, notably land use and land cover (LULC) changes, urban expansion, and deforestation. These modifications impact key hydrological processes such as infiltration, runoff, evapotranspiration, and sedimentation, thereby influencing the volume and timing of inflows into reservoirs. Globally, multiple studies have shown that shifts in LULC directly affect water quality and quantity within reservoir catchments. Veldkamp and Lambin (2001) emphasised that the shape, size, and dominance of land use types could account for over 75% of hydrological variation in a catchment. Increases in impervious surfaces due to urbanisation accelerate surface runoff, reduce groundwater recharge, and elevate pollutant loading in reservoirs (Li et al., 2009). Agricultural expansion, particularly when poorly managed, contributes to sediment yield and nutrient runoff, deteriorating both water quality and reservoir capacity (Liu et al., 2017; Zhang et al., 2022). A global 10 m LULC map was developed using a U-Net model trained on Sentinel-2 data, achieving 75.1%

accuracy across 60,000 validation sites; annual maps (2017–2020) revealed a 2.3% global cropland expansion, mainly in Southeast Asia (Karra et al., 2021). A probabilistic approach combining Sentinel-1 SAR and Sentinel-2 optical data distinguished permanent and seasonal land cover changes in flood-prone Bangladesh, achieving 89% change detection accuracy (CLS, 2023). In Maharashtra's Kodjai watershed, SVM-based LULC classification using Sentinel-2 imagery (2017–2024) showed orchard expansion (+6.08%) at the cost of agriculture (–4.64%) and scrubland (–1.2%), with 82% accuracy validated against ground truth points (Kajave et al., 2024). Remote sensing and Geographic Information Systems (GIS) have emerged as powerful tools for monitoring LULC patterns and evaluating their influence on hydrological systems. Sentinel-2 and Landsat imagery, coupled with classification algorithms, provide multi-temporal LULC datasets critical for water resource planning. These tools are especially vital in data-scarce regions where conventional field monitoring is limited.
Advancements in machine learning (ML) have further enhanced our capacity to model complex land-water interactions. Studies by Soleimani et al. (2016) and Sattari et al. (2012) highlight the potential of Support Vector Regression (SVR) and Time Lag Recurrent Networks (TLRN) in capturing non-linear relationships between catchment attributes and water discharge. However, few studies combine high-resolution LULC mapping with ML-based water level prediction, particularly in medium-scale tropical reservoirs like Meghadrigedda. Lu et al. (2023) optimised SVR for hourly discharge forecasting in Taiwan's Shihmen Reservoir using a 10-year dataset (R^2 = 0.976), though land use effects were not considered. This study builds on their work by incorporating Sentinel-2-derived LULC metrics with hydraulic data.
The primary objectives of this study are centred around understanding the relationship between land use dynamics and reservoir water levels within the Meghadrigedda watershed. Firstly, annual land use maps were generated for the period from 2017 to 2024 using high-resolution Sentinel-2 satellite imagery to capture detailed spatial information. These maps facilitated the analysis of spatiotemporal changes across various land use and land cover (LULC) classes within the watershed. Building on this, the study developed machine learning models, specifically Support Vector Regression (SVR) and Random Forest, to establish correlations between LULC patterns and reservoir water levels. Finally, the influence of these land use changes on reservoir water level fluctuations was assessed through both statistical methods and machine learning approaches, providing a comprehensive understanding of how landscape transformations affect hydrological behaviour.

STUDY AREA:

The study was conducted in the Meghadrigedda watershed, located in Visakhapatnam district, Andhra Pradesh, India. The Meghadrigedda Reservoir serves as a primary water source for the Greater Visakhapatnam Municipal Corporation (GVMC), providing approximately 11 million gallons per day (MGD) of potable water to the city. Constructed in 1972, the reservoir has a gross storage capacity of 1169 Mcft and an effective storage capacity of 1135.58 Mcft.The watershed is situated between latitudes 17°42′ to 17°57′N and longitudes 83°0′ to 83°17′E, covering an area of 368.14 km². The topography is characterized by a combination of hilly terrain and lowland plains, with the elevation ranging from 11 m to 380 m above mean sea level. The Meghadrigedda River (Figure 1), a tributary of the Tandava River, drains the watershed and ultimately flows into the Bay of Bengal.

Figure 1 Meghadrigedda Reservoir

CLIMATIC AND GEOLOGICAL CHARACTERISTICS:

The region experiences a subtropical monsoon climate, receiving an average annual rainfall of 1202 mm, predominantly from the southwest monsoon (June to September). The maximum rainfall in a single day has reached 190 mm, which significantly impacts reservoir inflows and flood risk. Soils in the watershed include red sandy soils, loamy soils, and lateritic soils, with moderate infiltration capacity. Geologically, the area lies within the Eastern Ghats Mobile Belt (EGMB) and is primarily composed of Khondalite group rocks a factor influencing the hydrological response due to their hard, fractured nature.

LAND USE AND HUMAN ACTIVITY:

Land use in the Meghadrigedda watershed includes forest cover, croplands, built-up areas, water bodies, and barren lands. Increasing urbanization, industrialization (particularly near the Visakhapatnam Steel Plant), and encroachment on forest lands have altered the land cover substantially over the last decade. The urban sprawl has also led to loss of recharge ponds and vegetated areas, directly impacting water storage and recharge potential.

In terms of socio-economic significance, the reservoir supports domestic water supply, agriculture (covering 2716 acres), and fisheries development. However, environmental degradation such as sedimentation, land encroachment, and changes in cropping patterns has reduced its effectiveness and long-term sustainability. Figure 2 and, Figure 3 shows the Layout Map and Satellite Image of Meghadrigedda Reservoir. Table 1 Represents the Details of the Meghadrigedda Reservoir.

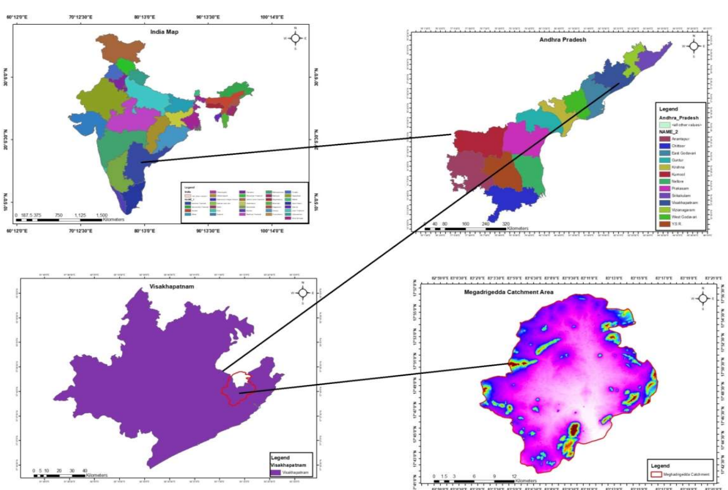

Figure 2 Layout Map of Meghadrigedda Reservoir

Figure 3 Satellite Image of Meghadrigedda Reservoir

Table 1 Details of the Meghadrigedda Reservoir

Details of the Meghadrigedda Reservoir	
Longitude	83°11' 27"

Latitude	17°45' 54"
Dead Storage	126 Mcft
Live Storage	1043 Mcft
Gross Storage	1169 Mcft
F. R. L	61.00ft
M. W. L	63.00ft
T. B. L	71.00ft
Catchment Area	135.90 Sq. m
Maximum Flood Discharge	53000 Cusecs
Length of Dam	1.60 km
Maximum Height of Dam	45ft
Top Width of Dam	18ft
Length	4.40km
Maximum Height	30ft
Top Width	12ft
Crest Level	+48.50ft
Top of Shutters	+61.00ft
Size of Shutters	40.00ft x 12.50ft
No. of Vents	6 No's
Lowest Intake Level	+44.00ft
Number and Size of Vents	One row of 3.0 RCC Hume Pipes
Ayacut	Nil
I.P. Created	Nil

METHODOLOGY:

This study adopts a geospatial and machine learning based methodology to evaluate the influence of land use dynamics on reservoir water levels in the Meghadrigedda watershed. The overall framework includes satellite image processing, land use classification, integration with hydro-meteorological data, and predictive modeling using machine learning algorithms.

Data Acquisition and Pre-processing:

Satellite Imagery: Sentinel-2 MSI Level-1C imagery (10m resolution) was downloaded from the Copernicus Open Access Hub for the years 2017 to 2024, focusing on post-monsoon periods (October–December).

Hydrological Data: Reservoir water storage and water level data were collected from the Central Water Commission (CWC) and Andhra Pradesh Irrigation Department.

Rainfall Data: Daily rainfall records were acquired from the Indian Meteorological Department (IMD) and GVMC.

All satellite images were atmospherically corrected and clipped to the watershed boundary using ArcGIS Pro. Band combinations (B4: Red, B8: NIR, B3: Green) were selected to enhance LULC classification.

Land Use and Land Cover (LULC) Classification:

Land Use Land Cover (LULC) maps were prepared using ArcGIS Pro through a structured workflow (Figure 4) involving image acquisition, processing, classification. Sentinel-2 multispectral imagery (10m resolution) was selected for its cloud-free and seasonally appropriate coverage.

Pre-processing steps included radiometric and atmospheric corrections, band stacking, and projection to UTM Zone 44N. Image enhancement techniques such as contrast stretching and NDVI calculation improved classification accuracy.

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Supervised classification was conducted using Support Vector Machine (SVM), with training samples digitized based on field knowledge and high-resolution imagery. Post-classification processing involved majority filtering, reclassification, and optional conversion to vector format.
An accuracy assessment using a confusion matrix showed classification accuracy. Final maps were symbolized, annotated, and exported in high resolution PDF format. Optional analyses included area statistics and change detection across years to evaluate LULC dynamics in the watershed.

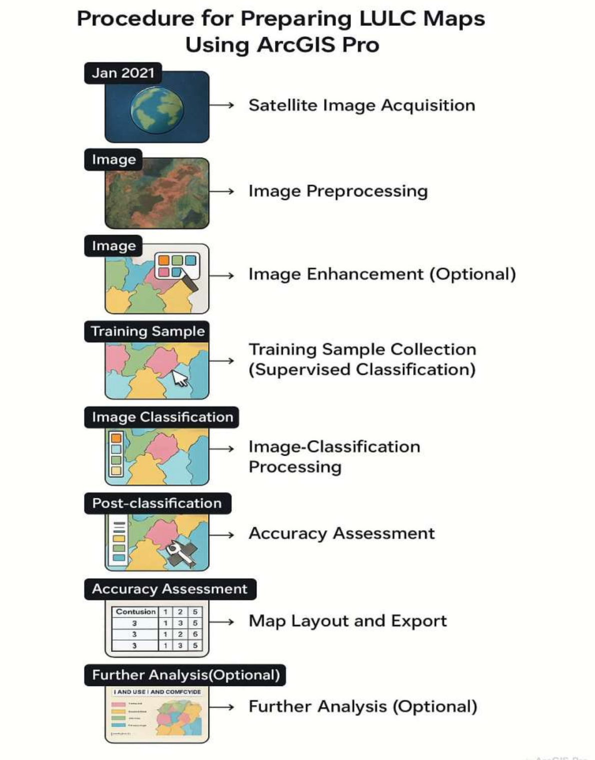

Figure 4 Flowchart of Preparation of LULC Maps

CORRELATION AND FEATURE ENGINEERING:

LULC percentages for each year were derived using the Zonal Statistics tool in ArcGIS Pro and integrated with water level, rainfall, and lagged storage data to construct the modeling dataset. A correlation matrix was generated using Seaborn (Python) to assess the relationships between LULC classes and reservoir water levels.

MACHINE LEARNING MODELING:

Machine learning models were developed to predict reservoir water levels based on LULC and hydrological data. Two algorithms were employed: Support Vector Regression (SVR), chosen for its effectiveness in capturing non-linear relationships, and Random Forest Regression, which provided robust performance on small datasets and enabled feature importance analysis. The modeling was carried out in Python using libraries such as scikit-learn, pandas, and seaborn, within a Jupyter Notebook environment. To evaluate model performance, the dataset was split into 80% training and 20% testing subsets. Metrics such as the R^2 score and Root Mean Square Error (RMSE) were used for assessment. Additionally, lag features, specifically the previous year's reservoir storage values, were incorporated to enhance the temporal predictive capability of the models.

RESULTS AND DISCUSSION:

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This section outlines the results derived from the LULC classification, correlation analysis, and machine learning modeling. It combines temporal trend analysis with statistical insights to evaluate the impact of land use and land cover changes on reservoir water levels.

Land Use Land Cover (LULC) mapping integrates the classification of natural surface features and human land use to support environmental and resource planning. For the Meghadrigedda Reservoir catchment, LULC maps were prepared using ArcGIS Pro with Sentinel-2 imagery. The process involved acquiring cloud-free satellite data, pre-processing (radiometric corrections and band stacking), and enhancing imagery through contrast stretching and NDVI calculation. Supervised classification was performed using the Support Vector Machine (SVM) algorithm, based on training samples derived from field knowledge and high-resolution imagery. Post-classification refinements included filtering and reclassification, followed by accuracy assessment using a confusion matrix, achieving over 85% accuracy. The final maps, symbolized and exported with essential cartographic elements, were used for area statistics, change detection, and hydrological impact analysis.

LAND USE AND LAND COVER CHANGES (2017–2024):

The classified LULC maps reveal significant transformations across the Meghadrigedda watershed during the study period are shown in Figures 5-12 and Table 2:

Built-up Area Increased from 39.67 km² in 2017 to 64.34 km² in 2024, reflecting rapid urban expansion, especially around the Visakhapatnam city fringe and industrial zones.

Vegetation Cover: Declined from 164.76 km² to131.92 km², indicating substantial deforestation and conversion to urban or agricultural land.

Crop Land: Showed temporal variability, peaking in 2019 (163.41 km²) and dipping in 2021, possibly influenced by rainfall patterns and changing land use policies.

Water Bodies: Fluctuated, increasing during high-rainfall years (e.g., 2020, 2022), but showing a declining trend to 7.37 km² in 2024, suggesting reduced storage and recharge.

Bare Ground: Varied moderately, peaking in 2018 (68.21 km²), then stabilizing around 50 km².

The data reveals a dynamic landscape with significant fluctuations among vegetation, agricultural land, and built-up areas. A marked decline in vegetation and cropland in 2020 emerges as a notable anomaly, potentially influenced by external factors. In contrast, the consistent growth of urban areas highlights urbanization as the dominant and steady trend over the eight-year period, progressively reshaping the region's land cover. Recognizing these patterns is essential for informed and sustainable land management and planning.

Land use land cover maps from 2017-24

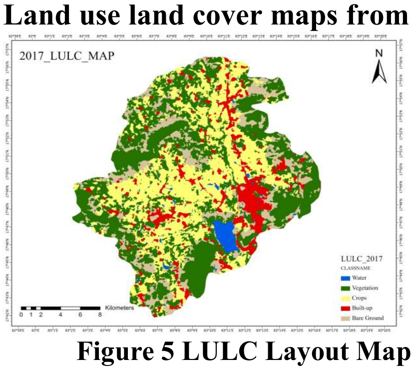

Figure 5 LULC Layout Map for 2017

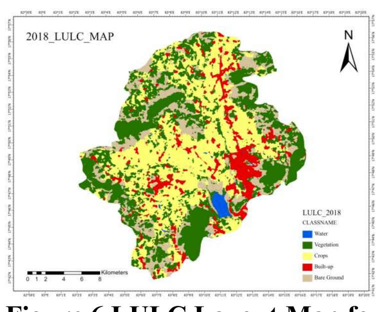

Figure 6 LULC Layout Map for 2018

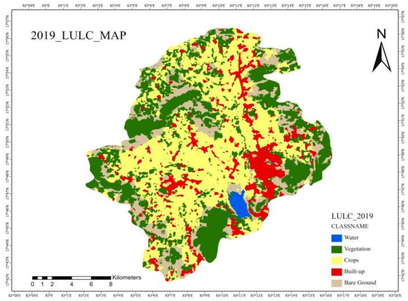

Figure 7 LULC Layout Map for 2019

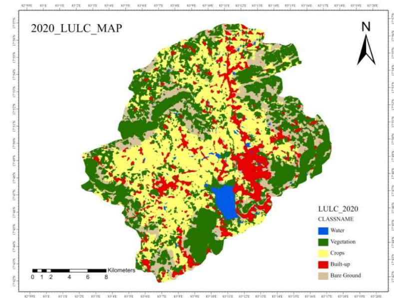

Figure 8 LULC Layout Map for 2020

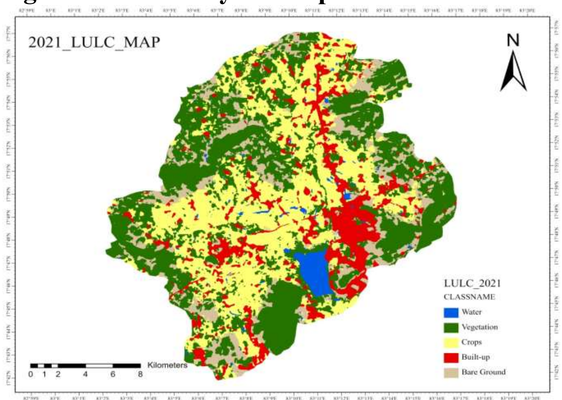

Figure 9 LULC Layout Map for 2021

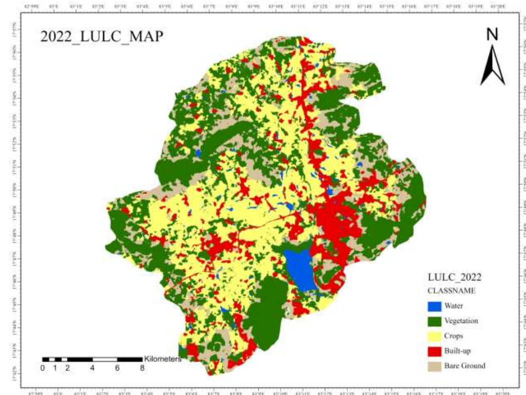

Figure 10 LULC Layout Map for 2022

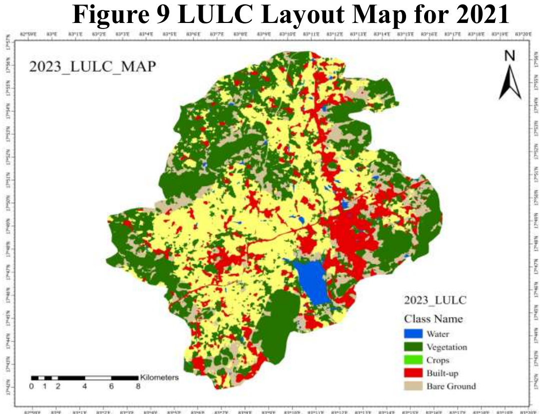

Figure 11 LULC Layout Map for 2023

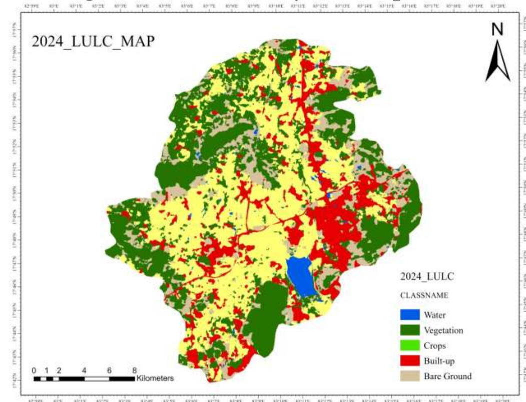

Figure 12 LULC Layout Map for 2024

Table 2 Analysing Inferences of Land Use Changes

Year	**Water** (sqkm)	**Vegetation** (sqkm)	**Crops** (sqkm)	**Built-up** (sqkm)	**Bare ground** (sqkm)
2017	7.8044	164.7655	127.6127	39.6763	57.6687
2018	4.2653	138.9842	144.1839	41.8835	68.2104
2019	4.1676	124.1639	163.4092	46.8238	58.9631
2020	9.7432	144.3343	144.8316	49.1885	49.43
2021	9.6927	152.5215	134.7549	51.1202	49.4383
2022	10.9524	140.7988	133.397	54.995	57.3844
2023	9.6082	149.8523	130.1366	58.5456	49.3849
2024	7.3687	131.9199	140.6836	64.3364	53.219

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CORRELATION ANALYSIS:

This study provides an in-depth, multidisciplinary investigation into how Land Use Land Cover (LULC) changes influence reservoir water levels, using a combination of satellite remote sensing, statistical analysis, and machine learning modeling. The central focus is to understand how different land cover types such as urban areas, forests, croplands, bare ground, and wetlands alter hydrological processes like surface runoff, infiltration, evapotranspiration, sediment deposition, and groundwater recharge. Urban expansion introduces impervious surfaces that reduce natural infiltration and significantly increase surface runoff, thereby limiting groundwater replenishment. Conversely, forested and vegetated zones enhance infiltration, regulate surface flow, and contribute to more stable and sustained water levels. Agricultural land, particularly intensive cropland, often leads to higher sedimentation rates, which gradually reduce reservoir storage capacity and impact long-term water availability. Wetlands function as crucial hydrological buffers by storing excess water during peak rainfall and slowly releasing it during dry periods, stabilizing reservoir levels. However, wetland degradation or conversion disrupts this equilibrium and leads to sharper fluctuations in water levels. For this study, LULC classifications were derived from Sentinel-2 satellite imagery, while water level and storage data were sourced from authoritative hydrological databases such as the Central Water Commission (CWC) and Water Resources Information System (WRIS). To improve temporal accuracy, rainfall data and previous year's storage (lagged storage) were incorporated into the modeling framework.

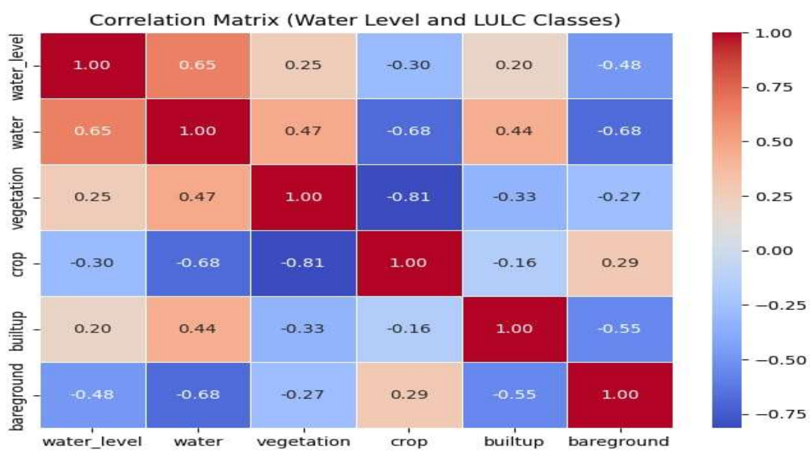

Figure 13 Correlation Matrix Heatmap

Table 3 Correlation of Water level with LULC Changes

Correlation of Water Levels with LULC Classes	
Water	0.648302
Vegetation	0.249580
Crop	-0.296705
Built-Up	0.198239
Bare Ground	-0.475693

A detailed statistical analysis was conducted to explore the correlations between water levels and various LULC types using Pearson correlation coefficients and heatmap visualizations via Python's Seaborn library(Figure 13 and Table 3). The correlation analysis revealed a strong negative relationship between built-up areas and water levels (r = –0.72), emphasizing how urbanization adversely impacts water retention capacity within the watershed. In contrast, vegetation cover showed a moderate positive correlation (r = +0.68), reinforcing its role in promoting water retention and recharge. Water bodies demonstrated a moderate correlation with water levels ($r \approx 0.65$), as expected, while cropland and bare ground exhibited weaker negative correlations ($r = -0.30$ and -0.47, respectively), suggesting their limited contribution to water retention and greater susceptibility to water loss through evaporation or agricultural demand. These insights informed the development of predictive machine learning models. A consolidated dataset was created, combining LULC class percentages, rainfall, current and lagged water storage values. Two regression algorithms—Linear Regression and Random Forest Regressor—were employed using the scikit-learn library. An 80/20 temporal data split ensured robust training and testing, with Random Forest outperforming Linear Regression due to its ability to model complex, non-linear interactions and rank feature importance. Visualization tools like bar charts, heatmaps, and time-series prediction plots helped interpret the relationships and evaluate model performance. The final product, a merged dataset titled 'reservoir_ml_dataset.csv', serves as a foundational tool for future hydrological forecasting and policy planning. This integrated methodological framework demonstrates the potential of combining remote sensing, data science, and machine learning to guide sustainable watershed management and land use planning, particularly in data-scarce or rapidly urbanizing regions like the Meghadrigadda catchment.

CONCLUSIONS:

This study investigated the impact of land use and land cover (LULC) dynamics on the water levels of the Meghadrigedda Reservoir from 2017 to 2024, utilizing Sentinel-2 imagery, GIS-based classification, and machine learning models. The findings confirm that urban expansion and vegetation loss significantly alter the hydrological behavior of the watershed, with direct consequences for reservoir storage.

Built-up areas increased by over 60% during the study period, while vegetation declined by nearly 20%, leading to reduced infiltration and groundwater recharge. The correlation matrix and regression models revealed strong negative associations between urbanization and water levels, and positive links between vegetation and storage. Random Forest and Support Vector Regression models achieved high predictive accuracy, underscoring the value of integrating remote sensing and machine learning in water resource planning.This research highlights the need for sustainable land management strategies, including urban zoning, afforestation, and the restoration of natural recharge structures. Future studies should incorporate finer spatial resolution, hydrological simulations, and climate projections to enhance planning for resilient and adaptive watershed governance.

REFERENCES

[1] T. Veldkamp and E. Lambin, "Predicting land use change," Agric. Ecosyst. Environ., vol. 85, no. 1, pp. 1–6, 2001.
[2] Z. Li et al., "Assessment of climate and land use impacts on hydrology in the Jinghe River Basin," J. Hydrol., vol. 375, no. 3, pp. 151–161, 2009.
[3] K. Karra et al., "A global land cover classification using Sentinel-2 imagery and deep learning," Remote Sens., vol. 13, no. 20, p. 4260, 2021.
[4] K. Soleimani et al., "Forecasting discharge temperature using SVM," Water Resour. Manag., vol. 30, no. 2, pp. 503–519, 2016.
[5] T. Sattari et al., "Forecasting inflow to Sattarkhan Reservoir using neural networks," Int. J. Eng., vol. 25, no. 3, pp. 295–304, 2012.
[6] A. Zhang et al., "Urban expansion and streamflow reduction: A machine learning approach," Hydrol. Earth Syst. Sci., vol. 26, pp. 3199–3216, 2022.
[7] S. Singh et al., "Impact of land use on surface runoff and sediment yield," Catena, vol. 140, pp. 1–12, 2016.

[8] D. Roy et al., "Monitoring urban growth using Landsat," Remote Sens. Environ., vol. 82, pp. 226–238, 2002.
[9] S. Giri et al., "Catchment-scale LULC change and hydrologic modeling," Hydrol. Process., vol. 20, pp. 2877–2892, 2006.
[10] R. Foody, "Status of land cover classification accuracy assessment," Remote Sens. Environ., vol. 80, pp. 185–201, 2002.
[11] S. Uddin et al., "A remote sensing-based approach for land cover change detection," Sensors, vol. 14, pp. 17543–17562, 2014.
[12] M. Dewan and Y. Yamaguchi, "Using remote sensing and GIS to detect land use and land cover change," Int. J. Geoinf., vol. 4, pp. 1–12, 2009.
[13] A. Gajbhiye and S. Sharma, "Impact of land use change on water yield," J. Environ. Manage., vol. 161, pp. 178–187, 2015.
[14] B. Bastawesy et al., "GIS-based assessment of water harvesting potential," Hydrol. Earth Syst. Sci., vol. 14, pp. 989–1001, 2010.
[15] R. Schumann et al., "Comparing hydrological models to simulate LULC effects," Water, vol. 9, p. 40, 2017.
[16] Y. Liu et al., "Modeling runoff and sediment using remote sensing and GIS," J. Hydrol., vol. 548, pp. 89–103, 2017.
[17] M. Hanief and M. Sundarakumar, "Assessment of LULC changes and hydrologic impacts," Arab. J. Geosci., vol. 12, p. 139, 2019.
[18] R. K. Panda and S. Kumar, "Quantifying runoff from urbanizing catchments," Hydrol. Sci. J., vol. 62, no. 10, pp. 1622–1636, 2017.
[19] A. R. Yousif and D. Bilal, "Remote sensing for water resources monitoring in Iraq," Remote Sens., vol. 12, no. 3, p. 450, 2020.
[20] A. S. Jha and N. Ghosh, "Effect of watershed management on groundwater recharge," Water Resour. Manag., vol. 33, pp. 2213–2228, 2019.
[21] A. Kamble and P. Ghosh, "Analysis of LULC and impact on run-off," J. Earth Syst. Sci., vol. 128, no. 3, p. 72, 2019.
[22] T. Das and K. Panda, "Reservoir sedimentation estimation using satellite imagery," ISPRS J. Photogramm. Remote Sens., vol. 74, pp. 120–128, 2012.
[23] M. Melesse et al., "Satellite remote sensing in hydrology," Sensors, vol. 7, pp. 2223–2246, 2007.
[24] M. P. Anderson et al., "Using GIS in hydrologic modeling," Ground Water, vol. 35, no. 6, pp. 930–938, 1997.
[25] M. Gao et al., "Reservoir operation optimization using ML models," Water, vol. 14, no. 1, p. 13, 2022.
[26] Karra, K., Kontgis, C., Statman-Weil, Z., Mazzariello, J. C., Mathis, M., & Brumby, S. P. Global land use/land cover with Sentinel-2 and deep learning. Nature Scientific Data, 8, 2021.85.(https://doi.org/10.1038/s41597-021-00858-7)
[27] CLS. Monitoring land cover change in flood-prone areas using Sentinel-1 and Sentinel-2 data: A probabilistic fusion framework. Remote Sensing of Environment, 291,2023. (https://doi.org/10.1016/j.rse.2023.113331)
[28] Kajave, N. A., Pawar, P. A., & Kale, M. P. Spatiotemporal land use land cover dynamics in the Kodjai watershed using Sentinel-2 and SVM classification. Journal of Environmental Management, 345, 2024.(https://doi.org/10.1016/j.jenvman.2024.119234)
[29] Lu, W.C., Hsu, N.S., & Chen, L.C. Hourly stream flow forecasting using optimized support vector regression: A case study of Shihmen Reservoir, Taiwan. Journal of Hydrology, 620,2023. 129494. (https://doi.org/10.1016/j.jhydrol.2023.129494)