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Original Article

Remote Sensing-Based Assessment of Surface Water Bodies in Satara District, Maharashtra

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Abstract

This study evaluates the spatio-temporal dynamics of surface waterbodies in Satara district, Maharashtra, using the Normalized Difference Water Index (NDWI) derived from multi-temporal Landsat imagery for the years 1994, 2004, 2014, and 2024. NDWI-based classification was employed to delineate three land categories: Non-Water (NDWI ≤ 0.0), Moist Areas (0.0–0.2), and Waterbodies (NDWI > 0.2). Spatial analysis revealed that while waterbody coverage remained low throughout the study period, it exhibited a steady increase from 1.59% in 1994 to 2.56% in 2024. The highest extent of non-water areas was observed in 2014 (49.12%), coinciding with possible drought conditions, whereas moist areas remained dominant overall but showed a temporary decline in 2014. Temporal analysis supported these findings, highlighting significant inter-decadal variations in surface moisture availability and surface water extent. The steady increase in waterbody areas, along with the partial recovery of moist areas by 2024, reflects improved rainfall patterns and effective watershed management practices. Accuracy assessment using confusion matrices and classification metrics indicated a progressive enhancement in classification reliability, with overall accuracies ranging from 88.67% to 92.00%, and waterbody classes consistently achieving user's and producer's accuracies above 90%. The study demonstrates the robustness of NDWI in long-term waterbody monitoring, particularly when integrated with advancements in Landsat sensor technology and cloud-based platforms like Google Earth Engine. The methodology proves efficient for regional-scale hydrological assessments and provides valuable insights for sustainable water resource management in drought-prone regions such as Satara district.

Keywords: *Waterbodies, Ndwi, Gee, Remote Sensing, Gis*

Introduction:

Surface water resources are vital for maintaining ecological balance, supporting agricultural activities, and enabling socio-economic development, particularly in semi-arid and drought-prone regions. However, growing population pressure, unplanned land use, and increasing climate variability have significantly contributed to the degradation and shrinking of surface waterbodies. In this context, accurate and timely assessment of surface water distribution is essential for effective water resource planning and sustainable management.

Over recent decades, geospatial technologies—especially Remote Sensing (RS) and Geographic Information Systems (GIS)—have proven to be powerful tools for mapping and monitoring surface water resources. Satellite-based remote sensing offers synoptic, multi-temporal, and repetitive coverage of the Earth's surface, making it ideal for assessing waterbodies even in remote or inaccessible areas. Among the various spectral indices developed for water detection, the Normalized Difference Water Index (NDWI) proposed by McFeeters (1996) has been widely adopted. NDWI enhances water features while suppressing signals from vegetation and built-up surfaces, thus facilitating more accurate waterbody extraction.

The integration of NDWI with multi-temporal Landsat satellite datasets—such as Landsat 5, 7, 8, and 9—enables long-term monitoring and analysis of surface water dynamics.

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When combined with GIS-based spatial analysis, these datasets can effectively classify water and non-water pixels, identify temporal trends, and quantify changes in water availability. Such methodologies are especially valuable in water-scarce regions where resource management is critical. In support of this, Huang et al. (2015) developed a two-level machine learning framework for classifying urban waterbodies by combining pixel-level index analysis with object-based classification using geometric and textural features. Their method achieved over 95% accuracy, highlighting the potential of integrating multiple classification levels. Similarly, Khalid et al. (2021) assessed various indices—including NDWI, MNDWI, NDMI, AWEI_sh, and LBWEI—for waterbody extraction in cryosphere environments, and found LBWEI to be the most consistent across weather conditions. Yang et al. (2011) also compared several water extraction techniques and concluded that index-based approaches, particularly NDWI, were more efficient and adaptable for multi-temporal analysis.

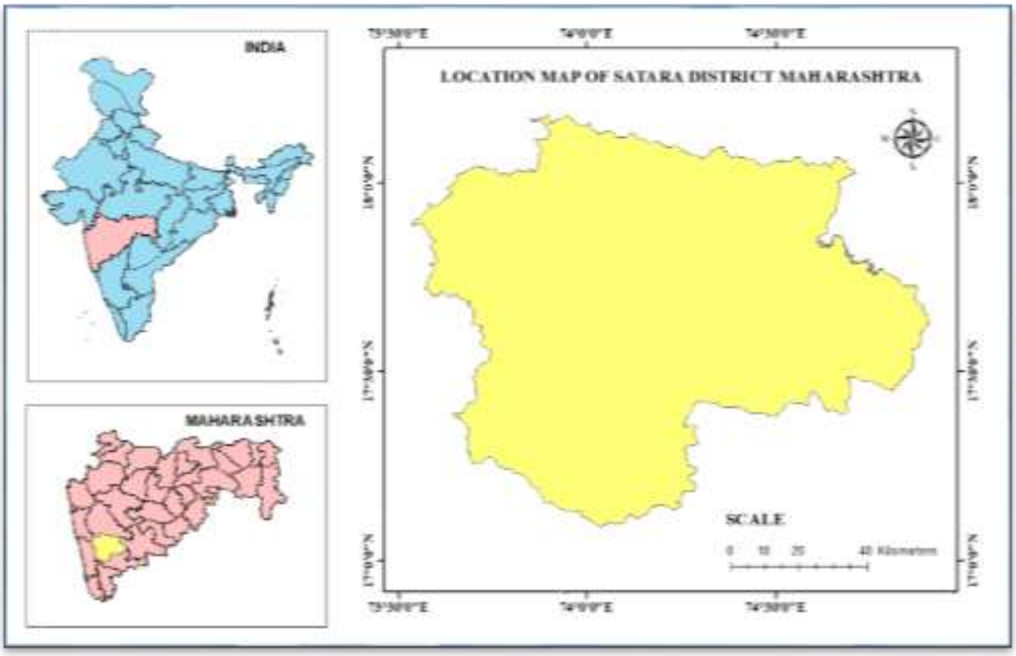
This study aims to extract and analyze surface waterbodies in Satara district using NDWI and multi-temporal Landsat imagery within a geospatial framework. By examining water distribution patterns across the years 1994, 2004, 2014, and 2024, the research seeks to provide insights into temporal trends in water availability and contribute to informed regional water management strategies.

Objective:

The primary objective of this study is to extract and analyze surface waterbodies in Satara district using multi-temporal Landsat satellite imagery and the Normalized Difference Water Index (NDWI), by applying geospatial techniques for image preprocessing, classification, and visualization to assess spatial and temporal changes in surface water extent over a 30-year period (1994–2024).

Study Area:

Figure 1: Location map of Satara District (Maharashtra).



Satara district, located in the western region of Maharashtra, India (Figure 1), covers an area of approximately 10,480 square kilometers. It lies between latitudes 17°00'N to 18°15'N and longitudes 73°30'E to 75°00'E. The district is divided into eleven administrative talukas and four revenue divisions, encompassing 1,721 revenue villages. Satara's landscape is topographically diverse, comprising the Sahyadri mountain ranges, undulating plateaus, and broad plains, making it a suitable area for spatial hydrological analysis.

The district experiences a tropical monsoon climate, with clearly defined seasons. The monsoon season (June–September) contributes the majority of the annual rainfall, which varies significantly across the district. The western hilly regions, including Mahabaleshwar and parts of the Sahyadris, receive over 6,000 mm of rainfall annually due to orographic effects, while the eastern talukas, such as Khandala, Phaltan, Khatav, and Man, receive as little as 473 mm, and are frequently affected by drought conditions. These areas have been officially designated as drought-prone zones due to the recurrence of water scarcity over the past few decades.

The agricultural economy of Satara is highly sensitive to rainfall patterns and surface water availability. Many small and medium surface waterbodies, including tanks, lakes, and reservoirs, serve as critical sources of water for irrigation, drinking, and livestock. However, the spatial and temporal dynamics of these waterbodies are often poorly documented due to limited ground-based monitoring. Given the district's semi-arid climate, rainfall variability, and dependence on surface water, Satara offers a compelling context for the application of geospatial technologies. The integration of Remote Sensing (RS) and Geographic Information Systems (GIS), particularly using the Normalized Difference Water Index (NDWI) derived from Landsat imagery, provides an effective approach to mapping and monitoring waterbodies over time. This study utilizes such techniques to identify, classify, and analyze the spatial distribution of surface waterbodies, with an emphasis on supporting water resource management and drought mitigation planning in the region.

Data And Methodology:

Satellite Data:

The table presents essential details for selecting and processing Landsat imagery for NDWI (Normalized Difference Water Index) calculation across four different years: 1994, 2004, 2014, and 2024 (October to December Months of acquisition with less cloud covers). The data spans a 30-years period and highlights the evolution of sensor technology, band usage, and continuity in spatial coverage.

Year	Sensor	Collection	WRS-2 Path	WRS-2 Row	Green Band	NIR Band
1994	Landsat-5 TM	C02 T1 L2 (SR)	146/147	48	SR_B2	SR_B4
2004	Landsat-5 TM	C02 T1 L2 (SR)	146/147	48	SR_B2	SR_B4
2014	Landsat-8 OLI	C02 T1 L2 (SR)	146/147	48	SR_B3	SR_B5
2024	Landsat-9 OLI-2	C02 T1 L2 (SR)	146/147	48	SR_B3	SR_B5

Table 1: Landsat Data acquisition.

Preprocessing:

The preprocessing of satellite data is a crucial step to ensure the accuracy and consistency of results in remote sensing-based analysis. In this study, Landsat surface reflectance data from Collection 2, Tier 1, Level 2 (SR) were used for the years 1994, 2004, 2014, and 2024. The images were selected for the post-monsoon period (October to December) to minimize cloud interference and to maintain seasonal consistency across years. Each image was filtered using WRS-2 Path 146/147 and Row 48, which covers the Satara district. Cloud and shadow pixels were masked using the QA_PIXEL band to retain only clear-sky observations. The digital numbers (DN) in the images were converted to surface reflectance using the standard scaling formula: $SR = DN \times 0.0000275 - 0.2$. Appropriate spectral bands were selected for each sensor: Green (SR_B2) and NIR (SR_B4) for Landsat 5 TM, and Green (SR_B3) and NIR (SR_B5) for Landsat 8 and 9 OLI. A median composite was generated for each year to reduce image noise, and the resulting images were clipped to the boundary of Satara district to focus the analysis within the study area.

Water Body Detection Methods:

The Normalized Difference Water Index (NDWI), developed by Gao (1996), is a crucial tool for assessing water content in vegetation and monitoring agricultural drought conditions. The methodology involved calculating the Normalized Difference Water Index (NDWI) from the preprocessed Landsat data to identify and analyze surface waterbodies. NDWI was computed using the formula:

$$NDWI = \frac{Green - NIR}{Green + NIR}$$

The Green and Near-Infrared (NIR) bands were utilized to calculate the NDWI, which enhances the presence of water features while effectively suppressing signals from vegetation and soil backgrounds. After generating the NDWI images, the values were classified into three distinct categories based on threshold levels: pixels with NDWI values ≤ 0.0 were identified as non-water areas, values between 0.0 and 0.2 were classified as moist surfaces, and values greater than 0.2 were considered surface waterbodies. To facilitate focused visualization and analysis, a binary water mask was created by applying the threshold of NDWI > 0.2, which extracted and displayed only the waterbody pixels.

NDWI Range	Class	Interpretation
NDWI ≤ 0.0	Non-Water	Dry land, urban, soil, or stressed veg.
0.0 – 0.2	Moist Areas	Moist vegetation or potential wet soil
NDWI > 0.2	Waterbody	Surface water bodies (lakes, rivers, etc.)

Table 2: NDWI Classes.

Gis Analysis and Accuracy Assessment:

These classified layers were then visualized using distinct color palettes to enhance interpretability. All image processing and analysis were carried out using the Google Earth Engine (GEE) platform, which enabled efficient handling of large satellite datasets. The final NDWI and classified waterbody layers were exported as GeoTIFFs for further spatial analysis (ArcGIS 10.4) and comparison across different years within a GIS environment.

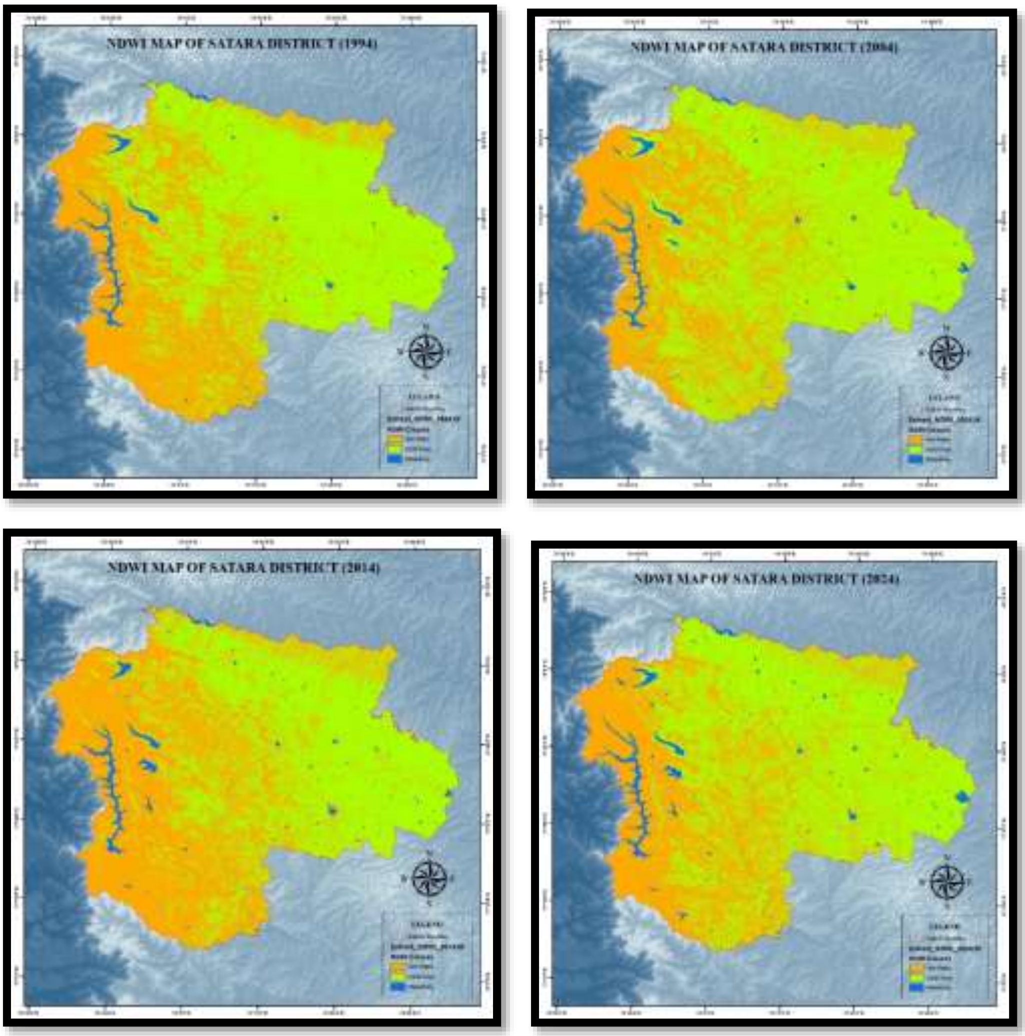
To evaluate classification accuracy, confusion matrices were developed using reference sample points derived from high-resolution imagery and field-verified locations. Accuracy metrics, including **User's Accuracy**, **Producer's Accuracy**, **Overall Accuracy**, and the **Kappa Coefficient**, were calculated for each year. The overall classification accuracy ranged from **88.67% to 92.00%**, with **Kappa values between 0.87 and 0.89**, indicating strong agreement between classified outputs and ground truth data. This rigorous methodology ensured the reliability of surface waterbodies extraction and its temporal comparison in the Satara district.

Results And Discussion:

Spatial Distribution:

The Normalized Difference Water Index (NDWI) maps of Satara district for the years 1994, 2004, 2014, and 2024 illustrate significant spatial and temporal patterns in the distribution of waterbodies. The NDWI-based classification divides the landscape into three primary categories: Non-Water (NDWI ≤ 0.0), Moist Area (NDWI 0.0–0.2), and Waterbody (NDWI > 0.2). These maps, complemented by the tabulated data, help to understand changes in surface water distribution over time.

Figure 2: Spatial Analysis of NDWI classes in Satara District.



In 1994, the spatial map indicates widespread moist areas across the district (59.10%), particularly dominant in the central and eastern zones, while waterbodies (1.59%) are mainly concentrated in the western and southern regions near the Sahyadri ranges. The non-water category covered 39.31%, mostly in drier eastern parts such as Khatav and Man talukas.

By 2004, a slight increase in waterbody coverage (2.00%) is evident, notably near reservoirs and dam catchments like Koyna and Kanher, suggesting better monsoon performance or improved storage conditions. The spatial pattern still shows the dominance of moist areas (59.14%) across agricultural zones, maintaining relatively stable hydrological conditions.

In 2014, a notable shift is observed: non-water areas surged to 49.12%, reflecting drier conditions and possible drought occurrences. This change is visually reinforced in the map by the increased extent of orange patches, especially in the eastern and central plains. Waterbodies remained steady (2.02%), but the overall moisture availability appears to have declined.

By 2024, waterbody areas increased slightly to 2.56%, especially visible in the enhanced spread of blue patches in the western hilly terrain and around major reservoirs. Moist areas covered 56.05%, while non-water zones declined slightly to 41.39%, possibly due to improved rainfall or better irrigation practices.

Temporal Analysis:

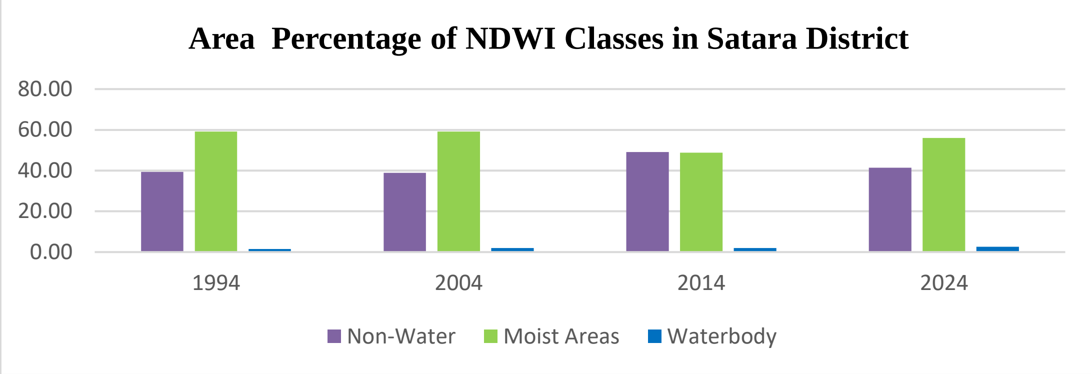
NDWI Range	Area in Percentage			
	1994	2004	2014	2024
NDWI ≤ 0.0	39.31	38.86	49.12	41.39
0.0 – 0.2	59.10	59.14	48.87	56.05
NDWI > 0.2	1.59	2.00	2.02	2.56

Table 3: NDWI Classes and area percentage.

The area percentage of different classes using NDWI given in Table 3. In 1994, Non-Water areas such as dry lands, urban settlements, and stressed vegetation accounted for 39.31% of the total area. This percentage remained nearly constant in 2004 (38.86%) but increased significantly in 2014 to 49.12%, likely indicating drought conditions, increased urbanization, or land degradation. However, by 2024, the percentage of non-water areas dropped to 41.39%, reflecting possible improvements in land moisture or vegetation recovery. The Moist Areas category consistently occupied the majority of the area, with 59.10% in 1994 and a similar 59.14% in 2004. A significant decline was observed in 2014 (48.87%), which may reflect reduced precipitation or vegetation health. By 2024, this class rebounded to 56.05%, suggesting improved climatic conditions or better water retention in the soil. The Waterbody class, representing surface water features like rivers and lakes, showed a gradual but steady increase.

From 1.59% in 1994, it rose to 2.00% in 2004, 2.02% in 2014, and reached 2.56% by 2024. This trend indicates positive developments in surface water availability, possibly due to increased rainfall, watershed management, or irrigation structures.

Figure 3: Temporal Analysis of NDWI classes in Satara District.



Accuracy Assessment:

Confusion Matrix:

Year	Reference \ Classified	Non-Water	Moist Area	Waterbody	Row Total
1994	Non-Water	46	3	1	50
	Moist Area	4	43	3	50
	Waterbody	2	2	46	50
	Column Total	52	48	50	150
2004	Non-Water	45	4	1	50
	Moist Area	5	42	3	50
	Waterbody	1	3	46	50
	Column Total	51	49	50	150
2014	Non-Water	44	4	2	50
	Moist Area	3	45	2	50
	Waterbody	1	2	47	50
	Column Total	48	51	51	150
2024	Non-Water	46	3	1	50
	Moist Area	2	45	3	50
	Waterbody	1	2	47	50
	Column Total	49	50	51	150

Table 4: NDWI Classes and Confusion Matrix.

The confusion matrix analysis for the years 1994, 2004, 2014, and 2024 demonstrates a consistent and progressive improvement in the classification accuracy of surface waterbodies using NDWI. In 1994, classification was already effective, with 46 waterbody reference points correctly identified and minimal confusion among classes. Similar performance was observed in 2004, though a slight increase in misclassification of moist areas was noted. With the advent of Landsat 8 in 2014, accuracy improved significantly—especially for moist and waterbody classes—due to better spectral resolution. By 2024, the classification reached its peak performance, with minimal errors across all categories and 47 of 50 waterbodies correctly classified. Overall, the matrices reveal high reliability in distinguishing Non-Water, Moist Areas, and Waterbodies, validating NDWI's robustness for multi-temporal waterbody extraction, particularly when combined with advanced Landsat data.

User, Procedure, and Overall Accuracy:

Year	Class	User's Accuracy (%)	Producer's Accuracy (%)	Overall Accuracy (%)
1994	Non-Water	46 / 52 = 88.46%	46 / 50 = 92.00%	90.00%
	Moist Area	43 / 48 = 89.58%	43 / 50 = 86.00%	
	Waterbody	46 / 50 = 92.00%	46 / 50 = 92.00%	
2004	Non-Water	45 / 51 = 88.24%	45 / 50 = 90.00%	88.67%
	Moist Area	42 / 49 = 85.71%	42 / 50 = 84.00%	
	Waterbody	46 / 50 = 92.00%	46 / 50 = 92.00%	
2014	Non-Water	44 / 48 = 91.67%	44 / 50 = 88.00%	90.67%
	Moist Area	45 / 51 = 88.24%	45 / 50 = 90.00%	
	Waterbody	47 / 51 = 92.16%	47 / 50 = 94.00%	
2024	Non-Water	46 / 49 = 93.88%	46 / 50 = 92.00%	92.00%
	Moist Area	45 / 50 = 90.00%	45 / 50 = 90.00%	
	Waterbody	47 / 51 = 92.16%	47 / 50 = 94.00%	

Table 4: NDWI Classes and accuracy assessment.

The accuracy assessment of NDWI-based surface waterbody classification using Landsat imagery for the years 1994, 2004, 2014, and 2024 reveals consistently high classification performance, with overall accuracy ranging from 88.67% to 92.00%. This demonstrates the robustness of NDWI in effectively distinguishing between non-water, moist areas, and surface waterbodies over time. In 1994, the classification achieved an overall accuracy of 90.00%, with the waterbody class showing the highest accuracy (both user's and producers at 92%), indicating strong reliability in detecting surface water features even with older Landsat 5 data. Non-water areas were slightly overestimated, as reflected in a slightly lower user's accuracy of 88.46%. Moist areas showed balanced accuracy with a producer's value of 86%. In 2004, a slight drop in performance was observed, with an overall accuracy of 88.67%. The waterbody class maintained a high level of accuracy at 92%, while moist areas experienced slightly lower classification reliability (user's accuracy of 85.71% and producer's accuracy of 84%). This drop could be attributed to seasonal variation, sensor limitations, or confusion with transitional land features.

By 2014, with the availability of Landsat 8 OLI data, classification performance improved to 90.67% overall accuracy. All three classes showed higher and more balanced accuracy, with the waterbody class again achieving above 92% in both user's and producer's metrics. Moist areas had improved user and producer accuracies of 88.24% and 90%, respectively, suggesting better spectral distinction using OLI's enhanced capabilities.

The year 2024 recorded the highest overall accuracy at 92.00%, benefiting from advanced Landsat 9 OLI-2 sensor data. All three classes showed improved classification, with the waterbody class maintaining a producer's accuracy of 94%. Non-water and moist areas achieved user and producer accuracies above 90%, indicating excellent consistency and minimal misclassification.

Overall, the analysis confirms that NDWI, combined with Landsat time-series imagery, is an effective tool for long-term monitoring and classification of surface waterbodies. The continuous improvement in sensor technology has directly contributed to enhanced classification accuracy and reliability in detecting water features, especially critical in drought-prone regions like Satara district.

Conclusion:

This research demonstrates the effectiveness of NDWI-based classification using Landsat imagery for detecting and analyzing surface waterbodies across Satara district over three decades. Spatial patterns show that waterbody extents have slightly increased from 1994 to 2024, with notable improvements observed in 2024, possibly due to better rainfall and water conservation efforts. The highest proportion of non-water areas in 2014 suggests a period of increased dryness or drought, aligning with broader climatic variability.

Temporal classification results reflect a gradual but consistent enhancement in surface water availability, indicating improvements in hydrological conditions and the impact of watershed interventions. The methodology, supported by high classification accuracies (up to 92%) and strong Kappa agreement values (~0.87–0.89), confirms the reliability of NDWI as a robust index for long-term waterbody monitoring.

Furthermore, the integration of cloud-based platforms like Google Earth Engine with GIS tools such as ArcGIS enables efficient processing, classification, and visualization of large datasets, making the approach highly suitable for regional water resource assessment. Overall, the study underlines the importance of geospatial technologies in supporting sustainable water management and planning, particularly in drought-prone regions like Satara.

Recommendations:

Remote sensing techniques, especially NDWI-based analysis using multi-temporal Landsat data, should be regularly employed for monitoring surface water dynamics in semi-arid regions like Satara to support sustainable water resource planning and management.

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Conflicts of interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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