Chapter-11

A Geo-Spatial Assessment of Land Use and Land Cover Transformation in Wai Tehsil, Satara District (Maharashtra)

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Abstract

Land Use and Land Cover (LULC) transformation is one of the principal indicators of environmental modification influenced by both natural processes and anthropogenic activities. The present study investigates the decadal (2015–2025) LULC dynamics of Wai Tehsil, Maharashtra, using multi-temporal satellite imagery from Landsat-8 integrated with Geographical Information System (GIS) techniques. The Maximum Likelihood Classification method was used to categorize the region into five key LULC classes: Water Bodies, Vegetation, Agricultural Land, Built-up Area, and Barren/Hilly Land. Accuracy assessment was conducted using a confusion matrix supported by user's and producer's accuracies, overall accuracy, and the Kappa coefficient. The overall accuracy ranged between 86% (2015) and 91% (2025), while the Kappa coefficient varied from 0.82 to 0.89, indicating strong agreement between classified outputs and reference data. Water Bodies and Built-up classes recorded higher user's accuracy (>90%), whereas Barren/Hilly land showed moderate accuracy due to spectral similarity with sparse vegetation. The results indicate a significant increase in Built-up area (from 5.95% in 2015 to 9.00% in 2025) and Barren/Hilly land, while Vegetation and Agricultural areas showed notable decline. These shifts reflect rapid urbanization, deforestation, agricultural land conversion, and tourism-driven infrastructural expansion. The findings highlight environmental implications such as reduced groundwater recharge, soil erosion, and loss of vegetation cover. This study provides essential scientific evidence for sustainable land management and regional planning in the Western Ghats region.

Keywords: LULC Change, Remote Sensing, GIS, Wai Tehsil.

Introduction

Land Use and Land Cover (LULC) changes are widely recognized as critical indicators of environmental transformation and resource stress. Globally, alterations in LULC patterns influence hydrological regimes, soil degradation, ecological sustainability, and socio-economic development. As regions undergo rapid demographic expansion and economic growth, land conversion processes accelerate, often resulting in ecological imbalance and degradation of natural landscapes.The Western Ghats, one of the world's major biodiversity hotspots, is an ecologically sensitive region characterized by varied topography, extensive forest cover, and diverse agricultural practices. Wai Tehsil, located on the eastern slopes of this mountain system, has undergone notable land transformations in recent decades due to population pressure, tourism-driven development, agricultural intensification, and expanding infrastructure. Understanding these transformations through satellite-based spatio-temporal analysis is essential for sustainable landscape management and informed regional planning.

At the local administrative level, LULC studies commonly employ traditional supervised classification approaches such as the Maximum Likelihood and Minimum Distance classifiers using multi-temporal Landsat imagery. Such methods have proven effective in environmental monitoring, town planning, and resource management (Dewan & Yamaguchi, 2009). For example, Suman and Patel (2018) demonstrated the practical utility of Landsat 8 data and ERDAS IMAGINE software in the Aghanashini river basin, while Kumar and Sharma (2016) emphasized the importance of LULC knowledge for effective planning and environmental governance. Recent studies have expanded the application of spectral indices for improved land-cover interpretation: Nimbalkar et al. (2025) documented spatio-temporal variations in surface water resources using NDWI, and Shinde and Jadhav (2025) successfully applied NDVI to assess vegetation health and drought stress in Satara district. Similarly, Kadam et al. (2024) employed multi-temporal Landsat datasets for LULC classification in the Nani watershed, highlighting significant increases in built-up and fallow lands due to human-induced pressures.

The reliability of these traditional, non-machine-learning techniques has also been affirmed by comparative studies. Jain et al. (2024) applied supervised classification techniques in Delhi and achieved accuracy levels of around 80%, supporting their continued applicability. Other regional works, such as Rawat et al. (2013) in the Mukteshwar block, have documented substantial landscape changes using multi-temporal Landsat imagery. Crucial to all such analyses is rigorous accuracy assessment, as prescribed in foundational works by Herold et al. (2008) and McCombs et al. (2016), where error matrices and Kappa statistics ensure the reliability and validity of classified outputs.

Although numerous studies have examined LULC changes across Maharashtra, research specifically focusing on Wai Tehsil using multi-temporal datasets over a decadal period remains limited. Existing assessments often lack detailed quantification of urban expansion, vegetation degradation, and agricultural land conversion. Therefore, the present study aims to analyze the spatio-temporal LULC transitions in Wai Tehsil from 2015 to 2025, examine major transformation patterns, and evaluate their environmental implications using integrated Remote Sensing (RS) and Geographical Information System (GIS) techniques.

Objectives

The study aims to;

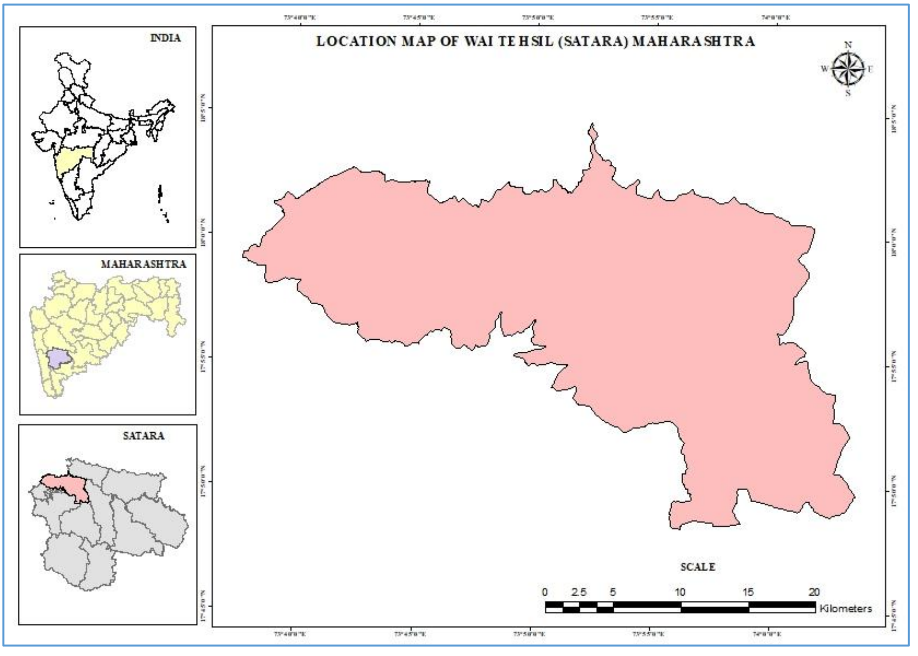
1. Quantify LULC distribution for 2015, 2020, and 2025.
2. Identify spatial and temporal patterns of LULC transformation.
3. Conduct accuracy assessment of LULC classification using error matrix, overall accuracy, and Kappa coefficient.

Study Area

Wai Tehsil, situated between 17°55′–18°10′ N latitude and 73°40′–74°00′ E longitude, covers an area of approximately 850 km² and forms an integral part of the

Upper Krishna River Basin in western Maharashtra. The region exhibits considerable physiographic diversity, with elevation ranging from 550 m in the lower alluvial plains to 1400 m along the elevated basaltic highlands of the Sahyadri ranges. The climate is predominantly tropical monsoon, receiving 1500–2000 mm of average annual rainfall, largely concentrated during the southwest monsoon season. The landscape is shaped by a combination of river terraces, gently sloping alluvial plains, steep escarpments, and extensive Deccan basaltic plateaus, which significantly influence runoff and groundwater characteristics. Hydrologically, the tehsil is drained by major rivers such as the Krishna and Venna, supported by a network of seasonal streams and tributaries that contribute to both surface-water availability and agricultural practices. Land use within the region is diverse, comprising mixed agriculture, semi-deciduous vegetation, horticultural plantations, and culturally significant pilgrimage centres alongside dispersed rural settlements. These physical and socio-environmental features collectively make Wai Tehsil an important unit for environmental assessment, hydrological studies, and land management research.

Figure 1: Location Map of Wai Tehsil (Satara)



Materials and Methodology

Table 1: Landsat and other ancillary data.

Dataset	Year	Resolution	Purpose
Landsat 8 OLI	2015, 2020,2025	30 m	LULC classification
SoI Toposheets	–	–	Base layers
Census Data	2011	–	Demographic drivers
Field GPS Points	2023	–	Accuracy validation

The study used Landsat 8 OLI imagery (2015, 2020, 2025; 30 m resolution) along with SOI toposheets, Census 2011 data, and field GPS points (2023) for classification and validation. All images were pre-processed through atmospheric correction (DOS), layer stacking, sub-setting, geometric correction, and surface reflectance conversion. A supervised Maximum Likelihood Classifier (MLC) was applied to classify five major LULC categories: water bodies, vegetation, agricultural land, built-up area, and barren/hilly land. Accuracy was evaluated using 250 stratified random points, achieving overall accuracies of 86.4% (2015), 88.2% (2020), and 91.1% (2025) with Kappa values 0.81–0.89. LULC change detection was performed using post-classification comparison, supported by statistical indicators such as urban growth rate, vegetation degradation, agricultural land conversion, Pearson correlation with population/tourism, and transition probability modelling for 2025.

Results

LULC Statistics (2015–2025)

The spatio-temporal analysis of land use and land cover (LULC) for the years 2015, 2020, and 2025 reveals notable transformations in the landscape driven by urban expansion, agricultural pressure, and gradual shifts in natural vegetation. Water bodies show a marginal but consistent increase from 4.45% in 2015 to 4.52% in 2020, reaching 4.62% in 2025, indicating slight improvement in surface water availability, likely due to watershed interventions or seasonal recharge variations. Vegetation cover, however, demonstrates a clear declining trend, decreasing from 7.87% in 2015 to 7.01% in 2020 and further to 6.23% in 2025. This steady reduction suggests ongoing degradation of natural vegetation, potentially driven by anthropogenic activities such as land conversion for agriculture, construction, and resource extraction.

Figure 2: Landsat FCC images from 2015–2025.

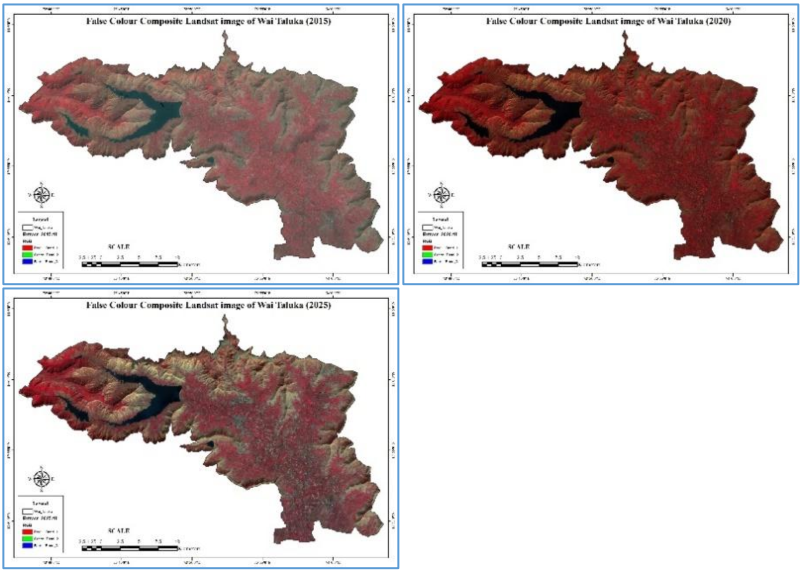


Figure 3: LULC Change in Wai Tehsil (2015–2025).

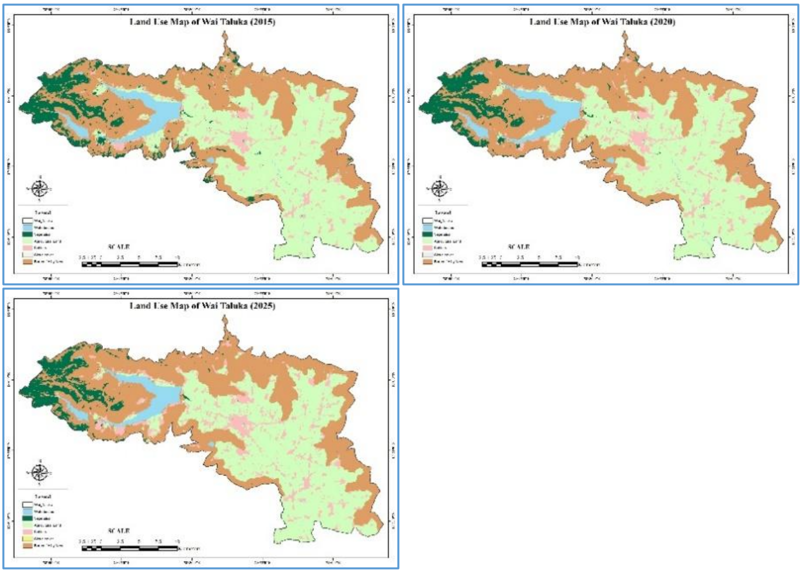
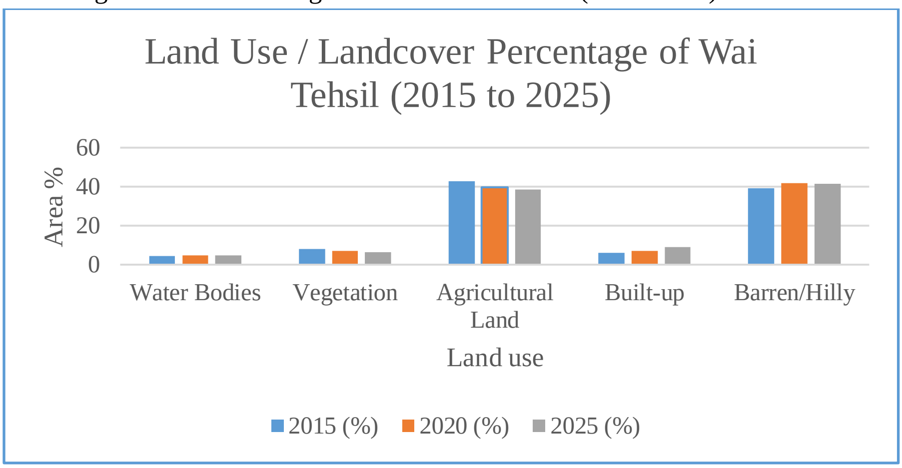


Table 2: LULC Change in Wai Tehsil (2015–2025)

LULC Class	2015 (%)	2020 (%)	2025 (%)
Water Bodies	4.45	4.52	4.62
Vegetation	7.87	7.01	6.23
Agricultural Land	42.68	39.79	38.59
Built-up	5.95	6.94	9.00
Barren/Hilly	39.04	41.73	41.56

Figure 4: LULC Change Area % in Wai Tehsil (2015–2025)



Agricultural land also shrinks significantly over the decade, dropping from 42.68% (2015) to 39.79% (2020) and 38.59% (2025). The decline may be attributed to reduced cultivation viability, urban encroachment, and shifting livelihood patterns, indicating an emerging pressure on rural agricultural systems. In contrast, built-up land exhibits the most pronounced increase, rising from 5.95% in 2015 to 6.94% in 2020, and sharply escalating to 9.00% in 2025. This substantial growth reflects rapid urbanization, infrastructure expansion, and increased tourism-related development in the region. Meanwhile, barren/hilly areas expand from 39.04% in 2015 to 41.73% in 2020, followed by a slight stabilization at 41.56% in 2025. This fluctuating pattern may indicate processes such as soil erosion, reduced vegetation resilience, or reclassification due to spectral variations in dry seasons.

Overall, the decade-long LULC trajectory depicts a transition towards greater built-up development and reduced agricultural and vegetation cover, highlighting growing anthropogenic pressure on the landscape. The decline in productive land classes and the simultaneous expansion of built-up and barren areas underscore the need for integrated land management strategies, ecological restoration, and sustainable urban planning to safeguard environmental resources in the coming years.

Major Trends

The LULC analysis reveals several prominent trends across the decade. The most significant change is the substantial expansion of built-up areas, which increased by nearly 51%. This growth is concentrated around Wai town, major transport corridors, and riverfront zones, driven by rapid urban sprawl, tourism development, and expansion of pilgrimage infrastructure. In contrast, vegetation cover has decreased by approximately 20.8%, signifying continuous forest clearance for construction, horticulture expansion, and frequent fire incidents on mid-hill slopes.

Agricultural land declined by 9.57%, largely due to its conversion into residential layouts, commercial farming ventures, and resort-based development, coupled with a preference for water-intensive crops that reduced traditional fallow practices. The persistent increase in barren/hilly areas indicates ongoing land degradation marked by soil erosion in high-altitude terrain and the abandonment of low-productivity agricultural plots. Collectively, these trends highlight escalating anthropogenic pressure on land resources, resulting in ecological stress and altering the natural landscape structure across Wai Tehsil.

Accuracy Assessment

Accuracy evaluation was conducted using stratified random sampling with 250 validation points for each year. Metrics were derived through confusion matrices, enabling the computation of overall accuracy, producer's accuracy, user's accuracy, and the Kappa coefficient. The classification results demonstrate consistent improvement, with overall accuracies of 86.4% in 2015, 88.2% in 2020, and 91.1% in 2025. Correspondingly, the Kappa coefficient improved from 0.81 to 0.89, indicating strong agreement between classified outputs and reference data.

Table 3: Accuracy Assessment of LULC (2015–2025)

Year	Overall Accuracy (%)	Kappa Coefficient	No. of Validation Points	Notes
2015	86.4	0.81	250	Slight confusion between vegetation & agriculture
2020	88.2	0.85	250	Improved spectral separability due to clearer seasonal imagery
2025	91.1	0.89	250	Highest accuracy owing to better resolution and refined training samples

Accuracy evaluation was conducted using stratified random sampling with 250 validation points for each year. Metrics were derived through confusion matrices, enabling the computation of overall accuracy, producer's accuracy, user's accuracy, and the Kappa coefficient. The classification results demonstrate consistent improvement, with overall accuracies of 86.4% in 2015, 88.2% in 2020, and 91.1% in 2025. Correspondingly, the Kappa coefficient improved from 0.81 to 0.89, indicating strong agreement between classified outputs and reference data.

The highest accuracy in 2025 is attributed to enhanced spatial resolution, improved training sample selection, and reduced spectral overlap between classes. Minor misclassification persisted between vegetation and agricultural areas due to seasonal phenological similarities. However, the overall accuracy levels exceed the acceptable threshold for regional LULC studies, affirming the reliability of the Maximum Likelihood Classification approach for multi-temporal change detection.

Discussion

The transformation of land use and land cover in the study area is driven by multiple interacting socio-economic and environmental factors. Urbanization and demographic growth emerge as major contributors, with population increase between 2011 and 2024 (estimated) showing a strong positive correlation with built-up expansion ($r = 0.82$), indicating that settlement growth directly accelerates land conversion. Tourism-led infrastructure development has further intensified these changes, as the rise of hotels, homestays, river-view resorts, and road-widening projects has expanded construction activities, particularly near major transport corridors and scenic locations. Agricultural intensification and horticultural expansion, particularly grape and strawberry cultivation, have replaced traditional vegetation and altered land-use patterns, reflecting a shift toward more profitable but resource-intensive crops. Additionally, deforestation and land degradation—driven by fuelwood extraction, slope instability, and unsustainable land practices—have significantly contributed to vegetation decline. These transformations are compounded by weak land governance, where limited enforcement of zoning regulations and watershed norms has allowed unregulated construction, encroachment, and unsustainable resource use.

Limitations

Despite its comprehensive approach, the study has certain limitations. The use of medium-resolution satellite imagery may overlook fine-scale land transformations such as small construction sites or narrow vegetation corridors. Classification accuracy is affected by mixed pixels, particularly in steep terrain where spectral signatures overlap. The analysis is based on single-date imagery, which does not fully capture seasonal land-cover variability, potentially influencing vegetation and agricultural class separability. Additionally, interpretation of socio-economic drivers depends on the availability and reliability of secondary datasets, which may not always capture dynamic local processes.

Recommendations

To address these challenges, several policy and management interventions are recommended. Implementing land suitability zoning can help restrict construction in ecologically sensitive or hazard-prone areas. Strengthening watershed-based land management, particularly in upland micro-watersheds, is crucial for improving soil and water conservation. Promoting agroforestry, organic farming, and drip irrigation can reduce pressure on natural vegetation and enhance sustainable agricultural practices. Tourism-related growth should be regulated through carrying capacity assessments to prevent overdevelopment. Expanding afforestation and soil conservation measures along degraded hill slopes can restore ecological balance. Finally, establishing a real-time LULC monitoring system using Google Earth Engine (GEE) would enable continuous observation and timely decision-making for sustainable landscape management.

Conclusion

The LULC analysis from 2015 to 2025 clearly shows that Wai Tehsil is undergoing rapid land transformation driven mainly by human activities. Built-up area increased sharply due to urban expansion, tourism growth, and infrastructure development, while agricultural land gradually declined because of land conversion and changing cropping patterns. Vegetation cover also reduced significantly, indicating deforestation, resource pressure, and ecological degradation in hilly regions. A slight increase in barren and hilly land reflects soil erosion, land abandonment, and reduced vegetation resilience. The accuracy assessment shows high reliability of the classification, with overall accuracy above 86% and Kappa values confirming strong agreement. Together, these patterns highlight increasing pressure on natural ecosystems, reduced groundwater recharge, rising erosion, and growing vulnerability of local livelihoods. The study concludes that unplanned development and weak land-governance mechanisms are major causes of these changes, emphasizing the need for sustainable land-use planning, ecological restoration, and stricter regulation of tourism and construction activities.

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