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Monitoring Forest Land use Change and Transformation in the Kore Rood Basin of Guilan by Processing Landsat Satellite Images

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ABSTRACT

Forests are vital ecosystems, but many have been greatly altered by human and natural factors, highlighting the need for ongoing monitoring and conservation. This study employs multitemporal satellite image analysis to quantify and characterize forest cover dynamics within the Kore Rood basin, Guilan Province, Iran. It is noteworthy that research on this critical region remains exceedingly scarce, thereby constituting a significant aspect of the novelty in the present study. Leveraging Landsat data from 2001, 2011, and 2023, we systematically assessed land-use and land-cover (LULC) transitions. Results indicate a progressive decline in forest area over the study period, with the maximum extent observed in 2001, followed by significant reductions by 2011 and 2023. Quantitatively, between 2001 and 2023, forest conversion occurred 1.1% to built-up areas, 2.0% to agricultural farms and 10.7% to tea Plantations.These findings demonstrate the substantial pressure exerted by agricultural land conversion, particularly tea cultivation, on the region's forest resources. Consequently, we strongly advocate for implementing advanced geospatial monitoring systems utilizing high-spatiotemporal-resolution satellite imagery to enable continuous surveillance and inform evidence-based conservation strategies and sustainable land-use management policies for Iran's forest ecosystems.

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NOMENCLATURE

GIS	Geographic Information Systems
LULC	Land-Use and Land-Cover
NDVI	Normalized Difference Vegetation Index
MLC	Maximum Likelihood Classification
USGS	United States Geological Survey

1. INTRODUCTION

Forest ecosystems, covering approximately one-third of the Earth's terrestrial surface, constitute a vital natural resource for human communities [1]. As essential components of global ecology, forests play a critical role in environmental enhancement and biodiversity conservation. They mitigate climate change by absorbing carbon dioxide and air pollutants, reduce global warming impacts, and provide crucial wildlife habitats [2]. Conversely, declining forest cover drives biodiversity loss, elevates flood risks, accelerates soil degradation, and disrupts climatic systems [3]. Globally, forests are experiencing significant transformations driven by both natural processes and anthropogenic activities [4]. Consequently, scientists and policymakers across institutions dedicate substantial resources to studying the multifaceted consequences of these changes [5]. Tracking forest cover dynamics over time is paramount for understanding forest structure and ecological processes, forming the foundation for effective management strategies [6]. Remote sensing methods offer substantial advantages over traditional field-based techniques for such monitoring. Key benefits include comprehensive global coverage, access to remote or inaccessible regions, scalability across diverse spatial extents, provision of high temporal and spatial resolution data, delivery of consistent and uniform information, extensive historical archives, and rapid data acquisition at minimal cost. These attributes collectively establish remote sensing as an indispensable tool for analyzing global environmental processes [6]. Consequently, diverse remote sensing techniques are increasingly employed to detect forest cover change and monitor fragmentation [2]. Among these resources, Landsat satellite imagery has emerged as the predominant dataset for assessing forest cover and tracking its temporal dynamics [6]. Initiated with the first satellite launch in 1972, the Landsat program established the foundation for systematic Earth surface observation. Its moderate spatial resolution, consistent global coverage, and unparalleled capacity for long-term time-series analysis have enabled detailed forest change assessments at local to national scales for decades. More recently, the consolidation of a comprehensive global Landsat archive has further facilitated worldwide analyses of forest dynamics [7].

Illustrating the application of such techniques, Liu et al. (2008) employed remote sensing and GIS data integrated with a Decision Tree Learning method to track changes in mangrove forests. Their study demonstrated that this integrated approach yields robust classification accuracy for mangroves using satellite imagery and ancillary data. By applying the decision tree technique, they generated detailed temporal maps, revealing that intensified human activities were the primary driver behind the sharp decline in mangrove forest area observed in recent decades [8]. Numerous studies globally have employed remote sensing and GIS to quantify forest cover dynamics and their drivers. Omarzadeh et al. (2021) assessed the changes in the forest environment of Guilan province using remote sensing data fusion. This study prepared a forest cover map of the Hyrcanian region, which was obtained by integrating the Normalized Difference Vegetation Cover Index (NDVI) at monthly and annual scales from MODIS continuous vegetation continuous field (VCF), and remote sensing images. The analysis was performed with supervised classification, support vector machine, and random forest model approaches. The findings showed that, the forests of Guilan decreased [9]. Afraz et al. (2025) investigated changes in the Hyrcanian forest in northern Iran using remote sensing and machine learning methods. This study was conducted using a variety of remote sensing data, including Normalized Difference Vegetation Index (NDVI) and MODIS Continuous Vegetation Field (VCF), along with Sentinel-1, Landsat-5, and Landsat-8 satellite images; in this process, support vector machine and random forest techniques were used for classification [10]. Investigating urban impacts, Zhang et al. (2020) evaluated forest cover and fragmentation patterns in Nanjing, China (1987-2017). By applying a vegetation change tracker and morphological spatial pattern analysis to dense

Landsat time series, they documented a decline in forest cover characterized by increased scattering, driven by urban expansion. The findings offer valuable tools for monitoring forest dynamics within rapidly urbanizing landscapes to support sustainable development [2]. Ghebrezgabher et al. (2016) employed supervised classification of Landsat data to quantify forest cover loss in Eritrea (1970-2014), identifying a significant decline. They concluded that deforestation, driven by anthropogenic pressures and climatic factors like prolonged drought and erratic rainfall, constituted a primary cause of environmental degradation [1]. Similarly, Reddy et al. (2013) used remote sensing and GIS to monitor forest cover change in Odisha, India, over 75 years (1935-2010). The study reported a net forest cover loss, with landscape metrics indicating rising fragmentation and patch numbers—signifying intensified human pressure. This approach demonstrated the utility of long-term monitoring and landscape analysis for informed forest management [11]. Focusing on forest reserves, Adedeji et al. (2015) assessed and projected changes in Nigeria's Gambari Forest Reserve (1984-2014) using multi-temporal Landsat data and GIS. Their results highlighted a substantial reduction in forest area, primarily due to timber extraction and agricultural conversion, compounded by encroaching settlements [12].

While extensive research has documented forest cover dynamics globally using remote sensing and GIS, the specific changes within the ecologically significant Kore Rood basin of Guilan remain underexplored. It is worth noting that the innovation of this research lies mainly in providing new data for a less studied region using validated methods. This study, therefore, aims to investigate forest vegetation cover changes in the Kore Rood basin utilizing remote sensing technology and maximum likelihood classification.

2. DATA USED

Satellite imagery for this study was acquired from the United States Geological Survey (USGS) EarthExplorer platform. The dataset comprises:

Landsat 5 Thematic Mapper (TM) scenes for June 2001 and July 2011.

Landsat 8 Operational Land Imager (OLI) scene for July 2023.

The spectral bands utilized as input for the land cover classification were:

Landsat 5 TM (2001 & 2011): Bands 1 through 7 (Visible, Near-Infrared, Shortwave Infrared, Thermal Infrared).

Landsat 8 OLI (2023): Bands 1 through 7 (equivalent spectral ranges to TM) plus Band 10 (Thermal Infrared 1).

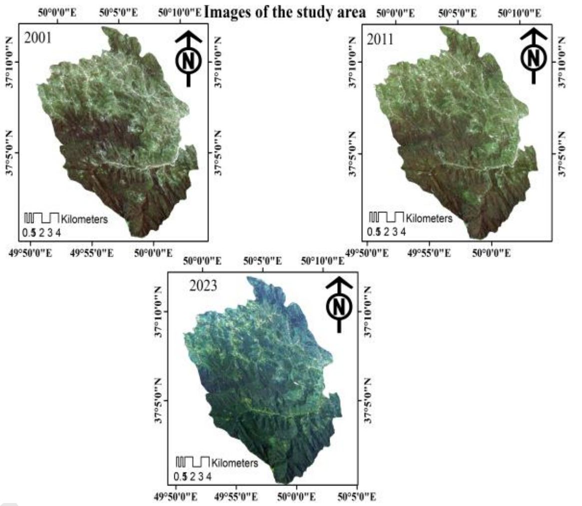


Fig. 1. Satellite images of the study area in 2001, 2011, and 2023.

3. RESEARCH METHOD

This study employed a systematic remote sensing workflow to quantify forest cover changes in the Kore Rood basin across 2001, 2011, and 2023. The methodology comprised six sequential stages:

Satellite Image Preparation: The acquisition of Landsat imagery was conducted for this study.

Image Preprocessing: The Landsat 5 and 8 images used in this study are Collection 2 Level 2 Surface Reflectance (L2SP) products with pre-applied atmospheric correction (via LEDAPS for Landsat 5 and LaSRC for Landsat 8), ensuring accurate surface reflectance for land-cover classification without further processing. Also, radiometric correction was performed using the conversion of digital numbers to reflectance.

Supervised Classification: Pixel-based classification was performed using the Maximum Likelihood algorithm.

Accuracy Validation: Quantitative assessment of the classification results was conducted.

Change Detection: Post-classification comparison of multi-temporal data was conducted.

Quantitative Analysis: Statistical assessment of land cover transitions was conducted.

The adoption of remote sensing and GIS technologies was motivated by their cost-effectiveness and temporal efficiency compared to traditional field surveys [13-15].

3.1 Classification Methodology

Maximum Likelihood Classification (MLC), a widely adopted supervised parametric algorithm [16], was applied to all three epochs. MLC calculates class-specific probability density functions using training data, then assigns each pixel to the class with the highest posterior probability via discriminant analysis [15 ,17]. Despite limitations such as sensitivity to the normal distribution of data in the Maximum Likelihood Classification method, this method is still widely used due to its high processing speed and reliable results, if the training samples are properly defined [18]. This approach generated thematic land cover maps with the following classes: Forest, Tea Garden, Farmland, and Built-up areas.

3.2 Training and Implementation

Reference samples were stratified into training (40%) and evaluation (60%) sets. To evaluate classified images, the selected samples for each class across the years are as follows: For 2001, the built-up areas class with 1043 samples, forest class with 19025 samples, farms class with 2055 samples, and tea gardens class with 491 samples were selected. For 2011, the built-up areas class with 1648 samples, forest class with 9976 samples, farms class with 3671 samples, and tea gardens class with 509 samples were selected. For 2023, the built-up areas class with 2966 samples, forest class with 19398 samples, farms class with 3975 samples, and tea gardens class with 831 samples were selected. For the 2023 baseline, training samples were derived from field knowledge and high-resolution imagery. Historical classifications (2001, 2011) utilized complementary data sources:

Landsat spectral signatures from 2023 training data, Time-series analysis of Google Earth historical imagery,Ancillary land cover maps.

3.3 Validation

Classification accuracy was quantified through error matrices (confusion matrices), with evaluation samples providing statistically robust validation metrics.

4. DISCUSSION AND RESULTS

4.1 Classification Accuracy Assessment

Classification accuracy was rigorously validated using error matrices derived from field reference points. The overall accuracy achieved was 94.44% (2001), 94.04% (2011), and 92.58% (2023), confirming the robustness of the Maximum Likelihood Classification (MLC) results for subsequent change analysis.

4.2 Forest Area Dynamics

Quantification of forest cover revealed significant temporal changes (Table 1):

Table 1. Forest cover changes from 2001 to 2023.

year	Area (ha)	changes
2001	14,976.45	
2011	14,327.19	(↓ 4.3% from 2001)
2023	14,639.49	(↑ 2.2% from 2011 but ↓ 2.2% from 2001)

4.3 Spatiotemporal Land Cover Patterns

Visual analysis of the MLC outputs (Fig. 2) revealed distinct trajectories:

Forest Cover: Peaked in 2001, declining notably by 2011 (particularly in northern and eastern sectors), with partial recovery by 2023.

Built-up Areas: Sustained reduction from 2001 to 2023 (2001 > 2011 > 2023).

Farmland: Expanded significantly by 2011 (concentrated in western regions), subsequently decreasing by 2023.Tea Plantations: Progressive increase (2001 < 2011 < 2023), with pronounced northern expansion by 2023.

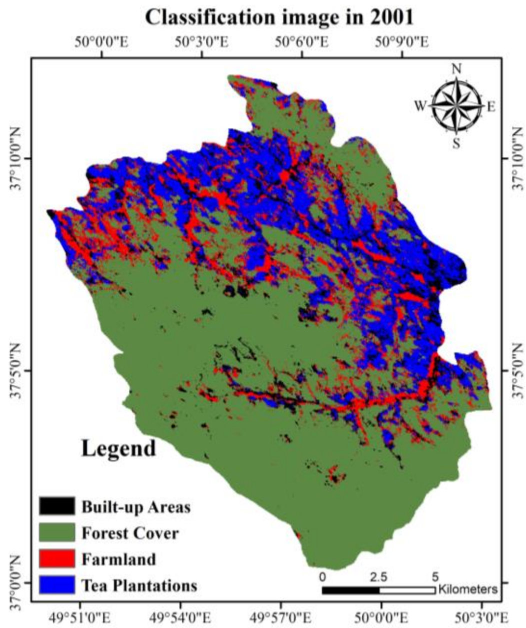
4.4 Key Change Drivers

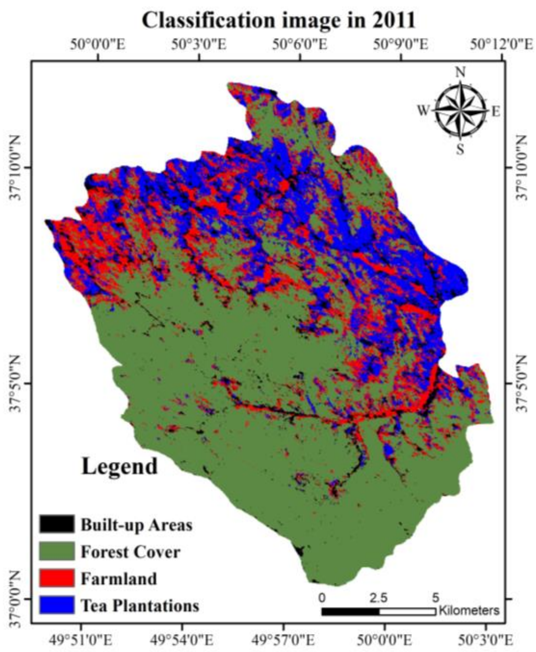
The observed transitions align with regional anthropogenic pressures:

Forest Loss (2001-2011): Primarily driven by conversion to farmland (western expansion) and tea plantations (northern encroachment).

Partial Forest Recovery (2011-2023): Suggests potential regrowth or conservation efforts, though net loss persists relative to 2001 baseline.

Settlement Dynamics: Declining built-up area may indicate rural-urban migration or spatial planning interventions.





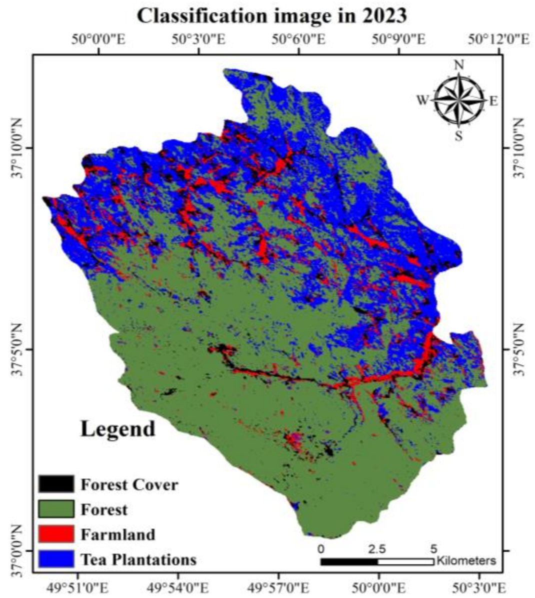


Fig. 2. Maximum likelihood classification image in 2001, 2011, 2023.

Figure 3 quantifies forest conversion dynamics in the Kore Rood basin (2001–2011), identifying three dominant transitions:Tea plantation expansion (purple) concentrated in northern sectors. Farmland encroachment (yellow) predominating in central zones. Built-up area development (red) focused in western corridors.This spatial clustering highlights regionally distinct drivers of deforestation during this decade.

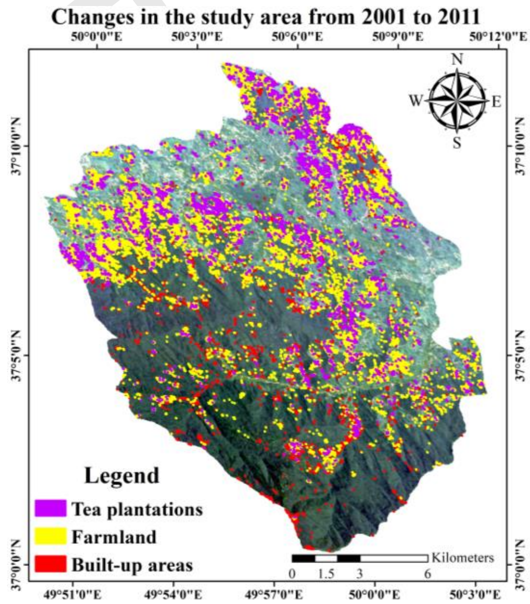


Fig. 3. Spatial distribution of primary forest conversion pathways (2001–2011): Tea plantations (purple), Farmland (yellow), Built-up areas (red). Background: Grayscale relief map.

Figure 4 delineates the dominant pathways of forest conversion across the Kore Rood basin over the 22-year study period (2001–2023), revealing three critical transitions: Tea plantation expansion (purple) concentrated heavily in northern and central sectors.Farmland establishment (yellow) primarily within southern zones.Built-up area development (red) focused along western peripheries. The most extensive land conversion occurred through tea plantation encroachment, constituting the primary driver of forest loss in the basin's core regions.

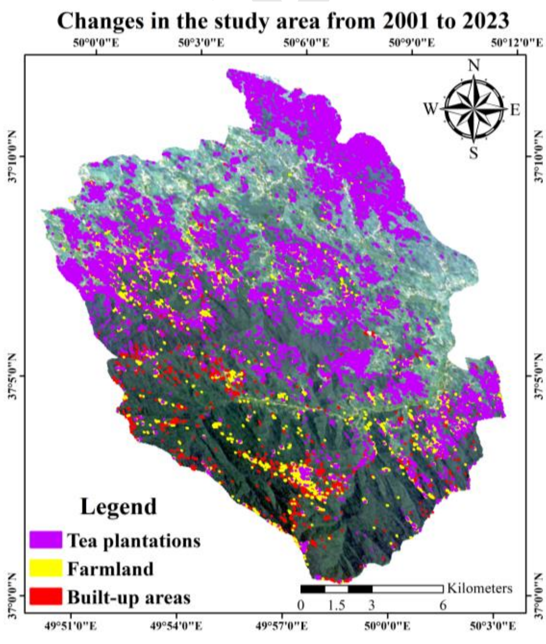


Fig. 4. Cumulative forest conversion (2001–2023): Tea plantations (purple), Farmland (yellow), Built-up areas (red). Background: Hillshade topography.

Figure 5 documents accelerating forest conversion pathways during 2011–2023, revealing distinct spatial patterns:Tea plantation expansion (purple) proliferated across northern, central, and western sectors. Farmland establishment (yellow) and built-up development (red) clustered predominantly in western corridors.

This spatial distribution demonstrates that agricultural development policies – particularly tea and crop subsidies – have emerged as the principal driver of systematic deforestation. Concurrently, regulatory shortcomings are evidenced by the indiscriminate issuance of construction permits within forest boundaries, facilitating widespread conversion to residential and recreational infrastructure. Deforestation has many social and economic consequences, including limited access to green spaces and loss of long-term economic opportunities such as the development of ecotourism and wood-based industries. Environmentally, it also leads to a decrease in biodiversity and increased soil erosion. To address this issue, some effective policies can include careful urban planning and proper construction control, sustainable management of agricultural lands, and education of local communities about the importance of natural resource management. These measures can play an important role in preserving forests and reducing the destructive effects of construction or their conversion to agricultural lands.

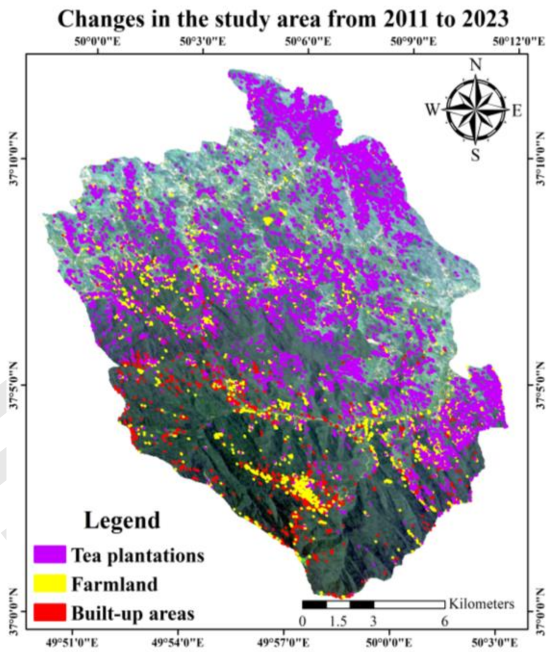


Fig. 5. Forest conversion hotspots (2011–2023): Tea plantations (purple), Farmland (yellow), Built-up areas (red). Background: Administrative boundaries overlay.

Table 2 quantifies land cover persistence and transitions (2001-2023), revealing critical dynamics:

Built-up Areas: Moderate stability (32.2% unchanged), Significant conversion to tea plantations (35.5%), Notable reversion to forest (20.3%).

Forest Ecosystems: Extreme fragmentation (86.0% unchanged), Primary conversion to tea plantations (10.7%), Minor urbanization (1.1%).

Farmland: Substantial persistence (30.8% unchanged), Limited transition to other classes.

Tea Plantations: Exceptional stability (72.3% unchanged), Secondary succession to forest

(15.9%), Marginal conversion to built-up areas (6.4%).

Table 2. Changes in built-up areas, forests, farms and tea gardens between 2001 and 2023 in percentage.

	Built-up areas	Forest	Farm	Tea Plantations
Built-up areas	32.2	1.1	7.0	6.4
Forest	20.3	86.0	20.0	15.9
Farm	11.7	2.0	30.8	5.2
Tea Plantations	35.5	10.7	42.0	72.3

5. CONCLUSION

This study quantifies significant deforestation in Guilan's Kore Rood basin (2001-2023), revealing peak forest coverage in 2001 (14,976 ha) followed by a net decline of 2.2% driven primarily by anthropogenic conversion—notably 10.7% of forests transformed into tea plantations concentrated in northern/central sectors, alongside 1.1% to built-up areas and 2.0% to farmland. These findings underscore unsustainable land-use practices threatening Iran's Hyrcanian forests, necessitating immediate implementation of high-resolution satellite monitoring (e.g., Sentine l-2 at 10m resolution) for real-time change detection and stricter policies limiting agricultural/residential encroachment. Future research should leverage advanced classification methods like neural networks to address spectral mixing challenges in tea-forest interfaces while integrating Sentine l-1 SAR data for cloud-persistent surveillance, establishing a robust framework for evidence-based conservation of these ecologically critical ecosystems.

CONFLICTS OF INTEREST

The authors declare that they have no conflict of interest.

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