Analyzing Land Use and Land Cover Changes in Bhaktapur District Using Landsat Data with SVM and MLC Classification Approaches

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Abstract: Reliable land cover information is essential for effective planning, yet its absence can hinder decision-making. This study analyzes land use/land cover (LULC) changes in Bhaktapur district, Nepal, between 2015 and 2025 using Landsat data and two supervised classifiers: Support Vector Machine (SVM) and Maximum Likelihood Classifier (MLC). Findings show rapid urban expansion, with built-up areas rising from 14% to 26% (SVM) and 14% to 18% (MLC), largely replacing agricultural, barren, and some vegetated areas. Vegetation increased slightly due to local restoration efforts, while forest cover remained mostly unchanged. SVM produced higher classification accuracy (79%, kappa 0.69) than MLC (73%, kappa 0.60). Overall, the study demonstrates the usefulness of remote sensing and GIS for monitoring LULC trends and shows the need for sustainable land management as Bhaktapur undergoes rapid urban growth.

Keywords: ***LULC, Change Detection, Support Vector Machine.***

Introduction

Accurate and up-to-date Land Use and Land Cover (LULC) information is essential for sustainable planning, environmental monitoring, and urban development (Hersperger et al., 2018; Shao et al., 2021; Maleki et al., 2020). Bhaktapur district of Nepal has undergone rapid urban transformation due to population growth, economic development, and land conversion from agriculture to built-up areas. This study analyzes decadal LULC changes (2015–2025) using Landsat imagery and compares two supervised classification techniques—Support Vector Machine (SVM) and Maximum Likelihood Classifier (MLC). The objective is to assess spatial change patterns, quantify class transitions, and evaluate the performance of both classifiers for urbanizing landscapes.

Study Area

Bhaktapur is the smallest district in Nepal (Figure 1), situated on the eastern edge of the Kathmandu Valley. It lies between 27°36’ N to 27°44’ N latitude and 85°21’ E to 85°32’ E longitude, covering an approximate area of 119 km^2. The altitude of Bhaktapur varies between 1,331 m and 2,191 m above sea level. A significant portion of Bhaktapur’s eastern region, along with nearly half of its northern and southern area, is covered by hills of the Mahabharat range and Midlands. The district experiences a moderate-temperate climate, with an average annual rainfall of 56 mm. Temperature variations range from a maximum of 33°C to a minimum of 0°C, with an average temperature of 23°C throughout the year.

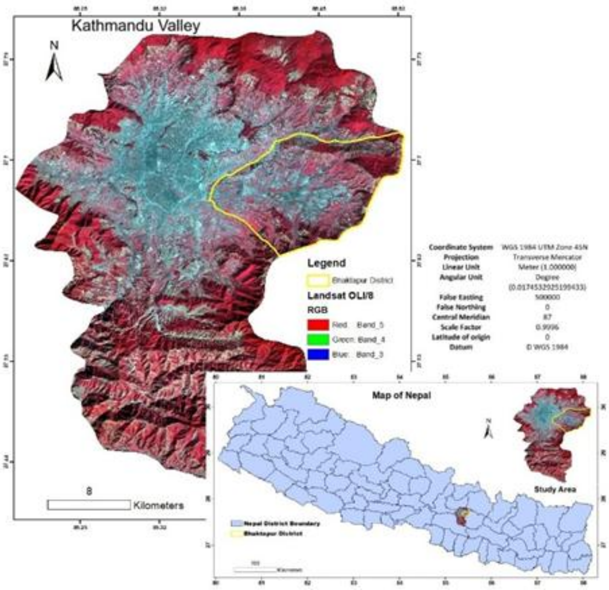

Figure 1, Landsat image of Kathmandu Valley showing the study area.

Methodology

Data acquisition and preparation

Landsat imagery was used to analyze LULC changes, selecting data based on quality, availability, and the dry season. Two Landsat images (2015 and 2025) were acquired from the United Stated Geological Survey (USGS) Earth Explores (https://earthexplorer.usgs.gov/) using specific Path/Row coordinates (Table 1). The images were processed in ArcGIS 10.4, to generate LULC maps. All images had 30 m spatial resolution, captured by OLI_TRIS at varying times. The selected images were pre-processed to insure radiometric and geometric consistency before classification. Throughout the study and data preparation, the spatial reference provided shown in Figure 1 was employed.

Table 1, Detailed data on Landsat images used in the study (USGS).

Year	Spacecraft ID	Sensor ID	Path/Row	Resolution (m)	Acquisition Date	Cloud Cover
2015	LANDSAT_8	OLI_TIRS	141/41	30	9 February 2015	17.57 % (not in the study area)
2025	LANDSAT_8	OLI_TIRS	141/41	30	20 February 2025	9.57 % (not in the study area)

Classification and accuracy assessment

SVM, a machine learning based supervised classifier and MLC, a statistical-based supervised classifier was used for digital classification. Comparison with high-resolution images revealed misclassifications, which were refined through post classification techniques for improved accuracy interpreted using Google Earth pro, field verification and previous land use maps. Each image was analysed categorizing the study area into 5 LULC classes: Built Up areas, Vegetation area, Forest area, Barren area, and Water bodies. Training samples were generated using high resolution imagery, field verification, and past land use maps. Post classification comparisons were used for LULC change detection, minimizing radiometric bias between dates. Confusion matrices and kappa statistics were computed using 100 reference samples for each map. Gain-losses and class transition matrices were developed to analyse landscape dynamics.

Results

LULC changes (2015-2025)

The results from the analysis indicate significant transformations in the LULC patterns of Bhaktapur district between 2015 and 2025 The classification results using both SVM and MLC show an increase in built-up areas and a corresponding decline in vegetation and forest cover. Table 2 shows the built-up area exhibited substantial growth over the study period, increasing from 13.36% (SVM) and 3.59% (MLC) in 2015 to 2025 respectively. The expansion of urban infrastructure, including residential, commercial, and industrial areas, is evident from the classification results. This trend somehow aligns with previous study (Chettri et al., 2017; Prajapati, RN., 2024), which reported a steady urban expansion in Bhaktapur.

Table 2, Change area (%) on LULC classification in 2025 and 2015.

		Built Up area	Vegetation area	Forest area	Barren area	Water bodies
% Change Area	SVM	12.36	4.92	-0.45	-16.83	-0.01
	MLC	3.59	21.09	-0.52	-24.21	0.06

Analysis of LULC transition and gains/losses (2015-2025)

Both classifiers indicate a major decline in barren land, with SVM showing conversions of 12.44% to vegetation and 8.09% to built-up, while MLC shows 22.01% and 5.79%, respectively reflecting agricultural expansion and urban growth. Built-up areas increased mainly at the cost of vegetation (SVM: 6.65%; MLC: 2.39%), confirming rapid urbanization. Forest areas show minimal net change (~0.5%), though internal shifts (e.g., forest to vegetation: SVM 3.46%; MLC 2.31%) indicate slight degradation. Overall gain–loss analysis shows vegetation gained the most (SVM: 17.87%; MLC: 26.91%), while barren land recorded the highest losses (SVM: 22.20%; MLC: 28.59%). Built-up areas expanded significantly (SVM: 16.52%; MLC: 8.76%), and forest cover remained largely stable with minor internal transitions (Figure 2 and 3).

Accuracy assessment and comparative analysis: SVM vs. MLC classification

A comparative evaluation of the classification techniques reveals that SVM generally outperforms MLC in terms of accuracy and precision. The accuracy assessment using the confusion matrix and kappa coefficient suggests that SVM provides higher classification reliability. The overall accuracy for SVM-based classification was 79% in 2025, compared to 73% for MLC. Additionally, the kappa coefficient for SVM (0.69) was higher than that of MLC (0.60), demonstrating better agreement with ground truth data (Table 3). The major advantage of SVM lies in its ability to effectively differentiate spectrally similar classes, such as built-up areas and barren land. MLC tends to classify more transitions toward vegetative categories (e.g., Barren to Vegetation, Built-Up to Vegetation), while SVM shows stronger internal class consistency. Both classifiers capture major LULC transitions, though their magnitude and direction differ. SVM outperformed MLC, offering higher accuracy and better separation of spectrally similar classes, while MLC's simplicity came with reduced effectiveness in complex urban settings. Overall, the results affirm the superiority of SVM for LULC change detection in remote sensing. The kappa coefficients for both methods indicate substantial agreement according to the Landis and Koch (1977) scale.

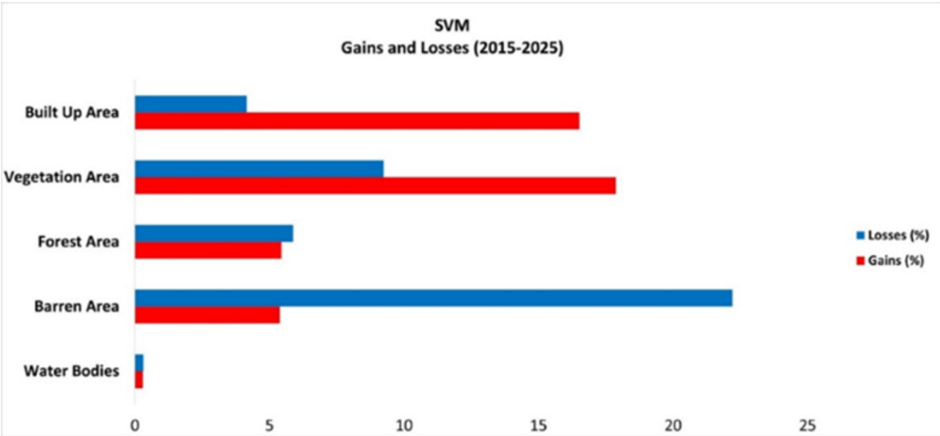

Figure 2, Gains and losses of LULC classes from 2015 to 2025 (SVM).

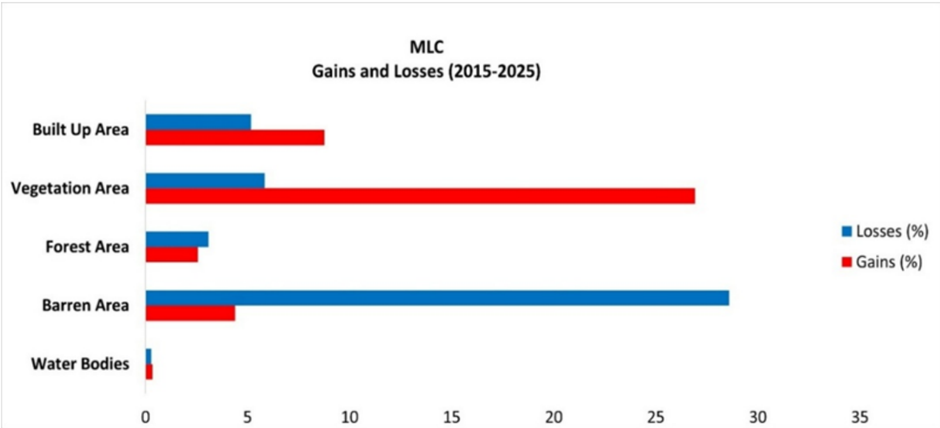

Figure 3, Gains and losses of LULC classes from 2015 to 2025 (MLC).

Table 3, Accuracy assessment of the LULC classification.

LULC	SVM				MLC			
	2015		2025		2015		2025	
	Producers Accuracy	User Accuracy	Producers Accuracy	User Accuracy	Producers Accuracy	User Accuracy	Producers Accuracy	User Accuracy
Built Up area	66.66	80	80	64	70	58.33	65	76.47
Vegetation area	51.51	85	74.5	92.68	52.63	100	87.8	67.92
Forest area	89.28	96.15	100	94.73	77.77	87.5	73.68	93.33
Barren area	95.23	52.63	63.63	46.66	91.17	59.61	52.63	66.66
Water bodies	0	0	0	0	0	0	0	0
Overall	74		79		72		73	
Kappa	0.65		0.69		0.60		0.60	

Conclusion

Remote sensing proved to be a highly cost-effective and reliable approach for analyzing LULC dynamics in Bhaktapur, offering a clear understanding of spatial and temporal land transformation patterns over the 2015–2025 period. Analysis of multi-temporal Landsat imagery revealed pronounced shifts, particularly the conversion of barren land into built-up and vegetated areas—changes largely attributable to rapid urban expansion, population growth, and the intensification of agricultural activities. In contrast, forest cover and water bodies exhibited relatively minor fluctuations, indicating a degree of ecological stability despite escalating development pressures.

Both the SVM and MLC classifiers consistently captured major transition pathways, especially the dominant barren-to-vegetation and barren-to-built-up conversions. However, SVM demonstrated superior performance, achieving 79% overall accuracy with a kappa coefficient of 0.69, compared with MLC's 73% accuracy and kappa of 0.60. These results not only highlight SVM's enhanced capability to distinguish spectrally similar classes but also confirm that both classifiers reach substantial agreement levels, reinforcing the reliability of the LULC change maps derived.

Collectively, the findings emphasize the need for integrated and balanced land-use policies that can guide sustainable urban growth while preserving critical environmental resources. They also point to the value of future work incorporating higher-resolution satellite data, advanced machine learning algorithms, and predictive modeling frameworks to improve monitoring precision and support more informed planning and decision-making in rapidly urbanizing districts like Bhaktapur.

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