Extended Abstract DOI: Not Included Open Access

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

Nirmal Kafle[1*]

[1]Khwopa College of Engineering, Bhaktapur, Nepal

(*Corresponding E-mail: nirmalkafle1917@gmail.com)

Received: July 25, 2025, Accepted: November 16, 2025

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.

Materials and methods

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.

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 image 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 provided spatial reference shown in Figure 1 was employed.

Classification and accuracy assessment

SVM, a machine learning based supervised classifier and MLC, a statistical-based supervised classifier were 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 analyzed 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 landuse maps. Post classification comparisons was 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 analyze landscape dynamics.

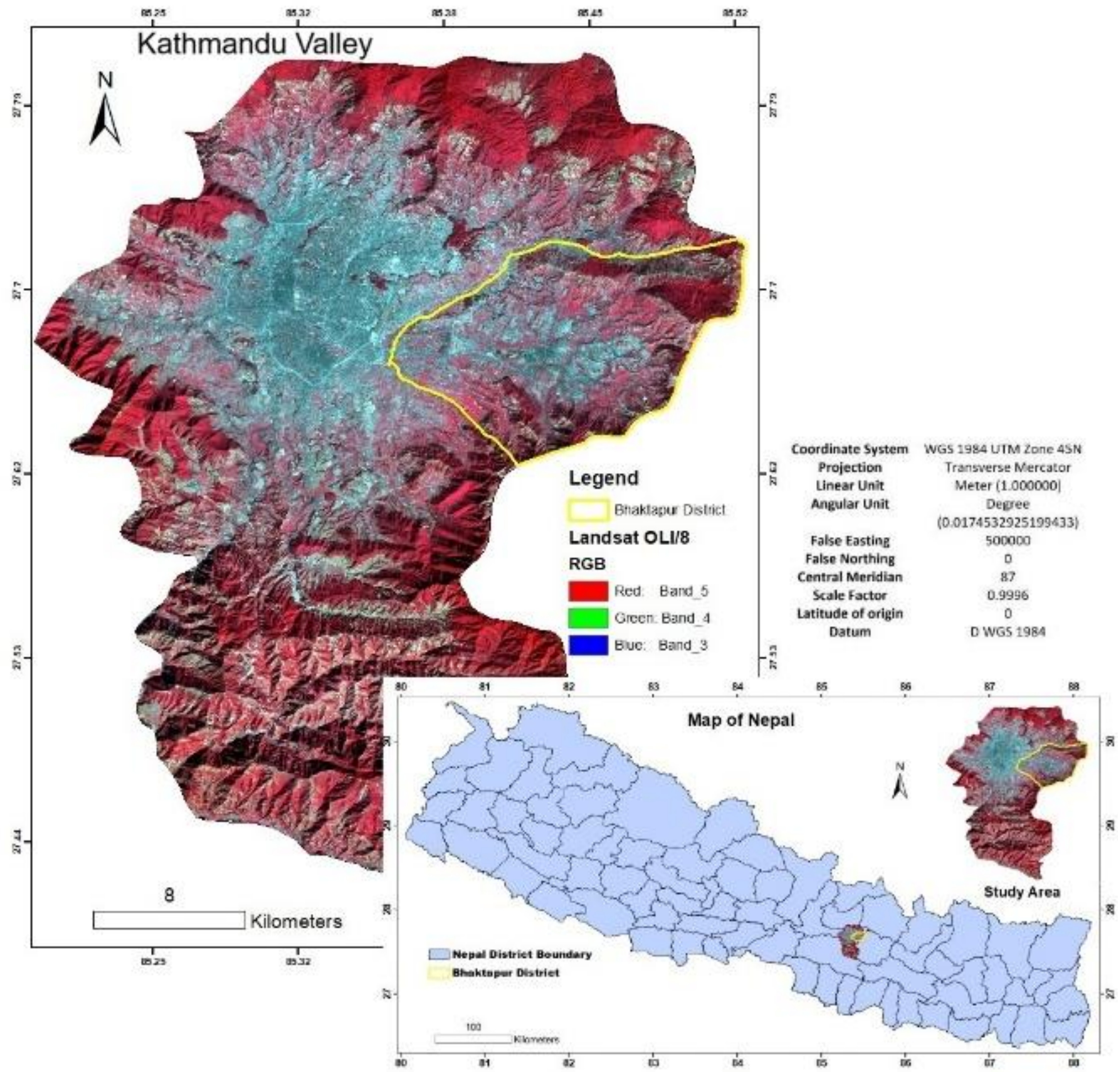

Figure 1, Landsat image of Kathmandu Valley showing the study area.

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 3 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 1, Detailed data on Landsat images used in the study (USGS)

		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

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

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)

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.bOverall 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 identify significant transitions among LULC classes, but the magnitude and direction vary notably. SVM proved to be a more effective classifier for LULC change detection due to its higher accuracy and ability to distinguish spectrally similar features. MLC, despite being computationally simpler, showed limitations in handling complex urban landscapes. The study highlights the superiority of SVM over MLC in remote sensing applications. The kappa coefficient for both of the classifiers shows substantial agreement based on the commonly used interpretation scale (Landis and Koch, 1977).

Conclusion

Remote sensing proved to be a cost-effective method for mapping LULC changes in Bhaktapur, revealing clear differences between SVM and MLC classifications. Landsat data (2015–2025) showed major conversions of barren land into built-up and vegetation areas, driven by rapid urbanization and agricultural expansion, while forest and water bodies remained largely stable. Both classifiers consistently indicated significant barren-to-vegetation and barren-to-built-up transitions. SVM performed better (79% accuracy, kappa = 0.69) than MLC (73%, kappa = 0.60), though both showed substantial agreement. Overall, the findings underscore the need for balanced land-use policies and future research utilizing higher-resolution data and predictive models to support sustainable development.

References

Chhetri, D. B. T., and Moriwaki, R. (2017). Monitoring urban growth, land use and land cover using remote sensing and GIS techniques: A case study of Bhaktapur District, Nepal. Engineering Science and Technology International Journal (ESTIJ), 7(1). Available at https://catalog.ihsn.org/citations/82257

Hersperger, A. M., Oliveira, E., Pagliarin, S., Palka, G., Verburg, P., Bolliger, J., and Grădinaru, S. (2018). Urban land-use change: The role of strategic spatial planning. Global Environmental Change, 51, pp.32–42. https://doi.org/10.1016/j.gloenvcha.2018.05.001

Landis, J. R., and Koch, G. G. (1977). The measurement of observer agreement for categorical data. *Biometrics*, 33(1), pp.159–174. https://doi.org/10.2307/2529310

Maleki, M., Van Genderen, J. L., Tavakkoli-Sabour, S. M., Saleh, S. S., and Babaee, E. (2020). Land use/cover change in Dinevar rural area of west Iran during 2000–2018 and its prediction for 2024 and 2030. Geographia Technica, 15(2), 93–105. https://doi.org/10.21163/GT_2020.152.10

Prajapati, R. N. (2024). Land use land cover and population changes in Bhaktapur District. Journal of Advanced Academic Research, 11(2),82-93. https://doi.org/10.3126/jaar.v11i2.76339

Shao, Z., Wu, W., and Li, D. (2021). Spatio-temporal-spectral observation model for urban remote sensing. Geo-Spatial Information Science, 24(3), 372–386. https://doi.org/10.1080/10095020.2020.1864232

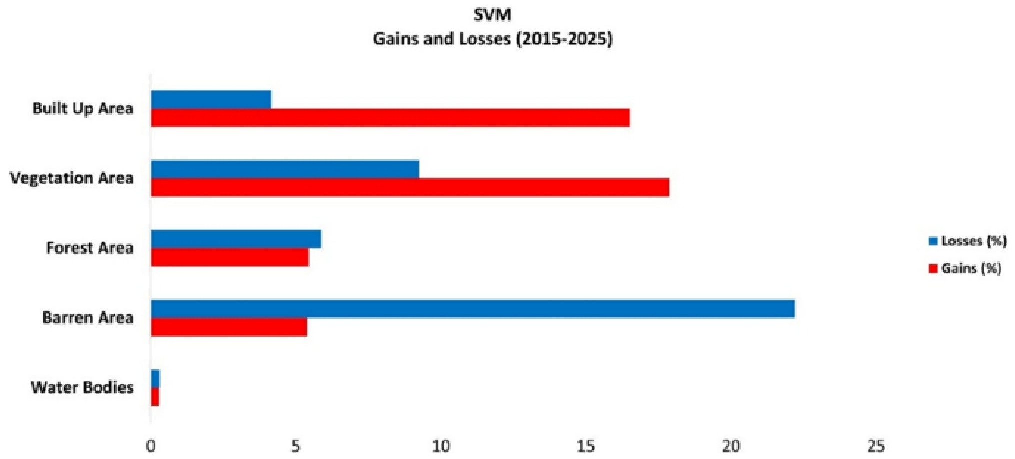

Figure 2, Gains and losses of LULC classes from 2015 to 2025 (SVM).

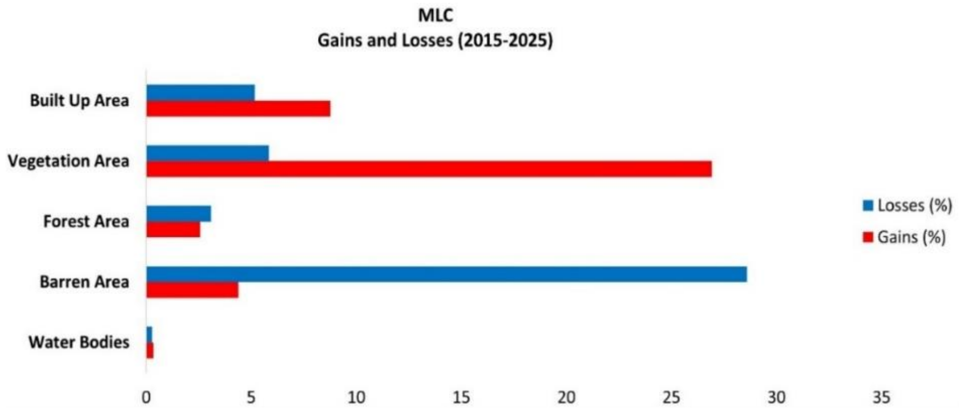

Figure 3, Gains and losses of LULC classes from 2015 to 2025 (MLC)

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	