Asian Journal of Engineering Geology, 2025, Vol. 2 No. 2, 9-18

Research Article DOI: https://doi.org/10.64862/ajeg.2025.202.02.265 **Open Access**

Comparative Evaluation of SVM and MLC for Land Use and Land Cover Change Mapping Using Landsat Data: A Case Study of Bhaktapur District, Nepal

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Received: August 08, 2025, Accepted: November 15, 2025

Abstract: The availability of reliable land cover maps is vital for effective planning, as their absence can compromise project validity. This study investigates the land use and land cover (LULC) changes in Bhaktapur district, Nepal, from 2015 to 2025 using Landsat imagery employing Support Vector Machine (SVM) and Maximum Likelihood Classifier (MLC). The primary objective is to compare the performance of SVM and MLC in LULC mapping and to calculate changes between two time periods. The results show increase in Built-up area and a reduction in barren land between the two time periods. Built-up area is increased by 12.36% (SVM) and 3.59% (MLC), between 2015 and 2025. Vegetation areas showed substantial gains, while forest area remained relatively stable. SVM achieved an overall accuracy of 79% (kappa = 0.69) whereas MLC achieved 73% (kappa = 0.60) indicating slightly higher classification accuracy for SVM. This study provides a comparative evaluation of two commonly used classifiers for LULC mapping and change analysis in Bhaktapur district. It also provides baseline spatial information for future planning studies.

Keywords: ***Bhaktapur, LULC, Support Vector Machine.***

Introduction

The growth of human populations and settlements is a common global drift influenced by human necessities and activities, which ultimately led to land-cover changes due to growing land-use requirements. While Land Use Land Cover (LULC) is frequently used interchangeably, these terms have distinct meanings (Dimiyati et al., 1996). A thorough spatial knowledge of urban expansion is essential for actual urban planning (Subasinghe et al., 2016). Accurate land cover information is vital for assessing these changes, enabling planners to implement up-to-date strategies for sustainable growth (Alharthi et al., 2020).

Encouraged by economic growth and infrastructure development, urbanization has emerged as a major inclination in developing countries. The conversion of vegetation land for urban purposes has become a topic for sustainable urban expansion. Accessibility and infrastructure development have further influenced settlement growth and urbanization (Xian and Crane, 2005).

Urban expansion studies have been key research since the 1990s (Batty and Xie, 1997). Remote sensing data has become a valuable resource for assessing LULC changes across various scales (Johnson and Iizuka, 2016). A common and effective way to obtain this information is through LULC classification of multispectral satellite imagery (Gibril et al., 2017). Remote sensing enables effective monitoring of both short-term and long-term land use processes, patterns, and their impacts (Wellmann et al., 2018). The understandings derived from remote sensing and Geographic Information Systems (GIS) such as spatial patterns and the extent of urban land changes (e.g., conversion of vegetation to Built-up area) can support urban planners (Simwanda and Murayama, 2018). Tracking land cover changes has remained a prominent research area in remote sensing and GIS over the past decade (MohanRajan et al., 2020). Various LULC change models have been developed to improve the accuracy of change (Maleki et al., 2020).

This study employs Maximum Likelihood Classifier (MLC) and Support Vector Machines (SVM) for change mapping and comparison between two classifiers. MLC is a widely used classification method for satellite image analysis which has demonstrated high accuracy in land-cover classification and change monitoring, often exceeding 80% (Huang et al., 2002; Kanellopoulos et al., 1992). In remote sensing, enhancing classification accuracy remains a key concern using advanced algorithms like Neural Networks and SVM. SVM is a supervised classification technique which have gained importance in remote sensing due to its ability to improve classification (Kavzoglu and Colkesen, 2009). Classes with large extents suffer from real-world variability and affects the MLC performance, while SVM is less dependent on data distribution (Naghadehi et al., 2021).

Bhaktapur is a historically significant city in Kathmandu Valley, Nepal (Figure 1). It has experienced various physical changes in recent decades marked by rapid urban expansion and internal transformation. The increase in Built-up area is prominent in Bhaktapur district over the years (1989-2015). The Built-up area increased from 1.8% to 24.0% between 1988 and 2015

(Chhetri and Moriwaki, 2017). The conversion of vegetation area into Built-up area reflects the pressure of population growth and shifting toward nuclear families (Yadav, 2013). In recent years, Bhaktapur has transitioned from a farming economy to a rapidly urbanizing District (Timsina, 2020). The land use and population analysis of Bhaktapur District (2001–2019) show significant urban expansion showing the increment to population growth and economic development. The Built-up area has been increased especially around Bhaktapur city and nearby municipalities (Prajapati, 2024). Additionally, population growth driven by rural-to-urban migration for better living has further increased these changes (Ishtiaque et al., 2017). Bhaktapur risks deteriorating into overcrowded and poorly managed settlements for its residents if urbanization remains unmanaged.

Despite several previous studies in Bhaktapur (e.g., Chhetri and Moriwaki, 2017; Prajapati, 2024), none of the studies have compared two classifiers (SVM vs. MLC). Therefore, the novelty of this study lies in providing a decade-based LULC comparison (2015–2025), and evaluating the relative classification performance of SVM and MLC under similar preprocessing and training conditions.

Materials and methods

Case study

Bhaktapur is the smallest district in Nepal (Figure 1) which lies 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, with an 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 Mahabharat range and Midlands. The district has a moderate temperate climate, with an average annual rainfall of 1300 mm (DHM, 2023). The variations in temperature range from a maximum of 33°C to a minimum of 0°C with an average temperature of 23°C throughout the year.

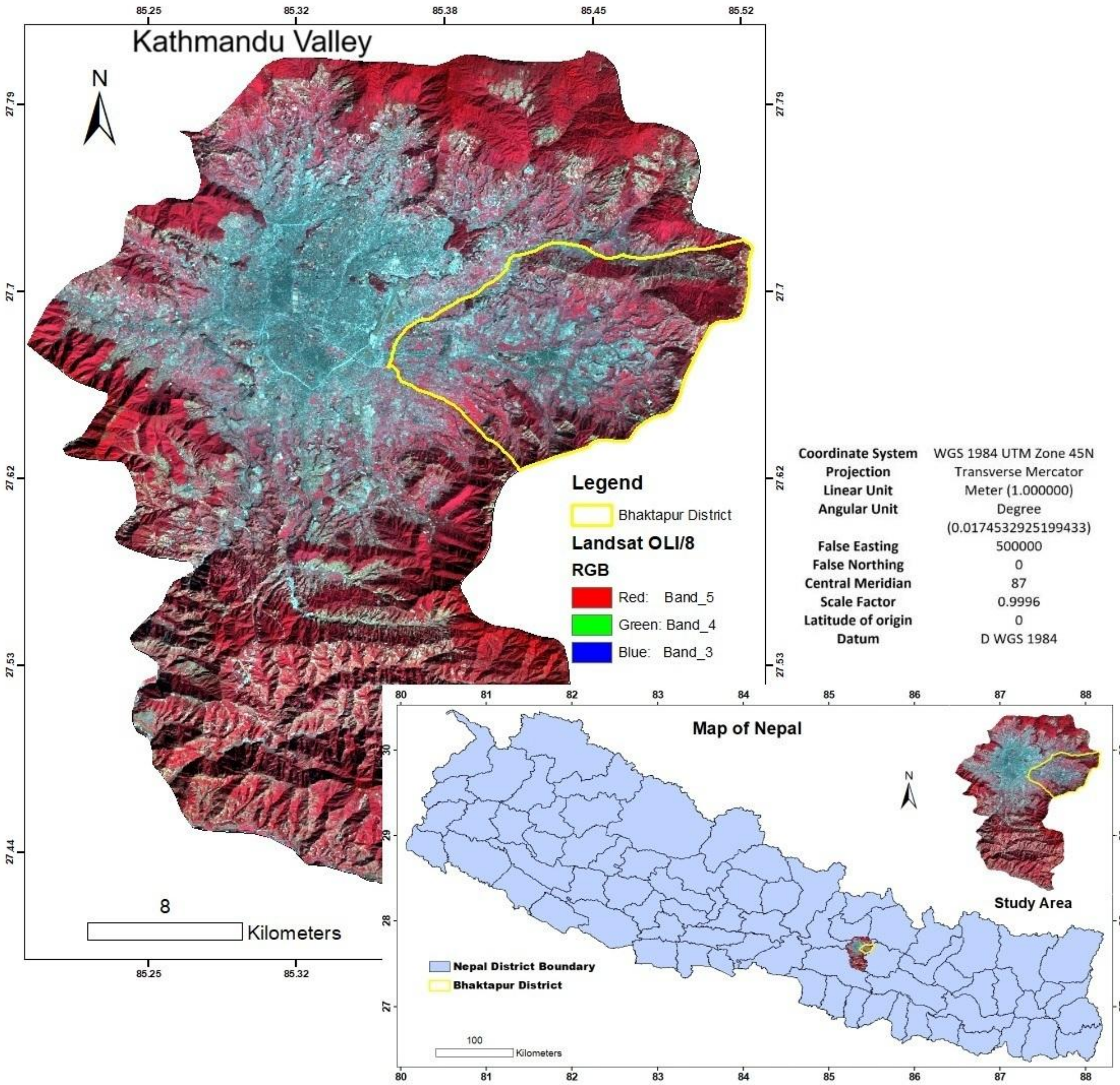

Figure 1, Landsat image of Kathmandu Valley showing the study area (Bhaktapur district).

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)

Data acquisition and preparation

Landsat imagery was used to analyze LULC changes, selecting data based on quality, availability, and the dry season (Table 1). Two Landsat images (2015 and 2025) were extracted from the United States Geological Survey (USGS) Earth Explorer (https://earthexplorer.usgs.gov/) specific Path/Row coordinates. The images were processed in ArcGIS 10.4, to generate LULC maps. All image had a 30 m spatial resolution, captured by OLI_TRIS at varying times. The selected images were pre-processed to ensure radiometric and geometric consistency before classification. Atmospheric correction was carried out using Landsat Surface Reflectance Code (LaSRC) which minimizes the atmospheric effects. Layer stacking, clipping to the Bhaktapur district boundary, and visual inspection for radiometric consistency were carried out before classification. Throughout the study and data preparation, the spatial reference provided in Figure 1 was employed.

Classification and change analysis

Two different supervised classifiers, SVM and MLC were used for digital classification. Comparison with high-resolution images revealed misclassifications, which were refined through post classification techniques for improved accuracy using Google Earth Pro, field verification and previous LULC maps. The study area was categorized into 5 LULC classes: Built-up area, Vegetation area, Forest area, Barren area, and Water bodies for each image (Table 2). Assessment of LULC changes was carried out using a post-classification comparison method where classified images from two different years were compared to identify transitions between land cover classes. This approach minimizes radiometric inconsistencies between multi-temporal images providing a detailed change matrix. The raster calculator was utilized to compare images from different years (Figure 2).

Using overlay procedures in GIS, a change matrix was generated which quantifies the gains and losses in each LULC category. The transitions between LULC classes were analyzed to understand the spatial extent and pattern of changes using SVM and MLC (Figure 3). The diagrams representing change in each class with gains and losses area were prepared implementing both techniques (Figure 4 and Figure 5).

Accuracy assessment

Accuracy assessment is crucial for evaluating individual classifications which ensures the reliability of classification data for change (Owojori and Xie, 2005). Typically, this assessment involves comparing two datasets: one derived from reference information, known as "ground truth," and the other obtained from analyzing remotely sensed data (Congleton, 1991). In the case of LULC maps generated from satellite imagery, a random sampling approach was employed for each of the four LULC maps to represent the various land cover classes. Training and validation samples were selected separately for the accuracy assessment to avoid bias. Approximately 100 training samples per class were used to develop the classifiers. An independent set of randomly distributed validation points was then used to generate the confusion matrix. These validation points were identified through visual interpretation of Google Earth imagery.

Table 2, LULC classification scheme.

LULC Category	Description
Built-up area	Includes residential, commercial, industrial, transportation infrastructure, and other structures.
Vegetation area	Includes grasslands, croplands and cultivated vegetation cover including agricultural lands.
Forest area	Densely wooded areas, including natural and planted forests.
Barren area	Land with little to no vegetation, including exposed rock or soil.
Water bodies	Represents surface water features such as rivers and ponds.

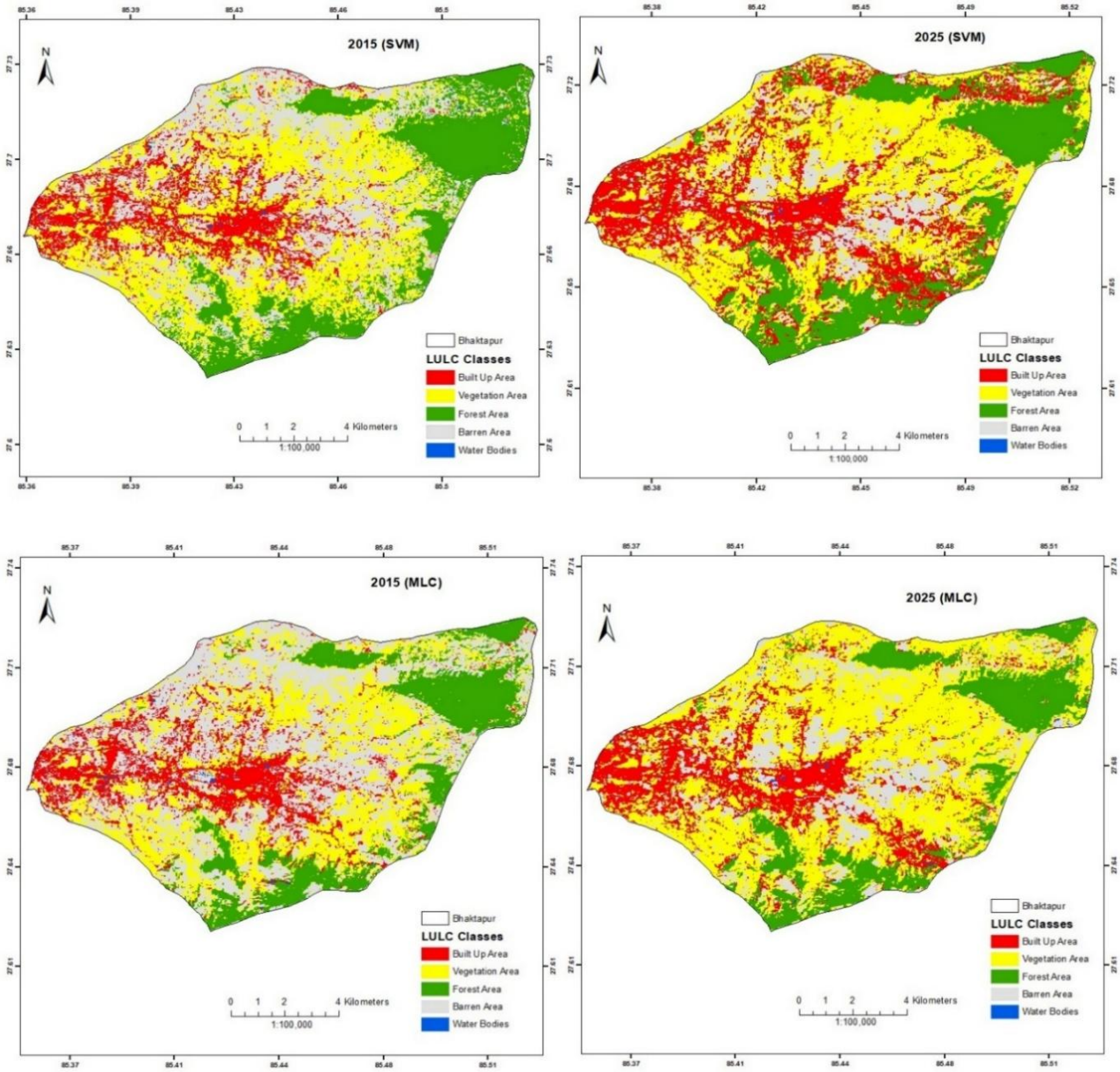

Figure 2, Status of LULC maps of Bhaktapur district in 2015 and 2025 with SVM and MLC classifier.

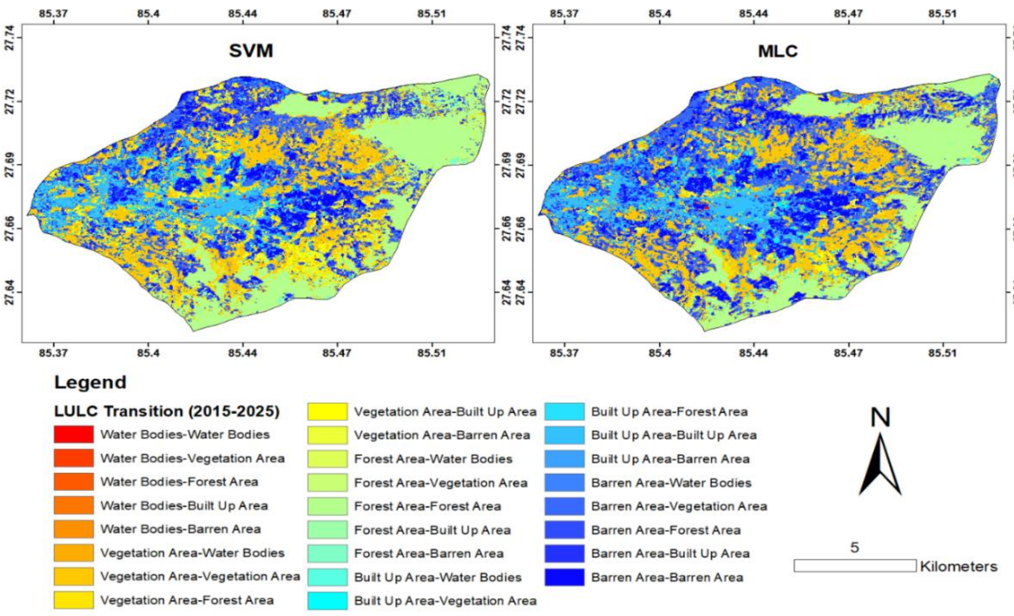

Figure 3, LULC change map from 2015 to 2025.

Result and discussion

LULC changes (2015-2025)

The results from the analysis indicate important 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 area and a decrease in vegetation and forest cover (Figure 6 and Figure 7). Table 3 shows the Built-up area revealed substantial growth over the study period with an increment from 12.36% (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. These results are consistent with previous studies (Chhetri and Moriwaki, 2017; Prajapati, 2024), which reported a steady urban expansion in Bhaktapur. Vegetation area also showed an increase over the decade with 4.92% (SVM) and 21.09 % (MLC). This expansion suggests important transformation of previously barren area into vegetation area. The forest area does not show noteworthy changes (0.5%) which might be due to government policies. The analysis also revealed a decline in barren area, decreasing from -16.83 % (SVM) and -24.21% (MLC), indicating a substantial increase in vegetation area.

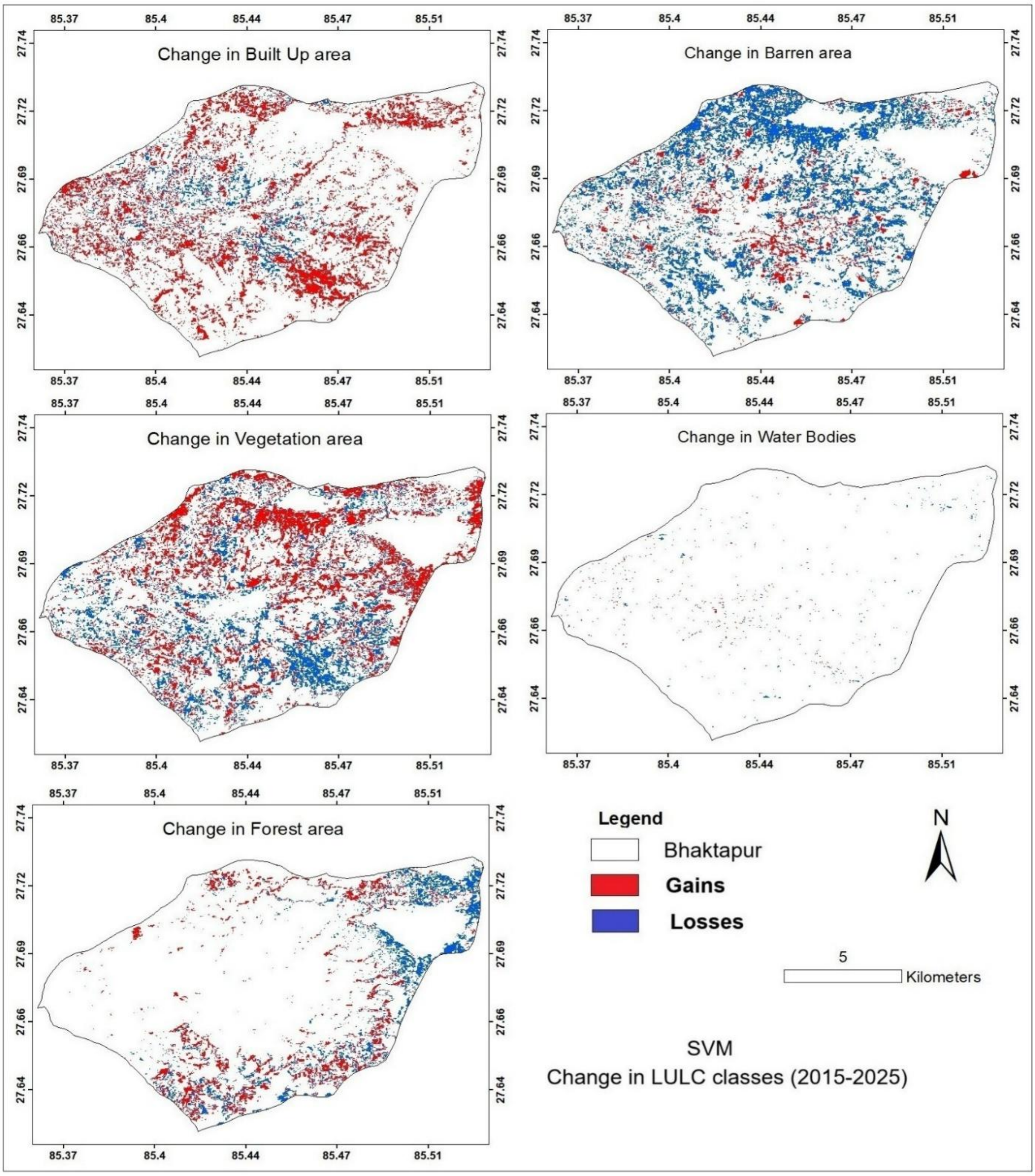

Figure 4, LULC change in different classes during 2015-2025 (SVM).

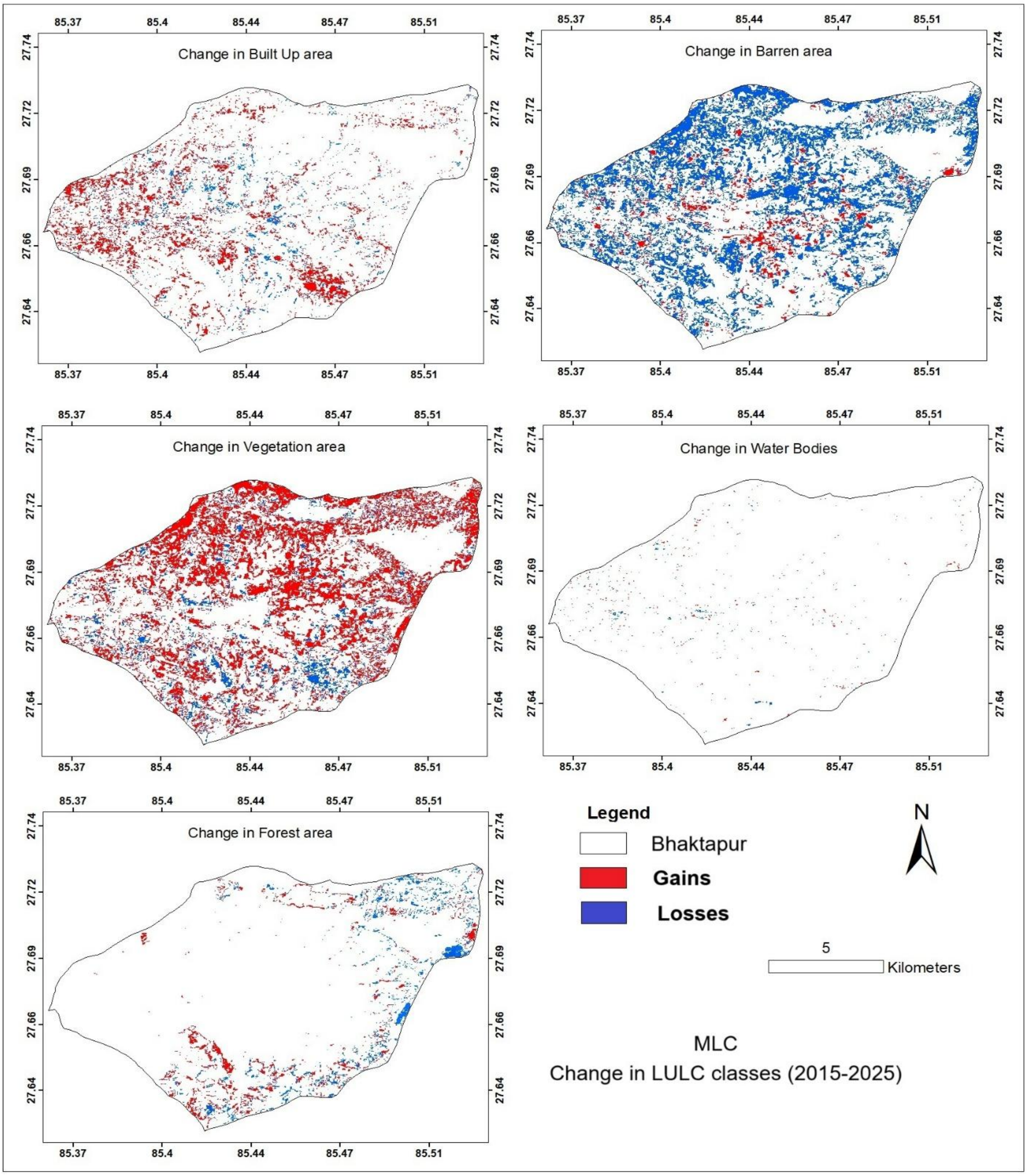

Figure 5, LULC change in different classes during 2015-2025 (MLC).

Table 3, 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

This reduction is the result of expanded vegetation area, afforestation efforts, and urban encroachment, as barren area were converted into vegetation, or Built-up area. Meanwhile, it is important to mention that the water bodies class showed very low classification accuracy, mainly because it occupies only a small portion of the study area. As a result, any interpretation regarding the stability or change of water bodies should be considered with caution. From a spatial perspective, the increase in Built-up area is mainly observed around the central parts of

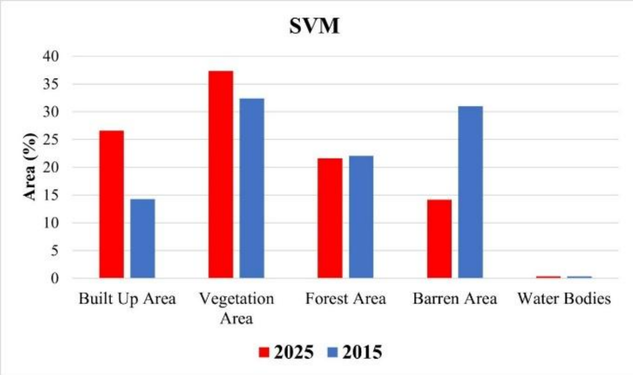

Figure 6, Status (%) on LULC classification in 2025 and 2015 (SVM).

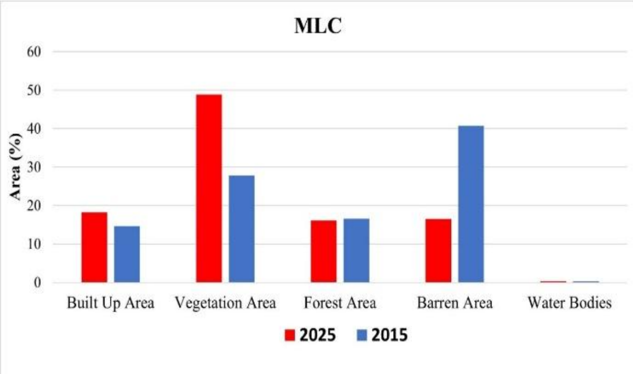

Figure 7, Status (%) on LULC classification in 2025 and 2015 (MLC).

Bhaktapur and its surrounding peri-urban zones. Overall, the pattern indicates gradual outward expansion from the existing core urban area rather than scattered developments. Conversion was primarily observed from previously barren or vegetated area.

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

Both classifiers agree on a reduction in barren area, with SVM showing 12.44% to vegetation and 8.09% to Built-up area, while MLC reports 22.01% to vegetation and 5.79% to built-up. This points towards the reclamation of marginal areas for expansion of vegetation and urban areas. Built-up area expanded primarily at the expense of vegetation (SVM: 6.65%; MLC: 2.39%), supporting rapid infrastructural growth. Forest area shows negligible net change (~0.5%) but internal shifts (e.g., forest-to-vegetation: SVM 3.46 %; MLC 2.31%) suggest minor degradation (Figure 8).

The LULC gain-loss analysis from both SVM and MLC classifications highlights consistent and significant landscape transformations. Vegetation Area recorded the highest gains, 17.87% in SVM and 26.91% in MLC, indicating re-vegetation or reclamation of previously unused areas in both cases. Barren Area consistently showed the highest losses, with 22.20% in SVM and 28.59% in MLC, suggesting noteworthy conversions into vegetated or urban areas. Built-up area expanded noticeably in both classifications (16.52% gain in SVM and 8.76% in MLC), reflecting rapid urbanization and infrastructure development (Figure 9 and Figure 10).

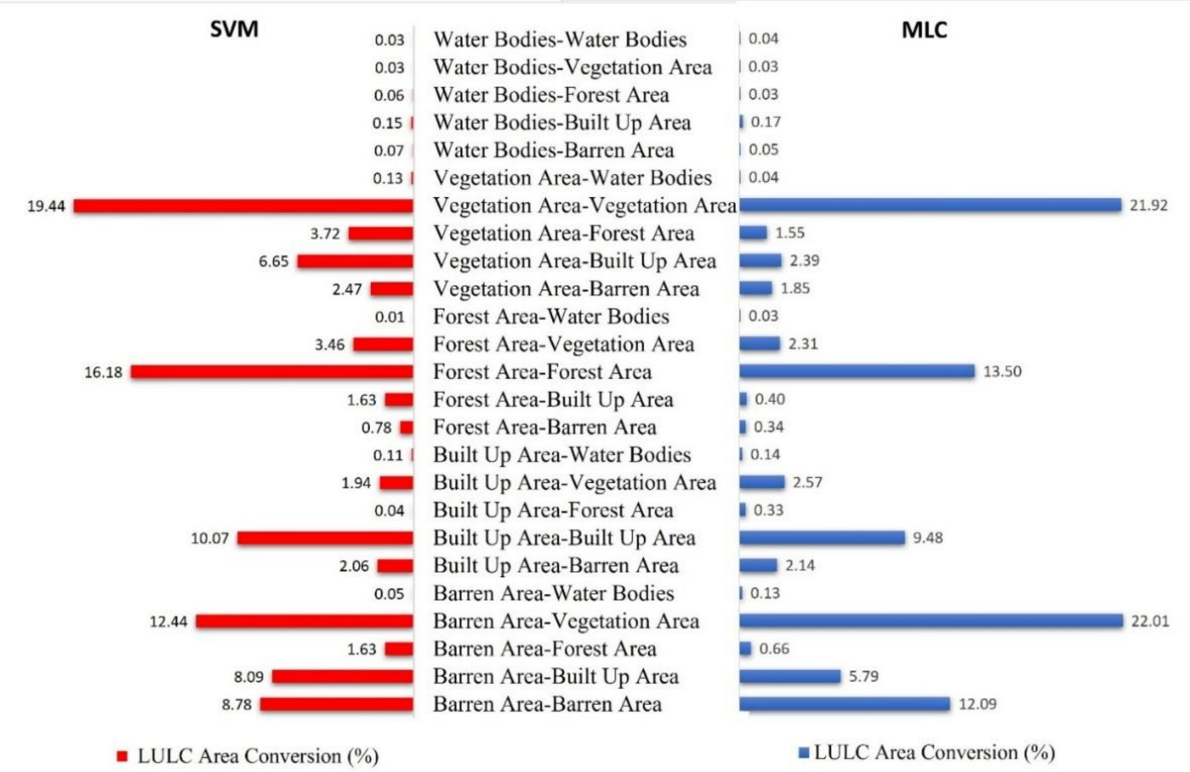

Figure 8, Transition (%) between LULC classes from 2015-2025.

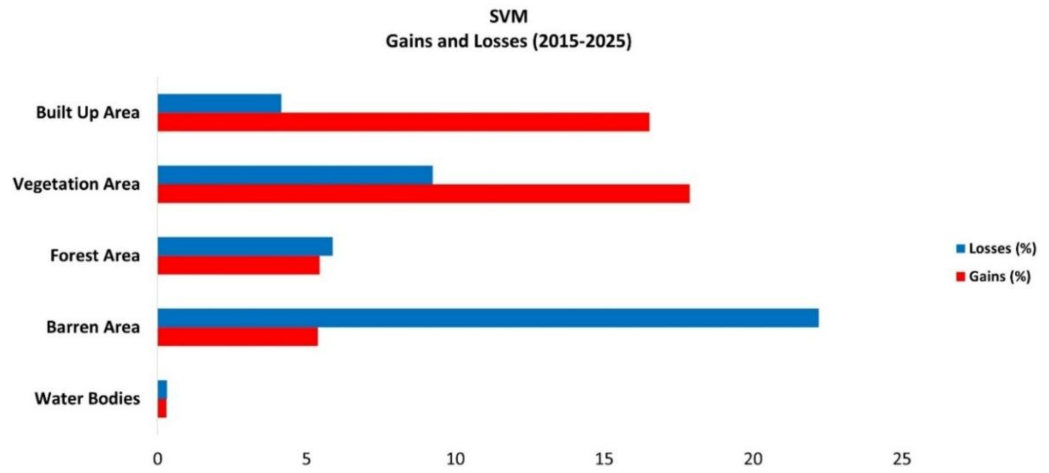

Figure 9, Gains and losses of LULC classes from 2015 to 2025 (SVM).

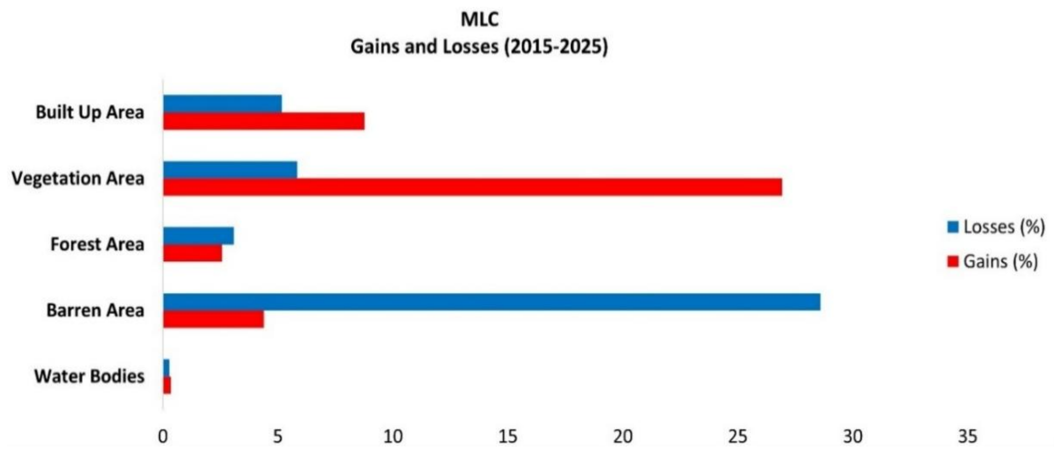

Figure 10, Gains and losses of LULC classes from 2015 to 2025 (MLC)

Accuracy assessment and comparative analysis: SVM vs. MLC classification

A comparative evaluation of accuracy assessment suggests that SVM provides slightly higher classification reliability compared to MLC. The overall accuracy for SVM-based classification was 79% in 2025, compared to 73% for MLC. The kappa coefficient for SVM (0.69) was higher than that of MLC (0.60), demonstrating improved agreement with ground truth data (Table 4). The major advantage of SVM lies in its ability to effectively differentiate similar classes, such as Built-up area and barren area. 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 transitions among LULC classes, but the magnitude and direction vary notably. It suggests the advantage of SVM over MLC in remote sensing applications. The kappa coefficient for both classifiers shows substantial agreement based on the commonly used interpretation scale (Landis and Koch, 1977).

This study employs a two-date post-classification comparison using data from 2015 and 2025. While this method effectively captures the overall changes that occurred between these two years, it does not fully reflect the gradual or year-to-year dynamics of LULC transformation. As a result, short-term fluctuations or intermediate transitions may not be represented. Future research that incorporates multi-year time-series datasets would provide a more comprehensive understanding of continuous LULC changes and help reveal long-term transformation patterns more clearly. This study also did not directly examine the environmental consequences behind the changes and no statistical significance tests were conducted.

Conclusion

These are exclusive concluding remarks from this study:

1. Utilizing freely available Landsat imagery enabled the quantification and mapping of LULC changes in Bhaktapur district, Nepal, with a particular focus on variations between SVM and MLC classifiers.

2. Analysis of Landsat imagery of 2015 and 2025 revealed variations in LULC change patterns. During the study decade, much of the land was converted into Built-up area and vegetation areas, with substantial reductions in barren area, and negligible reduction in forest area. These changes indicate ongoing urban expansion in the area. However, it is important to note that this study did not directly examine the specific causes such as environmental consequences behind these changes.

Table 4, Accuracy assessment of the LULC classification

	SVM				MLC			
	2015		2025		2015		2025	
LULC	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	

3. SVM achieved an overall accuracy of 79% with a kappa coefficient of 0.69, while MLC recorded 73% accuracy with a kappa coefficient of 0.60. These results suggest that SVM provides slightly higher agreement compared to MLC. Both classifiers fall within the substantial agreement category.

Overall, the study presents a comparative analysis of the SVM and MLC techniques for LULC mapping in Bhaktapur district using Landsat imagery. The analysis shows measurable changes in Built-up area, vegetation, and barren areas between 2015 and 2025. SVM achieved slightly higher classification accuracy compared to MLC. The results provide useful baseline spatial information that can support planners in monitoring future land-use changes.

Acknowledgements

The author would like to thank two anonymous reviewers for their valuable comments and suggestions, which helped to rectify the manuscript. The author also expresses sincere gratitude to Khwopa College of Engineering for its continuous support.

Data availability

The Landsat imagery used in this study is publicly available from the United States Geological Survey (USGS) Earth Explorer platform. Derived datasets and classification outputs generated during the study are available from the corresponding author upon reasonable request.

Declarations

The author declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

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