KPU International Journal of Engineering & Technology
Volume 6, Issue 1, Mar. 2026
e-ISSN:2790-0819, p-ISSN:2790-0800

Date Received: 2025-12-08
Date Accepted: 2026-03-07
Date Published: 2026-03-30

Accurate Detection of Land Use and Land Cover Changes in Kabul City Using Advanced Machine Learning Algorithms Applied to Pan-Sharpened Satellite Imagery (2015–2023)

MOHAMMAD KARIM SIRAT[1*], MOHAMMAD YAQOOB SULTANI[2] & SHIR ALI EBRAHIMI[3]

[1]Engineering Geodesy Department, Bamyan University, Bamyan City, Afghanistan. Email: karim.sirat68@gmail.com.

[2]Engineering Geodesy Department, Kabul Polytechnic University, KPU campus, 5th District, Kabul, Afghanistan. Email: yaqoobsultani90@gmail.com.

[3]Geographic Information Systems Department, Jawzjan University, Sheberghan City, Afghanistan.
Email: shirali.ebrahimi@gmail.com.

Abstract

Efficient implementation of remote sensing image classification plays a crucial role in supporting the extraction of spatial and temporal information for land use and land cover (LU/LC) analysis. Mapping LU/LC changes allows the examination of various social, economic, and environmental effects on the Earth's surface. This study aims to detect LU/LC changes in Kabul using an effective classification approach. Two classification techniques were evaluated: the Maximum Likelihood Classification (MLC) method and the Support Vector Machine (SVM) method, both implemented and compared using ENVI 5.6 software. To enhance the quality of the LU/LC map, the performance of the pan-sharpening algorithm was improved, increasing the spatial resolution of the satellite images from 30 meters to 15 meters. After classification, morphological operations with a 7×7 kernel were applied to reduce noise. LU/LC changes were analyzed using SVM for the years 2015 and 2023, achieving overall accuracies of 96.09% and 98.09% with Kappa coefficients of 0.92 and 0.94, respectively. The MLC method yielded overall accuracies of 94.03% and 97.34%, with Kappa coefficients of 0.88 and 0.91, respectively. Using the difference method on the SVM-classified images, the extent and pattern of LU/LC changes were assessed, and a detailed LU/LC change map for Kabul was generated. Results showed that between 2015 and 2023, urban land use increased by 7.31%, while vegetation cover, soil cover, and water bodies decreased by 1.18%, 6.11%, and 0.16%, respectively. The eight-year trend indicates that urban expansion in Kabul reflects broader patterns of social and economic development. This study offers new insights into detecting potential land use changes and supports the formulation of effective urban development strategies for future planning.

Keywords: Kabul City, Land Use/Land Cover (LU/LC), Landsat Imagery, Maximum Likelihood Classification, Pan-Sharpening, Support Vector Machine, Urban Expansion.

* Corresponding Author

1. Introduction

All over the world, natural land covers have been affected by urban growth. Currently, more than half of the world's population resides in urban areas [1]. Due to the growth in population, cities are growing quickly in terms of urban infrastructure and technological development in the last few years [2], with an aim to create sustainable and advanced societies in the future [3]. Although these urbanization processes have stimulated the technological development of modern societies and have resulted in the transformation and modification of landscape patterns and land cover specific to the city and the surrounding region [4], but it also has various destructive environmental effects, destruction The environment in the city areas is the loss of agricultural land and the reduction of underground water [5].

Land use change is a crucial component of world environmental change [6], and managers are usually interested in managing and predicting land use and land cover variations [7]. In general, the rapid growth of urbanization around the world can be classified according to demographics and urban expansion [8] urbanization activities are usually closely related to the political, cultural and financial growth of a country, for modern regions, whenever economic progress of a city is not enough to satisfy or support the needs for jobs and housing of new inhabitants, informal settlements are created, or a series of large communities are developedd on a massive scale. During the process of LU/LC analysis should be performed, here, LU/LC refers to the effects of human interventions and disturbances on the land surface, and the related human transformations can be the most direct measure to describe the changes of natural features, as well as environmental modifications, and the climate of the planet [9]. Despite the better utilization of available land to fulfill various human demands, traditional landscape elements and natural environments can be damaged through the breakdown and diversity of three-dimensional structures [10], and this can influence the species richness and long-lasting development of a city in Kuta, to have a prolonged effect [11].

With today's rapid economic growth and population increase caused by urban expansion, LU/LC has risen dramatically and attracted public interest, so hotspot studies have become especially crucial for future urban development. Based on recent research, LU/LC modification can indicate the negative effects of various environmental, societal, and financial factors on Earth's surface, for example, hydrological balance, climate, species diversity, and land-based ecosystems [12]. Among these elements, the effect of LU/LC on the ecosystems has become the most popular subject among scientists [13]. During the past decades, remote sensing technologies have collected crucial information from the Earth's surface. Although remote sensing offers essential data for researchers, conventional software tools are not fully capable of providing a complete solution for examining and managing terrestrial data [14]. During the past years, a variety of remote sensing devices, such as Moderate Resolution Imaging Spectroradiometer (MODIS), Satellite Pour l'Observation de la Terre (SPOT), Sentinel 2, and Landsat, have been developed [15]. Various techniques to derive information from these remote sensing datasets have been proposed and enhanced. Among these satellite data, Landsat is the only orbiter that has supplied information for more than four decades and is still

functional. The spatial detail of these datasets allows land surface changes, which is crucial for the advancement of management and scientific research [16].

There are many classification techniques for LU/LC mapping, including parallelogram method [15], Minimum Distance (MD) [17], Fuzzy Classifier (FC) [18], Random Forest (RF) [19], [20], Deep Learning (DL) [21], Deep Transfer Learning (DTL) [22], Maximum Likelihood (ML) [23], and Support Vector Machine (SVM), among these approaches SVM, due to superior performance and precision, Moreover, relatively low computational demands and the need for few inputs, it has been particularly favored and has become one of the top candidates in LU/LC mapping [17]. Although DL and DTL techniques have become an efficient computational strategy in machine learning in recent years, these approaches require large-scale data, and the calculations are also complicated [24].

Various approaches are used to analyze LU/LC change [25]. Researchers usually employ time series metrics derived from multispectral satellite imagery to analyze LU/LC changes. Change detection based on temporal and spatial variation of the biophysical characteristics of the Earth's surface is one of the most commonly used approaches. LU/LC classification attributes are generally classified into textural, spectral, and geometric features. The type of dataset, regional contexts, and the availability of supplementary data are the main factors for choosing one type or combination of these attributes in studies [26], Gilbertson et al., to distinguish between crop classes using different classification methods. used a pan-sharpening procedure for Landsat 8 multi-temporal images [27]. Obtaining detailed patterns of spatial variation is very important in developing cities such as Kabul. In this paper, Section 2 provides an overview of the study area, data, and MLC and SVM classification techniques in ENVI 5.6 software. In section 3, the results and analysis are shown. A discussion is presented in section 4, and finally, the conclusions of the article are summarized in section 5.

2. Materials and Methods

2.1. Study Area

Kabul, the capital of Kabul province, is located in eastern Afghanistan, at an altitude of about 1,800 meters above sea level. Kabul is the capital and one of the largest cities in Afghanistan, located at 34 degrees 32 minutes north latitude and 69 degrees 10 minutes longitude. It is located in the East and according to the estimate of 2020, it has a population of more than 5.3 million [28]. The city of Kabul is administratively divided into 22 urban districts. In this study, an area of 105879.24 hectares has been investigated.

2.2. Datasets

In this research, the total Landsat remote sensing imagery was acquired from the United States Geological Survey (USGS) website for free. The comprehensive description of different categories of Landsat imagery, along with the acquisition dates and the corresponding spatial resolution, is presented in Table 1. In general, the images were obtained from the Operational Land Imager (OLI) at different intervals in 2015 and 2023. Landsat sensors typically repeat their orbit on Earth every 16 days, which is sufficient to monitor long-term land-use dynamics in a specific geographic area.

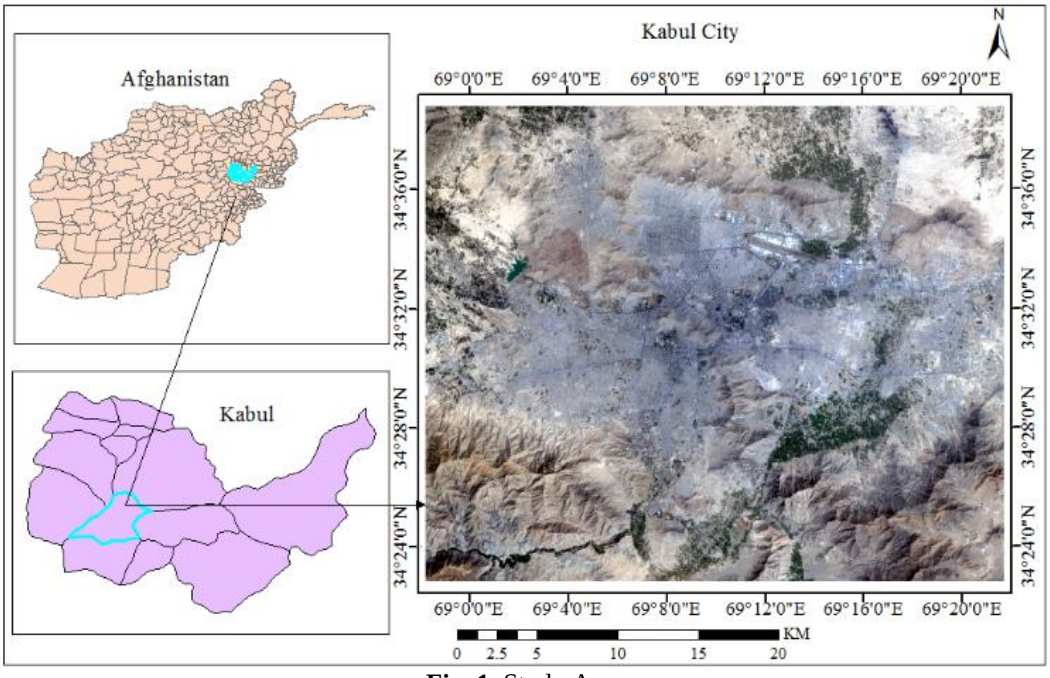


Fig. 1. Study Area

Table 1. Overview of the Dataset in the Study

Landsat Dataset	Description	Acquisition date	Spatial detail (m)	Path/row	Temporal Resolution
Landsat 8 OLI	Includes 9 spectral bands: 3 visible, 1 red, 1 near-infrared (NIR), 2 shortwave infrared (SWIR), 1 panchromatic (PAN), and 1 cirrus band.	9 September 2015	Spatial resolution: 30 m for the bands and 15 m for the panchromatic band.	153/036	16-day repeat cycle
Landsat 8 OLI	Includes 9 spectral bands: 3 visible, 1 red, 1 near-infrared (NIR), 2 shortwave infrared (SWIR), 1 panchromatic (PAN), and 1 cirrus band.	15 September 2023	Spatial resolution: 30 m for the bands and 15 m for the panchromatic band.	153/036	16-day repeat cycle

2.3. Training and Validation Data

In this research, four categories of LU/LC in the area were examined, recognized, and analyzed. To ensure high accuracy in the results, training and validation datasets were chosen independently. Table 2 provides additional information about the training and validation data based on the complexity of the studied region. This methodology allows the development of more precise analytical models and enhances the reliability of the resulting evaluations.

Table 2. The Mean Number of Training and Validation Points for Each LU/LC Category.

Land Cover Type	Number of Training Pixels	Number of Validation Pixels	Year
Water	302	197	2015
Built up	4,645	3132	
Vegetation	3163	1987	
Soil	19,422	13524	
Water	259	183	2023
Built up	5,662	3478	
Vegetation	2962	1756	
Soil	22,429	15543	

2.4. Methodology

Figure 2 shows the research steps to produce LU/LC map changes, that after introducing the data set; The radiometric error, atmospheric error and geometric error are corrected, in the next step, the spatial accuracy of the images is improved from 30 to 15 meters using the panchromatic band, and then it is classified using MLC, and SVM classifiers, and the classified images are the use of morphological operators has been improved, and after the improved classifications, an evaluation was made, and finally, by using the difference of those classifications, the map of LU/LC changes of Kabul city was found and the percentage of changes was calculated.

2.4.1. Preprocessing

To avoid the influence of clouds above the images, cloud-free images were obtained from the Landsat 8 instrument, in which there were no clouds. Therefore, the alterations detected through Landsat imagery match the actual environmental conditions and modifications in land use patterns. After collecting the appropriate dataset, geometric correction, radiometric correction, and atmospheric correction were performed, and Pan-sharpening was done after the necessary corrections.

2.4.2. Pan-Sharpening

Pan-sharpening combines the spectral information of the lower-resolution multispectral bands with the relatively higher spatial resolution of the panchromatic band in the same region [29]. There are several sharpening techniques, although it is unavoidable to lose some spectral details from the original multispectral information during pan-sharpening, certain algorithms aim to preserve spectral information [27]. Most panchromatic enhancement methods exploit the high-frequency content of the panchromatic image and apply various models to incorporate this extracted information into multispectral bands through resampling [29]. In this research, the Gram-Schmidt approach was used for sharpening.

2.4.3. Image Classification

Image classification is a subfield of computer vision that focuses on the classification and labeling of pixel groups in an image [30]. Several pixel-based methods for LU/LC classification are commonly used, including supervised, unsupervised, contextual, and hybrid approaches [29]. The performance of these techniques depends on the complexity of the classes, the amount of training data, the number and type of input features, and the classification algorithm. MLC and SVM classifiers are among the most effective solutions frequently employed in classification.

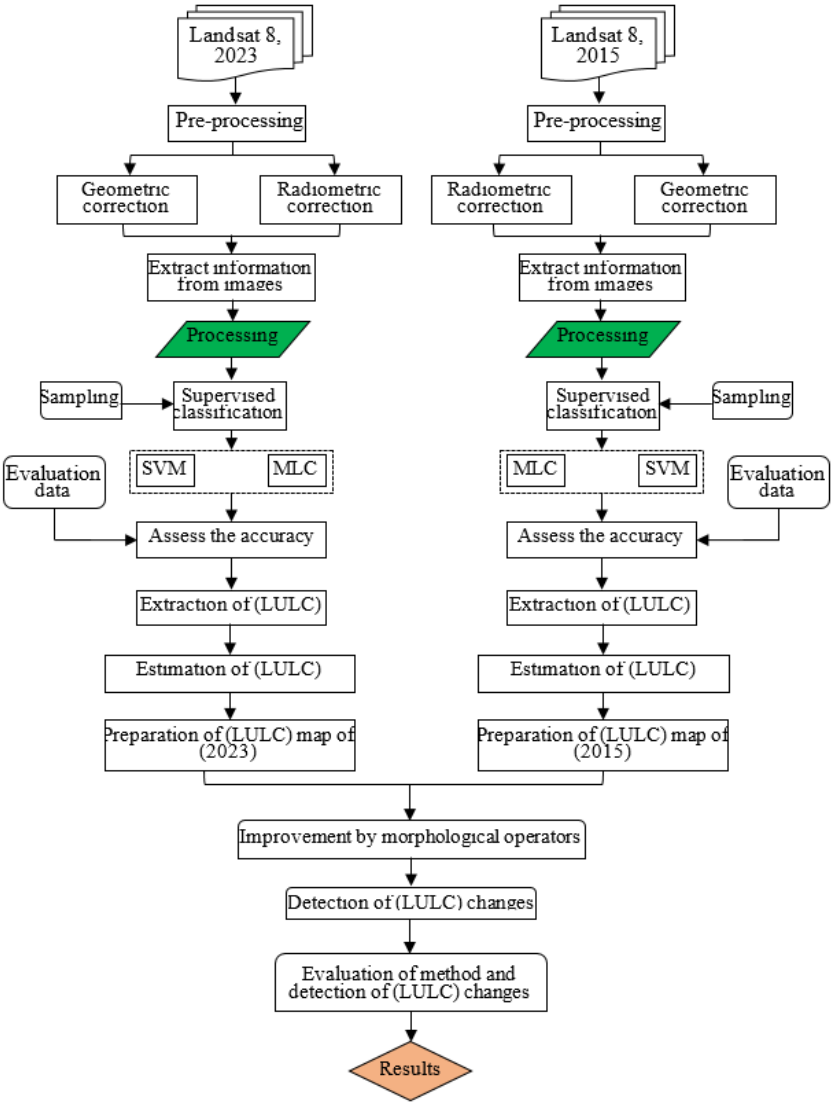


Fig. 2. Research Methods

SVM Classifier

The SVM approach is convenient and accurate for multi-source classification, especially in remote sensing applications [31]. This method aims to identify an optimal hyperplane that improves the separation between classes of data using the minimum required number of training samples. Such a hyperplane maximizes the distinctions between classes, and the support vectors are defined as the data points nearest to the hyperplane and are regarded as the training dataset [32]. Considering the principle of Structural Risk Minimization (SRM), the K-function has been proposed to convert a low-dimensional nonlinear problem into a high-dimensional linear problem through a specific mapping to position the hyperplane [33].

$$T = \{(I_1, O_1), (I_1, O_1), \dots, (I_i, O_i) \in (I_n, O_n) \dots\dots\dots\

Where: T is the training dataset, (Oi, Ii); is the sample point, Ii; is the input variable, and Oi is the output variable, In and On; are input and output sets, respectively, i; is the index of training points, n; is the dimensionality.

MLC classifier

Assuming that the reflectance values of each class follow a normal distribution in each band, the MLC algorithm allocates a pixel to the class with the highest probability, the pixel probability is evaluated by the multivariate normal Cumulative Distribution Function (CDF) through the mean, variance, and covariance of the training samples [35], the formula of the MLC algorithm is shown in equation 2:

$$P(X|W_i) = \frac{1}{\frac{n}{\left((2\pi)|V_i|.5\right)}} \exp[-0.5(X - M_i)^T V_i^{-1}(X - M_i)] \ldots\ldots\ldots\ldots\ldots\ldots (2.2)$$

Here: n; total number of multispectral bands, X; unknown observation vector, Vi; covariance matrix for each training class, and M; It is the mean vector of each class.

2.4.4. Morphological Operators

Morphological operators are nonlinear transformations frequently used in image processing. Their theoretical basis is rooted in mathematical morphology, and it is a known result that the class of image operators can be expressed in terms of two primary operations: erosion and dilation. Practically, effective operators can be created by combining these two operations, and novel operators can be designed to perform more advanced transformations. Morphological operators were initially developed for binary images, based on a set-theoretic approach, and later extended to grayscale and multispectral images [35]. These operators are used for processing and analyzing binary images, grayscale images, and for noise removal, shape characterization, edge detection, and feature extraction. Skeletonization and multiscale filtering are applied in applications such as medical imaging, geological image analysis, automatic industrial inspection, and image compression [36].

2.5. Accuracy Assessment

Accuracy evaluation is one of the most critical final stages of image classification. Accuracy evaluation helps provide a quantitative indicator of how well pixels are allocated to the correct LU/LC classes. Various approaches and indicators have been proposed and developed to evaluate accuracy over the years. Overall accuracy (OA) and the kappa coefficient are two commonly applied measures of accuracy [37]. OA is the mean classification accuracy, which represents the proportion of correctly identified pixels to the total amount of known pixels [38]. Meanwhile, the kappa coefficient ranges between (-1_+1), and indicates how much the classification agrees with a random classification. A negative value for kappa suggests that the classification is considerably poorer than random classification, whereas a value approaching 1 demonstrates that the classification is highly accurate [39].

3. Results

The present study was conducted with the aim of developing a method for accurate LU/LC classification, as described in Section 2. Our approach consists of 6 main stages. First, we presented the Landsat images; in the next step, we performed error correction,

and after that, we performed pan-sharpening and introduced the pan-sharpened images for classification. Then, SVM and MLC classification were used to classify the images. Then, the classified images were improved by morphological operators. Finally, we conducted an accuracy assessment using validation data to assess the effectiveness of the LU/LC map outputs and the significance of each input parameter in the region. We received the determination cable and finally the changes.

Pan-sharpening is one of the procedures used for Landsat 7 and Landsat 8 data, and it was implemented on the data acquired by the (ETM+) and (OLI) sensors mounted on Landsat 7 and 8, because the panchromatic band is not present in the earlier-generation sensors. At this stage, a panchromatic band has been used to increase the spatial accuracy of RGB bands, so that more details of land features such as land use, vegetation, and infrastructure can be seen, which improves the quality of decisions. Figure 3, shows an example comparing the results of the 15m pan-sharpened imagery with the original version of the 30m RGB bands in 2023. According to Figure 3, the buildings and roads are more clearly seen and help the classifier to extract them better.

This study shows the importance of morphological operators to eliminate noise on Landsat images. As shown in Figure 4, it is clearly seen that after applying closing operators and then opening with a kernel (7x7), unwanted details are removed, and boundary objects can be seen more clearly, which helps to identify and distinguish different coatings. In addition, improving the quality of the image through these operators can increase the accuracy of the results in the next stages of analysis, such as classification.

Below you can see the maps classified by SVM and MLC algorithms in different years after applying morphological operators, which in these classifications are of 4 classes: Water, Vegetation, Built Up, and Soil have been used, and each of these classes can be clearly seen on the maps of figures 5 and 6.

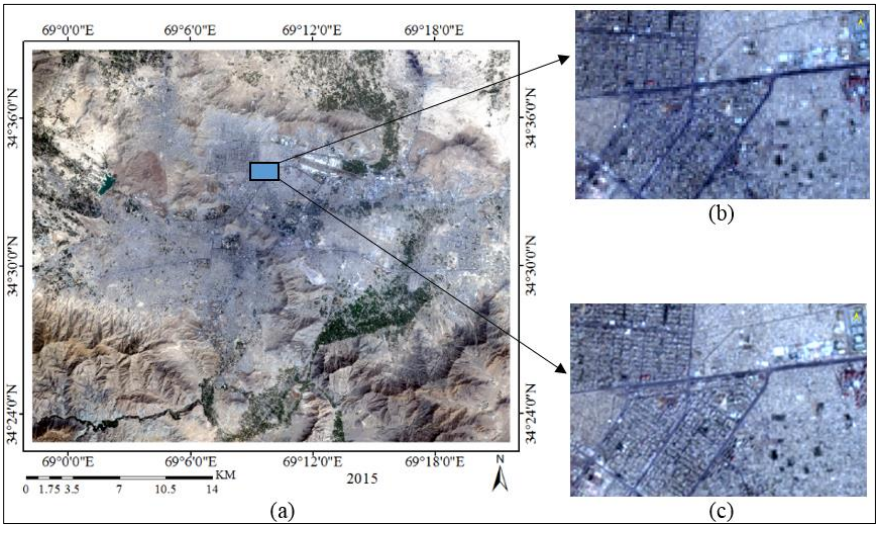


Fig. 3. Impact of Pan-Sharpening on the 2023 Image; (A) Entire Region, (B) Selected Area Before Enhancement, (C) Selected Area After Enhancement

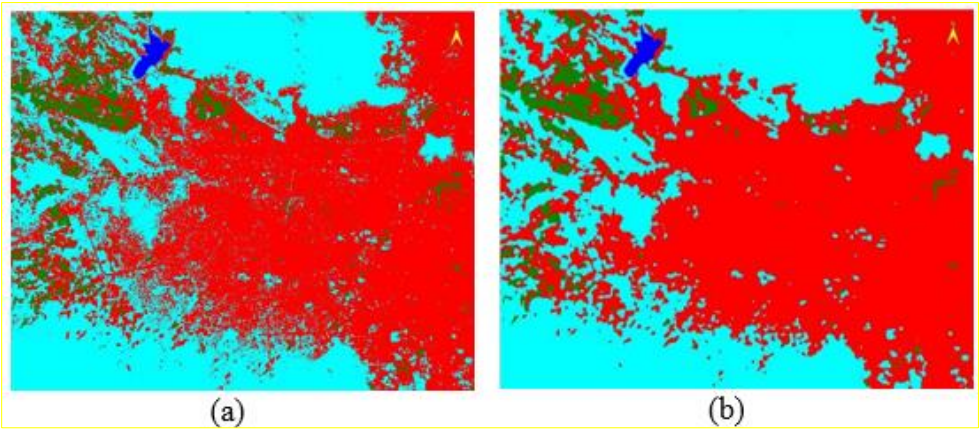


Fig. 4. Part of the Classified Map: (A) before Applying Morphological Operators, (B) after Applying Morphological Operators

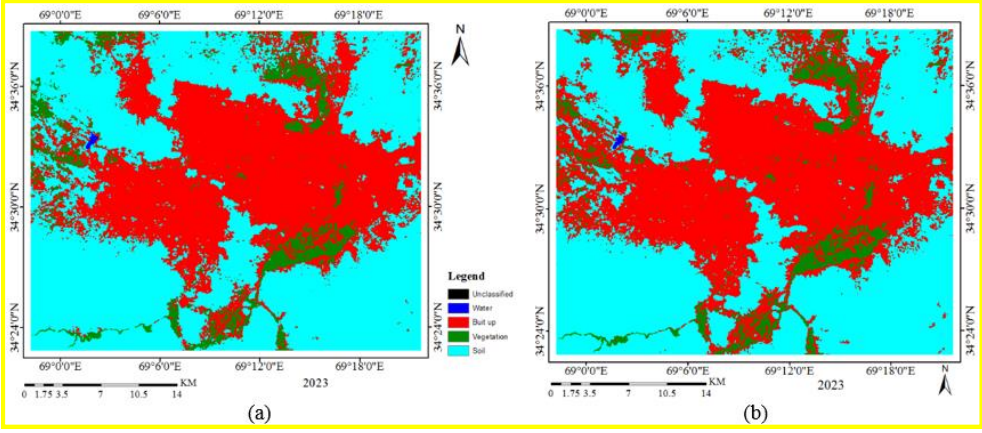


Fig. 5. Classified Map of 2015: (A) by SVM Algorithm, (B) by MLC Algorithm

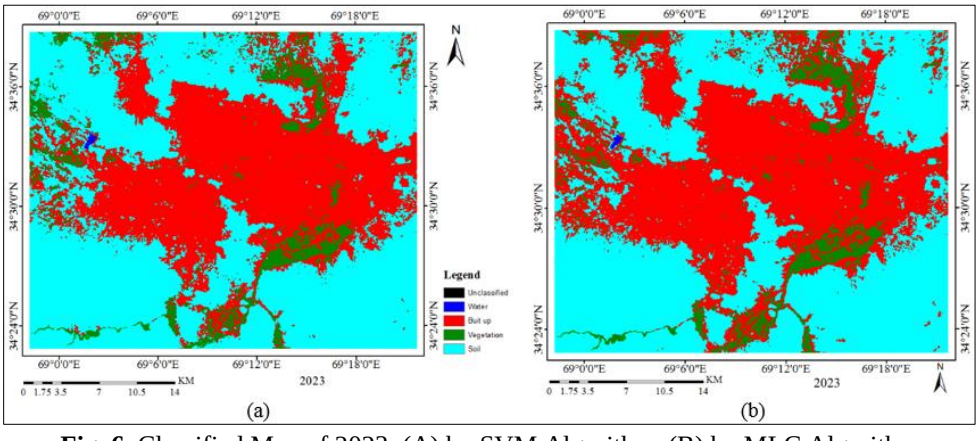


Fig. 6. Classified Map of 2023: (A) by SVM Algorithm, (B) by MLC Algorithm

3.1. Accuracy Assessment

In order to evaluate the performance and effectiveness of the algorithms regarding the number of training samples in the supervised classification, the re-sampling technique

was applied, the data was resampled up to 75%, and the overall accuracy and Kappa coefficient were obtained.

Table 3. Accuracy Evaluation

Year	2015		2023	
Methods	Overall Accuracy(%)	Kappa Coefficient(%)	Overall Accuracy(%)	Kappa Coefficient(%)
Support Vector Machine	96.09	0.92	98.09	0.94
Maximum Likelihood	94.03	0.88	97.34	0.91

3.2. Extraction of Changes Map

Figure 7, showing the change map of 4 classes: water, vegetation, built up, and soil between 2015 and 2023 using both SVM and MLC classifiers.

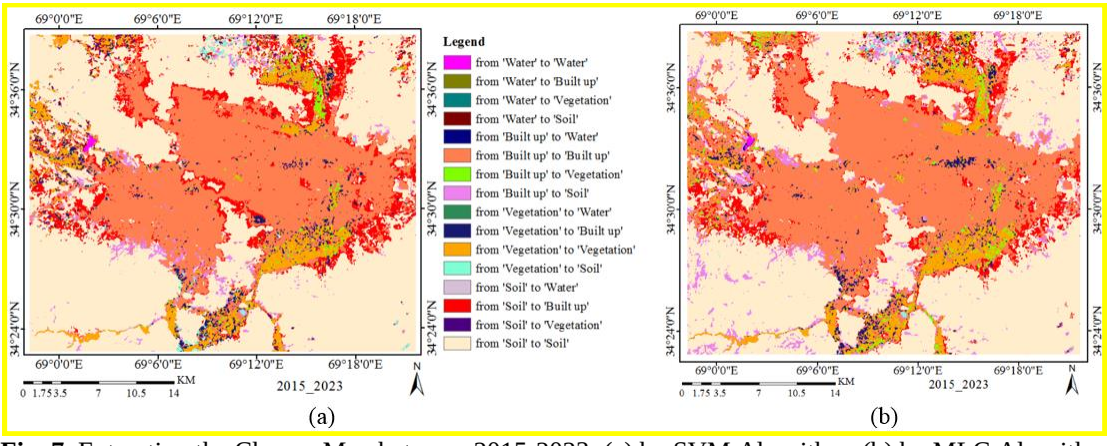


Fig. 7. Extracting the Change Map between 2015-2023: (a) by SVM Algorithm, (b) by MLC Algorithm

According to Table 3, the images classified by the SVM algorithm have better accuracy than the MLC algorithm in terms of overall accuracy and Kappa coefficient, so all calculations, such as Area, changes in hectares, and percentage of SVM algorithm, are used.

Table 4. Area and Number of Changes between 2015 and 2023

Year & Class	Area to ha		Changes to ha	Changes in Percentage (%)
	2015	2023	2015 and 2023	2015 and 2023
Water	96.39	79.16	-17.23	-0.16
Built Up	33031.64	40774.93	7743.29	7.31
Vegetation	8131.34	6876.68	-1254.66	-1.18
Soil	64619.86	58148.48	-6471.38	-6.11
Total	105879.24	105879.24		

In Table 4, the area and the number of changes in the period of 8 years are shown that the built-up area has increased by 7743.29 hectares, and the vegetation, water, and soil areas

have decreased by 1254.66, 17.23, and 6471.38, respectively, between 2015 and 2023. In Figure 8, the area of each class is displayed as a graph.

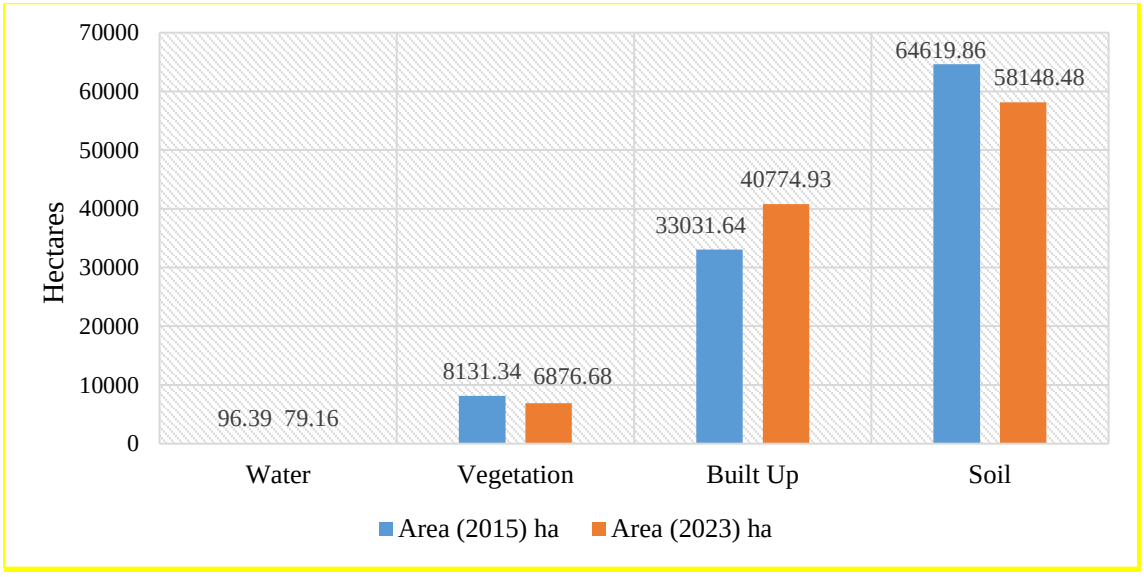


Fig. 8. Graph of Area in Hectares between 2015 and 2023

The number of changes in four classes in Figure 9 is shown as a graph, including the built-up class, which has increased, and the three classes of vegetation, water, and soil areas have decreased.

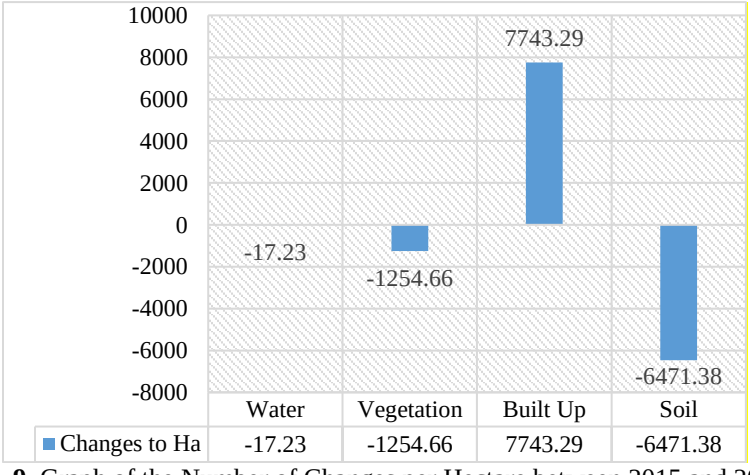


Fig. 9. Graph of the Number of Changes per Hectare between 2015 and 2023

4. Discussion

LU/LC mapping is an important tool for environmental observation and planning due to the continuous growth of urbanization. LU/LC serves as the basic foundation for identifying global ecological or environmental variations. Land use/cover classification is a crucial component and includes various factors. Land cover information is obtained

through remote sensing technology in terms of spatial, spectral, and temporal resolutions. Accurate land cover maps are one of the characteristics of the earth's surface in many cases for decision-making, because 80% of human decisions are spatial [40]. Remote sensing technology plays an important role at different times; in the field of urban changes, vegetation changes, urban expansion, etc.

In this research, SVM and MLC algorithms are used for classification, and the results are better than those of the SVM algorithm. The number of training samples is the same for each classification method; the error matrix for each classification method was analyzed, and the coverage of class separation performance was checked for each method. The difference between the two methods is obvious; the SVM method shows a more coherent spatial map than MLC. Built-up areas are further characterized by the SVM method, and the accuracy values reflect these differences. This research shows that an area of 7743.29 hectares has been developed into an urban class between 2015 and 2023 in the studied area. This shows that many factors, such as economic reasons, accelerate urban growth and exert significant pressure on the well-being of the natural environment and humans. This urban growth is also caused by the increase in the rate of migration from the village to the city, which is caused by the destruction of the environment, especially in megacities such as; It becomes a cable.

The results show that vegetation and water layers have been facing fluctuations in this period of time. This phenomenon has been affected by several reasons, including climate change, which has led to severe dryness. To mitigate the long-term impacts of this phenomenon, it is essential to develop a detailed LU/LC map and establish a practical management plan.

5. Conclusion

Monitoring the rapid growth of the city with the changes in land use and land cover is evident in this study; a major concern is the lack of up-to-date information about LU/LC changes. Providing such information is necessary for a country to understand and manage the urban environment more effectively and to adopt an approach. In this study, the potential of remote sensing techniques in measuring land use change and land cover has been used.

Irregular urban expansion is seen as one of the potential threats to sustainable development in urban areas. This study presents a method for LU/LC mapping with a spatial accuracy of 15 meters for Landsat 8 images. For this purpose, two SVM and MLC algorithms were used for classification, the results showed that although both methods have good accuracy, the SVM algorithm had better results, the SVM algorithm in 2015 and 2023, respectively, with an overall accuracy of 96.09. The image, amount, and manner of changes were checked, and the LU/LC changes map was extracted. The quantity of changes in the years 2015 and 2023 was investigated, and it was found that in a period of 8 years, urban land use changes increased by 7.31%, and vegetation cover decreased by 1.18%, soil cover by 6.11%, and water by 0.16% in this area. The results of examining the changes in an eight-year period in the city of Kabul show that the classification algorithm SVM performs better than the maximum likelihood classifier in the field of examining LU/LC changes and provides higher accuracy. Information about

LU/LC and their features is necessary for selecting, planning, and implementing land use plans to meet the ever-increasing demands. In addition, the LU/LC map offers a better understanding of the spatial, environmental, social, and economic patterns and enables governments to reduce the expenses and adverse impacts of these changes. The findings of this study can be applied to land use management and urban development planning.

References

[1] S. Angel, J. Parent, D. L. Civco, A. Blei, and D. Potere, 'The dimensions of global urban expansion: Estimates and projections for all countries, 2000–2050,' *Progress in Planning*, vol. 75, no. 2, pp. 53–107, 2011.

[2] B. Güneralp, M. Reba, B. U. Hales, E. A. Wentz, and K. C. Seto, 'Trends in urban land expansion, density, and land transitions from 1970 to 2010: A global synthesis', Environ. Res. Lett, vol. 15, p. 44015, 2020.

[3] C.-L. Goi, 'The impact of technological innovation on building a sustainable city', International Journal of Quality Innovation, vol. 3, pp. 1–13, 2017.

[4] J. Li, X. Zheng, C. Zhang, and Y. Chen, 'Impact of Land-Use and Land-Cover Change on Meteorology in the Beijing–Tianjin–Hebei Region from 1990 to 2010', Sustainability, vol. 10, p. 176, 2018.

[5] H. B. Wakode, K. Baier, R. Jha, and R. Azzam, 'Impact of urbanization on groundwater recharge and urban water balance for the city of Hyderabad, India', International Soil and Water Conservation Research, vol. 6, no. 1, pp. 51–62, 2018.

[6] N. R. Magliocca et al., 'Synthesis in land change science: methodological patterns, challenges, and guidelines', Regional Environmental Change, vol. 15, no. 2, pp. 211–226, 2015.

[7] P. Shehu, L. S. Rikko, and M. B. Azi, 'Monitoring urban growth and changes in land use and land cover: a strategy for sustainable urban development', Int. J. Hum. Cap. Urban Manag, vol. 8, pp. 111–126, 2023.

[8] Y. Sato and K. Yamamoto, 'Population concentration, urbanization, and demographic transition', Journal of Urban Economics, vol. 58, no. 1, pp. 45–61, 2005.

[9] A. L. Brenkert and E. L. Malone, 'Modeling vulnerability and resilience to climate change: A case study of India and Indian states', Climatic Change, vol. 72, no. 1–2, pp. 57–102, 2005.

[10] S. Leyk, D. Bulk, B. Jones, M. R. Montgomery, and H. Engin, 'The heterogeneity and change in the urban structure of metropolitan areas in the United States, 1990–2010', Sci. Data, vol. 6, p. 321, 2019.

[11] K. C. Seto, B. Güneralp, and L. R. Hutyra, 'Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools', Proc. Natl. Acad. Sci. USA, vol. 109, pp. 16083–16088, 2012.

[12] A. Salazar, G. Baldi, M. Hirota, J. Syktus, and C. McAlpine, 'Land use and land cover change impacts on the regional climate of non-Amazonian South America: A review', Glob. Planet. Change, vol. 128, pp. 103–119, 2015.

[13] Y. Pan et al., 'A Large and Persistent Carbon Sink in the World's Forests', Science, vol. 333, pp. 988–993, 2011.

[14] S. Abburu and S. B. Golla, 'Satellite Image Classification Methods and Techniques: A Review', Int. J. Comput. Appl, vol. 119, pp. 20–25, 2015.

[15] M. A. Wulder et al., 'Landsat continuity: Issues and opportunities for land cover monitoring', Remote Sens. Environ, vol. 112, pp. 955–969, 2008.

[16] M. Hemati, M. Hasanlou, M. Mahdianpari, and F. Mohammadimanesh, 'A systematic review of landsat data for change detection applications: 50 years of monitoring the earth', Remote sensing, vol. 13, no. 15, p. 2869, 2021.

[17] P. Kamavisdar, S. Saluja, and S. Agrawal, 'A survey on image classification approaches and techniques', Int. J. Adv. Res. Comput. Commun. Eng, vol. 2, pp. 1005–1009, 2013.

[18] A. Badhe and S. Chang, 'Fast image classification by boosting fuzzy classifier', Neural Netw. Mach. Learn, vol. 327, pp. 175–182, 2016.

[19] L. Breiman, ‘Random forests’, Mach. Learn, vol. 45, pp. 5–32, 2001.
[20] L. Khelifi and M. Mignotte, ‘Deep Learning for Change Detection in Remote Sensing Images: Comprehensive Review and Meta- Analysis’, IEEE Access, vol. 8, pp. 126385–126400, 2020.
[21] L. Alzubaidi et al., ‘Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions’, Journal of big Data, vol. 8, pp. 1–74, 2021.
[22] M. Gomroki, M. Hasanlou, and P. Reinartz, ‘STCD-EffV2T Unet: Semi Transfer Learning EfficientNetV2 T-Unet Network for Urban/Land Cover Change Detection Using Sentinel-2 Satellite Images’, Remote Sensing, vol. 15, no. 5, p. 1232, 2023.
[23] M. K. Sirat and M. Gomroki, ‘Investigating Land Use Changes in Herat City Using Satellite Images during 2015 and 2022’, gisj, no. Online First, Feb. 2024, doi: 10.48308/gisj.2024.234087.1192.
[24] L. Alzubaidi et al., ‘Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions’, J. Big Data, vol. 8, p. 53, 2021.
[25] B. Rimal, L. Zhang, H. Keshtkar, N. Wang, and Y. Lin, ‘Monitoring and Modeling of Spatiotemporal Urban Expansion and Land-Use/Land-Cover Change Using Integrated Markov Chain Cellular Automata Model’, ISPRS Int. J. Geo-Inf, vol. 6, p. 288, 2017.
[26]G. Myburgh and A. Niekerk, ‘Effect of feature dimensionality on object-based land cover classification: A comparison of three classifiers’, S. Afr. J. Geomat, vol. 2, pp. 13–27, 2013.
[27] J. K. Gilbertson, J. Kemp, and A. Niekerk, ‘Effect of pan-sharpening multi-temporal Landsat 8 imagery for crop type differentiation using different classification techniques’, Comput. Electron. Agric, vol. 134, pp. 151–159, 2017.
[28] Afghanistan statistical yearbook, no. August. 2020. doi: 10.29171/azu_acku_musalsal_ha4570_6_alif2_seen22_v1391s.
[29] K. R. Rahaman, Q. K. Hassan, and M. R. Ahmed, ‘Pan-Sharpening of Landsat-8 Images and Its Application in Calculating Vegetation Greenness and Canopy Water Contents’, ISPRS Int. J. Geo-Inf, vol. 6, p. 168, 2017.
[30] M. Pal, ‘Random forest classifier for remote sensing classification’, Int. J. Remote Sens, vol. 26, pp. 217–222, 2005.
[31] M. K. Sirat, S. J. Tamim, M. Y. Sultani, and M. A. Saraj, ‘Comparative Analysis of Vegetation Change Detection Using the Normalized Difference Vegetation Index and Support Vector Machine Algorithm Based on Landsat-8 Data: A Case Study of Bamyan City’, vol. Volume 5, no. Issue 2, pp. 95–113, 2025.
[32] G. M. Foody, D. S. Boyd, and C. Sanchez-Hernandez, ‘Mapping a specific class with an ensemble of classifiers’, Int. J. Remote Sens, vol. 28, pp. 1733–1746, 2007.
[33] S. Cuentas, R. Peñabaena-Niebles, and E. Garcia, ‘Support vector machine in statistical process monitoring: a methodological and analytical review’, International Journal of Advanced Manufacturing Technology, vol. 91, no. 1–4, pp. 485–500, July 2017.
[34] J. Il Shin, W. W. Seo, T. Kim, J. Park, and C. S. Woo, ‘Using UAV multispectral images for classification of forest burn severity-A case study of the 2019 Gangneung forest fire’, Forests, vol. 10, no. 11, pp. 1–15, 2019.
[35] N. S. T. Hirata and G. A. Papakostas, ‘On machine-learning morphological image operators’, Mathematics, vol. 9, no. 16, pp. 1–22, 2021.
[36] M. L. Comer, ‘Morphological operations for color image processing’, Journal of Electronic Imaging, vol. 8, no. 3, p. 279, 1999.
[37] C. Liu, P. Frazier, and L. Kumar, ‘Comparative assessment of the measures of thematic classification accuracy. Remote Sens’, Environ, vol. 107, pp. 606–616, 2007.
[38] P. Olofsson, G. M. Foody, S. V Stehman, and C. E. Woodcock, ‘Making better use of accuracy data in land change studies: Estimating accuracy and area and quantifying uncertainty using stratified estimation’, Remote Sens. Environ, vol. 129, pp. 122–131, 2013.
[39] J. R. Jensen, Introductory Digital Image Processing: A Remote Sensing Perspective. Hoboken, NJ, USA: Prentice-Hall Inc, 1996.
[40] X. Zhu et al., ‘Development and implementation of a dynamic and 4D GIS based on semantic location model’, Geo-Spatial Information Science, vol. 22, no. 3, pp. 193–213, 2019.