

Application of GIS and remote sensing for assessing land cover change: a case study in selected communes of Phu Tho province

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Ứng dụng GIS và viễn thám đánh giá biến động lớp phủ mặt đất: nghiên cứu tại một số xã trên địa bàn tỉnh Phú Thọ

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ABSTRACT

This study applies Geographic Information Systems (GIS) and remote sensing techniques to assess land cover change in Luong Son, Cao Duong, and Lien Son communes (former Luong Son district), Phu Tho province, Vietnam, during the period 2014 - 2024. Landsat 8/9 satellite imagery was processed and classified using the Random Forest algorithm on the Google Earth Engine platform. The classification results achieved an overall accuracy of 83.31% with a Kappa coefficient of 0.7900 for the year 2014, and 86.48% with a Kappa coefficient of 0.8294 for the year 2024, demonstrating the high reliability of the land cover maps for both study periods. Transition matrix analysis conducted in ArcGIS reveals that perennial cropland (CLN) increased by 7.4%, reaching 23,844.38 ha, while built-up land (CTXD) expanded significantly by 22.1% to 5,841.87 ha, reflecting rapid urbanization. Water bodies (MN) also increased by 13.8% to 937.35 ha, mainly due to irrigation and water resource development. In contrast, annual cropland (CHN) slightly decreased by 3.7% to 5,000.85 ha, and bare land (DT) declined sharply by 74.5% to 898.35 ha, indicating a trend toward more sustainable land-use restructuring. Markov chain modeling predicts that by 2034, built-up land will continue to increase by 11.7% to 6,527.89 ha, perennial cropland will grow by 2.1% to 23,360.78 ha, and water bodies will expand by 9.0% to 1,021.84 ha. Conversely, annual cropland is expected to decrease by 4.3% to 4,787.37 ha, while bare land will further decline by 8.2% to 824.92 ha. These findings provide a robust scientific basis for land-use planning and management in Phu Tho province, highlighting the strong potential of integrating GIS and remote sensing for sustainable land resource management, and recommend incorporating Sentinel imagery to enhance multi-temporal analysis in future research.

TÓM TẮT

Nghiên cứu ứng dụng GIS và viễn thám đánh giá biến động lớp phủ mặt đất tại các xã Lương Sơn, Cao Dương và Liên Sơn (huyện Lương Sơn cũ), tỉnh Phú Thọ từ năm 2014 đến 2024, sử dụng dữ liệu ảnh Landsat 8/9 phân loại bằng thuật toán Random Forest trên Google Earth Engine. Kết quả phân loại đạt độ chính xác tổng thể 83,31% với hệ số Kappa là 0,7900 cho năm 2014, và 86,48% với hệ số Kappa là 0,8294 cho năm 2024, cho thấy độ tin cậy cao của các bản đồ lớp phủ mặt đất ở cả hai thời điểm nghiên cứu. Kết quả phân tích ma trận chuyển đổi qua ArcGIS cho thấy diện tích đất cây lâu năm (CLN) tăng 7,4% lên 23.844,38 ha, đất công trình xây dựng (CTXD) tăng mạnh 22,1% lên 5.841,87 ha phản ánh đô thị hóa, đất mặt nước (MN) tăng 13,8% lên 937,35 ha do phát triển thủy lợi, trong khi đất cây hàng năm (CHN) giảm nhẹ 3,7% xuống 5.000,85 ha và đất trống (ĐT) giảm 74,5%

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Từ khóa:

Biến động lớp phủ mặt đất, GIS, Landsat 8/9, mô hình Markov, Random Forest, tỉnh Phú Thọ.

còn 898,35 ha, thể hiện tái cấu trúc sử dụng đất bền vững. Dự báo mô hình Markov đến năm 2034 dự kiến CTXD tăng thêm 11,7% lên 6.527,89 ha, CLN tăng 2,1% đạt 23.360,78 ha, CHN giảm 4,3% còn 4.787,37 ha, MN tăng 9,0% lên 1.021,84 ha và ĐT giảm 8,2% xuống 824,92 ha, cung cấp cơ sở khoa học cho quy hoạch đất đai tại Phú Thọ và nhấn mạnh tiềm năng tích hợp GIS-viễn thám trong quản lý tài nguyên, với khuyến nghị mở rộng dữ liệu Sentinel cho phân tích đa thời gian.

1. INTRODUCTION

Research on land cover change provides an essential basis for developing appropriate strategies for effective and sustainable land management and use [1, 2]. This is a complex process influenced by multiple groups of various factors, ranging from natural characteristics to socio-economic drivers [3]. Specifically, land cover changes reflect both the natural conditions and the socio-economic context of a given area [4, 5]. Understanding land use and land cover (LULC) and their associated impacts is a prerequisite for effective natural resource planning and management [6, 7]. Over recent decades, industrialization, urbanization, and rapid population growth in developing countries have exerted substantial pressure on land resources [8]. This has resulted in significant transformations among different land cover types, including agricultural land, forest land, and urban land. Such changes pose considerable challenges to land resource management and sustainable development [9, 10].

In this context, analyzing the causes, trends, and spatial extent of land cover change is essential to support land cover planning and management at different administrative levels. This issue is particularly critical in developing countries such as Vietnam. In Phu Tho province, rapid urbanization following recent administrative mergers has led to significant changes in land cover in several areas. Land cover change maps provide a clear visualization of spatial and temporal dynamics, serving as a foundation for formulating rational land cover strategies aligned with sustainable economic, social, and environmental development goals. Moreover, monitoring land cover changes enables the identification of land cover practices that do not comply with approved planning schemes, thereby supporting management agencies in adjusting policies and allocating resources more effectively [11].

The integration of remote sensing data and Geographic Information Systems (GIS) is widely

regarded as an effective approach for land cover change analysis [12, 13]. Remote sensing offers multi-temporal and large-scale data, while GIS facilitates detailed and intuitive spatial analysis. In recent years, several cloud computing platforms have been implemented, offering on-demand technical infrastructure, storage services, software packages, and computing power to handle large volumes of data processing and calculations [14]. In addition, machine learning algorithms such as Random Forest have demonstrated strong capabilities in improving image classification accuracy [15], whereas the Cellular Automata – Markov model supports the prediction of land cover change trends over time [4].

Previous studies in the former Luong Son District, including Nguyen Thi Bich et al. (2019), primarily applied Maximum Likelihood classification and focused mainly on agricultural land use change. While these studies provided useful historical insights, they were limited to traditional parametric classification methods and did not comprehensively assess the dynamics of all land cover classes. In addition, analyses were conducted under the former district-level administrative framework and prior to the 2025 administrative merger.

Random Forest, as a non-parametric machine learning algorithm, offers higher robustness in handling spectral heterogeneity and nonlinear relationships compared with Maximum Likelihood. However, its application for integrated land cover assessment within the newly established commune boundaries has not yet been implemented. To date, no study has systematically evaluated post-merger land cover dynamics across all land cover categories within this new administrative configuration.

Therefore, a clear research gap exists in developing an updated, machine-learning-based land cover assessment aligned with the current governance structure. This study

addresses that gap by applying GEE-based Random Forest classification to comprehensively evaluate land cover change within the newly consolidated communes.

2. RESEARCH METHODS

2.1. Study Area

The study area comprises Luong Son, Cao Duong, and Lien Son communes, which were formed through the recent administrative reorganization of the former Luong Son district in Hoa Binh province and are currently under the jurisdiction of Phu Tho province according to regulations implemented in 2025. The geographical location of these communes serves as an important linkage between provinces in the Northeast, the Northern Delta, and the Northwest regions of Vietnam, thereby creating favorable conditions for comprehensive socio-

economic development, particularly in transportation, trade, and tourism.

The total natural land area of the study region is 36,482.72 ha. According to the statistical report of the Luong Son District People’s Committee, the current land-use structure of the study area is dominated by agricultural land, covering 29,763.96 ha and accounting for 81.58% of the total natural area. This is followed by non-agricultural land, which occupies 5,885.20 ha (16.13%), while unused land covers 833.56 ha, representing 2.28% of the total area and highlight the substantial land resources available for agricultural activities and sustainable development (Figure 1). At the same time, they emphasize the necessity of assessing land cover changes across the study area [16].

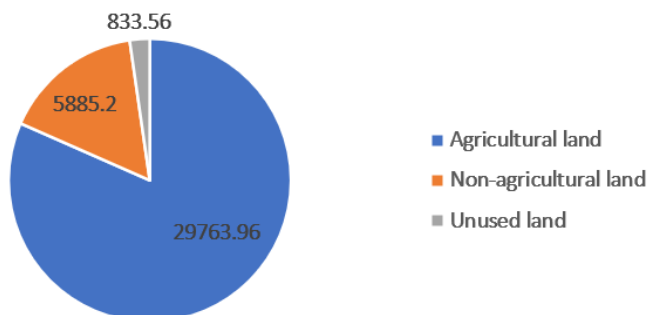


Figure 1. Land cover structure of Luong Son district in 2024

2.2. Data Collection

Secondary documents and datasets were collected from official and reliable sources to ensure data currency, accuracy, and representativeness for the study area. The main data sources included: (i) the 2024 report on natural conditions and socio-economic

characteristics of the study area; (ii) land cover status quo map (2014); (iii) Landsat 8 and Landsat 9 remote sensing images for the years 2014 and 2024 (Table 1), used for land cover change analysis; and (iv) relevant scientific studies and publications to strengthen the theoretical foundation of the research.

Table 1. Remote sensing image information of the study area

No.	Image ID	Acquisition date	Path/Row	Spatial resolution
1	LC08_L2SP_127045_20140119_20200912_02_T1	19/01/2014	127/045	30m
2	LC09_L2SP_127045_20240428_20240501_02_T1	28/04/2024	127/045	30m

Source: <https://earthexplorer.usgs.gov/> [17]

2.3. Remote Sensing Method

This study employed remote sensing techniques to generate land cover maps for the 2014 -2024 period with the support of Google Earth Engine (GEE), a cloud-based platform for large-scale geospatial data analysis. Two satellite images were used, including Landsat 8

acquired on 19 January 2014 and Landsat 9 acquired on 28 April 2024, both with a path/row of 127/045 and a spatial resolution of 30 m, obtained from the United States Geological Survey (USGS). All images were referenced to the WGS 84 coordinate system using the UTM Zone 48N projection.

The satellite images were selected based on optimal quality criteria, including minimal noise, high radiometric quality, and low cloud cover (<10%). Pre-processing steps included image clipping to the administrative boundaries of the study area, image quality enhancement through atmospheric correction using the `ee.Algorithms.Landsat.LA_SR` function, and false-color composite generation using the SWIR–NIR–RED band combination (Bands 6-5-4 for Landsat 8/9).

Based on visual interpretation factors such as color, texture, and spectral reflectance characteristics, combined with the SWIR–NIR–RED band composite (Bands 6-5-4), the study developed an interpretation key for five land cover classes: perennial crops (CLN), annual crops (CHN), built-up areas (CTXD), water bodies (MN), and bare land (DT). A total of 300 sample points were generated for these land cover classes. The sample dataset was randomly and independently divided into two subsets: Group 1, comprising 70% of the total samples, was used for satellite image classification, while Group 2, accounting for the remaining 30%, was used for post-classification accuracy assessment.

This study employed the Random Forest (RF) machine learning algorithm to classify land cover types from Landsat 8 and Landsat 9 imagery. The classification was implemented on the GEE cloud-computing platform using the JavaScript programming language. The input dataset comprised all seven Landsat spectral bands (Bands 1 - 7), complemented by two spectral indices, namely the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Water Index (NDWI), both derived using the *normalizedDifference* function. The inclusion of these spectral indices aimed to enhance class separability and improve classification performance. Specifically, NDVI was employed to characterize vegetation vigor and density, thereby facilitating the discrimination between perennial cropland, annual cropland, and non-vegetated surfaces. Meanwhile, NDWI was used to improve the identification of surface water bodies by emphasizing moisture content and reducing the influence of built-up areas. The integration of multi-band spectral

information with spectral indices provided a more comprehensive representation of land surface characteristics, thereby enhancing the robustness and reliability of the Random Forest classification.

The number of trees in the Random Forest classifier was set to five (`numberOfTrees = 5`). This value was determined based on preliminary experiments indicating that classification accuracy stabilized with a relatively small number of trees, given the limited number of land cover classes and the use of informative input features, including multispectral Landsat bands and spectral indices (NDVI and NDWI). Accordingly, five trees were selected to achieve an optimal balance between classification performance, computational efficiency, and model stability.

Classification accuracy was evaluated using two indicators: overall accuracy and the Kappa (κ) coefficient. Kappa analysis is a discrete multivariate statistical technique widely used for accuracy assessment. The κ coefficient ranges from 0 to 1, where values ≥ 0.8 indicate high classification reliability, values between 0.4 and < 0.8 indicate moderate reliability, and values < 0.4 indicate low reliability. To assess classification accuracy, a confusion matrix was generated using the *confusionMatrix()* function, resulting in a 5×5 error matrix corresponding to the five land cover classes.

2.4. GIS method

The land cover classification results generated in GEE were exported in raster format and subsequently converted into vector format (*.shp) using ArcGIS software for editing and the production of land cover maps for 2014 and 2024. Land cover change maps for the 2014-2024 period were developed by overlaying the land cover maps from 2014 and 2024, enabling the identification and analysis of spatial and temporal changes within the study area.

2.5. Land Cover Change Prediction Method

This study applied the CA-Markov model, which integrates Cellular Automata with Markov Chain analysis, to predict land cover changes up to the year 2034 based on the transition probability matrix derived from the 2014-2024 period. The Markov Chain approach was then employed to evaluate the magnitude

and direction of land cover transitions and to project future land cover dynamics for the study area in 2034.

The areas of land cover change were exported from ArcGIS to Microsoft Excel to serve as the basis for quantitative analysis and

interpretation of land cover change projections.

Based on the aforementioned research methods, the overall research framework can be summarized and illustrated in the research flowchart presented in Figure 2.

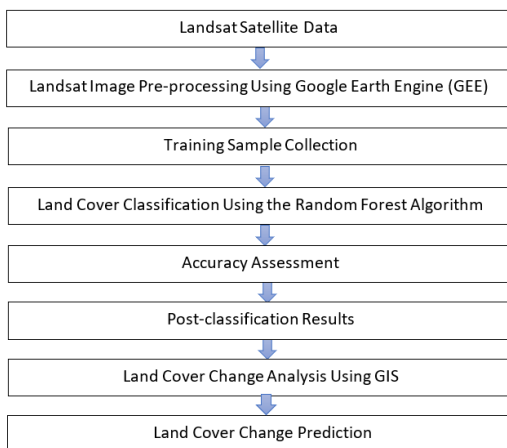


Figure 2. Methodological Flowchart

3. RESULTS AND DISCUSSION

3.2. Land cover classification and accuracy Assessment

After developing the image interpretation key and selecting training samples from satellite imagery, the study applied the Random Forest classification algorithm available in the Google Earth Engine (GEE) library, using the ee.Classifier.smileRandomForest(numberOfTrees) function. The number of decision trees (numberOfTrees) was optimized based on the number of target land cover classes.

The classification process was conducted on

a randomly partitioned sample dataset, in which 70% of the samples were assigned to the training set (Group 1). Satellite image classification was efficiently performed on the GEE platform, focusing on five main land cover classes: perennial crops (CLN, ID=1), built-up areas (CTXD, ID=2), annual crops (CHN, ID=3), water bodies (MN, ID = 4), and bare land (DT, ID = 5).

The classification results clearly captured land cover changes during the 2014-2024 period. The classified land cover maps for the two study years are illustrated in Figure 3 (2014) and Figure 4 (2024).

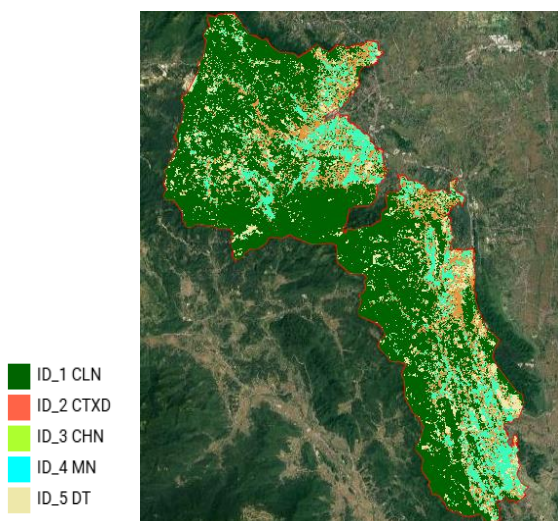


Figure 3. Land cover classification map in 2014

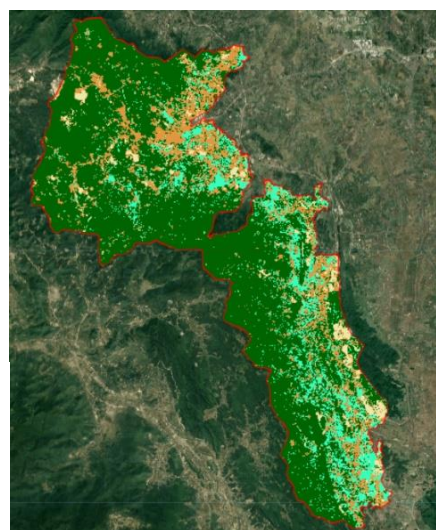


Figure 4. Land cover classification map in 2024

To evaluate the classification accuracy, this study employed a 5×5 confusion matrix implemented in Google Earth Engine (GEE) using the *confusionMatrix()* function. Independent validation points were collected

from field survey data and satellite imagery to ensure objectivity and representativeness for each land cover class. The accuracy assessment results for the two study periods are presented in Table 2 (2014) and Table 3 (2024).

Table 2. Accuracy assessment of the 2014 image classification results

Land-use type	(1)	(2)	(3)	(4)	(5)	Row total (pixels)	User's accuracy (%)
Perennial cropland (1)	610	56	18	0	28	712	85.67
Built-up land (2)	53	494	8	48	68	671	73.62
Annual cropland (3)	36	11	659	0	46	752	87.63
Water bodies (4)	0	0	58	381	3	442	86.20
Bare land (5)	2	82	15	0	512	611	83.80
Column total (pixels)	701	643	758	429	657	3188	
Producer's accuracy (%)	87.02	76.83	86.94	88.81	77.93		
Overall accuracy						83.31%	
Kappa coefficient						0.7900	

Table 3. Accuracy assessment of the 2024 image classification results.

Land-use type	(1)	(2)	(3)	(4)	(5)	Row total (pixels)	User's accuracy (%)
Perennial cropland (1)	752	41	22	5	37	857	87.75
Built-up land (2)	62	823	18	24	59	986	83.47
Annual cropland (3)	32	25	712	8	45	822	86.62
Water bodies (4)	12	0	36	451	3	502	89.94
Bare land (5)	7	45	26	20	632	730	86.58
Column total (pixels)	865	934	814	508	776	3897	
Producer's accuracy (%)	86.94	88.11	87.47	88.78	81.44		
Overall accuracy						86.48%	
Kappa coefficient						0.8294	

Based on Table 2, the overall classification accuracy for 2014 reached a relatively high level (83.31%), indicating that more than 83% of the validation points were correctly classified. The Kappa coefficient was 0.79, reflecting a strong agreement between the classification results and reference data after excluding random agreement.

In terms of class-specific accuracy, the water bodies and annual cropland classes achieved the highest values, with both producer's and user's accuracies exceeding 86%, demonstrating clear class separability due to their distinct spectral characteristics. In contrast, the built-up land class exhibited the

lowest user's accuracy (73.62%). Among the classified land-cover categories, built-up land (CTXD) exhibited the lowest classification accuracy, mainly due to spectral confusion with bare land, sparsely vegetated areas, and agricultural land during post-harvest periods. In addition, the heterogeneous spatial structure of built-up areas in the study region - characterized by small, fragmented settlements interspersed with agricultural land - combined with the 30 m spatial resolution of Landsat imagery, increases mixed-pixel effects and classification uncertainty. To overcome these limitations, future studies should consider incorporating urban-specific spectral

indices, such as the Normalized Difference Built-up Index (NDBI), and integrating higher spatial resolution satellite data, particularly Sentinel-2 imagery, to enhance the discrimination of built-up land in complex landscapes.

Overall, these results provide sufficient reliability for subsequent analysis of land cover change in 2014.

For 2024, Table 3 indicates that the overall classification accuracy increased to a high level (86.48%), confirming that more than 86% of the validation points were correctly classified. The Kappa coefficient reached 0.8294, falling within the “very good” range (0.80 - 0.90), which demonstrates strong agreement between the classification results and the reference data, independent of random effects.

The water bodies and perennial cropland

classes continued to exhibit high accuracy levels (above 87%), while the built-up land class showed a substantial improvement, with a user’s accuracy of 83.47%. This improvement may be attributed to the enhanced quality of more recent satellite data. These results not only confirm the reliability of the classification model but also provide strong support for subsequent land cover change analysis in the study.

3.3. Land Cover Mapping for 2014 and 2024

The classification outputs were exported in shapefile format (*.shp) and imported into ArcGIS software for map editing, topology error checking, and vector data integration, resulting in finalized land cover maps (Figure 5 and Figure 6). These maps depict the spatial distribution of land cover types across the study area and serve as a fundamental basis for subsequent land cover change analysis.

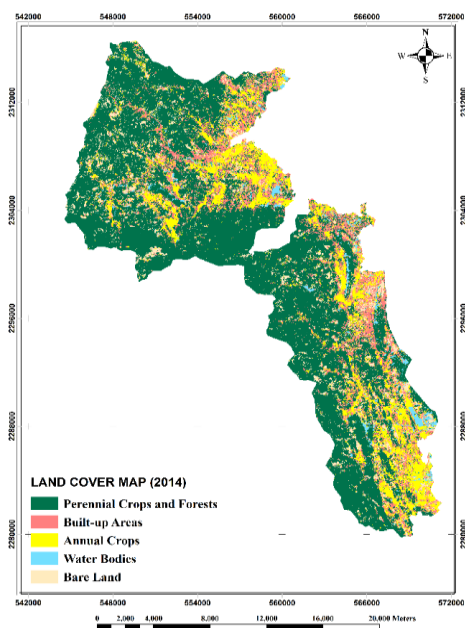


Figure 5. Land cover map for 2014

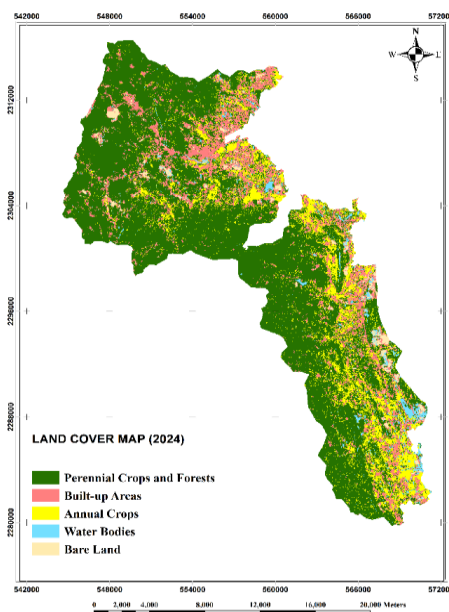


Figure 6. Land cover map for 2024

3.4. Assessment of Land Cover Change during the 2014-2024 Period

Based on the classified land cover maps for the two reference years, 2014 and 2024, land cover changes in the study area were assessed using a bi-temporal comparison approach. In this study, the two selected years represent

discrete time points that characterize land cover conditions at the beginning and end of the 2014 - 2024 period, thereby allowing the identification of dominant change trends over the decade rather than continuous annual dynamics. The resulting land cover change map for the 2014 - 2024 period (Figure 7).

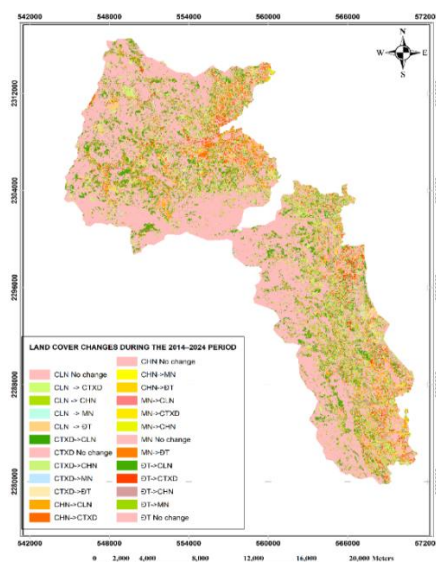


Figure 7. Land cover change map for the 2014–2024 period.

During the 2014 - 2024 period, land cover in Luong Son, Cao Duong, and Lien Son communes (formerly part of Luong Son district) in Phu Tho province experienced notable changes, reflecting local socio-economic development, including urbanization, agricultural expansion, and improvements in

land resource management. Land cover transitions were summarized in the form of a land-use transition matrix (Table 4), indicating that while the total study area remained stable at 36,522.8 ha, the land cover structure underwent significant redistribution.

Table 4. Land cover transition matrix for 2014-2024

Unit: ha

Land cover	Area in 2024					Total
	CLN	CTXD	CHN	MN	DT	
CLN	19,910.60	1,450.79	493.60	190.44	154.43	22,199.86
CTXD	276.06	3,520.77	246.36	398.28	343.10	4,784.57
CHN	805.33	575.87	3,638.67	81.32	89.01	5,190.20
MN	153.09	46.35	330.64	209.01	84.83	823.92
DT	2,699.30	248.09	291.58	58.30	226.98	3,524.25
Total	23,844.38	5,841.87	5,000.85	937.35	898.35	36,522.80

Analysis of the land cover transition matrix for the 2014-2024 period indicates a sustainable transformation of the land cover structure in the study area. Bare land experienced a substantial decrease of 74.5%, declining from 3,524.25 ha to 898.35 ha, primarily converting into perennial cropland (2,699.30 ha) and built-up land (248.09 ha). This trend reflects efforts to improve land-use efficiency and reduce land resource wastage.

At the same time, perennial cropland increased by 7.4%, from 22,199.86 ha to 23,844.38 ha, mainly originating from bare land, annual cropland (805.33 ha), and water bodies (153.09 ha). This pattern is consistent with the ongoing shift toward high-value perennial crops in agricultural restructuring.

Built-up land exhibited the most pronounced change, increasing by 22.1% from 4,784.57 ha to 5,841.87 ha. This expansion was largely derived from perennial cropland (1,450.79 ha), annual cropland (575.87 ha), and bare land, highlighting rapid urbanization and infrastructure development aligned with local socio-economic growth.

Annual cropland showed a slight decrease of 3.7%, from 5,190.20 ha to 5,000.85 ha, mainly due to conversion to perennial cropland and built-up land, suggesting relatively low economic efficiency of certain annual crops. In contrast, water bodies increased by 13.8%, from 823.92 ha to 937.35 ha, primarily originating from built-up land (398.28 ha) and perennial cropland (190.44 ha). This increase

may be attributed to the construction of irrigation facilities, aquaculture ponds, as well as natural changes or seasonal effects inherent in remote sensing data.

The land cover changes observed during the 2014 - 2024 period clearly reflect the impacts of socio-economic development and land - use policies in Phu Tho Province and are generally consistent with the land-use planning orientation for the study area during the 2021 - 2030 period. The substantial expansion of built - up land indicates a rapid urbanization process, closely associated with the expansion of residential areas, increased investment in transportation infrastructure, and the development of public service facilities. The conversion of agricultural land and bare land into built-up areas reflects the growing demand for land, driven by population growth and economic development.

In addition, the increase in perennial cropland aligns with agricultural restructuring policies that promote high-value crops and improve land - cover efficiency. In contrast, the decline in annual cropland suggests a gradual shift away from low - efficiency farming practices. Meanwhile, the significant reduction in bare land highlights improvements in land management and land allocation, contributing to the more efficient utilization of previously underused land resources.

The overall classification accuracy achieved

in this study (83 - 86%) is comparable to, or higher than, that reported in previous studies conducted in geographically similar regions. For instance, Nguyen Thi Bich et al. (2019), in a study of Luong Son district (Hoa Binh province) using Landsat imagery and the Maximum Likelihood Classification method, reported Kappa coefficients of 0.68 for 2008 and 0.72 for 2018. Although the classification accuracy in the earlier study was slightly lower, the observed land cover change trends - particularly the expansion of built-up land and perennial cropland, along with the reduction of unused land - show a high level of consistency. This agreement further reinforces the reliability of the land cover change results identified in the present study.

3.5. Prediction of land cover change

Based on the analysis of land cover changes during the 2014 - 2024 period, this study applied the Markov Chain model to predict land cover change trends up to 2034. The model is grounded in transition probability theory, using the historical transition matrix as input to simulate future scenarios. This approach aims to support sustainable land management, resource allocation, and policy planning in Phu Tho Province. The prediction results enable the identification of areas with a high likelihood of land cover conversion, thereby facilitating timely and targeted management interventions.

Table 5. Land cover change probability matrix

	CLN	CTXD	CHN	MN	DT
CLN	0.897	0.065	0.022	0.009	0.007
CTXD	0.058	0.736	0.051	0.083	0.072
CHN	0.155	0.111	0.701	0.016	0.017
MN	0.186	0.056	0.401	0.254	0.103
DT	0.766	0.070	0.083	0.017	0.064

The transition probability matrix (Table 5), constructed from land cover data for the 2014-2024 period, reflects both the stability and the conversion potential among different land cover types. The main diagonal values (e.g., 0.897 for perennial crops - CLN) indicate a relatively high level of stability for certain land categories, whereas the off-diagonal values reveal dominant conversion pathways, such as the transformation from bare land (DT) to

perennial crops (CLN) with a probability of 0.766. Using this matrix as the transition matrix, the Markov model was applied by treating 2014 and 2024 as two discrete reference time points representing the 2014–2024 interval. Assuming that the transition probabilities remain constant, the model was subsequently used to project land cover distribution for 2034, as presented in Table 6.

Table 6. Projected areas of land cover classes in 2034

No.	<i>Unit: ha</i>				
	CLN	CTXD	CHN	MN	DT
1	21,385.54	1,558.26	530.16	204.55	165.87
2	337.06	4,298.79	300.80	486.29	418.92
3	775.95	554.86	3,505.92	78.35	85.76
4	174.17	52.73	376.16	237.78	96.51
5	688.07	63.24	74.33	14.86	57.86
Total	23,360.78	6,527.89	4,787.37	1,021.84	824.92

The Markov model projection to 2034 indicates that land cover in the study area will continue to be restructured in a sustainable direction. Built-up land (CTXD) is projected to increase substantially by 11.7%, reaching 6,527.89 ha, mainly through the conversion of perennial cropland (CLN) and annual cropland (CHN), reflecting growing demands for residential areas, commercial-service activities, and transportation infrastructure driven by urbanization. Perennial cropland is expected to increase slightly by 2.1% to 23,360.78 ha, reinforcing its role as the backbone of local agriculture. In contrast, annual cropland is projected to decline by 4.3% to 4,787.37 ha, indicating a shift toward more efficient land cover patterns. Water bodies (MN) are forecast to expand by 9.0%, reaching 1,021.84 ha, supporting the development of irrigation systems and aquaculture activities, while bare land (DT) is expected to continue decreasing by 8.2% to 824.92 ha, in line with policies promoting optimal land resource utilization.

The land cover changes projected to 2034 reveal important implications for sustainable land management in the study area. The continued expansion of built-up land underscores the need for effective spatial planning to prevent excessive conversion of agricultural land and to ensure balanced urban development. At the same time, the projected increase in perennial cropland supports the long-term sustainability of agricultural production but also requires careful management to avoid encroachment into environmentally sensitive areas.

The decline in bare land and annual cropland reflects a positive trend toward land-use optimization. However, proactive land-use policies are essential to ensure food security, protect natural resources, and mitigate potential environmental impacts associated

with rapid urbanization. These findings provide an important scientific basis for local authorities to develop adaptive land-use strategies aligned with sustainable development goals.

4. CONCLUSION

This study successfully applied GIS and remote sensing techniques to assess land cover change in Luong Son, Cao Duong, and Lien Son communes (former Luong Son district), Phu Tho province, using Landsat 8 imagery (2014) and Landsat 9 imagery (2024). Land cover classification was conducted based on the integration of satellite data, existing land cover maps, and Google Earth Pro to construct interpretation samples for five main land cover types: perennial cropland (CLN), built-up land (CTXD), annual cropland (CHN), water bodies (MN), and bare land (DT).

Satellite image classification using the Random Forest algorithm on the Google Earth Engine (GEE) platform achieved high accuracy, with overall accuracies of 83.31% (Kappa = 0.7900) for 2014 and 86.48% (Kappa = 0.8294) for 2024. These results confirm the feasibility and reliability of the proposed approach for land cover monitoring and environmental assessment.

The land cover analysis reveals clear and consistent transformation trends in the study area over the past decade, characterized by rapid urban expansion, structural shifts in agricultural land use, and a continuous reduction of unused land. Built-up areas have expanded significantly, reflecting accelerated urbanization and infrastructure development, while agricultural land has undergone reorganization toward more stable and economically efficient land-use types. The progressive decline of bare land indicates improved land management and more effective utilization of available land resources.

Projections to 2034 suggest that these trends

are likely to persist, underscoring the need for proactive and sustainable land-use planning to balance urban growth with agricultural protection and environmental conservation. In this context, the integration of Google Earth Engine with the CA–Markov model demonstrates clear added value for local-scale land-use monitoring and forecasting. Compared to traditional approaches, this integrated framework enables efficient multi-temporal analysis, improves classification consistency, and provides reliable spatial simulations to support evidence-based decision - making.

Despite the robust performance of the integrated GEE–Random Forest and CA–Markov framework, several limitations should be acknowledged. First, the analysis was based on bi-temporal Landsat imagery with a spatial resolution of 30 m, which may introduce mixed-pixel effects and limit the detection of fine-scale land cover heterogeneity. Second, the Markov model assumes that transition probabilities remain constant over time, which may not fully capture unexpected socio-economic or policy-driven changes. Third, the number of training samples and the relatively small number of decision trees in the Random Forest classifier may affect classification generalization under more complex landscape conditions. Future research should incorporate higher spatial resolution data (e.g., Sentinel-2), multi-temporal time-series analysis, and advanced machine learning or deep learning approaches to enhance classification precision and improve the robustness of land cover change simulations under dynamic development scenarios.

Overall, these findings provide a solid scientific basis for land-use planning in Phu Tho Province and highlight the strong potential of integrated GIS and remote sensing approaches for natural resource management. Future studies should focus on multi-temporal analyses and the integration of Sentinel data to enhance spatial resolution and improve predictive accuracy.

REFERENCES

[1]. Braimoh Ademola K. & Osaki M. (2010). Land-use change and environmental sustainability. *Sustainability Science*. 5: 5-7.
[2]. Van Niekerk, A. & Musakwa, W. (2013). Implications of land use change for the sustainability of urban areas: A case study of Stellenbosch, South Africa.

Cities. 32: 143 - 152.

[3]. Srivastava, P., & Chinnasamy, A. (2021). Water management using traditional tankcascade systems: a case study of semi-arid region of Southern India. *SN Applied Sciences*. 3(3): 1–23.

[4]. Nguyen, T. B., Nguyen, T. H., Le, H. C., Tran, T. T., Nguyen, T. O., & Bui, T. C. (2019). Application of GIS and remote sensing to assess changes in agricultural land use in Luong Son district, Hoa Binh province during 2008 - 2018. *Journal of Agriculture and Rural Development*. 142: 142–149.

[5]. J. S. Rawat, & Kumar, M (2015). Monitoring land use/cover change using remote sensing and GIS techniques: A case study of Hawalbagh block, district Almora, Uttarakhand, India. *The Egyptian Journal of Remote Sensing and Space Science*. 18(1): 77-84.

[6]. S. Gull, Shah, S. R., & Dar, A. M. (2022). Assessing land use/land cover change detection of north-eastern watersheds of Kashmir valley using GIS and remote sensing techniques. *Water Practice & Technology*. 17(8): 1603-1614.

[7]. G. Meraj, Kanga, S., Kranjčić, N., Durin, B. & Singh, S. K. (2021). Role of natural capital economics for sustainable management of earth resources. *Earth*. 2(3): 622–634.

[8]. Nguyen, T. T. N., Trinh, L. H., Vu, D. T., & Bui, T. P. (2017). Assessment and prediction of urban land change in the inner area of Hanoi using remote sensing data and GIS. *Journal of Science*. 14(3): 176 - 187.

[9]. Duong, T. L. (2023). Application of remote sensing and GIS in assessing land use change in Dan Phuong district, Hanoi city. *Journal of Science*. 68(1): 118 - 128.

[10]. Nguyen, H. H., & Nguyen, V. Q. (2017). Using Landsat remote sensing imagery and GIS to map forest area changes in the buffer zone of Xuan Son National Park. *Journal of Forestry Science and Technology*. 3: 46 - 56.

[11]. Vo, M. Q., Pham, H. T., & Nguyen, N. T. (2021). Assessment of land cover change using remote sensing data in Le Thuy district, Quang Binh province during 2010 - 2020. *Hue University Journal of Science: Agriculture and Rural Development*. 130(3D): 183 - 202.

[12]. Pham, T. L., Le, T. T. H., & Nguyen, T. Q. (2014). Assessment and prediction of land use change in the Ba Lat estuary area based on multi-temporal remote sensing data and GIS. *Journal of Mining and Geology*. 48: 13 - 19.

[13]. Pham, V. T., Nguyen, T. T. H., & Nguyen, K. T. (2014). Assessment of land use/land cover change in Tien Yen district, Quang Ninh province during 2000–2010. *Journal of Science and Development*. 12(1): 43 - 51.

[14]. B. Alshehri, Zhang, Z., & Liu, X. (2025). A review of Google Earth Engine for land use and land cover change analysis: Trends, applications, and challenges. *ISPRS International Journal of Geo-Information*. 14(11): 416.

[15]. Breiman L. (2001). Random Forests. *Machine Learning Journal Paper*. 45(1): 5-32.

[16]. People’s Committee of Luong Son District (2025). Comprehensive explanatory report on the 2025 land use plan of Luong Son district. Luong Son District People’s Committee, Hoa Binh province.

[17]. United States Geological Survey (USGS). <https://earthexplorer.usgs.gov/> [Online].