RESEARCH AND APPLICATION OF REMOTE SENSING AND GIS TECHNOLOGIES IN DETERMINING AND FORECASTING LAND USE CHANGES BY MARKOV CHAIN IN Y YEN DISTRICT - NAM DINH PROVINCE

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Abstract

The land's natural resources are invaluable and a requisite for the existence and development of humans and other organisms on Earth. In recent years, under the strong impact of new directions in economic and social development, the demand for land has been increasing. The percentage of land used for residential living, transportation, irrigation and infrastructure tends to increase, while the share of agricultural land is continuously decreasing. Consequently, the allocation and efficient use of land is one of the most important concerns in order to enable sustainable development, environmental protection and ecology. Therefore, research to determine the volatility and changing trends in land use is necessary. This study uses remote sensing and GIS technology, combined with the Markov Chain to determine variation and forecast the changes in land use in the Y Yen district of the Nam Dinh province of Vietnam. This will create a basis for helping land managers grasp the situation in local land use management.

Keywords: ErDAS, GIS, MARKOV CHAIN, Remote Sensing, Land, Land use change.

JEL Classification: R14

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1. Introduction

Determining the volatility and trends in land use is a pressing problem that has arisen in consequence of the intense development process of Vietnam. Currently, information technology is continuously developing, facilitating the solving of complex social economic problems of the country in general,

and land management sectors in particular. Remote sensing technology brings us sources of information and data from satellite images of increasing resolution, a large number of spectral channels, short iteration cycles and vast space cover, faithfully reflecting the Earth's surface at the time of shooting. In addition, combined with the high processing capabilities and powerful data analysis of GIS technology, it creates a useful tool for studying the volatilities and management of land resources. Moreover, the support of the Markov Chain can be useful in the basic assessment of trends in land use. This new method adopted by many of technologically advanced countries in the world, provides better efficiency as compared to traditional methods, allowing for managing and updating revised land information in a quickly and timely manner.

The Y Yen district in Nam Dinh Province has a total natural land area of 24,129.74 hectares (2013). In recent years, under the strong impact of the new directions in economic and social development, the demand for land used for residential purposes, transportation, irrigation, and infrastructure has had a tendency to increase, with the opposite holding true for agricultural land. Therefore, the suitable allocation and efficient use of land are major issues that the government and local authorities must cope with. In light of the above, we have conducted a study on: Research and applications of remote sensing and GIS technologies in determining volatility and forecasting the changes in land use by Markov Chain in Y Yen district - Nam Dinh province.

2. Research methodology

2.1. Method of supervised classification

The method of supervised classification is one in which the classification criteria are established based on the sample area, and decisions are made based on appropriate algorithms to label each pixel corresponding to a specific land use. The sample areas are the regions of the image corresponding to each kind of land use that people know the spectral characteristics of. Based on data collected in each sample area, statistical parameters are determined. Then, the classification criteria are used in the process of appointing the pixels to particular categories (Asian Association on Remote Sensing 2014).

Fig. 1: Method of supervised classification. Sources: NGUYEN KHAC THOI et al. (2011).

In this study, the method of supervised classification according to the algorithm of maximum likelihood was chosen to categorize the image (maximum likelihood) (NORRIS 1998):

$$g_i(x) = \ln p(\omega_i) - \frac{1}{2} \ln |Z_i| - \frac{1}{2} (x - m_i)^T \Sigma_i^{-1} (x - m_i) \quad (1)$$

where:

- i - object of classification,
- x - number of spectral channels,
- $p(\omega_i)$ - probability value occurring when object ω_i is the same as the others,
- $|Z_i|$ - covariance matrix of object ω_i ,
- Σ_{i-1} - inverse matrix of object ω_i ,
- m_i - values of changing spectral vector.

Classification by means of the maximum likelihood method assuming that the statistics of each class in each image channel is dispersed in a normal way, with the method taking into account the possibility of a pixel belonging to a certain class to increase the differences between the land uses. If a probability threshold is not chosen, it must classify all pixels. Each pixel is assigned to the class with the highest probability. By this method, the spectral channels follow normal distribution and the pixels are classified in the class that has the highest probability. This is the most accurate method of classification, but it takes time to calculate and relies on the normal distribution of data. The method comprises the following steps (RICHARDS 1999):

- Identify the types: Because Satellite image data always factually and objectively reflects the surface of the Earth at the time of shooting, this results in a land use map. In order to construct a training set, it is first necessary to determine the type of land use in the study area.
- Selection of features: The features here include spectral and structural features. This selection is very important as it makes it possible to distinguish the object classes.
- Selection of the sample areas: The selection of sample areas is crucial to the classification results.

To ensure accuracy in choosing appropriate sample areas, attention should be paid to the following requirements:

- The number of the sample areas for each type of object must be appropriate. Too few sample areas will not guarantee accuracy, whereas too many sample areas will increase the volume of calculations, sometimes distorting their results,
- The area of the sample should be sufficiently large, and not located near the border between different object classes,
- The selected sample should be presented for the classified object and evenly distributed across the study area,
- Calculation of sample statistical indicators: After choosing the sample, it is necessary to calculate the statistical indicators and the difference between samples (WANG et al. 2009).

Assessing the precision of the sample file: each classification sample will be calculated to compare the difference with the remaining samples.

Assessing the accuracy of the image classification: The accuracy of the image classification depends not only on the accuracy of the sample areas, but also on the density and the distribution of sample plots. The nature of the errors made during the classification process is assessed based on the Kappa (κ) index. This index ranges from 0 to 1, indicating the proportional reduction in error, and is performed by completely random classification (CHUVIECO 2016).

$$\kappa = \frac{N \sum_{i=1}^r x_{ii} - \sum_{i=1}^r (x_{i+} \cdot x_{+i})}{N^2 - \sum_{i=1}^r (x_{i+} \cdot x_{+i})} \quad (2)$$

where:

- N - total number of sampling points,
- r - the number of classified object classes,
- x_{ii} - number of actual sampling points in the 1st class,
- x_{i+} - total number of points in the i^{th} class of the sample,
- x_{+i} - total number of points in the i^{th} class after classification.

2.2. Method of determining the volatility of land use by comparison after classification

The nature of this approach is that we obtain two maps of land use from the results of image classification at two different times. We then overlay these two maps of land use to build the volatility map (Figure 2). These maps can take the form of raster or vector maps.

The comparison method after classification is the most widely used method, as it is very simple, and easy to understand and implement. After the 2 satellite images are geometrically corrected, independent classification will be implemented to build two land use maps. These two maps are overlaid by comparing pixels to form a volatile matrix (CROSETTO, MROZ 1998).

According to J. Jensen, the advantage of this method is that it shows any kind of change from one kind of land use to others; its disadvantage is that classification has to be carried out independent of remote sensing images. Therefore, its precision depends on the accuracy of each kind of classification

and is normally not very high because errors in the classification of each photo continue to remain in the volatile map (JENSEN 1996; PONTIUS, PETROVA 2010).

Fig. 2. Comparison method after classification. Sources: own study.

2.3. Method of determining the trend in land use changes by Markov Chain

Using the Markov Chain forecasts trends in changes of land use over a certain period of time. The Markov Chain model is used to determine the ability to change land use based on its evolution and the factors affecting such change. General modeling is as follows:

$$\left(\begin{matrix} \text{The proportion of} \\ \text{land use in the} \\ \text{1st period} \end{matrix} \right) \times \left(\begin{matrix} \text{Matrix of change} \\ \text{in land use between} \\ \text{the 1st and 2nd period} \end{matrix} \right) = \left(\begin{matrix} \text{The proportion of} \\ \text{land use types} \\ \text{in the 2nd period} \end{matrix} \right)$$

and can be rewritten as a generalization of the matrix (NORRIS 1998):

$$[V1, V2, V3]_1 \times \begin{bmatrix} Y_{11} & Y_{12} & Y_{13} \\ Y_{21} & Y_{22} & Y_{23} \\ Y_{31} & Y_{32} & Y_{33} \end{bmatrix} = [V1, V2, V3]_2$$

In which, Y_{ij} is the probability of change that is determined from the overlay of the land use maps at different times. The above model can be used to predict the distribution of land use in the future.

2.4. The process of identifying and forecasting the volatility of land use change

Fig. 3: The process of identifying and forecasting the volatility of land use change. Sources: own study.

3. Results

3.1. Introduction of Landsat satellite system

Landsat is a series of American experiment satellites managed by the NASA (National Aeronautics and Space Administration) aerospace agency. This is a marginal orbit satellites system (their orbital plane angle compared to the equatorial plane is 98.2°), initially named ERST (Earth Remote Sensing Satellite); 2 years after the launch of ERST - 1, its name changed to Landsat, and then to Landsat - TM and Landsat - ETM (MRÓZ 2002).

The first Landsat satellite was launched into orbit on the 23rd July, 1972 and retired on the 1st June, 1978 with the name of Landsat 1. As of now, there have been 8 generations of Landsat. Landsat images have been applied in many fields of research, from status research to monitoring land use change, and are characterized by popularity and low cost (KOK, WINOGRAD 2002).

Table 1

The Landsat satellite system

Satellite	Launch	Decommissioned	Sensor
Landsat 1	23.07.1972	06.01.1978	MSS - TM
Landsat 2	22.01.1975	25.02.1982	MSS - TM
Landsat 3	05.03.1978	31.03.1983	MSS - TM
Landsat 4	16.07.1982	15.06.2001	MSS - TM
Landsat 5	01.03.1984	08.1995	MSS - TM
Landsat 6	05.03.1993	Failure lunch	TM/ ETM
Landsat 7	15.04.1999	Active	ETM +
Landsat 8	11.02.2013	Active	OLI - TIRS

Sources: own study.

3.2. Research data

Satellite images used in the study are downloaded directly from the site (<http://earthexplorer.usgs.gov/>) of the United States Geological Survey (USGS) for the Y Yen District of Nam Dinh Province, including:

Landsat 5 data with 30 meters resolution for spectral channels 1, 2, 3, 4, 5, 7, and 60 meters for the 6th spectral channel received on the 6th November, 2006, with the Path number of 126 and Row number of 46.

Landsat 8 Data with 30 meters resolution for spectral channels 1, 2, 3, 4, 5, 6, 7 and 9, 15 meters for the 8th channel, and 100 meters for the 10th and 11th spectral channels received on 11th October, 2014, with the Path number of 126, and Row number 46.

Table 2

Collected satellite data

Satellite	Data name	File date	Path / Row
Landsat 5	LT51260462006310BJC00	06.11.2006	126 / 46
Landsat 8	LC81260462014284LGN00	11.10.2014	126 / 46

Sources: own study.

Table 3

Comparison of the characteristic spectral channels of an image between Landsat 5 and Landsat 8

Landsat 5 TM		Landsat 8 OLI and TIRS	
		30m Coastal/ Aerosol	0.435-0.451 µm Band 1
Band 1 30m Blue	0.441-0.514 µm	30m Blue	0.452-0.512 µm Band 2
Band 2 30m Green	0.519-0.601 µm	30m Green	0.533-0.590 µm Band 3
Band 3 30m Red	0.631-0.692 µm	30m Red	0.636-0.673 µm Band 4
Band 4 30m NIR	0.772-0.898 µm	30m NIR	0.851-0.879 µm Band 5
Band 5 30m SWIR-1	1.547-1.749 µm	30m SWIR-1	1.566-1.651 µm Band 6

Band 6 60m TIR	10.31-12.36 μm	100m TIR-1	10.60-11.19 μm	Band 10
		100m TIR-2	11.50-12.51 μm	Band 11
Band 7 30m SWIR-2	2.064-2.345 μm	30m SWIR-2	2.107-2.294 μm	Band 7
		15m Pan	0.503-0.676 μm	Band 8
		30m Cirrus	1.363-1.384 μm	Band 9

Sources: own study.

3.3. Results and Discussion

3.3.1. Creation of interpreted keys

For any kind of image interpretation, it is necessary to determine the type of land use in the study area. Based on the current use of land, material characteristics of satellite images and image resolution, the authors distinguished 4 types of land use presented in the classification tables (Table 4). Based on these, the keys for interpretation were constructed with the support of handle GPS during field research (Table 5) (SOHL, SAYLER 2008).

Table 4

Classification of land use types in Y Yen district

Land use type	Description
Agriculture	Paddy rice; Annual crops, Pedestrial crops; ...
Building	Residential land; land used for transportation; land in industrial zones; Land for construction of offices and public service institutions; land for cemeteries, graveyards; other building land
Water surface	Land with rivers, streams, canals, and specialized water surfaces.
Unused land	Unused land.

Sources: own study.

Table 5

Sample satellite image interpretation Landsat 5-2006 and Landsat 8-2014

Land cover type	Image 2006	Image 2014	Field image
Agriculture
Building
Water surface
Unused land

Sources: own study.

3.3.2. Construction and assessing the accuracy of sample files

With the support from the field research and survey data, land use maps have been delineated directly onto the image with 4 types of selected land use (Figure 4).

Class #	Signature Name	Color	Red	Green	Blue	Value	Order	Count	Prob.	P	I	H	A	FS
1	Agriculture	Green	0.000	1.000	0.000	23	34	137	1.000	✓	✓	✓	✓	
2	Building	Red	1.000	0.000	0.000	27	35	103	1.000	✓	✓	✓	✓	
3	Water surface	Blue	0.000	0.000	1.000	31	36	68	1.000	✓	✓	✓	✓	
4	Unused land	Dark Green	0.000	0.392	0.000	32	37	71	1.000	✓	✓	✓	✓	

Fig. 4: Sample Files of Landsat 8-2014. Sources: own study.

Based on the characteristics of reflected spectral energy of the object selected in the sample files, the differences between samples were calculated, and the feature space method was selected for analysis (Spectrum Space change). The results showed that the fewer techniques of interferometry are used, the higher the accuracy. The results also reflected that the accuracy of the selected sample files for both images are good (Figure 5).

Fig. 5: Results of evaluating the accuracy of Landsat 5 - 2006 (a) and Landsat 8 - 2014 (b) sample files image. Sources: own study.

3.3.3. Classification and assessing the accuracy of its results

In the method of supervised classification under the maximum likelihood algorithm (Maximum likelihood), the obtained results were land use maps for 2006 and for 2014 (Figure 6), and an interference filter used on the obtained classification results to dissolve the pixels (RAY, PIJANOWSKI 2010).

To assess the accuracy of image classification results for image classification in 2014, we used handheld measuring GPS equipment for field control with 100 GPS points; for image classification in 2006, the authors combined field surveys and land use maps from 2005 with 103 points to evaluate the accuracy. The evaluation process was done automatically using ERDAS 2014 software and achieved good results (SOHL et al. 2008; VOGELMANN, TOLK, ZHU 2009).

- The accuracy of Landsat 5-2006 image classification results was 97.00%, and the Kappa index was 0.9575 (Figure 7 (a)),
- Accuracy of Landsat 8-2014 image classification results was 85.44% ,and the Kappa index was 0.7914 (Figure 7 (b)).

Fig. 6: Results of Landsat 5 - 2006 (a) and Landsat 8 - 2014 (b) image classification. *Sources:* own study.

(a)

CLASSIFICATION ACCURACY ASSESSMENT REPORT

ERROR MATRIX

		Reference Data			
Classified Data	Agriculture	Building	Water surface	Unused land	Row Total
Agriculture	34	0	2	1	37
Building	0	35	0	0	35
Water surface	0	0	17	0	17
Unused land	0	0	0	11	11
Column Total	34	35	19	12	100

----- End of Error Matrix -----

ACCURACY TOTALS

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Agriculture	34	37	34	100.00%	91.89%
Building	35	35	35	100.00%	100.00%
Water surface	19	17	17	89.47%	100.00%
Unused land	12	11	11	91.67%	100.00%
Totals	100	100	97		
Overall Classification Accuracy =		97.00%			

----- End of Accuracy Totals -----

KAPPA ($K^{\wedge}$) STATISTICS

Overall Kappa Statistics = 0.9575
Conditional Kappa for each Category.

Class Name	Kappa
Agriculture	0.8771
Building	1.0000
Water surface	1.0000
Unused land	1.0000

----- End of Kappa Statistics -----

(b)

CLASSIFICATION ACCURACY ASSESSMENT REPORT

ERROR MATRIX

Classified Data	Agriculture	Reference Data			Row Total
		Building	Water surface	Unused land	
Agriculture	32	3	3	1	39
Building	2	33	4	2	41
Water surface	0	0	14	0	14
Unused land	0	0	0	9	9
Column Total	34	36	21	12	103

----- End of Error Matrix -----

ACCURACY TOTALS

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Agriculture	34	39	32	94.12%	82.05%
Building	36	41	33	91.67%	80.49%
Water surface	21	14	14	66.67%	100.00%
Unused land	12	9	9	75.00%	100.00%
Totals	103	103	88		
Overall Classification Accuracy =		85.44%			

----- End of Accuracy Totals -----

KAPPA ($K^{\wedge}$) STATISTICS

Overall Kappa Statistics = 0.7914
Conditional Kappa for each Category.

Class Name	Kappa
Agriculture	0.7321
Building	0.7000
Water surface	1.0000
Unused land	1.0000

----- End of Kappa Statistics -----

Fig. 7: Evaluation results of Landsat 5 - 2006 (a) and Landsat 8 - 2014 (b) image classification accuracy.

Sources: own study.

4. Transfer from image classification into vector

The final step to forming maps of land use based on remote sensing and GIS was to transfer the images from raster to vector formats (Figure 8). The main purpose of this is to integrate remote sensing and GIS.

Table 6

Area statistics by types of land use

Land use type	Year 2006		Year 2014		Increase (+) Reduction (-)
	Area (ha)	Percentage (%)	Area (ha)	Percentage (%)	
Agriculture	16,516.39	68.45	15,970.68	66.19	- 545.71
Building	4,921.43	20.40	5,755.79	23.85	+ 834.36
Water surface	2,471.74	10.24	2,190.34	9.08	- 281.40
Unused land	219.05	0.91	211.80	0.88	- 7.25
Total	24,128.61	100	24,128.61	100	

5. Determination of land use change

Analyzing the land use change should be based on the pivot table between various types of land use, especially land designated for construction. The Union Function was used to define the change of land

use in a given area by overlaying the two land use maps, i.e. from 2006 and 2014, to recognize the change in the area of land use (Figure 9), and the Tabulate Area function applied to build the pivot table cycle between various types of land use (Table 7); the results of volatility have been presented in Figure 10 (PONTIUS, PETROVA 2010).

Fig. 8: Results of Landsat 5 - 2006 (a) and Landsat 8 - 2014 (b) image classification accuracy assessment. *Sources:* own study.

Figure 9: Results of Landsat 5 - 2006 (a) and Landsat 8 - 2014 (b) image classification accuracy assessment. *Sources:* own study.

Table 7

Chart of changes in land use over 2006 – 2014 (Unit: ha)

Land use type	Agriculture	Building	Water surface	Unused land	Total - 2014
Agriculture	15,816.39	0	153.00	1.29	15,970.68
Building	501.65	4,921.43	329.65	3.06	5,755.79
Water surface	198.35	0	1,989.09	2.90	2,190.34
Unused land	0	0	0	211.80	211.80
Total - 2006	16,516.39	4,921.43	2,471.74	219.05	24,128.61
Increase	154.29	834.36	201.25	0	1,189.90
Reduction	700.00	0	482.65	7.25	1,189.90
Land use change	-545.71	+834.36	-281.4	-7.25	

Sources: own study.

Figure 10: Changes in land use over 2006 – 2014. Sources: own study.

6. Forecasting of land use change

Forecasting the changes in land use will be based on the volatile proportion of transferring from other types of land use into urban land. Based on the results of volatility in the types of land use in Table 7, the authors determined the percentage change in Table 8.

Table 8

Proportion of land use change in the period 2006 – 2014

Land use type	Agriculture	Building	Water surface	Unused land
Agriculture	0.96	0.03	0.01	0
Building	0	1	0	0
Water surface	0.06	0.13	0.81	0
Unused land	0.01	0.02	0.01	0.97

Sources: own study.

In order to predict changes in the future of land use by the Markov Chain, we multiply 2 matrices, i.e. the matrix of land use in 2014 by the matrix of change rate in the period 2006 – 2014 (Table 8).

$$\begin{array}{|c|c|c|c|} \hline \textbf{Current land use in 2014} \\ \hline \text{Agriculture} & \text{Building} & \text{Water surface} & \text{Unused land} \\ \hline 15,970.68 & 5,755.79 & 2,190.34 & 211.80 \\ \hline \end{array} \times \begin{array}{|c|c|c|c|} \hline 0.96 & 0.03 & 0.01 & 0.00 \\ \hline 0.00 & 1.00 & 0.00 & 0.00 \\ \hline 0.06 & 0.13 & 0.81 & 0.00 \\ \hline 0.01 & 0.02 & 0.01 & 0.97 \\ \hline \end{array} = \begin{array}{|c|c|c|c|} \hline \textbf{Future land use in 2022} \\ \hline \text{Agriculture} & \text{Building} & \text{Water surface} & \text{Unused land} \\ \hline 15,430.64 & 6,535.94 & 1,957.24 & 204.79 \\ \hline \end{array}$$

Similarly, in order to predict the process of land use volatility over the next years, we multiply the land use in the following year by the change rate.

Figure 11 shows that, from 2006 to 2014, the amount of land used for building purposes increased the most, i.e. by 834.36 hectares, while agricultural land, water surfaces and unused land decreased by 545.71 ha, 281.4 ha and 7.25 ha respectively. In the forecasts for 2022, building land is expected to reach 6,523.39 hectares, while agricultural land, water surfaces and unused lands are expected to amount to 15,463.27 ha, 1,936.00 ha and 205.45 ha respectively. In 2030, the area of building land is forecasted to be 7,243.64 ha, agricultural land - 14,960.81 ha, water surfaces - 1,724.87 ha, and unused land - 199.29 hectares (Table 9 and Figure 11).

Table 9

Forecast of land use change up to 2030 (Unit: ha)

Year	Agriculture	Building	Water surface	Unused land
2006	16,516.39	4,921.43	2,471.74	219.05
2014	15,970.68	5,755.79	2,190.34	211.80
2022	15,430.64	6,535.94	1,957.24	204.79
2030	14,899.02	7,268.51	1,763.08	198.01

Sources: own study.

Fig. 11. Forecasted land use change up 2030. Sources: own study.

7. Conclusion

Based on images from Landsat 5 in 2006 and Landsat 8 in 2014 of the Y Yen District, we developed a deciphering key for 4 land use types, including agricultural land, building land, water surfaces and unused land as the basis for interpreting remote sensing images.

The results of the deciphering process in the period of 2006 – 2014 showed that the total area of non-agricultural land increased by 834.36 hectares, of which 545.71 hectares of agricultural land changed to non-agricultural land, 281.4 hectares of water surface area changed to non-agricultural land, 7.25 hectares of unused land changed to other types of land use. This change demonstrates an increasing pace of the district's development.

Remote sensing and GIS combined with the Markov Chain when forecasting changes in land use up to the year 2030 did not achieve the highest accuracy; the reason behind this is that land use policies may change in the forecasted time period. The Markov Chain is an appropriate choice in cases where there is no change in policies in the period covered by the forecast.

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