USING REMOTE SENSING AND GIS TO ANALYZE LAND COVER/LAND USE CHANGE IN QUANG XUONG DISTRICT, THANH HOA PROVINCE, VIETNAM

Nguyen Huu Hao

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Abstract: *Identification of land use change in different periods of time has become a central key to monitoring of land resources. It is relatively important for effective land management to protect the land resources, especially the land used for agricultural production from overuse and environmental changes. The sprawl of inhabitant areas, development of rural infrastructures, and industrialization are responsible for serious losses of agricultural land. In this study, remote sensing techniques were applied to studying the trends of land cover change in the Quang Xuong District in a period of about 24 years from 1989 to 2013. ArcGIS software was adopted to develop the land cover and the change of land use maps from 1989 to 2013. Two satellite images with moderate resolution were collected from USGS Earth Explorer website, Landsat 5 TM for 1989 and Landsat 8 OLI & TIRS for 2013. After image geo-processing, the images were classified into six land cover categories by applying supervised classification method (Maximum Likelihood). The six main obtained land cover types were built-up areas, agricultural land, forest land, water surface area, salty land, and unused land. The overall accuracies of land cover maps for 1989 and 2013 were 94.08% and 92.91%, respectively. The results of change detection analysis indicate that the cultivated, water surface and unused lands decreased by 22%, 17%, and 91%, respectively. In other side, the built-up and salty land increased by 78%, 58%, respectively and forest land increased from 52.69 ha in 1989 to 395.76 ha in 2013.*

Keywords: *Remote sensing, Landsat, Quang Xuong District, Change detection, Land cover/Land use.*

1. Introduction

Presently, remote sensing (RS) is used as a powerful tool that can be applied to handle the problem of thematic maps which have to be updated. It has capabilities to map and extract information of the earth resources for different purposes. RS and GIS have abilities to create update solutions, build and analyze data efficiently [14]. According to Thom and Que (2014), RS and GIS are leading to dramatic changes in the management of natural resources because of their outstanding advantages such as shortening time, increasing accuracy, logic, and the current state of the map information [15].

Nguyen Huu Hao
Faculty of Agriculture, Forestry and Fishery, Hong Duc University
Email: Nguyenhuuhao@hdu.edu.vn (✉)

One of the most important applications of RS is land cover mapping [3]. According to Casady and Palm (2002) RS for agriculture can be defined as "observing or a field crop without touching it". It integrates new technologies that can offer increasingly efficient, complete, precise and timely information [4].

RS has been used in studies on vegetation for many years with various perspectives such as building the map of forest fires, vegetation cover or detecting changes in vegetation through different periods [7], [12]. Townshend et al., (1991) used RS to calculate the changes in the vegetative cover of the land surface on a global scale [16]. RS has been widely used in natural research for mapping vegetation since it can quickly determine the data, distribution, and change of vegetation for large areas. In addition, it provides the possibility of inferring results of mapping to regional extent, even in large inaccessible areas [11]. Using RS to create a picture or map is a quick approach for calculating the extent of an essential crop characteristics or a field that has the same characteristics [4].

One of the most influential factors causing ecological systems and climate change is land cover change [18]. It reflects human activities and physical environments on Earth. Information about land use and land cover is needed for water-resources inventories, flood control, water supply planning, and waste water treatment [1]. However, knowledge of land cover and its dynamics is particularly limited by the paucity of accurate land cover data [9]. Primary causes of changes to land use are commonly urbanization and new residential settlements, which has impacts on local communities' environmental, social and economic sutainability [20].

In this study, maximum likelihood supervised classification and post-classification change detection techniques were used to find out land cover changes over the period of 1989 - 2013 in Quang Xuong District. Land cover monitoring of the research site over-time demanded a specific dataset of Landsat imageries in order to meet different local land use changes. This was one of the first important tasks in the project of land use planning and land evaluation. Moreover, monitoring of land cover also provided precious information for land users, decision makers, and land planners to make reasonable development strategies of land use in the short-term as well as in the long-term.

2. Study area

Quang Xuong is one of a coastal district of Thanh Hoa Province and is located in the tropical and temperate zone. It's geographical location is at $19^{0}34'$ - $19^{0}47'$N latitude and $105^{0}46'$ - $105^{0}53'$E (Figure 1). The topography of Quang Xuong District is saddleback and relatively flat, which runs from the north to the south. The average height above sea level is from 3 to 5 meters. Similar to the climate of the entire province, this district is characterizes by strong monsoon influence, a considerable amount of sunny days, and with a high rate of rainfall and humidity. The weather of the district is divided into four distinct seasons: spring, summer, autumn and winter. It is hot and humid weather by influence of the south-westerly dry wind in the summer; dry and little rain, occasional appearance of frost in the winter. The total temperature is about 8300 - 8400^{0}C per year. The annual average precipitation ranges from 1600mm to 2000mm and is irregularly distributed. The humidity is rather high. The average account is over 80% in most of the months and is rarely under 60%.

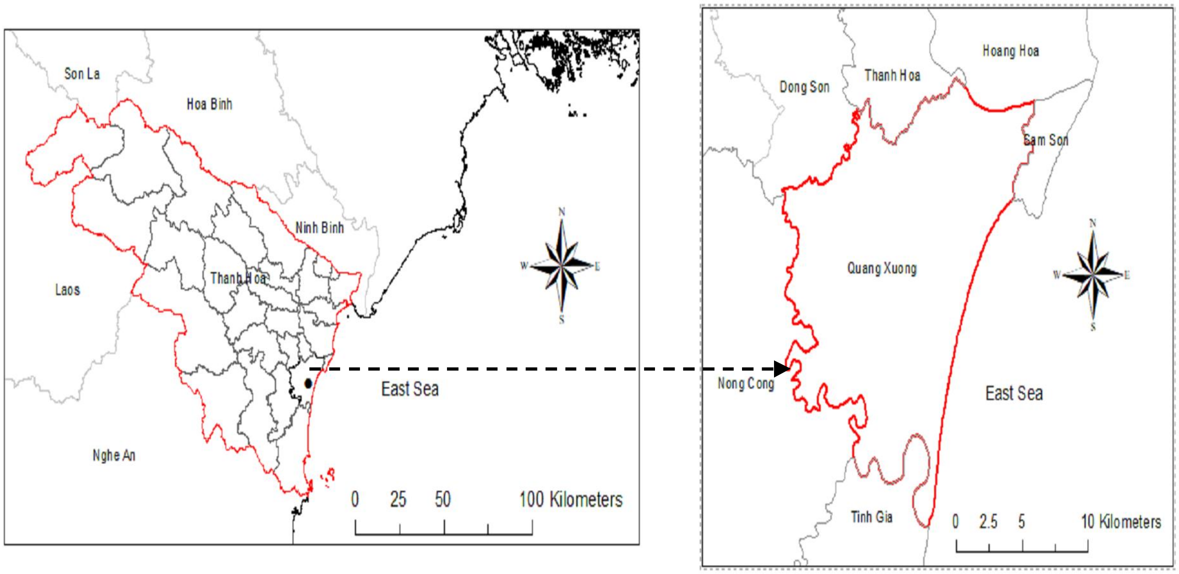

***Figure 1**. Location of the study area*

3. Materials and Methodology

3.1. Satellite Data

Landsat 5 TM acquired on September of 1989 and Landsat 8 OLI and TIRS acquired on September of 2013 (Table 1) were used for classification and land cover change detection from 1989 to 2013. The data were selected for this study as it has wide spectral coverage and availability of a high resolution band for enhancing spatial resolution and features. These satellite images were acquired for relatively cloud free (maximum 10%) in both period of time for visual interpretation and on screen digitizing.

***Table 1.** Characteristics of Landsat 5 TM, Landsat 8 OLI and TIRS data*

Image	Resolution	Path	Row	Date of pass
Landsat TM	30.0m (band 1-5 & 7)	127	046	September 11, 1989
Landsat OLI and TIRS	30.0m (band 1-7 & 9)	126	046	September 22, 2013

3.2. Methodology

The principle of classification based on the land cover and land use classification system developed by A. Anderson et al., (1976) was applied first. Supervised classification approach was independently used for classification stage for each image to generate the thematic map of land cover; afterward change detection technique was also applied to examine how land cover change from 1989 to 2013 in Quang Xuong District by comparing independently classified images. Six separable land cover types have been identified in this research including water surface, built-up, agricultural land, forest land, salty land, and unused land (Table 2).

Table 2. *Land cover classification scheme*

No.	Classes	Description
1	Built-up area	Area covered by residential, commercial, industrial, public infrastructure and services buildings, transportation, roads, mixed urban, and other urban.
2	Agriculture land	Characterized by agricultural area, crop fields, fallow lands, vegetable lands and regularly planted crops.
3	Water surface	All area of open water with 95% covers of water, including rivers, streams, lakes, ponds and reservoirs.
4	Forest	Area covered by forest with relatively darker green colors.
5	Salty land	Area used for salt production.
6	Unused land	Sandy, rock mountains and other disused areas.

3.2.1. Image pre-processing

In this study, Landsat TM of 1989 and Landsat OLI & TIRS of 2013 were rectified to UTM zone 48, WGS 84. The geometric correction of the images was performed using topography of Quang Xuong district with the help of Ground control points (GCPs). As to prevent possible changes to the original pixel values of the image data, neighbor resampling method was applied. Therefore, both images of 1989 and 2013 were geometrically corrected by using 35 control points. The root mean square errors (RMSE) for Landsat TM of 1989 and Landsat OLI of 2013 were 0.020 pixels and 0.017 pixels, respectively. The next stage was clipping the images to focus on the processing of the study area.

3.2.2. Selection of training samples

The training samples were selected based on the basis of the unsupervised classified image and the current land use map of 2012. These training samples were selected from all cover land founding in the study area with the average of 26 training areas for each land cover type of 1989, 30 training areas for each land cover type of 2013, and a minimum average of 12 pixels for each training sample of both images. Besides, the statistical analyses were computed based on Jeffrey-Matusita distance [19]. The number of land use/land cover classes were defined based on field work and available land use statistics for the study area, and the defined classes for image classification were Built-up, Agriculture land, Water surface, Forest land, Salty land, and Unused land area.

3.2.3. Image classification

In the next step, the supervised classification is applied for the classification process. It is performed with the maximum-likelihood algorithm, where the training samples are homogeneous reflectance of certain areas. This approach demonstrates that data is best collected from remote areas if each class contains some Gaussian distribution [2]. In this stage, the maximum likelihood classifier was conducted, since it could obtain some reliable results. Contrarily, parallelepiped classifier would bring problem when overlapping and minimum distance classifier is insensitive to the discrepancy in each class. Finally, the classified images were smoothed by using a 3 × 3 majority filter to reduce the number of misclassified pixel in the land use/land cover maps [8].

3.2.4. Accuracy assessment

The number of the reference pixels is a key component in computing the precision of classification. According to Congalton (1991), it needed more than 250 reference pixels to determine the means of a class to within plus or minus five percent [6]. In this research, a standard method suggested by Congalton (1991) was used to assess the overall accuracy, producer's and user's accuracy. After performing the image classification, the results of the accuracy assessment were presented in the confusion matrix by using quantitative analysis. Furthermore, a discrete multivariate approach of Kappa analysis is also used in accuracy assessment from the confusion matrix [13]. It is known as a Khat statistic approach to measure the agreement or accuracy [5]. The Kappa statistic illustrates the agreement between the classified land use and the observed land use. Unlike the overall, producer's and user's accuracies, in general, Kappa analysis can take the chance allocation of class labels into consideration by using the main diagonal, columns, matrix rows, and error matrix [17]. The Kappa statistic is calculated as:

$$Kappa(K) = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_i \times x_{+i})}{N^2 - \sum_{i=1}^{r}(x_i \times x_{+i})}$$

Where r is the number of rows in the matrix, X_{ii} is the number of observations in row i and column i, $x_i = x_{+i}$ is marginal totals for row i and column i respectively, and N is the total number of pixels.

3.2.5. Post classification processing

The land use/land cover classification was generated by two Landsat TM and Landsat OLI & TIRS images acquired in September of 1989 and 2013. After classification, detection of land cover changes was achieved by overlaying and post-classification comparison of the land cover/land use maps of the different time periods. This step gave not only the size and distribution of changed areas, but also the percentages of other land cover classes that share in the change of each land cover class individually. For the maximum quality of spectral data from classification process, the original resolution of the satellite images was used to determine the quantity of the conversions [10]. The map of the change was accompanied by the respective cross tabulation matrices showing the change pathways.

4. Results and discussion

4.1. Land cover/Land use status in 1989 and 2013

The land use/land cover classification was examined based on the results from the interpretation of two Landsat images acquired in September of 1989 and 2013 (Table 2 and Figure 2). Afterwards, the results of classification were exported to ArcGIS for further processing.

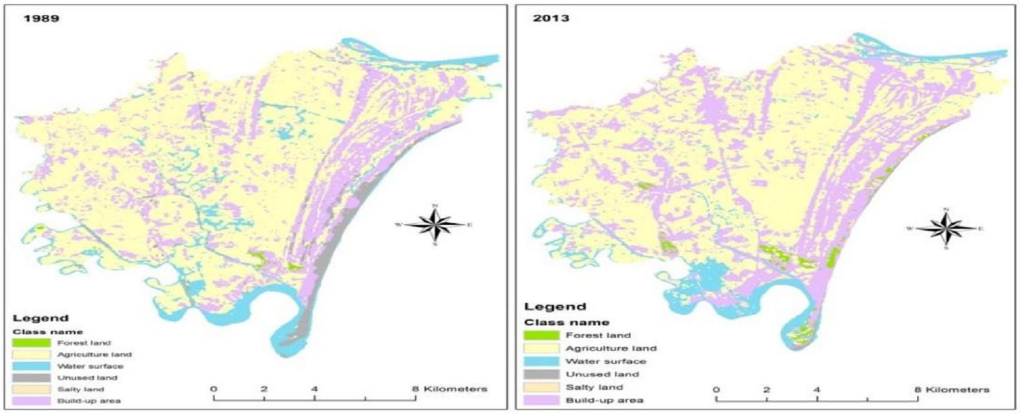

Figure 2*. Supervised Maximum likelihood classification of 1989 and 2013*

Table 2 shows that approximately 63% and 49.17% of the total area was for agricultural uses in 1989 and 2013. The built-up area covered approximately 22.7% and 40.32% of the total geographical area of Quang Xuong District in 1989 and 2013, respectively. The water surface covered about 9.3% and 7.72% of the total area of the region in 1989 and 2103, respectively. About 0.3% and 0.42% area was under salty practices in 1989 and 2013, respectively. There was about 0.2% and 1.97% of the total study area under the forest cover in 1989 and 2013, respectively. The unused area covered about 4.5% and 0.40% of the total natural area in 1989 and 2013. The spatial pattern reveals that the study area is flat and more than a half of the natural area was used for agricultural practices in 1989 and nearly half of the area used for agricultural activities in 2013. However, the natural area for agricultural productivity is decreasing due to the expansion area for inhabitants as well as for rural infrastructure development.

Table 2. *Land cover/land cover classification in 1989 and 2013*

No.	Class	1989		2013		Change
		Area (ha)	%	Area (ha)	%	
1	Water surface	2122.29	9.3	1759.48	7.72	-362.81
2	Salty land	60.51	0.3	95.47	0.42	35.16
3	Built-up area	5172.48	22.7	9185.44	40.32	4012.96
4	Agriculture land	14362.12	63.0	11200.30	49.17	-3161.82
5	Forest land	52.69	0.2	448.45	1.97	395.76
6	Unused land	1010.25	4.5	91.00	0.40	-919.25

4.2. Accuracy assessment

Accuracy assessment was examined for image classification of 1989 and 2013. A stratified random sampling design was adopted in the accuracy assessment. For the land use/land cover classification of 1989, a total of 591 pixels were randomly selected. The results indicated that an overall accuracy is of 94.08% and a Kappa index of agreement is of 0.91 (Table 3). In examining the producer's accuracy, all classes are over 85%, except salty land which was 77.78%. In examining of the user's accuracy, all classes are over 90%, except forest land which was 87.50%.

***Table 3.** Accuracy assessment of Landsat 5 TM of 1989*

Classified data	Reference data 1989							
	Agricultural land	**Build-up-land**	**Water surface**	**Salty land**	**Unused land**	**Forest land**	**Row total**	**User's accuracy (%)**
Agricultural land	**289**	6	5	1	2	1	304	95.07
Build-up area	6	**112**	0	0	4	0	122	91.80
Water surface	3	0	**87**	0	0	0	90	96.67
Salty land	0	0	0	**7**	0	0	7	100.00
Unused land	0	1	3	1	**47**	0	52	90.38
Forest land	1	1	0	0	0	**14**	16	87.50
Column total	299	120	95	9	53	15	**591**	
Producer's accuracy (%)	96.66	93.33	91.58	77.78	88.63	93.33		
Overall accuracy = 94.08% Kappa index = 0.91								

For the land use/land cover classification of 2013, a total of 494 pixels were selected. The results presented that an overall accuracy is of 92.91% and a Kappa index of agreement is of 0.896 (Table 4). In term of the producer's accuracy, all classes are over 90%, except salty land class which made up 66.67%. In terms of the user's accuracy four classes exhibit over 90% with the exception of salty and unused land classes, which are 54.55% and 68.75%, respectively. The salty and unused land classes show clear confusion because of similar reflection value of them.

***Table 4.** Accuracy assessment of Landsat 8 of 2013*

Classified data	Reference data 2013							
	Agricultural land	**Build-up land**	**Water surface**	**Salty land**	**Unused land**	**Forest land**	**Row total**	**User's accuracy (%)**
Agricultural land	**157**	1	1	0	0	11	170	92.35
Build-up area	2	**198**	0	2	1	1	204	97.06
Water surface	3	2	**63**	0	0	0	68	92.65
Salty land	0	0	5	**6**	0	0	11	54.55
Unused land	0	3	1	1	**11**	0	16	68.75
Forest land	0	1	0	0	0	**24**	25	96.00
Column total	162	205	70	9	12	36	**494**	
Producer's accuracy (%)	96.91	92.09	90.00	66.67	91.67	92.31		
Overall accuracy = 92.91%								
Kappa index = 0.896								

5.3. Land cover/Land use change detection

The surface distribution (in ha) of the proportion of each land cover/land use class in the different time from 1989 to 2013 is as presented in Table 1. All the land cover types have been changed from 1989 to 2013, the largest change namely build-up area, cultivated, unused, and forest lands. Table 1 shows that about 3,161.82ha, 919.25ha and 362.81ha decrease is observed in agricultural areas, unused land, and water surface areas. Meanwhile there is an increase of 4,012.96ha in built-up area, 395.76ha in forest, and 35.16ha in salty lands between 1989 and 2013. The detail dynamics of the land use/land cover changes in the study area between 1989 and 2013 is shown in Table 5. The table is a cross tabulation matrix of the land use/land cover change, displaying the conversion from each class to another class. For instance, from 1989 to 2013, 10130.41ha agricultural area production remained stable, 1069.89ha of new cultivated land are mostly generated at the expense of water surface, unused land and build-up area. Contrarily, 4231.71ha of agricultural land are lost to built-up areas (3323.18ha), water surface (757.06ha), forest (126.23ha), unused land (15.62ha), and salty land (10.62ha). The land cover categories of forest and build-up areas are expanded the most over other types of land use, with 395.76ha and 4012.96ha, respectively, mostly from cultivated, water surface, unused areas. During this period of 24 years, the area of agricultural, unused lands and water surface are the greatest reduction in area, with 4231.71ha, 1156.11ha and 988.11ha, respectively.

Table 5. *The change of land cover/land use from 1989 to 2013 in ha*

1989 - 2013	Forest land	Agriculture land	Water surface	Unused land	Salty land	Built-up area	Total	Expansion
Forest land	**25.43**	126.23	15.34	233.56	7.2	40.69	448.45	423.02
Agriculture land	13.95	**10130.41**	473.61	98.68	0.1	483.55	11200.3	1069.89
Watersurface	0.13	756.06	**966.18**	26.89	0.41	9.81	1759.48	793.3
Unused land	0	15.62	41.28	**22.14**	1.98	9.98	91	68.86
Salty-land	0	10.62	41.22	29.43	**13.86**	0.54	95.67	81.81
Built-up area	13.18	3323.18	584.66	499.55	36.96	**4727.91**	9185.44	4607.53
Total	52.69	14362.12	2122.29	1010.25	60.51	5173.66	22781.34	
Reduc-tion	27.26	4231.71	1156.11	988.11	46.65	594.57		

5. Conclusion

Not any studies have been applied remote sensing and satellite images to analyze land use change in Quang Xuong District before. At the time, the land cover distribution of the proportion from 1989 to 2013 in this research was the very first study of land cover change detection by applying remote sensing techniques and Landsat images in this district. The results of image classification in this study illustrate that the Maximum Likelihood supervised method is a useful tool for classifying and mapping broad categories of land cover/land use. In addition, change detection statistics is a helpful approach for determining the change of land cover/land use in different period of times. These results clearly suggest that satellite images of Landsat could be used to identify, classify and compare the change of land cover types in Quang Xuong District in particular and Thanh Hoa Province in general.

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