Mapping Land Cover Dynamics in Nakhon Nayok Province of Thailand

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Abstract: The spatial distribution of land cover information and its changes is very valuable for any planning, management and monitoring at local as well as regional scale. In this paper, multi-temporal Landsat TM/ OLI data were used to classify the land cover of the Nakhon Nayok province in Thailand over the period 2004-2015. The supervised classification maximum likelihood method was implemented to assign probability to land the cover classes considered. The random sampling point method was used for field survey and accuracy assessment. The overall accuracy and kappa coefficient in 2015 were found to be 72% and 0.6626 respectively. The results also indicated that important changes concerned mainly urban (308.46 %), water (-50.46%), and agricultural (-12.14%) areas, and least changes forest areas (3.17%). These results also highlighted that over the last 10 years, urban areas have been characterized by the highest expansion, mainly from the conversion of agricultural land.

Keywords: Remote sensing, Landsat, Land cover dynamics, Change detection

Introduction

Over the past decades, Thailand has experienced many disturbances on its land surface caused by natural and human activities. In particular, anthropogenic impacts mainly in the form of agricultural and urban expansion due increase in population have become an issue of major concern. In order to monitor potential ranges of the impacts of these dynamics on land cover requires accurate mapping and monitoring of land cover changes over long periods.

Remote sensing images can capture the land cover and its changes over larger spatial and temporal scale including remote areas repetitively (Furkuo et al., 2012; Fichera et al., 2012). Satellite images have been used for land cover mapping in various studies (Yuan et al., 2005). The most standard global land cover data is provided by Food and Agriculture Organization (FAO), which is analyzed from several satellite sensors such as the Advanced Very High Resolution Radiometer (AVHHR), Satellite Pour l'Observation de la Terre (SPOT), Medium Resolution Image Spectrometer (MERIS), and Moderate Imaging Spectrometer (MODIS) (Vittek, et al. 2014) with aim to create global land cover database for various global applications.

However, the low spatial resolution of this land cover database causes high uncertainty to observe dynamic on a local scale. Therefore, it is required to analyze with appropriate methods for particular study areas with an acceptable accuracy assessment using field surveys (Hames and Al-Ahmadi, 2008; Lu et al., 2004). Instead of using high distribution low-resolution data sources on a local scale, Landsat images (moderate resolution) have been used in this study to overcome the sparse information and uncertainty in the classification.

Change detection is an efficient method in order to monitor the interactions and impacts of land cover between human to geography over various periods of time (Fichera1 et al., 2012; Vittek et al., 2014). This research aims to implement a method to detect land cover change from 2004 to 2015 in the Nakhon Nayok province of Thailand. This approach will extract five major types of land cover using remote sensing methods (unsupervised, supervised classification with maximum likelihood method and Image differencing) and field survey data in order to track down the change dynamics over this 10-years period.

Materials and Methods

A. Study Area

Nakhon Nayok Province is located in the central part of Thailand at latitude 14.20 degrees and longitude 101.21 degrees. This study focuses on the total area of the Nakhon Nayok province, which has an area of 2122 sq. km (Figure 1). The southern part of the province is the prolongation of Dong Phaya Yen mountain range and northern part is in Sankamphaeng Range, with the elevation 1292 meters. The

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Khao Yai National Park covers most of the area of this province, the central part of the province is rather flat which is formed by the Nakhon Nayok River, which is the main river of the province.

B. Landsat data

Clear, cloud free Landsat 5TM and Landsat 8 OLI images were collected from the United States Geological Survey (USGS) Global Visualization Viewer (GloVis) website (Table1). All images were converted to Universal Transverse Mercator (UTM) projection zone 47. The Landsat 5 TM and Landsat 8 OLI images are acquired in six spectral bands with a spatial resolution of 30 x 30 m (and a TM thermal band at 120 m and OLI band 1,8 ,9,10 and 11 has not been used in this study) and a revisiting period of 16 days.

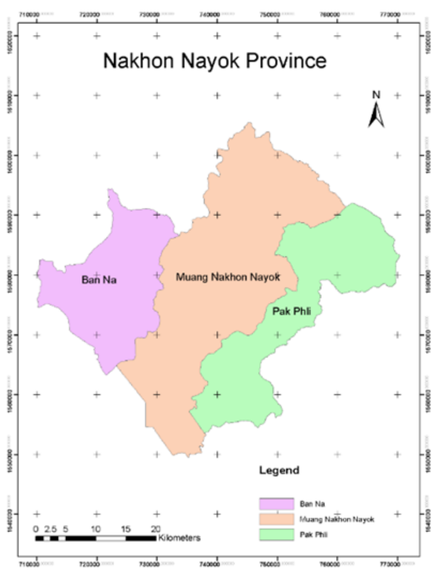

Figure 1. Map of Nakhon Nayok study area

Table 1. Landsat 5 TM and Landsat 8 OLI specifications

ID	Date of Acquisition	Satellite/ Sensor	Reference system/Path/Row
1	21/11/2004	Landsat 5 TM	WRS -2 /129/50
2	20/01/2015	Landsat 8 OLI	WRS -2 /129/50

C. Methodology

I. Image preprocessing

Based on the selected Landsat imagery over the study area, a series of pre-processing has to be performed prior to the classification and change detection procedure. These pre-processing include the radiometric and atmospheric calibration (Bruce et al., 2004; Rokni et al., 2014). The radiometric correction consisted in changing the 8 Bit digital values of Landsat 5 TM and 16 Bit digital value of Landsat 8 OLI into radiance and reflectance values (Chander et al., 2009; USGS, 2015). The atmospheric correction was performed to remove/ reduce the negative effect caused by the atmosphere (such as scattering absorption by aerosol and water vapors). The Dark Object Subtraction (DOS) method was used for atmospheric correction; it is a simple and widely used image-based method (Chavez, 1988).

II. Training sites

The land cover classification scheme was based on a classification system developed by the Land Development Department (LDD), Thailand. According to LDD land use / cover classification system, the land use and land cover classified as water, bare soil, urban area, agricultural and forest. The unsupervised classifications (ISO data or K-means) were carried out prior to field survey in order to determine the strata for ground truth. The field survey was performed out to collect geolocations information for training and validating land use/ land cover interpretation from Landsat images of 2015. The ground control data were collected using stratified random sampling method (Musa et al., 2003). The target validation points were limited to areas accessible by roads. This constrain was necessary in order to reduce filed survey time. However, collecting ground control points from all those random locations is practically impossible. Therefore, a modification has been made especially areas which are far from the road. In total 23 random ground-control points were collected and the rest was obtained using google earth. The survey was conducted in collaboration with experts from the Royal Forest Department (RFD), Thailand.

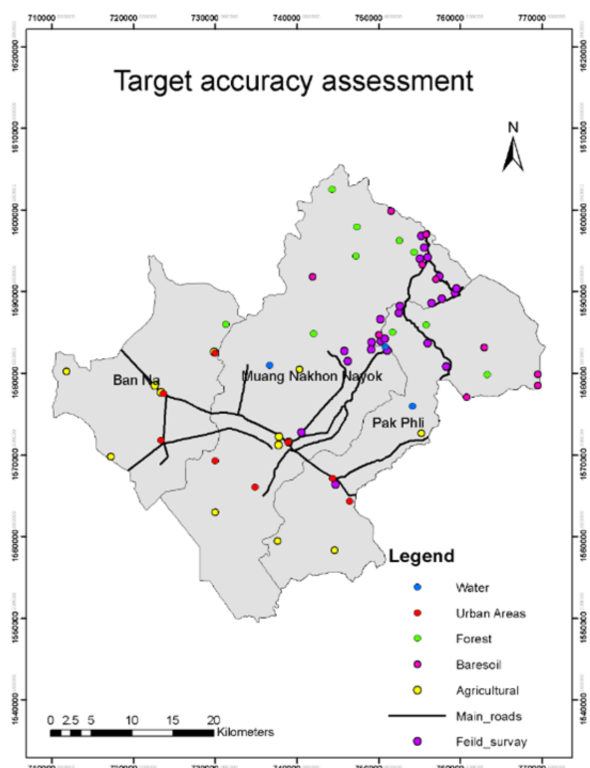

Figure 2. Target accuracy assessment points

III. Land cover classification and change detection

Our classification scheme, with five classes, was based on the land cover and land use classification developed by LDD for interpretation of remote sensor data at various scales and resolutions. A reflective spectral band from 2004 and 2015 was used for classification (Table1). Combined unsupervised- supervised approach was used for clustering. Two dated Landsat images over Nakhon Nayok regions were compared using supervised classification technique. In order to obtain automatic image classification, at the locations where ground control points were collected (training data via field survey) same locations were chosen to create areas of interest (AOI). Once training sites were determined using unsupervised classification and geolocations by field survey/AOI, maximum likelihood algorithm was used for performing supervised classification (Bauer et al., 1994). The maximum likelihood algorithm is one of the most widely used algorithms for supervised classification (Wu et al., 2002; McIveret et al., 2002; Mengistu et al., 2007; Reis, 2008).

Three standard criteria were used to assess the accuracy of the supervised classification images: (1) The User accuracy was defined as the proportion of the correctly classified pixels in a class to the total pixels that were classified in that class. It indicates the probability that a classified pixel actually represents that category in reality (Diallo et al., 2009; Rogan, 2002); (2) The overall accuracy was defined as the total number of correctly classified pixels divided by the total number of reference pixels (total number of sample points) (Rogan et al. 2002); and (3) The Kappa coefficient was defined as a statistical measure of accuracy that ranges between 0 and 1. It measures how much better classification is as compared to randomly assign class values to each pixel (Diallo et al., 2009). The Kappa coefficient is the proportion of agreement between observed and predated class from the classifier (Furkuo and Frimpong, 2012).

Results and Discussion

A. Changes in Land cover (2004-2015)

Figure 3(a) and (b) shows land cover maps in 2004 and 2015. The overall area in each particular land cover class of individual year is shown in Figure 4(a) and (b) as sq.km^2 and a percentage of the distribution. During the periods considered, the agriculture and forestland constituted the most extensive type of land cover in the study area. They accounted for about 48 and 38% in 2004, and 42 and 39% in 2015 respectively. This is followed by urban land occupying 3 to 11% of the total area respectively for the above-mentioned periods.

In 2004 and 2015 however, the forest and urban areas increased to about 1 and 8% of the total area while agricultural and water areas decreased 6 and 3% respectively. The area of bare land slightly increased in 2015. The average rates of change are summarized in Figure 4(a) and (b). The area change of water, agricultural, urban, bare soil and forest over the period 2004-2015 was identified to be 60.88, 92.94, -131.26, -3.13, and -19.47 km^2 respectively (the positive values indicate an increased in area and negative values an decreased in the area).

B. Accuracy assessment

Accuracy assessment was performed by using confusion matrix ground truth sampling (Figure 2). Data in Table 2 show that the classification in 2015 has achieved satisfactory accuracies; the obtained overall accuracy, followed by the kappa statistics is 72.72% and 0.6626 respectively. In 2015 the agricultural and urban areas were characterized by the lowest accuracy; this is because some pixels were misclassified as urban areas.

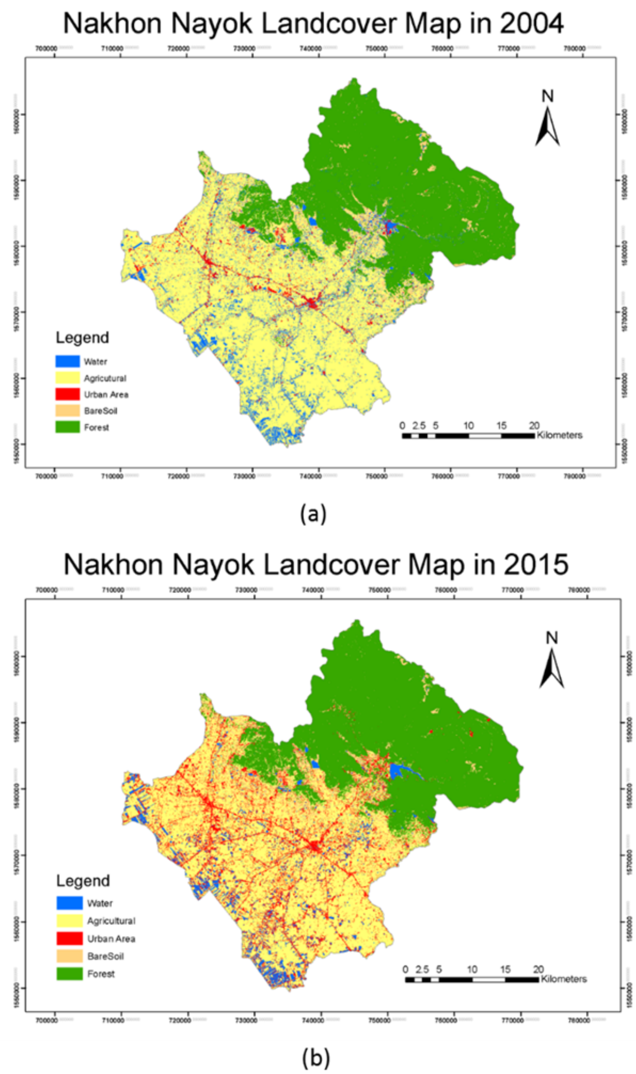

Figure 3. Land cover maps in 2004 (a) and 2015(b)

C. Land cover change from 2004–2015 (Discussion)

The accuracies of classification turned out to be better than expected. The good overall accuracies can be explained by the fact that the total number of correctly classified pixels was high. The land cover classes were correctly selected.

The precision of the classification might have been different if other land cover types had been classified separately (Shrimp farm, irrigated and non-irrigated agriculture). The lower accuracy results obtained from urban and agricultural areas could be explained by the fact that some agricultural areas were misclassified as urban areas and vice-versa. This indicates that the spectral signature of agricultural and urban areas is quite similar in satellite imagery. However, most of the classes had quit high accuracy scores.

The Landsat TM and OLI satellite based analysis reveals some interesting trends in Nakhon Nayok province as regards to the land cover developed over the period 2004-2015. Table 3 shows the loss, gain and net change of each land cover area distribution. It is clear that from 2004 to 2015, urban areas, bare soil and forest areas have been characterized by positive changes (increasing) in area while water and agricultural areas have been the subject of negative changes (reducing). The expansion of urban areas is mainly due to the decrease in agricultural and water areas. Some of the areas covered with agricultural land and water have shifted to urban /building areas. In other words, additional pressures have been placed to expanding urban area and increased the food demand. However, the prime food and water sources (agriculture and water) were lost. A better scenario can be forecasted by studying the socio economic condition of the study area. As a result, better government policies can be created in order to sustainable use of existing natural resources and aim to encourage the rural development.

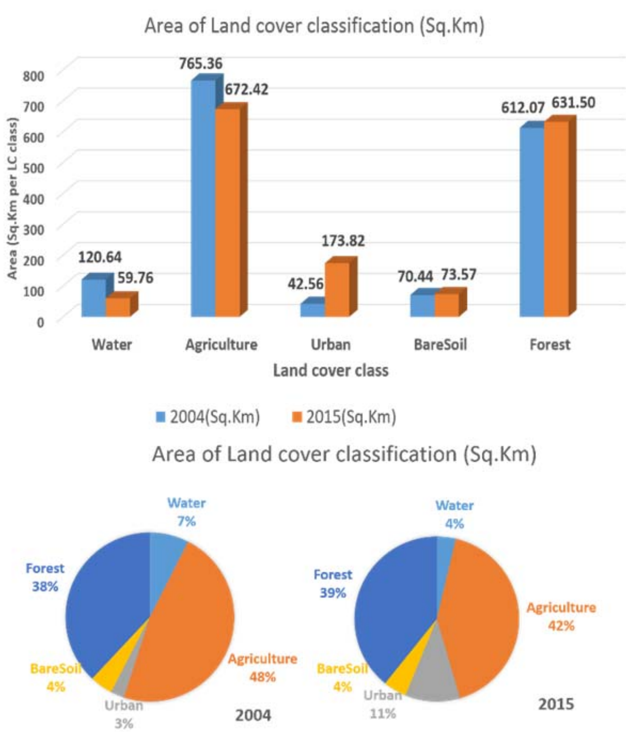

Figure 4. Areas of class distribution in 2004 and 2015 in square kilometers (a) and percentage of the distribution (b)

Table 2. Land cover accuracy assessment

Land cover class	Producers Accuracy (%)	Users Accuracy (%)
Water	100	100
Baresoil	100	90.91
Agricultural	42.86	75
Urban Areas	75	50
Forest	100	90.91
Overall Accuracy = 72.72%		
Kappa Coefficient = 0.6626		

Table 3. Land cover dynamic from 2004 to 2015 (percentage)

Land cover class	Water	Agriculture	Urban	Bare soil	Forest
Water	21.38	4.00	3.90	1.17	0.15
Agriculture	39.95	75.16	30.02	35.90	1.79
Urban	30.49	13.35	62.19	7.97	0.45
BareSoil	3.31	5.81	3.54	27.61	0.68
Forest	4.88	1.69	0.35	27.35	96.93
Class Total	100.00	100.00	100.00	100.00	100.00
Class Changes	78.62	24.84	37.81	72.39	3.07
Image Difference	-50.46	-12.14	308.46	4.44	3.17

Conclusions

The Landsat satellite imagery based change detection analysis has provided an interesting account of the situation in the study area over the period 2004-2015. Drivers of land cover change were identified to be strongly influenced by changes in agricultural area, which themselves were identified to be influenced by infrastructure and urban development. The results of this study revealed that the conversion of agricultural areas intensified with urban development. The results also indicated that severe changes in land cover occurred in urban (308.46%), water (-50.46%), and agricultural (-12.14%) areas. Least changes were observed in forest (3.17%) areas. This paper highlights the importance of digital change detection in apprehending the agricultural production situation in Nakhon Nayok Province. Further research should be carried out to help better understand about the variations in agricultural and urban areas across the province as well as the conversion and modification mechanisms of the above land cover types.

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