COMPARISON OF PIXEL AND OBJECT BASED APPROACHES USING LANDSAT DATA FOR LAND USE AND LAND COVER CLASSIFICATION IN COASTAL ZONE OF MEDAN, SUMATERA

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ABSTRACT

As an archipelagic country, Indonesia has the second longest coastal areas in the world after Canada. Coastal zones have dynamic characteristics. There are many changes here because of unique ecology systems, sedimentation as well as human activities. Because of the coastal zone dynamics especially land use and land cover therefore it is important to identify them by using remote sensing technology. This paper discusses the application of Landsat satellite remote sensing image to classify land use and land cover by using object-based classification approach in part of the coastal zone of Medan, North Sumatera, Indonesia. Conventional classification methods use per pixel approaches that rely only on the spectral information or colors contained in the image. Otherwise, object-based classification approach firstly the image is segmented into objects. In subsequent steps, segments are merged based on their level of similarity. The user uses a scale parameter which indirectly controls the size of objects by specifying how much heterogeneity is allowed within each. User-defined color and shape parameters can also be set to change the relative weighting of reflectance and shape in defining segments. The methodology consists of satellite data acquisition, existing topographic map and statistical data collection, rectification of Landsat image, classification of land use and land cover using maximum likelihood algorithm and object-based approach. Finally, the result shows that the use of an object-based classification system provides a more reliable classification result than using a traditional method such as the maximum likelihood classification system.

Keywords: object-based method, maximum likelihood, LANDSAT, land use, land cover, coastal zone

1. Introduction

As an archipelagic country, Indonesia has the second longest coastal area in the world after Canada. Coastal zones have dynamic characteristics. There are many changes here because of unique ecology systems, sedimentation as well as human activities. One of the land uses which is very important for humans to live is residential areas. Recently, expansion of land use for residence is increasing because of population growth. A number of residential areas are located adjacent to the shoreline. In addition, there are many industrial areas built in coastal areas. An alternative technology which has been a promising approach to detect the change is remote sensing. This paper discusses the application of LANDSAT satellite remote sensing image to classify land use and land cover by using object-based classification approach in part of the coastal zone of Medan, North Sumatera, Indonesia.

Many papers have discussed the use of conventional classification method such maximum likelihood to identify land use and land cover on the ground. Townshend et al. (1987) generated multiple datasets of NDVI in South American for land cover classification. Before use of the maximum likelihood algorithm to classify land cover types, they used a principal component analysis to compress 13 multi-temporal NDVI images. To analyze forest in

Northern Lake state in US, Wolter er al. (1995) used multitemporal Landsat imagery. They achieved 80.1% accuracy for forest classes by using maximum likelihood classification approach. Furthermore, maximum likelihood technique was extensively applied by many researchers for urban mapping (Mesev, 1998; Smith et al. 1998; Shaban and Dikshit, 1999), agricultural land mapping (Panigrahy and Sharma, 1997; Orthiz et al. 1997; Oetter et al 2001; South et al. 2004), global studies (Defries and Townshend, 1994; Hansen et al. 2000; Friendl et al. 2002).

However, interpretation of remote sensing imagery tends to be the extraction of objects which is closest to the real interpretation by human perception. Recently, the object-based classification system, a promising method as it is closed to human perception, is generally applied. A typical object-based classification system starts with segmenting the image into smaller homogeneous regions (or image objects). These objects correspond to approximations of real-world objects (definiens.com). Every object is characterized by several features defined based on layer values, texture, shape and context of the object. Generally, the objects are classified using a defined rule base. This is where human intervention cannot be avoided, thus hindering the possibility to automate the classification process. With a few input samples for every class and using the enormous object feature-space to our advantage, it is possible to automatically generate such a rule base (Marpu et al. 2009). Object-based classification of imagery was found to be an efficient way to generate accurate and detailed vegetation maps in significantly shorter time than with previous methods (Stow et al. 2003).

Akbar and Mulder (1998) obtained an overall accuracy of 97% in comparison with 83% in improved maximum likelihood classification. They selected a specific case of agricultural fields for study area. Object based classification method has been applied by many researchers to analyze urban study (Stow et al. 2003; Herold et al. 2006; Mathieu et al. 2007; Stow et al. 2007; Li et al. 2009; Small and Miller, 2009), land use and land cover studies (Abkar and Mulder, 1998; Matinfar et al. 2007; Zhou et al. 2008; Santos et al. 2009; Kamagata et al. 2009; Grenier et al. 2009), forestry (de Kok et al. 1999; Jobin et al. 2008), ecology (Krishnaswamy et al. 2004), coastal study (Wang et al. 2004), disLandsat management (Matsumoto et al. 2006; Hussain et al. 2009; Uddin et al. 2009; Schmitz et al. 2009; Vu, 2009; Blaschke, 2010). This study tries to identify land use and land cover classes in coastal zone in Medan city, Sumatera, Indonesia. The study used two approaches, the traditional approach (i.e., maximum likelihood method) and the object-based classification method developed by Definiens (www.definiens.com).

2. Study area and data

The study area is located in Hamparan Perak region about 37 kilometers from Medan City. It has elevation from 0 to 15 above mean sea level therefore the area is a coastal zone. The study area is dominated by swamp, plantation and paddy fields. Figure 1, 2 show the location of the study area in North Sumatera, Indonesia, and LANDSAT satellite image recorded in 2007, respectively.

LANDSAT (Advanced Spaceborne Thermal Emission and Reflection Radiometer) is an imaging instrument flying on Terra, a satellite launched in December 1999 as part of NASA's Earth Observing System (EOS). LANDSAT captures high spatial resolution data in 14 bands, from the visible to the thermal infrared wavelengths; and provides stereo viewing capability for digital elevation model creation (http://Landsatweb.jpl.nasa.gov). LANDSAT image was used for many purposes such as wetland and forest mapping (Kato et al. 2001), mineral exploration (http://www.borstad.com), snow mapping (Shi, 2000), land use and land cover mapping (Aynekulu et al. 2008) and agricultural land mapping (Perveen et al. 2010).

Figure 1. Study area bordered by red color

Figure 2. LANDSAT satellite image

3. Methods

3.1. Pre-processing

Pre-processing images focuses on geometric correction or geo-referencing. The geo-referencing of remotely sensed data is needed for the following purposes (Kardoulas et al. 1996); (a) to bring an image into standard projection, (b) to locate points of interest, (c) to bring adjacent images into registration, (d) to overlay images of the same area from different dates and sensors, (e) to overlay an image on a map or merge it into a geographic database (GIS). The LANDSAT image was projected onto the Universal Transverse Mercator (UTM) with WGS 84 datum corresponding to the topographic map published by Bakosurtanal at scale of 1: 50.000. Twelve ground control points distributed over the study area were derived from the map. The LANDSAT image was rectified based on a polynomial method using GCP collected above with a sub-pixel precision (RMSE<0.50 pixel).

3.2. Image segmentation

The project-based classification software used in this research was eCognition Professional 4.0 (Definiens). eCognition uses a multi-resolution segmentation approach which is a bottom-up region merging technique starting with a one-pixel object. In numerous iterative steps, smaller image objects are merged into bigger ones (Baatz et al. 2004). The outcome of the segmentation algorithm is controlled by a scale factor and a heterogeneity criterion. The scale factor is indirectly related to the average size of the objects to be detected. The heterogeneity criterion controls the merging decision process, and is computed using spectral layers (e.g., multispectral images) or non-spectral layers (e.g. thematic data such as elevation). The heterogeneity criterion includes two mutually exclusive properties: color and shape. Colour refers to the spectral homogeneity whereas shape considers the semantic characteristics of the objects. Shape is divided into two equally exclusive properties: smoothness and compactness (Mathieu et al. 2007).

After segmenting the image into primitive objects, a few samples are collected. This can be done manually by selecting samples in the image based on human interpretation or statistically by selecting specific regions in the concerned image histograms. For example, if the objects of class of interest are characterized by bright regions compared to other objects in the image, then 2-5% of the objects in the image histogram which have high mean values are taken as samples of class if interest and 2-5% of image objects which have low mean values are assigned as samples to the background class (Marpu et al., 2010).

3.3. Object based classification system

Firstly, the image is segmented into objects. The image segmentation algorithm used in this study followed the fractal net evolution approach, which is embedded in Definiens Developer (formerly known as e-Cognition). The outcome of the segmentation algorithm is controlled by a scale factor and a heterogeneity criterion. The scale factor is indirectly related to the average size of the objects to be detected (Mathieu et al. 2007). The segmentation algorithm is a bottom-up region merging technique, which is initialized with each pixel in the image as a separate segment. In subsequent steps, segments are merged based on their level of similarity. Parameters are defined by the user for the scale, spectral properties and shape properties. These image segments have to be calculated on several hierarchical levels in a "trial and error" process to result in final image segments to represent single objects of interest (Moeller et al. 2004).

The process is conducted as follows; to input image, to segment multispectral image, to determine image object hierarchy, to create class hierarchy, to classify it using training samples with standard nearest neighbor, to classify base segmentation, to repeat steps for the best result, and finally to merge classification result (Laliberte et al. 2004).

The optimum segmentation parameters depend on the scale and nature of the features to be detected. They were determined using a systematic trial and error approach validated by the visual inspection of the quality of the output image objects, i.e., how well the image objects matched feature boundaries in the image (Mathieu et al. 2007). Once an appropriate scale factor was identified, the color and shape criterion were modified to refine the shape of the image objects. Most published works have found that more meaningful objects are extracted with a higher weight for the color criterion (Herold et al. 2022; Laliberte et al. 2004).

The optimal features can be identified visually by looking at the feature values graphically. Unless we have a good understanding of the type of classes and can intuit what features can be possible candidates, it can be a laborious task to identify them as the objects can be characterized by a huge number of features. When we have samples of the classes, we can automatically identify the optimal features (features are the characteristics defined for an object, e.g, mean value, standard deviation, length, width, area, etc (Baatz et al. 2004)) which can separate the two classes effectively based on Jeffries-Matusita distance, J (Nussbaum et al, 2005). For two classes C1 and C2 of size n1, n2 with mean m1, m2 and standard deviations σ1, σ2 respectively (Marpu et al. 2010).

$$B = \frac{1}{8}(m_1 - m_2)^2 \frac{2}{\sigma_1^2 + \sigma_2^2} + \frac{1}{2}\ln\left(\frac{\sigma_1^2 + \sigma_2^2}{2\sigma_1\sigma_2}\right) \tag{1}$$

B is the Bhattacharya distance. Then,

$$J = 2(1 - e^{-B}) \tag{2}$$

A distance measure different to that of the Jeffries-Matusita distance can also be used in this step to identify the optimum feature space.

With respect to the means of the samples of two classes and in the feature, space defined by the optimal features identified in the previous step, clusters are formed using the minimum distance criterion. This clustering is an approximation of the desired classification. To represent all the features on a common scale, a transformation has to be made on the feature values before clustering. This transforms all the feature values in the range of [0,1]. For every object feature value F of a particular feature,

$$F_1 = F - F_{min}$$

$$F' = \frac{F_1}{F_{1max}} \quad (3)$$

F_{min} is the minimum of the object feature values of that feature, F_{1max} is the maximum of values F_1 obtained in the first step. F_1 is the transformed feature value of F. A different clustering algorithm can also be used at this stage.

The final threshold for features to separate the two classes is then found based on Bayes' conditional probability principle. For classes C1 and C2, the threshold can be found as (Nussbaum et al, 2005).

$$T = \frac{m_2\sigma_1^2 - m_1\sigma_2^2 \pm \sigma_1\sqrt{(m_1^2 - m_2^2) + 2A(\sigma_1^2 - \sigma_2^2)}}{(\sigma_1^2 - \sigma_2^2)} \quad (4)$$

Where,

Using this, the thresholds of features are calculated for the two classes (i.e., class of interest and the background), based on the distribution of objects classified in the previous step. The real thresholds are near these calculated thresholds.

An accuracy assessment of the classification results was performed using reference data created from visual interpretation of the image data. A stratified random sampling method was used to generate the random points in the software of Erdas Imagine. A total number of 50 random points were sampled, with at least 10 random points for each class. Error matrices that describe the patterns of mapped class relative to the reference data were generated, from which the overall accuracies, user's and producer's accuracies, and Kappa statistics were derived to assess the accuracies of the classification maps.

In this study the color and shape criteria were assigned in several values whereas the compactness and smoothness were kept in 0.5. Two major classes covered the study area, they swamp and a second, another major class, that is open areas.

4. Results

Band 1,2,3 and 4 of LANDSAT image was used to classify land cover and land use over the study area which is dominated by wetland areas such as swamp. Band 1, 2, 3 has a 15-m spatial resolution while Band 4 has a 30-m spatial resolution. Amount of 5 polygons for each class were taken from the study area as training sites for maximum likelihood classification and object-based classification approach. Each polygon has window size 3x3 and 4x4 pixels. We classified the study area into nine classes including cloud cover and shadow. The largest class is swamp, plantation and open area because of the characteristics of the coastal zone north of Medan City. Other classes are paddy field, ocean, rivers, fishpond and residential areas. Plantation areas are dominated by corn and sugarcane. Open areas are usually protected areas where grass and shrubs are dominant land cover types.

Supervised classification was applied using integration of band 1, 2, 3, and 4 of LANDSAT. A maximum likelihood algorithm was used to classify the land use and land cover over the study area. In supervised classification, in general the basic steps followed are (1) select training samples which are representative and typical for that information class; (2) perform classification after specifying the training samples set and classification algorithms; (3) assess the accuracy of the classified image through analysis of a confusion matrix which is generated either through random sampling or using test areas as reference data (Matinfar et al. 2007). Unfortunately, in this study, accuracy assessment is not done because of limited information related to the landscape characteristics of the study area. We have a topographical map published by Bakosurtanal which also includes land cover of the study area but the scale map is small therefore it can be used as reference data in assessment step.

Segmentation is the main process in the object-based classification approach and its aim is to create meaningful objects. This means that an image object should ideally represent the shape of each object in question (Matinfar et al. 2007). In this study object-based segmentation was tried using different values of color and shape criteria however maintain values of compactness and smoothness. By testing different segmentation parameters (color criterion values of 0.9; 0.8; 0.6; 0.5 and shape criterion values of 0.1; 0.2; 0.4; 0.5), finally according to visual comparison between each other as well as personal knowledge a set of segmentation parameters were selected. Based on these parameters, a segmentation process is performed. We concluded that classification results with color weight of 0.8 and shape weight of 0.2 whereas compactness and smoothness values of 0.5 provides reliable results according to visual performance, landscape characteristics and its comparison to pixel-based classification results. Figure 3 shows classification results using pixel based and object-based approaches, respectively.

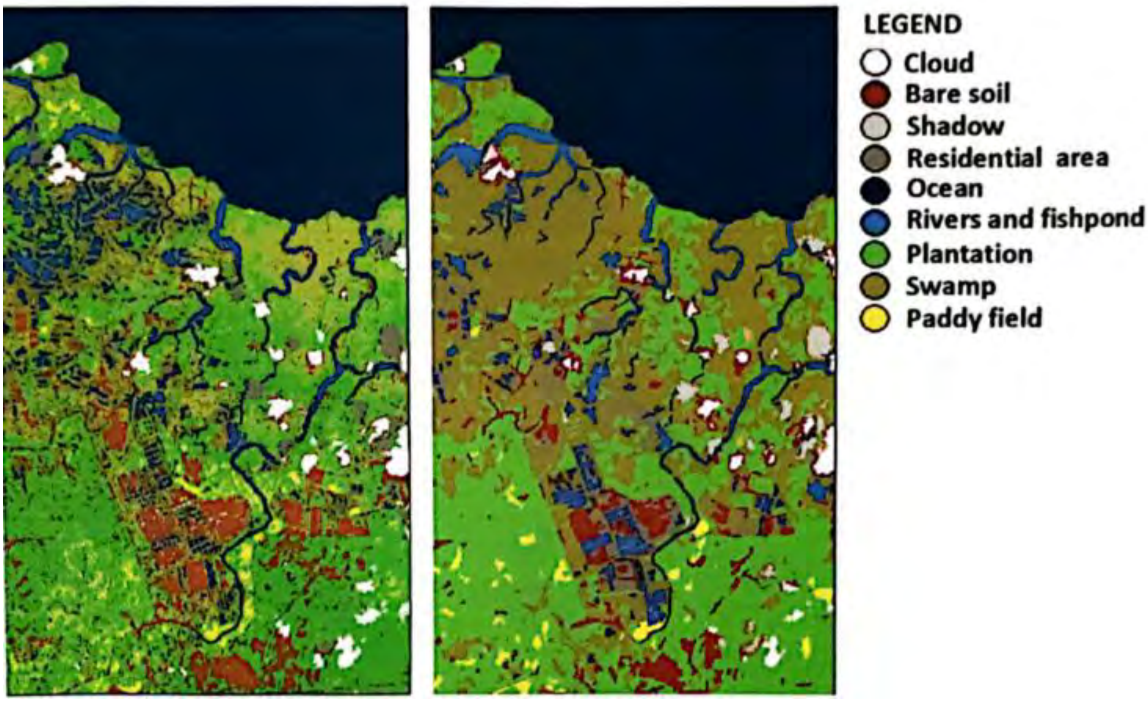

Figure 3. Classification results: Pixel based (on the left side) and object-based (on the right side)

5. Conclusions

A pixel and object-based approaches have been carried out to classify land use and land cover in Hamparan Perak region in northern Medan City, Indonesia. We show that the object-based classification is a powerful tool to extract visible texture automatically. Multispectral bands 1, 2, 3, and 4 from the LANDSAT image were used. Visually, an object-based classification approach provides reliable results because it can discriminate wetland types (rivers, swamp, fishpond) in more detail than a pixel-based approach. Accuracy assessment results show that by using pixel-based classification techniques such maximum likelihood classification providing an accuracy of 70% while by using object-based classification approach, an accuracy of 80% was obtained.

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