A COMPARISON OF THE PERFORMANCE OF PIXEL-BASED AND OBJECT-BASED CLASSIFICATIONS OVER IMAGES WITH VARIOUS SPATIAL RESOLUTIONS

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ABSTRACT:

In the last two decades, advances in computer technology, earth observation sensors and GIS science, led to the development of "Object-based Image Analysis (OBIA)" as an alternative to the traditional pixel-based image analysis method. It was recognized that traditional pixel-based image analysis is limited because of the following reasons: image pixels are not true geographical objects and the pixel topology is limited; pixel based image analysis largely neglects the spatial photo-interpretive elements such as texture, context, and shape; the increased variability implicit within high spatial resolution imagery confuses traditional pixel-based classifiers resulting in lower classification accuracies (Hay and Castilla 2006). Different from pixel-based method, OBIA works on (homogeneous) objects produced by image segmentation and more elements can be used in the classification. As an object is a group of pixels, object characteristics such as mean value, standard deviation, ratio, etc can be calculated; besides there are shape and texture features of the objects available which can be used to differentiate land cover classes with similar spectral information. These extra types of information give OBIA the potential to produce land cover thematic maps with higher accuracies than those produced by traditional pixel-based method. In this paper, we look at the performance of OBIA with different spatial resolution satellite images; comparing the classification results with those produced by the pixel-based method, we intend to find out how spatial resolution of satellite images influences the performance of OBIA. Experiment results showed that with the two sets of images of four different spatial resolutions, object based image analysis obtained higher accuracies than those of the pixel based one; with the increasing of the spatial resolution, the difference in accuracy values between object based and pixel based is decreasing. This paper showed that the object-based image analysis has advantage over the pixel-based one, and in accuracy rating, the advantage was better represented by higher spatial resolution satellite images.

1. INTRODUCTION

There is a steadily increasing need for timely and accurate geo-spatial information. The automatic classification of remotely sensed data is an essential action within the process of generating or updating GIS databases. Remote sensing image classification is a commonly adopted method to obtain land cover information from Satellite images and many classification algorithms have been extensively applied to (Ouattara 2004, Borak *et al*. 1999, Chintan *et al*. 2004, Casals-Carrasco *et al*. 2000). Since remote sensing images consist of rows and columns of pixels, naturally conventional land cover mapping has been based on single pixels (Dean *et al*. 2003). Pixel based image classification utilizes spectral information-digital values (DNs) stored in the image and classifies images by considering the spectral similarities with the pre-defined land cover classes (Casals-Carrasco *et al*. 2000). Although the techniques are well developed and have sophisticated variations such as soft classifiers, sub-pixel classifiers and spectral un-mixing techniques, it is argued that it does not make use of the spatial concept (Blaschke *et al*. 2000). For example Zhou (2001), Pizzolato *et al*. (2003), Dean (2003) claimed that Maximum likelihood classifier (MLC) was limited by utilizing spectral information only without considering contexture information. And texture information was ultimately necessary if one is to obtain accurate image classifications (Zhou 2001).

The concept of OBIA as an alternative to pixel based analysis was introduced in 1970s (de Kok *et al*. 1999). The initial practical application was towards automation of linear feature extraction (Flanders *et al*. 2003). In addition to the limitation from hardware, software, poor resolution of images and interpretation theories, the early application of object based image analysis faced obstacles in information fusing, classification validation, reasonable efficiency attaining, and analysis automation (Flanders *et al*. 2003). Since mid-1990s, hardware capability has increased dramatically and high spatial resolution images with increased spectral variability became available. Pixel based image classification encountered serious problem in dealing with high spatial resolution images and thus the demand for OBIA has increased (de Kok *et al*. 1999). OBIA works on objects instead of single pixels. The idea to classify objects stems from the fact that most image data exhibit characteristic texture features which are neglected in conventional classifications (Blaschke *et al*. 2001). In the early development stage of OBIA, objects were extracted from pre-defined boundaries, and the following classifications based on those extracted objects exhibited results with higher accuracy, comparing with those by pixel based methods (Smith *et al*. 2001, Dean *et al*. 2003, de Wit *et al*. 2004). This technique-classifying objects extracted from pre-defined boundaries-is applicable for agriculture plots or other land cover classes with clear boundaries, while it is not suitable to the areas with no boundaries readily available, such as semi-natural areas. Image segmentation is the solution for obtaining objects in areas

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without pre-defined boundaries. It is a preliminary step in object-based image analysis. By image segmentation, image is divided into homogeneous, continuous, and contiguous objects. Image segmentation is a kind of regionalization which is to divide the image regarding to a certain criteria of homogeneity, and at the same time, requires spatial contingency. There are many techniques to perform image segmentation and those techniques can be categorized into three classes: thresholding/clustering, region based, and edge based (Fu and Mui 1981, Haralick and Shapiro 1985). Image segmentation is analogous to the common multi-spectral clustering of individual pixels but with grouping taking place in the spatial domain in addition to the multispectral domain (Lobo 1997). A more detailed description and evaluation of segmentation is in methodology part. Based on image segmentation, OBIA uses information from spectral, textural and contextual, and spatial domain. Particularly, image objects allow shape characteristics and neighbourhood relationships to be used for the object's classification.

Due to the problems encountered in thematic mapping, much work has been done to increase the accuracy of thematic maps which are derived from remote sensing data (Foody 2004). Thus, there is a very large literature involving the relative comparison of different classification techniques for example between per pixel and per object classification (Dean 2003), and in those studies, the key focus is on the difference among the estimated classification accuracies.

This paper looks at the performance of OBIA with different spatial resolution satellite images; comparing the classification results with those produced by the pixel-based method, we intend to find out how spatial resolution of satellite images influences the performance of OBIA. We use images with four spatial resolutions: 10m, 30m, 100m, and 250m; the coarse images were generated from a SPOT-5 image with 10 m spatial resolution, one set by mean filtering, and another using a method simulating the real response of a satellite sensor moving across the scene, which was based on the method designed by Justice *et al*. (1989).

2. THE STUDY AREA AND DATA

2.1 The study area

The study area is located at south-east of Tancítaro mountain peak. It covers approximately 27*28 km^2, ranging in latitude from approximately 19º 02' to 19º 17' N and in longitude 102º 00' to 102º 16'W (figure 1). The dominant land cover types are: irrigated agriculture, grassland, tropical dry forest, human settlement, orchards, and temperate forest.

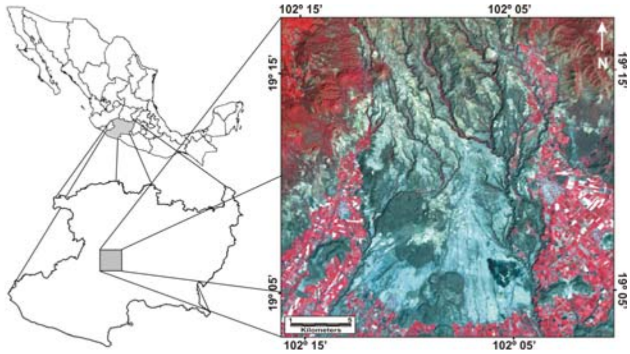

Figure 1: *The study area. The satellite image was presented with false colour composite of R.G.B bands represented by near infrared, red, and green.*

2.2 Data and software programs

Three types of imagery are used in this paper: SPOT-5, Landsat-7 ETM+ (Enhanced Thematic Mapper plus), and MODIS (Moderate Resolution Imaging Spectral-radiometer). SPOT-5 image was obtained on 13th of March, 2004. The multi-spectral sensor of SPOT-5 imagery produces images in 4 channels: band 1: 0.50-0.59µm (green), band2: 0.61-0.68µm (red), band 3: 0.78-0.89µm (near infrared), and band 4: 1.58-1.75µm (mid-infrared). The optical and near infrared bands 1, 2, and 3 have spatial resolution of 10 m, while the mid-infrared band has spatial resolution of 20 m.

The Landsat-7 ETM+ image was obtained on February 16th, 2003. The ETM+ instrument on the Landsat-7 spacecraft contains sensors to detect earth radiation in three specific bands: visible and near infrared (VNIR) bands - bands 1 (blue), 2 (green), 3 (red), 4 (near infrared), and 8 (Panchromatic) with a spectral range between 0.4 and 1.0 micrometer (um); short wavelength infrared (SWIR) bands - bands 5 and 7 with a spectral range between 1.0 and 3.0 um; and thermal long wavelength infrared (LWIR) band - band 6 with a spectral range between 8.0 and 12.0 um. In this study, the thermal band was not used.

The MODIS image was obtained on 8th of March, 2005. MODIS imagery has 36 spectral bands and spectral bands 1-7 are closely related to land cover mapping. In this study, a multi-spectral MODIS image with bands 1-7 is used: Spectral band 1 (red), band 2 (near-infrared), band 3 (blue), band 4(green), and bands 5-7 (mid-infrared). Bands 1 and 2 have spatial resolution of 250m and bands 3-7 have spatial resolution of 500 m.

Pixel-based image classification was carried out in ILWIS (ILWIS 2005), and object-based image classification was carried out in eCognition (Definiens, 2006).

3. METHODS

3.1 Image pre-processing

The SPOT-5 image was corrected geometrically: 28 evenly distributed Ground Control Points (GCPs) extracted from ortho-corrected photographs were used and the correction was carried out at a sub-pixel level. The Landsat-7 ETM+ imagery was geometrically corrected with 86 GCPs and the RMS error is 16.8m which is well below one pixel.

3.2 Generating the multi-spectral images with coarser spatial resolutions

We used images with four spatial resolutions: 10m, 30m, 100m, and 250m; the coarse images were generated from a SPOT-5 image with 10 m spatial resolution, one set by mean filtering, and another using a method simulating the real response of a satellite sensor moving across the scene, which was based on the method designed by Justice *et al.* (1989). In this work, this method is referred to as cubic filtering. The method filtered windows of 3*3, 10*10, and up to 25*25 pixels. Mean filtering assigned the mean reflectance value of a user-defined window, in this case windows of 3*3, 10*10, and 25*25 pixels to a single pixel covering the whole window. For this study, it was decided to interpolate the original kernel values, as proposed by Bastin (1997), in order to generate kernels 3*3, 10*10, and 25*25. As for the mean filter, one value was calculated for each window of cells, and a coarser cell was created containing this value.

The mean filtering tended to smooth the image, while the second method-cubic filtering-retained differences between the resulting pixels and thus retained the local contrast. When local image variance was calculated for these filtered images it was higher at any point in the cubic filtered image than in the corresponding mean filtered image.

3.3 Pixel-based image classification

Classical pixel-based image classification automatically categorizes all pixels in an image into land cover classes or themes in a pixel by pixel manner. Usually, multispectral data are used and the spectral pattern present within the data for each pixel is used as the numerical basis for categorization. The classical pixel-based methods are minimum-distance/nearest neighbour, parallelepiped and maximum likelihood classifiers (MLC), whose detailed information can be found in Lillesand and Kiefer (1994).

3.4 Object-based image classification

Object-based image analysis comprises two parts: 1) image segmentation and 2) classification based on objects' features in spectral and spatial domains. Image segmentation is a kind of regionalization, which delineates objects according to a certain homogeneity criteria and at the same time requiring spatial contingency (Lang *et al*. 2006). By segmentation, the image is divided into homogeneous, continuous and contiguous objects. Several parameters are used here to guide the segmentation result. The Scale parameter determines the maximum allowed heterogeneity for the resulting image objects. The Colour criterion defines the weight with which the spectral values of the image layers contributes to image segmentation, as opposed to the weight of the shape criterion. The relationship between colour and shape criteria is: colour + shape = 1. Maximum colour criterion 1.0 results in objects spectrally homogeneous; while with a value of less than 0.1, the created objects would not be related to the spectral information at all. Smoothness is used to optimize image objects with regard to smooth borders, and compactness allows optimizing image objects with regard to compactness (Baatz *et al*. 2004). The resulting objects also depend on the image data. For a given set of segmentation parameters, heterogeneous image data result in smaller image objects than homogeneous image data. The image objects can then be described and classified by an extensive variety of features that include colour-, texture-, form-, and context properties in several forms. This can be done using two classifiers, a (standard) nearest neighbour (NN) classifier and fuzzy membership functions, or a combination of both. The first classifier describes the class by user-defined sample objects, while the second classifier describes intervals of feature characteristics (Hofmann 2001b). The variety of object features can be used either to describe fuzzy membership functions, or to determine the feature space for NN. More detailed description of image segmentation and classification is given in Hofmann (2001a) and Gao *et al*. (2006). In this paper, the object based image analysis was performed with a standard NN classifier.

4. RESULTS AND DISCUSSION

4.1. Spectral separability analysis for land-cover classes

Seven land cover types exist in the study area: irrigated agriculture, rain fed agriculture, grassland, tropical dry forest, human settlement, and orchards. Representative samples are selected to analyze the spectral separability of those land cover types, and the result shows that there is overlapping to different extent between land cover classes in all the combinations of the spectral feature space. There are three types of irrigated agriculture which appear distinctively in the image: agriculture fields with crops, dry agriculture fields without crops, and wet agriculture fields without crops. One type of irrigated agriculture -wet fields without crops- significantly overlaps with tropical dry forest because they share a very similar spectral signature in most of the spectral bands. Also, classes 'rain fed agriculture' and 'grassland' evidently overlap and both of them overlap with class 'human settlement' which is a spectrally very heterogeneous land-use class. In this study area, parts of the settlements are constructed with natural materials, causing substantial problems in spectral detection. The near-infrared band is important in distinguishing most of the land-use / land cover types, for example, in all the spectral feature combinations with near infrared band, the two classes irrigated agriculture and orchards are distinguishable, while they are not distinguishable when the near infrared band is not present.

4.2. Pixel-based image classification result

The original SPOT-5 image, the simulated images, the Landsat-7 ETM+, and the MODIS multispectral image were classified with both pixel-based MLC and pixel-based NN classifiers, based on the selected training samples for the seven land-use / land cover classes of interest. The classified images were first evaluated visually. This revealed that for the original SPOT-5 image, the classification had a strongly speckled result which gave it a "blurred" appearance. The class 'human settlement' was seriously mis-classified although its training samples were greatly reduced to only one sample. Results show that with the increase of the spatial resolution, the speckled-appearance problem becomes less serious. In the very coarse spatial resolution image, the mixed pixels were the majority in the image and some classes, for example rain fed agriculture, orchards, and human settlement, represented by small areas in the image, are wrongly represented by the coarse spatial resolution image. Images generated by the mean-filtering method produced classified results with more homogeneous appearance in the classified images.

4.3. Object-based image analysis result

Object-based image analysis was carried out for the SPOT-5 image, two sets of simulated images, Landsat-7 ETM+, and MODIS image. Firstly, image segmentation was performed. The parameters to guide the segmentation process were explained in the method section 3.4. For SPOT-5, the segmentation parameters were: scale factor 20, colour factor 0.8, and smoothness 0.5 and it resulted in 23759 objects. For the two simulated images of 30m spatial resolution and Landsat-7 ETM+, the segmentation parameters settings were: scale factor 10, colour factor 0.8 and smoothness 0.5; it resulted in 10814 objects for the mean-filtered image, 11721 objects for the cubic-filtered image, and 7209 objects for the Landsat-7 ETM+ image. For the two simulated images at 100m spatial resolution, the parameters for segmentation were: scale factor 5, colour 0.8 and smoothness 0.5; it resulted in 4696 objects for the mean-filtered image, 5388 objects for the cubic-filtered image. And for the two images with 250m spatial resolution and MODIS image, the parameter settings for image segmentation were: scale factor 3, colour 0.8 and smoothness 0.5; it resulted in 2265 and 3532 objects for mean-filtered and the cubic-filtered image, respectively, and 3075 objects for MODIS image. Those parameter settings were decided based on checking visually that the produced segments optimally represent the primitive earth objects. The segmentation results showed that with the same set of parameter settings, the images simulated using cubic-filtering produced more objects than those of images simulated using mean-filtering. This was related to the fact that the cubic-filtering retains the local contrast in the image while mean-filtering smoothes the contrast. The segmented images were classified by standard NN classifier using the same set of training samples as were used for pixel-based classification.

4.4. The comparison of pixel-based and object-based image analysis results

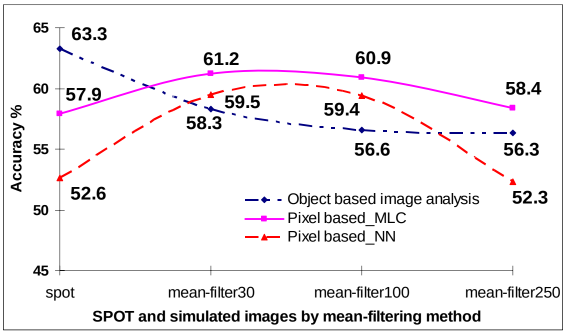

Figure 2. Classification accuracies in function of image spatial resolution.

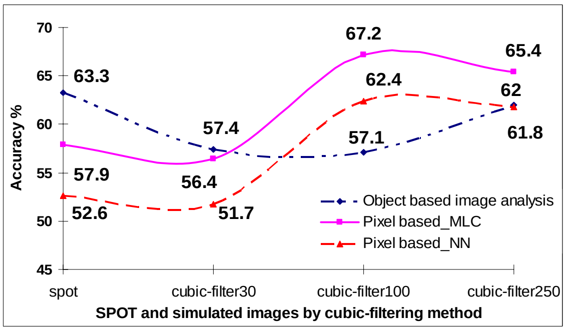

Figure 3. Classification accuracies in function of image spatial resolution.

In figure 2 and 3, the accuracy of the classifications using images produced by cubic-filtering tends to be higher than using images produced by mean-filtering, except for simulated images with 30m spatial resolution. By averaging the pixel values of the windows, the mean-filtering produced images that have a smoother appearance than those by cubic-filtering. Images produced by cubic-filtering preserved the contrast in the original image and are more “heterogeneous” in appearance and in pixel values, and the produced images are closer to the images taken by the satellite sensors. When classification accuracy is evaluated using homogeneous areas, images produced by mean-filtering have the tendency of optimizing the results. However, the classification accuracy here was evaluated by points and thus the classification results of images by mean-filtering did not present higher accuracy. Instead, images by cubic-filtering which preserved the local contrast in the image obtained higher accuracy. As for the images with 30m spatial resolution, mean filtering clustered the pixels with similar spectral values, removed the spectral noises in the high spatial resolution images, while it did not remove important local spectral contrast in the image, and thus obtained higher accuracy than images by cubic-filtering. Further observing figure 2 and 3, we can see that in the case of the two sets of simulated images, classification accuracies by pixel-based MLC are higher than those produced by pixel-based NN classifier. Furthermore, on simulated cubic-filtered SPOT-5 image, object-based image analysis obtained higher accuracy than pixel-based MLC and pixel-based NN methods. This result showed that first, pixel-based MLC is indeed a well established pixel-based method which is able to obtained higher classification accuracy; second, for SPOT-5 image, object-based image analysis has advantage over pixel-based one regardless of which pixel-based classification methods used. By classifying an object which is a group of homogeneous pixels, object-based image analysis produces classification results closer to human interpretation results, free of speckled appearance, and with comparatively higher accuracies. With the increase of the spatial resolution, object-based image analysis obtained lower accuracy than that by pixel-based methods, which showed that in accuracy rating, the advantage of object-based image analysis over the pixel-based one is only represented by images with high spatial resolutions.

Landsat-7 ETM+ and MODIS images were also classified and the results were compared with classifications of images with the same spatial resolution. Pixel-based Landsat image classifications had an accuracy of 50.1% by MLC, and NN obtained accuracy 48.8%. Object-based NN classification of Landsat image obtained an accuracy of 51.7% (figure 4). For MODIS image, pixel-based MLC and NN classifiers obtained an accuracy of 47.6% and 46.1% respectively, and object-based

NN classification obtained an accuracy of 43.9% (figure 5). On Landsat image, object-based image analysis still obtained a higher accuracy than those by pixel-based MLC and NN classifiers, while for MODIS, the object-based method obtained lower accuracy than those by both pixel-based MLC and NN methods. This result proved again that for coarse spatial resolution images, object-based image analysis shows no advantage over the pixel-based one.

Figure 4 showed that Landsat image obtained results closer to the results of the images generated by cubic-filtering. This is because cubic-filtering method was developed by simulating the way Landsat sensor is taking the images. MODIS image did not present classification accuracy results closer to those by cubic-filtering method, possibly due to the difficulty in locating precisely the reference points on the MODIS image (figure 5).

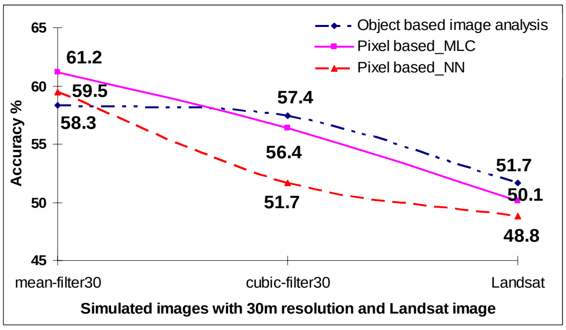

Figure 4. Comparison of the accuracies of the classifications between Landsat-7 ETM+ image and the simulated images with 30m spatial resolutions.

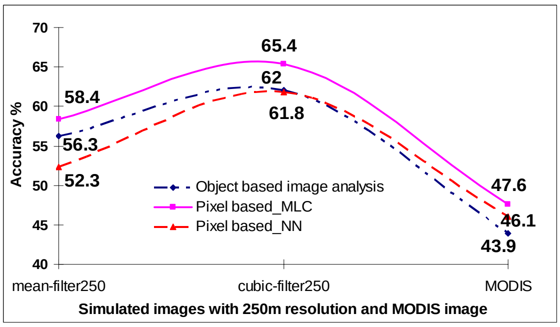

Figure 5. Comparison of the accuracies of the classifications between MODIS image and the simulated images with 250m spatial resolutions.

Comparing with pixel-based image analysis, object-based image analysis has many advantages (Hay and Gastilla, 2006), such as: the way it classifies an image by partitioning it into objects is similar to the way humans comprehend the landscape; image-objects exhibit useful features (shape, texture, context relations with other objects) that single pixels lack; image-objects can be more readily integrated in vector GIS. This work performed pixel-based and object-based analysis to images with spatial resolutions from relatively fine to coarse. Both pixel-based and object-based image analysis results were evaluated with a set of stratified random sampled reference data comparing 420 points. Based on the result, a general conclusion was drawn that the advantage of object-based image analysis over the pixel-based one was only represented by images with higher spatial resolutions. Increased spectral variability within high resolution imagery confuses traditional pixel-based classifiers, while by object-based method, pixels with similar spectral information are firstly grouped into objects then those objects are analyzed. Images with medium to low spatial resolution have lower spectral variability and thus are easily handled by pixel-based method. As for the images with low spatial resolution, such as MODIS, by applying object-based image analysis, pixels belonging to different land cover types could possibly be grouped together thus are mis-classified and produce lower accuracy than that by pixel-based method. As stated before, the obtained values from this paper should never be taken in an absolute sense; there are too many factors which influence classification accuracy such as image data quality, the reliability of training data and testing/reference data, the accuracy assessment method adopted, among others.

As to the accuracy assessment method, though accuracy evaluated by random points (simple random or stratified random points) is generally recognized to be more trustworthy than that evaluated using homogenous areas of land cover types, it may not hold true when it comes to object-based image analysis results. Due to that single points/pixels are usually merged into surroundings by object-based method, and thus evaluated by single pixels, the accuracy of object-based image analysis could be under-evaluated, which may explain that although the object-based image analysis results appeared to be more appealing, their accuracy results tended to be low. This is proved by checking the classification results on a simulated mean-filtered image with 30m spatial resolution ('mean-filter30'): 5.2% of the wrongly classified points for object based classification came from those isolated pixels. If we add this number to the already obtained object based classification accuracy, we get 63.5%, which is higher than those by both pixel based MLC and NN classifications of the image "mean-filter30" (figure 2.).

5 CONCLUSIONS

In this paper, pixel-based and object-based image analysis was performed on satellite images with different spatial resolutions. The coarser spatial resolution images are generated by degrading spatial resolution of a multi-spectral SPOT-5 imagery with a 10m spatial resolution. Two simulating methods were used: 1) mean-filtering which averages the pixel values in a certain sized window (3*3, 10*10, 25*25) and, 2) cubic-filtering which is a method modified from Justice *et al.* (1998) that keeps the local contrast in the image during the interpolation and produced images closer to the "real" images. These two sets of images were classified by pixel-based MLC and NN classifier, and object-based NN classifier, respectively. Accuracy assessment results showed that for SPOT-5, and a simulated cubic-filtered 30m resolution images, object-based image analysis obtained higher accuracies than those produced by pixel-based MLC and NN classifiers. With the increase of the spatial resolution of the images, object-based image analysis did not show more advantage over the pixel-based ones. This study showed that the object-based image analysis has advantage over the pixel-based one but the advantage, in accuracy rating, only holds true for high spatial resolution images.

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