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A Comparison of the Performance of Pixel Based and Object Based Classifications over Images with Various Spatial Resolutions

Yan Gao and Jean François Mas
Centro de Investigaciones en Geografía Ambiental, Universidad Nacional Autónoma de México (UNAM),
Antigua Carretera a Pátzcuaro No. 8701, Col. Ex Hacienda de San José de la Huerta
C.P. 58190 Morelia, Michoacán, México

Abstract: In the last three decades, advances in computer technology, earth observation sensors and GIS science, led to the development of “Object-based Image Analysis” as an alternative to the traditional pixel-based image analysis. Many studies have shown that traditional pixel-based image analysis is limited because it uses only spectral information of single pixels and this approach produces poor results especially with high spatial resolution satellite images. By contrast, object-based image analysis works on (homogeneous) objects which are produced by image segmentation and allows using more elements in the classification. As an object is a group of pixels, object characteristics such as mean value, standard deviation of spectral values, etc. can be calculated; besides shape and texture features of the objects are available and can be used to differentiate land cover classes with similar spectral information. These extra types of information give object-based image analysis the potential to produce land cover thematic maps with higher accuracies than those produced by traditional pixel-based method. In this study, we look at the performance of object-based image analysis in classifying satellite images with different spatial resolutions; 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 object-based image analysis. The experiment showed that with relatively high spatial resolution images such as SPOT-5 and Landsat-7 ETM+, object-based image analysis obtained higher accuracy than that by the pixel-based one; while for coarse resolution images with 100 and 250 m spatial resolution, object based image analysis did not obtain higher accuracy. This study shows that the object-based image analysis has advantage over the pixel-based one, however the advantage was only found in the higher spatial resolution images.

Key words: Pixel-based image analysis, object-based image analysis, accuracy assessment, simulated images

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. According to previous investigation, traditional pixel-based image analysis is limited because it only uses spectral information of single pixels and the approach produces poor results especially with high resolution satellite images. Because of the high spatial resolution of the advanced sensors the within field spectral variability increases and therefore, the classification with the traditional pixel-based method yields lower accuracy and it produces classification results with speckled appearance.

Object-based image analysis classifies objects instead of single pixels. The idea to classify objects stems from the fact that most image data exhibit characteristic texture which is neglected in conventional classification methods (Blaschke and Strobl, 2001). Based on image segmentation, object-based image analysis uses textural and contextual information as well as the spectral information and thus it has the potential to produce image analysis results with higher accuracy. This study looks at the performance of object-based image analysis on satellite images with different spatial resolution; comparing the classification results with those produced

Corresponding Author: Yan Gao, Centro de Investigaciones en Geografía Ambiental-Universidad Nacional Autónoma de México (UNAM), Antigua Carretera a Pátzcuaro No. 8701, Col. Ex Hacienda de San José de la Huerta C.P. 58190 Morelia, Michoacán, México

by the pixel-based method, we intend to find out how spatial resolution of satellite images influences the performance of object-based image analysis. In this study, images with four types of spatial resolutions ranging from 10 and 250 m are used.

MATERIALS AND METHODS

The study area: The study area is located to the South-east of the Tancítaro peak, in the state of Michoacán, in the center-west of Mexico (Fig. 1). It covers approximately 27*28 km², ranging in latitude from approximately 19° 02' to 19° 17' N and in longitude 102° 00' to 102° 16'E. The dominant land cover types are: Irrigated agriculture, grassland, tropical dry forest, human settlement, orchards and temperate forest.

Data and software programs: Three types of imagery are used in this study: 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: 0.50-0.59 μm (green), band2: 0.61-0.68 μm (red), band 3: 0.78-0.89 μm (near infrared) and band 4: 1.58-1.75 μm (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 seven specific bands belonging to Visible and Near Infrared (VNIR) spectrum: 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 but only 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: 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 250 m and bands 3-7 have spatial resolution of 500 m.

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

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 16.8 m which is well below one pixel. MODIS image was also geometrically corrected and the correction error was below one pixel.

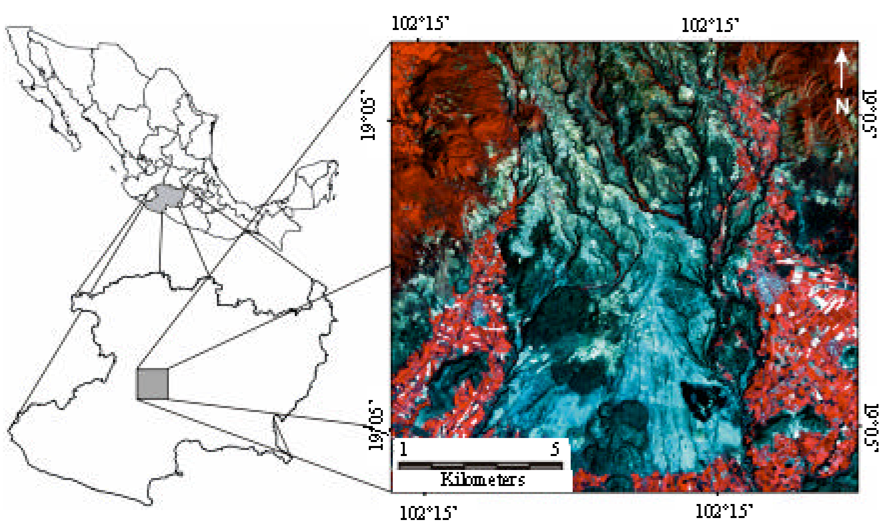

Fig. 1: The study area on SPOT-5 imagery. The satellite image was displayed as a false colour composite with R.G.B represented by spectral bands near-infrared, red and green, respectively

Generating the multi-spectral images with coarser spatial resolutions: We also produced images with four spatial resolutions: 10, 30, 100 and 250 m; two sets of coarse images were generated from a SPOT-5 image with 10 m spatial resolution, the first one by mean filtering and another one 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 research, 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. 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.

Pixel-based image classification: The overall objective of classical pixel-based image classification procedure is to automatically categorize all pixels in an image into land cover classes or themes. Usually, multispectral data are used to perform the classification and the spectral pattern present within the data for each pixel is used as the numerical basis for categorization. The standard 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).

Object-based image classification: Object-based image analysis comprises two parts: Image segmentation and 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. 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 study, the object based image analysis was performed with a standard NN classifier.

Accuracy assessment of the classification results: Classification accuracy is used to describe the degree to which the derived image classification agrees with reality (Campbell, 1996) and a classification error is, thus, the discrepancy between thematic map and reality. The elaboration of a confusion matrix is currently the most common method to assess the classification accuracy. As a simple cross-tabulation of the mapped class label against that observed in the ground or reference data for a sample of cases at specified locations, the confusion matrix provides an obvious foundation for accuracy assessment (Campbell, 1996; Canters, 1997), by providing the basis to both describe classification accuracy and characterize errors, which may help to refine the classification or estimates derived from it. Many measures of classification accuracy may be derived from a confusion matrix (Stehman, 1997). One of the most popular is the percentage of cases correctly allocated which is often regarded as overall accuracy. For the accuracy of individual classes, the percentage of cases correctly allocated may be derived from the confusion matrix by relating the number of cases correctly allocated to the class to the total number of cases of that class. This can be achieved from two standpoints, depending on whether the calculations are based on the matrix's row or column marginal (Foody, 2002).

Both pixel-based and object-based image classifiers were evaluated with independent reference data which were generated by interpreting in total 420 points. These points were generated with a stratified random sampling method. Based on the land use map for the year 2000, 60 random points were extracted from the 7 classes of interest. The properties of these points were interpreted based on the information from air photographs, land use map from year 2000 and satellite images. In the study, classifications were performed on images with four different resolutions: 10, 30, 100 and 250 m. Reference data for images with 10 m spatial resolution may not represent the property of images with 100 and 250 m spatial resolution. In order to evaluate the classifications of the images with different spatial resolutions, the same reference points were interpreted for taking into account an increasing surrounding size depending on images resolution. So altogether there were six sets of reference data to evaluate the accuracy of the classifications.

RESULTS AND DISCUSSION

Spectral separability analysis for land-cover classes: Altogether 7 land cover types are present in the study area: Irrigated agriculture, rain fed agriculture, grassland, tropical dry forest, human settlement and orchards. Figure 2 shows that there is overlapping in 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. From Fig. 2, we can see that 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.

Pixel-based classification results: 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.

Object-based image analysis results: 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. For SPOT-5, the segmentation parameters were: Scale factor 20, color factor 0.8 and smoothness 0.5 and it resulted in 23759 objects. For the two simulated images of 30 m spatial resolution and Landsat-7 ETM+, the segmentation parameters settings were: scale factor 10, color 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, color 0.8 and smoothness 0.5; it resulted in 4696 objects for the mean-filtered image, 5388 objects for the cubic-filtered image. For the two images with 250m spatial resolution and the MODIS image, the parameter settings for image segmentation were: Scale factor 3, color 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 determined 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

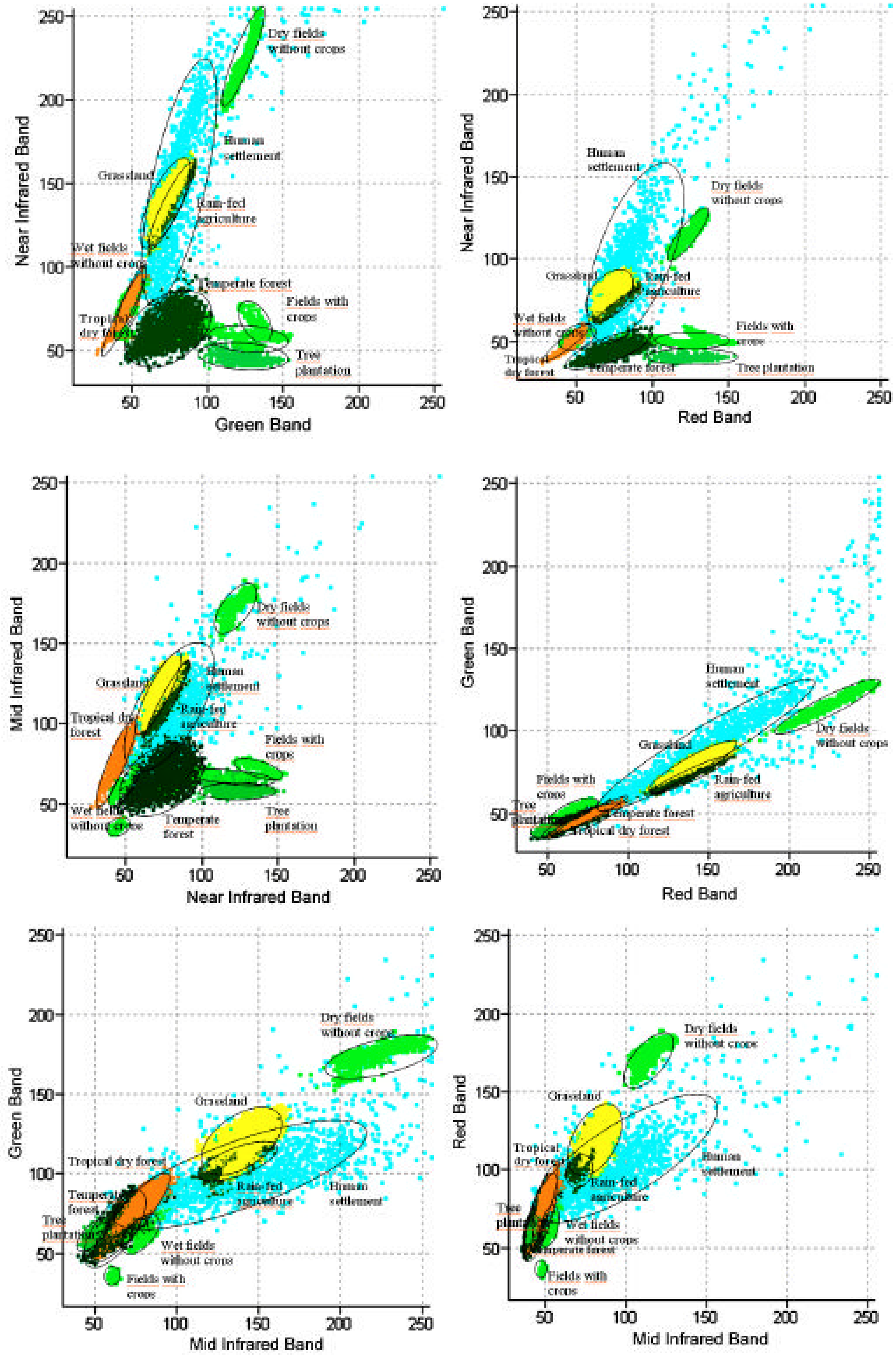

Fig. 2: Feature space with spectral-band-combinations of green, red, near infrared and mid-infrared in the example of SPOT-5 imagery

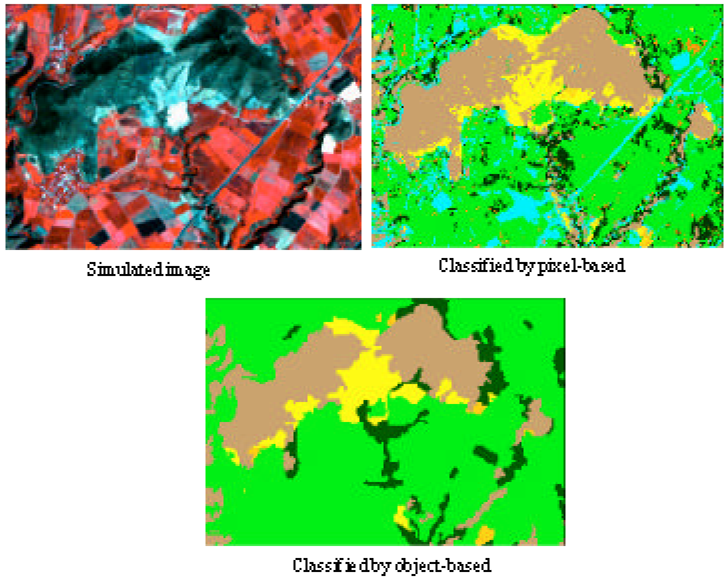

Fig. 3: An example of pixel-based and object-based classifications on a simulated image with 30 m spatial resolution

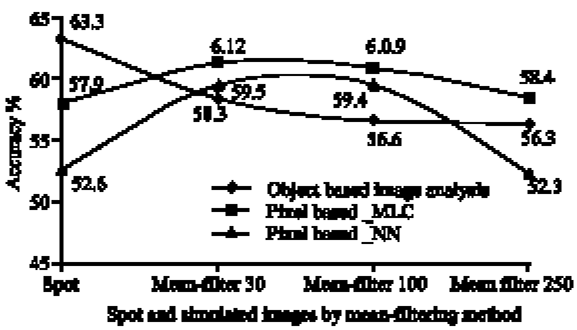

Fig. 4: Classification accuracies in function of image spatial resolution

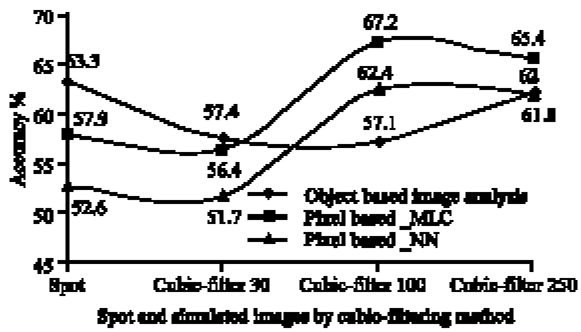

Fig. 5: Classification accuracies in function of image spatial resolution

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 used for pixel-based classification.

The comparison of pixel-based and object-based image analysis results: Figure 3 is an example of classified images by pixel- and object-based methods. As shown by Fig. 3, the object-based classified image presents a more homogeneous and thus more appealing appearance. While for pixel-based result, the salt and pepper effect makes the image appear blurred. The accuracies of the classified images were presented in Fig. 4 and 5.

In Fig. 4 and 5, comparing the classification results produced by pixel-based and object-based approaches on the two sets of simulated images, the accuracy of the classifications on images produced by cubic-filtering tends to be higher than on the images produced by mean-filtering, except for simulated images with 30 m 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 are closer to the images taken by the satellite sensors. If the 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,

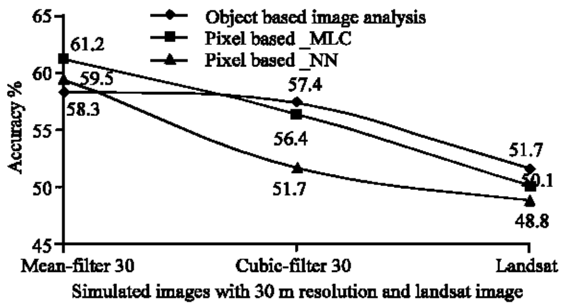

Fig. 6: Comparison of the accuracies of the classifications between Landsat-7 ETM+ image and the simulated images with 30 m spatial resolutions

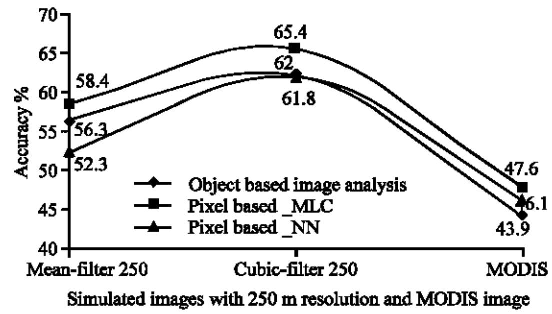

Fig. 7: Comparison of the accuracies of the classifications between MODIS image and the simulated images with 250 m spatial resolutions

images by cubic-filtering which preserved the local contrast in the image obtained higher accuracy. As for the images with 30 m 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 Fig. 4 and 5, 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 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 the advantage of object-based image analysis over the pixel-based one is only represented by images with high spatial resolutions.

Landsat 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% (Fig. 6). 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% (Fig. 7). 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 6 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 (Fig. 7).

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 research 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 420 reference points selected by a stratified random sampling. 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 study should never be taken in an absolute sense; there are too many factors which influence classification accuracy such as the 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 (Fig. 3), 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" (Fig. 4).

CONCLUSION

In this study, 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 10 m 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 30 m 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 approach. This study showed that the object-based image analysis has advantage over the pixel-based one but the advantage only holds true for high spatial resolution images.

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