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Research Article

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A Comparison of Pixel Based and Object Based approach for Land Use/Land Cover Classification: A Case Study in Mediterranean Region

Gürkan Aysel

Mustafa Kemal University, Faculty of Architecture, Department of Landscape Architecture, 31040 Antakya, Hatay, Turkey

Abstract This paper aims to compare between application of pixel-based and object-oriented classifications of Mediterranean region in Turkey. In pixel-based classification a supervised Maximum Likelihood Classification (MLC) algorithm was utilized; in object oriented classification, a soft nearest neighbour classifier were used. The classification data was a high resolution with 0.50 meter of WorldView-2 2014 imagery. Classification results were compared in order to evaluate the suitability of the two classification techniques. The study comprised 3 stages; first stage is pre-processing of imagery, second stage is classification, third stage is accuracy assessment of these classifications. The object-based classifier achieved a high overall accuracy (90.24%), whereas maximum likelihood classifier produced a lower overall accuracy (85.58%). This study demonstrates that the object-based classifier is a significantly better approach than the pixel based classifiers.

Keywords Hatay, Maximum Likelihood Classification (MLC), Nearest neighbour classifier, Worldview imagery

Introduction

For more than 40 years, satellite images and aerial photographs have formed a strong basis for land cover classifications. Pixel-based land cover classification methods, such as maximum likelihood classification, use the spectral information contained in individual pixels to generate land cover classes. This method has been shown to perform accurately for the classification of certain land use/cover classes and has proven accurate in change detection analysis [1-2]. In particular, object-based image analysis (OBIA) techniques enable connecting information from the image with database information [3-4]. Object-oriented classification does not operate directly on single pixels, but objects consisting of many pixels that have been grouped together in a certain way by image segmentation [5-6]. Object-based image analysis is quickly gaining acceptance among remote sensors, and has demonstrated great potential for classification and change detection, compared to pixel-based approach [7-9]. The advantage of the object-based approach is that it offers new possibilities for image analysis because image objects can be characterised by features of different origin incorporating spectral values, texture, shape, context relationships and thematic or continuous information supplied by ancillary data. Integration of additional knowledge is a valuable means to distinguish ecologically meaningful habitat types that don't have necessarily very distinct spectral features. Moreover integration with existing vector-databases can be achived during all steps of the classification proces [10-11]. Object-based, has emerged, and has generally had better success with narrow band and high spatial resolution data [12]. An object based image analysis (OBIA) approach has been proposed as an alternative analysis framework that can mitigate the deficiency associated with the pixel-based approach [7, 13].

Therefore, the study aims to compare classification of city land use land cover using pixel based and object based approaches in Mediterranean region of Turkey in Hatay city, which can be performed and provides the ground cover information. Secondly, to achieve accuracy assessment for the two classification approaches.

Materials and Methods

Data and Study areaa

A WorldView-2 Ortoready Pansharpened (WV2-NT/ORPNP) image data over a central region in the city of Hatay acuired on 14 October 2014 is used. The study area is 8*9 km area covering Hatay city center (Figure 1). It is surrounded by forest cover of Amanos Mountain in the west, Amik Plain in the north and Habibi Neccar Mountain in the east. The data set has 50 cantimeter spatial resolution with 3 channels. The radiometric resolution of the dataset is 16 bit. Antakya is a city in the Mediterranean region of the southern part of Turkey, with a population of 500.749 [14].

Methodology

Study comprises 3 stages: (1) Image pre-processing, (2) Land cover mapping (3) Accuracy assesment (Figure 2).

1) Image Pre-processing: The image was geometrically corrected and geocoded to the Universal Transverse Mercator (UTM), WGS-84 coordinate system. The transformation had a root mean square (RMS) error of less than <0.5 pixels indicating that the image was accurate within one pixel. A nearest neighbor algorithm takes the value of the pixel in the input image that is closest to computed co-ordinate.

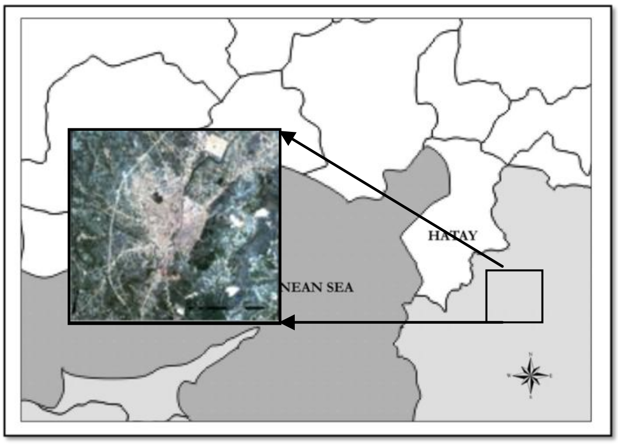

Figure 1: Site location of study area.

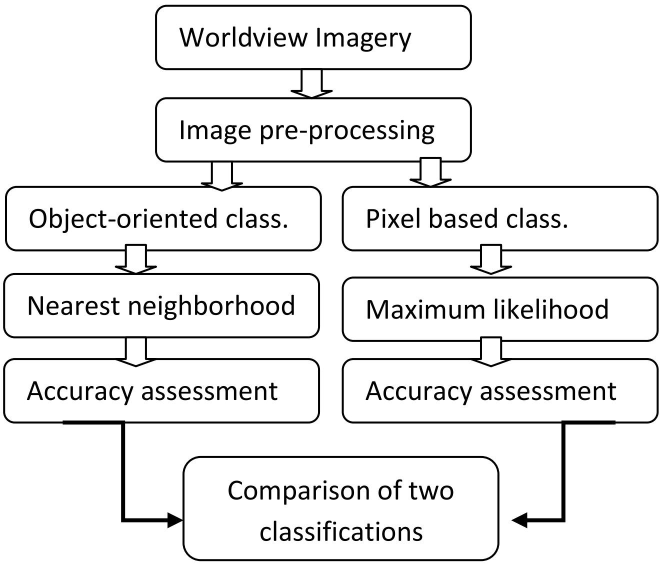

Figure 2: Workflow of methodology

2) Land cover mapping: ***Supervised classification (Maximum Likelihood Classification):*** The maximum likelihood classifier is one of the most popular classification methods in remote sensing, in which a pixel with the maximum likelihood is classified into the corresponding class. For mathematical reasons, a multivariate normal distribution is employed as the probability density [15].

In the case of normal distributions, the likelihood can be expressed as follows:

$$Lci(x) = \frac{1}{(2\pi)^{k/2} |\ Vi\ |^{1/2}} \exp\left[-\frac{1}{2}\left(x - \overline{xi}\right)^t Vi^{-1}\left(x - \overline{xi}\right)\right] \quad (1)$$

where $Lci(x)$ = the likelihood of x belonging to class i; k = the number of image characteristics; x = the image data of k; xi = the mean vector of class i; Vi = the variance- covariance matrix of class i [16-17]. The field work supported the image interpretation of the land cover types defined in the classification.

Object-based image classifications: Object based analysis provides rich opportunities for expert (predefined) knowledge integration for the classification process, it also makes the classification more vulnerable to operator-/scene-/sensor-/target-dependency, which in turn hampers the repeatability and transferability of rules [18]. It was preferred in the classification process. Image objects are described and classified by using a wide range of attributes including image features such as spectral variables, shape, texture, size, but also potentially thematic data such as slope, aspect, soil properties provided by digital maps. Image objects may also be classified by reference to expert rules such as rules based on the spatial relationship between objects (contiguity) or the distance between objects [19]. The software used in this research, ArcGIS 10.2.

3) Accuracy assesment: An error matrix, and a Kappa coefficient for each classification were generated. Once a classification exercise has been carried out, there is a need to determine the degree of error in the end-product. These errors could be thought of as being due to incorrect labelling of the pixels. Conversely, the degree of accuracy could be sought. First of all, if a method allowing a 'reject' class has been used then the number of pixels assigned to this class (which is conventionally labelled as “0”) will be an indication of the overall representativeness of the training classes. If large numbers of pixels are labelled as “0” then the representativeness o the training data sets is called into question - do they adequately sample the feature space? The most manly used method of representing the degree of accuracy of a classification is to build confusion matrix (error matrix) [20].

Kappa Statistic is an index that compares the agreement against what might be expected by chance

$$\kappa = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_{i+} * x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+} * x_{+i})} \quad (2)$$

Kappa coefficient (k) used to summarise the information provided by the error matrix. The x_{ii} are the diagonal entries of the confusion matrix The notation x_{i+} and x_{+i} indicates, respectively, the sum of row I and the sum of column I of the confusion matrix. N is the number of elements in the confusion matrix. Rows total (x_{i+}) for the confusion matrix shown in Table 8.4 are listed in the column headed (I) and columns totals are given in the last row [20].

Results and Discussion

Land cover mapping

Worldview Image was pre-processed and then a pixel-based classification with MLC, and an object-oriented classification with nearest neighbor as the classifier were performed. The classified maps discriminated seven classes: urban, agriculture, forest, shrub land, bare, and water. The classification results are shown in Figure 3, 4.

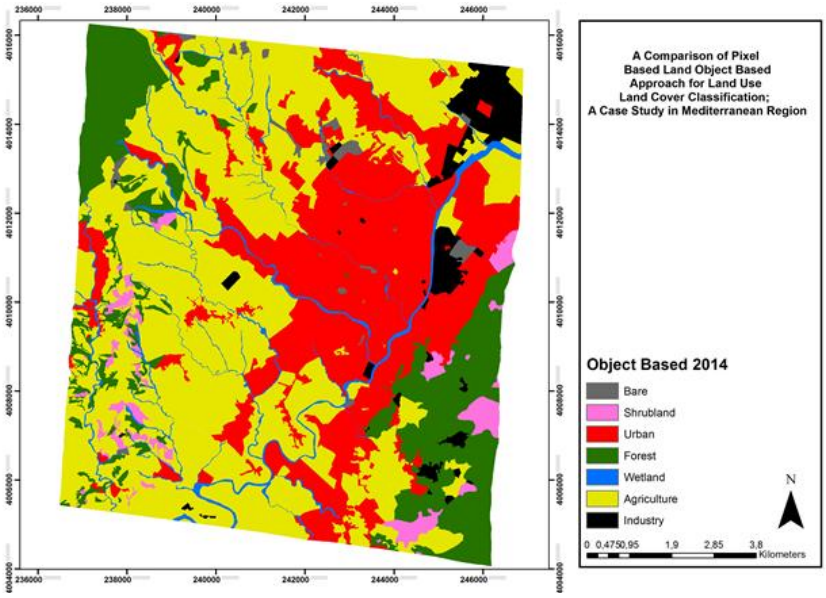

Figure 3: Object based image classification

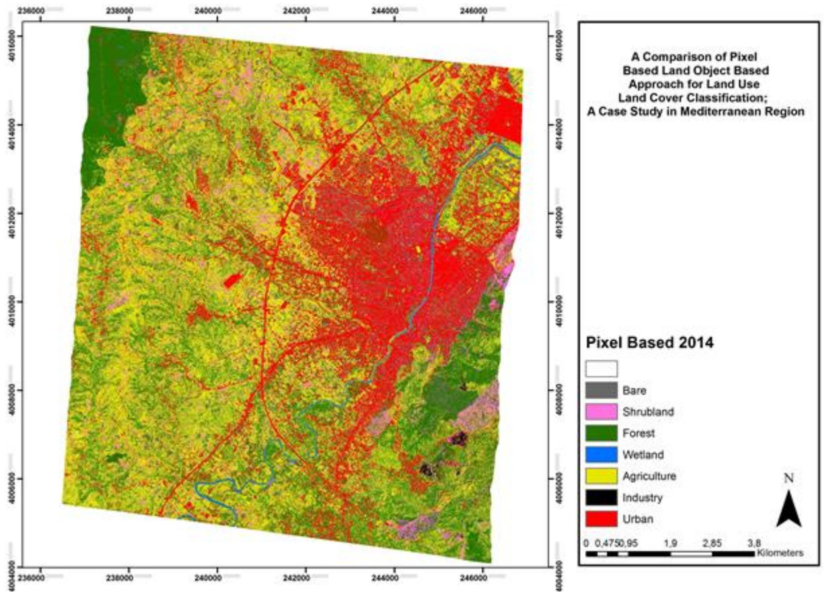

Figure 4: Pixel based image classification.

Validating classification results

Table 1 and Table 2 shows that indicate the level of consistency between observed land cover for object-based and pixel based respectively. Confusion or error matrix consist for seven classes. The row labels are those given by an operator using ground reference data. The column labels are those generated by the classification procedure. The four right-hand columns are as follows: (I) number of pixels in class from ground reference data; (II) estimated classification accuracy (percent); (III) class i pixels in reference data but not given label by classifier; and (IV) pixels given label I by classifier but not class I in reference data [20]. The sum of the diagonal elements of the confusion matrix is 185, and the overall accuracy is therefore (185/205) x 100 = 90.24% (Table 1). Overall acuuracies and Kappa values were over %86 in most cases which is acceptable rate for accuracy [21]. Water had the highest accuracy values. Forest, industry, schrubland, agriculture, bare, urban, follow respectively. Accuracies for urban areas in object based classification are slightly higher than pixel based approach, around 82.92%.

Table 1: The sum of the diagonal elements of confusion matrix for object-based approach

LU/LC Type	Urban	Agriculture	Forest	Schrubland	Bare	Water	Industry	I	II	III	IV
Urban	35	1	1	1	1	0	1	40	82.92	5	3
Agriculture	1	30	1	1	1	0	0	34	88.24	4	3
Forest	0	0	40	1	0	0	0	41	97.56	1	3
Schrubland	0	2	1	30	1	0	0	34	88.24	4	6
Bare	0	0	0	3	20	0	1	24	83.33	4	3
Water	0	0	0	0	0	15	0	15	100.00	0	0
Industry	2	0	0	0	0	0	15	17	88.24	2	2
Total	39	33	43	36	23	15	17	205		20	20

The sum of the diagonal elements of the confusion matrix for pixel based approach is 184, and the overall accuracy is therefore (184/215) x 100 = 85.58% (Table 2).

Table 2: The sum of the diagonal elements of confusion matrix for pixel based appeoach

LU/LC Type	Urban	Agriculture	Forest	Schrubland	Bare	Water	Industry	I	II	III	IV
Urban	34	1	1	2	2	0	2	42	80.95	8	8
Agriculture	1	30	1	1	1	0	1	35	85.71	5	5
Forest	1	2	40	0	0	0	0	43	93.23	3	5
Schrubland	2	1	2	30	1	0	0	36	83.33	6	4
Bare	2	1	0	1	20	0	1	25	80.00	5	5
Water	0	0	1	0	0	15	0	16	93.75	1	0
Industry	2	0	0	0	1	0	15	18	78.94	3	4
Total	42	35	45	34	25	15	19	215		31	31

Conclusions

This paper investigated the utilization of satellite imagery and image pre-processing techniques to derive land-cover information or an urban area. Different image classification techniques were tested to obtain good land-cover mapping. Land use/Land cover maps were created using high resolution remote sensing data. High resolution satellite images like WorldView-2 images can be used for these kinds of studies. It can save time and efforts for fieldwork. Additionally there are also some disadvantages such as high price of digital imagery, difficulty in finding qualified staff to work about GIS.

The contribution has shown that the traditional pixel based approaches were not very effective in land use/land cover classification than object based approach. This was proven by the classification of the entire WorldView-2 image using maximum likelihood classification. The discriminant analysis received an overall accuracy of 85.58%. On the other hand object-based classifier produced a significantly higher overall accuracy with the rate of 90.24%.

Some advantages of object based classification; Since both classifiers available in the object-based approach are non-parametric rules, they are independent of the assumption that data values need to be normally distributed [8].

The results presented in the paper show that object oriented classification is a valuable method for land use/land cover in urban area.

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