A hierarchical scale setting strategy for improved segmentation performance using very high resolution images

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Abstract

Land use/land cover (LULC) classification is a specific implementation to define terrain features to the closest real world object. Object-based image analysis (OBIA) has been proved to improve classification accuracy, particularly for very high resolution remotely sensed images. In this study, multiresolution segmentation algorithm was utilized in the image segmentation process using a pan-sharped Qickbird-2 image. Segmentation scales were determined by widely-used estimation of segmentation parameter (ESP-1) tool that produces rate of change graph (LV-RoC) in terms of local variance of the image. In this study, the LV-RoC graph of the image was evaluated to determine optimal scale values ranging from fine to coarse levels. An attempt was made to estimate optimal scale parameter for an image considering not only single-scales but also multi-scales for an image using a hierarchical scale setting strategy. Nearest neighbour classifier was used on single-scale segmented images and fuzzy classifier employing membership functions was used on multi-scale segmented image. Equal numbers of pixels for each class were randomly selected to estimate accuracy metrics (i.e. overall accuracy and kappa coefficient). The differences in classifier performances (~ 6%) were statistically significant according to McNemar's test. It was found that the proposed strategy has a great potential for LULC classification using very high resolution imagery.

Keywords: Object-based classification, Segmentation, Scale parameter, ESP, Quickbird-2

I Introduction

Parallel with the increasing use of very high spatial resolution images, object based classification has become more advanced (Kim et al., 2011). As stated by Blaschke et al. (2014), the object based classification technique that uses image objects instead of pixels has been widely used in last decade primarily applied to very high resolution images. Object-based image analysis (OBIA) offers several unique advantages in comparison to pixel-based classification, one of which is the removal of the so-called salt-and-pepper effect. In OBIA, shape, context and textural information of image objects are considered instead of individual pixels. At the same time, each object is considered both by its spectral, shape or texture features, and by its unique neighbours, its sub- and super-objects (Benz et al., 2004). The recent availability of OBIA provides various opportunities for sensitive and detailed LULC classification.

OBIA is generally applied in three stages: image segmentation, classification and accuracy assessment. Image segmentation process is the first and crucial step to define image objects. Although there exists several techniques, multiresolution segmentation introduced by Baatz and Schäpe (2000) has been one of the most commonly used image segmentation algorithm. Multiresolution segmentation produces highly homogeneous image objects in arbitrary resolution on different types of data and is applied to many problems in the field of remote sensing (Baatz and Schäpe, 2000). It includes the setting of three major parameters, namely scale, shape and compactness. Setting of these parameters is of critical importance for the performance of a subsequent classification process (Witharana and Civco, 2014). Of these parameters, it is agreed that scale parameter is the most important one as it determines the objects size and thereby affects largely the resulting thematic map accuracy (Kim et al., 2011; Myint et al., 2011). The optimal value for scale parameter varies depending on the structure of the study area, land cover types and scale of the imagery (Myint et al., 2011).

Results of classification accuracy are affected by quality of segmentation process (Marpu et al., 2010). For this reason, many studies have already been carried out to determinate optimal scale parameter. In a previous research, Kavzoglu and Yildiz (2014) endeavoured to prepare guidelines for the selection of scale parameter. Besides selection of the scale parameter without relying on any method, evaluation methods of segmentation quality can be divided into two categories as supervised (Clinton et al., 2010) and unsupervised (Johnson et al., 2011; Gao et al. 2011).

In recent years, researches mainly focused on the use of statistical methods for determination of optimal scale parameter in segmentation (Witharana and Civco, 2014). However, only a few studies have led to automatically determining results that produce fast and applicable solutions. Woodcock and Strahler (1987) utilized local variance (LV) graphs to ascertain the spatial structure of each type of image. Then, the estimation of scale parameter (ESP) tool was developed by Drăguţ et al. (2010) for automated detection of scale parameter. The tool has been recently extended to multi-scale analysis based on single layers (Drăguţ et al., 2014). With this tool, LV was generated for each scale value from an image. Furthermore, a graph is generated using LV of image and rate of change (RoC) values of LV. Thus, LV-RoC graph is obtained on each scale step in an image considering a single layer.

The purpose of this study is to determine optimal scale parameter(s) of the image using the LV-RoC graphs produced by the ESP tool and perform usage of single- and multi-scale analysis on classification process. Nearest neighbour classifier was employed in single-scale classification process and membership functions were used in multi-scale classification process. The differences in classifier performances were analysed with McNemar's test, which is a statistical test for differences.

II Study area and Dataset

The study area chosen for this research covers approximately 80 ha area located in the Yomra district of Trabzon province, Turkey. A multi-spectral pan-sharpened Quickbird-2 satellite image having four spectral bands at 0.6 m spatial resolution acquired in May 2008 was used for the study site. It has high mountainous terrain covered by forest, sea and urban classes. For the purpose of evaluation, image was clipped to a subset of 1500x1500 pixels (Figure 1). eCognition Developer (v9.1), a widely-used object based image processing software, was used for all segmentation and classification experiments in this study.

The study area is mainly covered by eleven land use/cover features, namely bare ground, concrete surface, forest, asphalt road, gravel, pasture, shadow, water, red, blue and white roof.

III Image segmentation

Image segmentation is the first and crucially important process of object based classification, since the initial objects are created on this stage. The most widely used algorithm in image segmentation is multiresolution segmentation introduced by Baatz and Schäpe (2000). It is a bottom up region merging technique based on local homogeneity criteria. It merges neighbour and similar spectral pixels into image objects. Size of image objects is adjusted in conjunction with segmentation parameters including scale, shape, compactness and band weights. Scale parameter sets the image size and considering most crucial parameter. In general, higher values for the scale parameter result in larger image objects, smaller values in smaller ones (Yildiz et al., 2012).

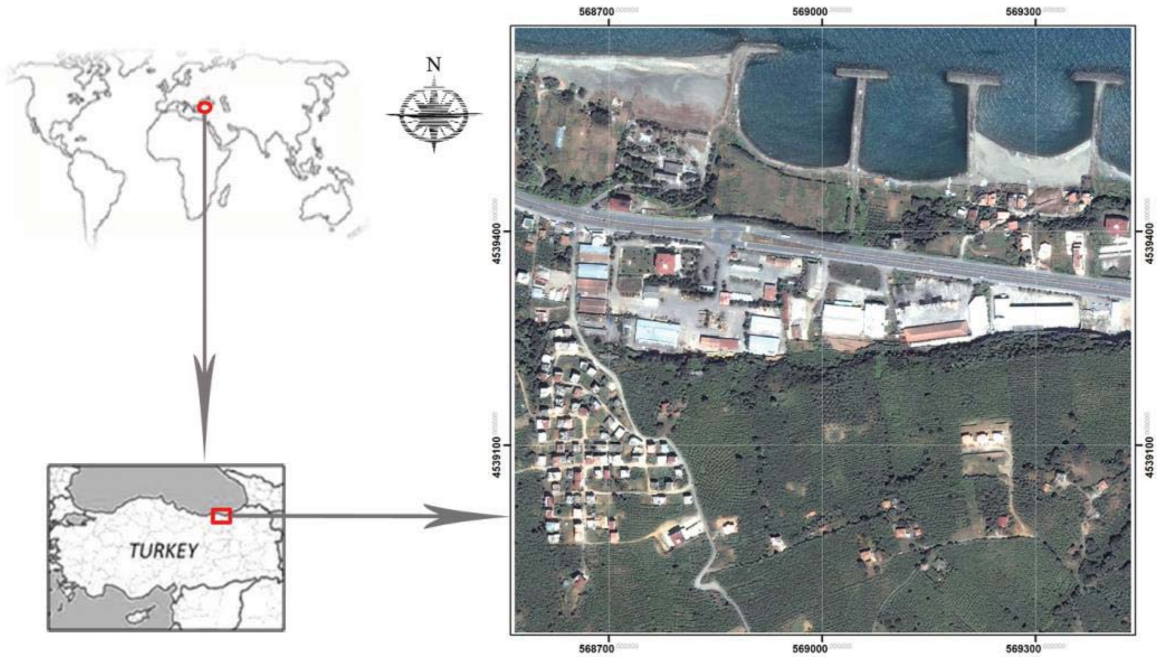

Figure 1. Location of the study area, Trabzon province of Turkey.

Estimation of scale parameter (ESP) tool was developed for automated detection of scale parameter by Drăguţ et al. (2010) who states that “the ESP tool iteratively generates image objects at multiple scale levels in a bottom-up approach and calculates the local variance (LV) for each scale image”. Rate of change (RoC) values of LV is determined for each scale levels using Eq. 1. The RoC is calculated as:

$$RoC = \left[\frac{L-(L-1)}{L-1}\right] * 100 \qquad (1)$$

where L is local variance at the target level and L-1 is local variance at next lower level. The peaks in the LV-RoC graph designates the object levels at which the image can be segmented in the most appropriate way, according to data properties at the scene (Drăguţ et al., 2010).

IV Classification

Classification proccess which is the next step after the image segmentation uses segmented images. Two types of classifiers were applied in this study. Nearest neighbour classifier uses a set of samples of different classes in an attempt to assign class values to a segmented object. The procedure contains two major steps: teaching the system by giving it certain image objects as samples and classifying image objects in the image object domain based on their nearest sample neighbours. Membership functions allow describing the relationship between feature values and the degree of membership to a class using fuzzy logic. It can be defined by the degree of membership; for example, any value between one and zero (Definiens, 2008). In other words, Myint et al. (2011) states that “the membership function describes intervals of feature characteristics that determine whether the objects belong to a particular class or not”.

V Results

This study aims to investigate optimal scale parameter(s) for single- and multi-scale segmentation. A pan-sharpened Quickbird image includes many land use/cover features such as urban, sea, forest and gravel was used in this study. For detecting optimal scale parameter(s), local variances for each of scale parameter were estimated using ESP tool in the image. As can be seen in Figure 2, the prominent peaks are apparent in the LV-RoC graph created using Eq. 1. Peaks at 26, 41, 53 and 77 on the graph appeared to be suitable values. The four scale levels were denoted s_ESP1, S_ESP2, S_ESP3 and S_ESP4, where S_ESP1 represented the finest object scale and S_ESP4 the coarsest scale. These scale parameter values specified by LV-RoC graph was individually applied to multiresolution segmentation for single-scale segmentation. Furthermore, all scale values were used in multi-scale segmentation using a hierarchical strategy (M_ESP). It should be noted that shape and compactness parameters were keep constant as 0.1 and 0.5, respectively.

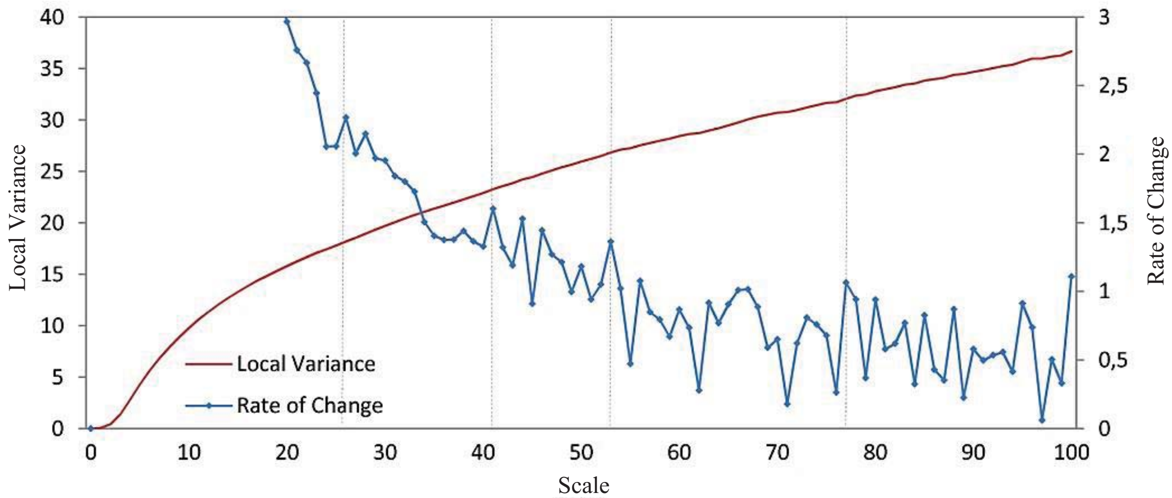

Figure 2. LV-RoC graph of the image. Scale values of 26, 41, 53 and 77 were selected as potential optimal scale values.

For single-scale segmentation, segmented images obtained from the estimated scale parameters were classifed using nearest neighbour classifier. Membership function classifier was applied on multi-scale segmentation and different segmentation scale levels were applied to detect feature classes. Each scale level was generated within a hierarchy, where scale parameters of 77, 53, 41 and 26 were set as scale levels of 1, 2, 3 and 4, respectively. Land use/cover classes were classified at mentioned levels. To be more specific, while water and gravel classes were extracted using scale level 1, blue roof and forest was extracted with scale level 2, asphalt road and white roof with scale level 3, and other classes with scale level 4.

Classifications were achieved using test datasets on the basis of contingency matrices. It should be noted that test datasets were prepared using random pixel selection. Equal numbers of samples for each class (700 pixels) were selected. For the assessment of classification results, overall classification accuracy (OA) and Kappa statistics were computed from the contingency matrices (Table 1).

	Scale Unit	Overall Accuracy (%)	Kappa
Single-scale	S_ESP1	86.10	0.847
	S_ESP2	84.65	0.831
	S_ESP3	81.18	0.793
	S_ESP4	80.39	0.784
Multi-scale	M_ESP	91.56	0.907

Table 1. Overall accuracies of single- and multi-scale segmentations.

The overall classification accuracies for single-scale parameters of 26, 41, 53 and 77 were estimated as 86.10%, 84.65%, 81.18% and 80.39%, respectively, suggesting superior performance when fine level scale values were used. For multi-scale segmentation applied through a particular strategy with fuzzy approach, a classification accuracy of 91.56% was achieved. As can be seen from Table 1, classification accuracies on single-scale segmentation range between 80% and 86% in terms of overall accuracy. All classified image results are shown in Figure 3.

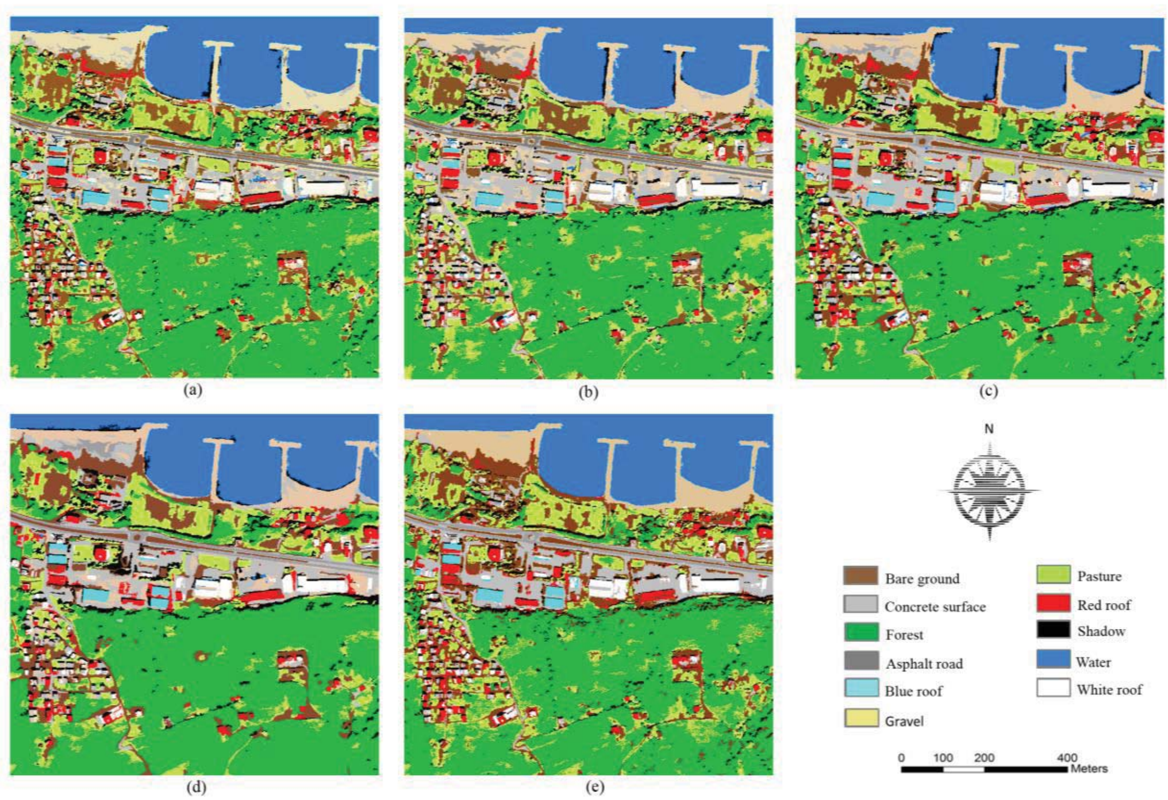

Figure 3. Single-scale classification results for (a) S_ESP1, (b) S_ESP2, (c) S_ESP3, (d) S_ESP4 and multi-scale classification result with hierarchical scale (e) M_ESP.

Although some classes (e.g., water and forest) were delineated easily, there were misclassification problems between some classes (e.g., gravel, bare soil, asphalt road and red building roofs). It should also be noted that low accuracies, compared with the accuracies produced for fine scale selection (i.e. 26 of scale value), were achieved in the classification of coarser scale selection (i.e. 53 and 77 of scale values). The reason could be related to training objects containing two or more classes in same object. Overall, the highest classification result was estimated by multi-scale segmentation using membership functions. One reason for this can be that scale levels separated to identify objects of different classes and each land use feature was represented according to its spatial features. Another reason may be related to using membership functions in classification process. Thus, some classes were easily defined by object features such as spectral bands, NDVI, band ratio, brightness etc.

McNemar's test based on χ^2 distribution is a popular non-parametric test that is generally performed to compare the classification errors (Kavzoglu et al., 2015). In this study, McNemar's test was implemented to determine statistical significance of the differences between classifications according to scale selections (Table 2). It was found that there is statistical significance among all five classification results at 95% confidence interval ($\chi^2_{0.05}$ = 3.84).

	S_ESP1	S_ESP2	S_ESP3	S_ESP4	M_ESP
S_ESP1	-	210.72	463.59	539.13	930.44
S_ESP2		-	60.84	101.82	324.38
S_ESP3			-	17.19	132.64
S_ESP4				-	79.78
M_ESP					-

Table 2. McNemar's test result for single- and multi-scale segmentation.

VI Conclusion

Determination of the optimal scale parameter of an image is currently an important research for object based image analysis. The more representative segments are introduced to a segmentation process, the more accurate classification results can be produced. Land use/cover features of used imagery are usually composed of a complex combination of buildings, roads, water area, trees, and pasture. Scale parameter depends on certain structural features such as spatial resolution of image, land use/cover characteristics and study area.

In this study, LV-RoC graph derived from ESP tool was utilized for determine optimal scale parameter. Thus, each scale parameter was separately applied as single-scale segmentation and hierarchical usage of scale parameters was used in multi-scale segmentation. Nearest neighbour and membership function classifiers were applied on single- and multi-scale segmentation to perform the land cover classification, respectively.

The scale parameter of 26 was selected as an optimum scale parameter of single-scale segmentation after estimated segmentation levels, determined through LV-RoC graph analysis, were individually tested for multiresolution segmentation process. However, scale parameter of 77 produced the lowest accuracy of classification. The reason may be related to the fact that the large image objects produced for the coarse scale, thus several land cover properties were represented in a single object. Particularly, about 6% classification accuracy improvement was achieved when considering the optimal scale parameters in multi-scale segmentation process compared to single-scale segmentation. Consequently, overall accuracies of the classification based on multi-scale segmentation were higher than single-scale segmentation. As a result, it can be concluded that multi-scale segmentation shows better performance compared to single-scale segmentation. Main reason for poor performance of single-scale may be related to construction of objects including several land cover features, especially in coarse scale values. In summary, the analyses conducted in this study clearly showed that the multi-scale segmentation based on hierarchical scale setting strategy is an effective approach for classifying very high resolution imagery.

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