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Impact of Multiresolution Segmentation Technique on Feature Extraction in Object Based Classification

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ABSTRACT

High-Resolution Imagery is futile until its spectral, spatial, and contextual properties are utilized. Object-based classification makes it possible with the help of powerful image segmentation (Multiresolution segmentation) algorithm. With the single segmentation level, it is difficult to extract all available features in a digital image. This research aimed to find the ideal parameter for extracting all features. And used those features for classifying the images (with the difference of a decade period) using two supervised classifiers, Fuzzy Nearest Neighbor and Support Vector Machine.Classificationresults showed that Scale parameter in multiresolution segmentation is directly proportional to the expandability of the image features. Moreover, it also showed that urban land has been increased in a decade period, while drastic reduction has occurred in green land. Correlating between two classifiers, SVM performed better with less execution time and higher overall accuracy of 0.98 and kappa statistics.
Of 0.97.

Key words: Fuzzy Nearest Neighbor, Image Segmentation, Multiresolution Segmentation, Support Vector Machine.

1.INTRODUCTION

Currently, High-Resolution Imagery (HRI) is available to every researcher in remote sensing society. Having high spatial and spectral resolution [1], it can efficiently be used for generating precise land cover maps and extraction of different features. In past literature [2-3] traditional classification method reckons only on the pixel and its spectral values; which result is deplorable [4]. For maximum output, Object-Based Classification(OBC) is considered a worthy tool [5]. However, feature selection and integration of training samples are still a critical task [6]. In OBC, image objects are formed using the segmentation process, which merges homogeneous pixels in terms of shape, color, texture, contextual information and their interrelationship. These image objects take part in further image analysis and classification [7]. Moreover, segmentation is an iterative process and it is an extremely difficult task to get, up to the mark segments [8,9]. Various segmentation algorithms i.e. Quadtree Segmentation, Chess-board segmentation, and Multiresolution segmentation are available in eCognition (Definiens cognition network technology). Among all, the Multiresolution segmentation is preferred for extraction of hidden features i.e. vegetation in barren hill and encroachment of green land. In OBC, segmentation is directly proportional to better classification and feature extraction. On the same segmented HRI, two supervised classifiers have been correlated; one is Fuzzy Nearest neighbor (NN) and other is Support Vector Machine (SVM) in terms of their classification accuracy and kappa statistics.
This research is aiming to use eCognition built-in image segmentation algorithm (Multiresolution segmentation) for extracting different features, classification of different land cover classes and the change occurred in a decade period of the same HRI.

2. IMAGE SEGMENTATION

Image segmentation is a process of segregating the entire digital image into segments and to classify these segments using classification methods [10]. Each segment is the combination of identical pixels in respect of texture, color and shape [11]. It is mostly used for identifying borders and curves in an image. Several approaches are brought under consideration based on its specific requirement, e.g. for finding the edges; edge detection techniques and for feature extraction; region-based segmentation is used [12].

2.1 Multiresolution Segmentation

Multiresolution segmentation (MRS) is a built-in image segmentation algorithm in eCognition. It starts working on considering a single pixel as an object along with its neighboring pixels and merges it based on the predefined criteria i.e. homogenous color, homogenous shape, texture and intensity [13] In OBC, these merged pixels are known as image objects. As image objects can be utilized for feature extraction and land cover classification, so MRS can be categorized as region-basedsegmentation. The size ofimage object is directly proportional to the user defined threshold, the Scale Parameter (SP); the higher SP leaves the algorithm to repeat several times to make larger image objects. Other parameters are shape(compactness, smoothness) andcolor. [14]. Various levels of segmentation process are needed till the findingof appropriate image objects; especially in feature extraction.

3.STUDY AREA AND IMAGERY UTILIZED

The focused area of this research is the urbanized area of Peshawar, Pakistan.SPOT-5 satellite imagery has been acquired from Pakistan Space Upper Atmosphere and Research Commission (SUPARCO) for the year 2005 and 2015 for more than 40 square kilometers. These imageshave four bands (Red, Green, Blue, and NIR) with 10m spatial resolution.

4. IMPLEMENTATION

4.1 Segmentation Measures

Each SPOT-5 HRI (2005 and 2015) is processed in a separate eCognition project. And the same techniques, already discussed in section II are applied. According to the ground truth data, the total five featured classes including (urban land, green land, barren hill, bare land, and wetland) are identified. For these five classes, the images are segmented in three levels also shown in the table.1 but the segmentation result was similar for level 2 and level 3. This is because of the maximum capacity of the algorithm to merge the pixels. The segmentation results in the figures 1,2 and figures 3, 4 for 2005 and 2015 respectively, clearly show that the objects in level2 have large sizes as compared to the objects in level1.

Table 1: Multiresolution segmentation parameters for Level 1,2 and 3 respectively

Segmentation Algorithm	Levels	Scale Parameter (SP)	Color	Shape
				Compact/Smooth
Multiresolution Algorithm	Level1	16	0.8	0.4/ 0.2
	Level2	40	0.7	0.7/0.3
	Level3	80	0.6	0.8/0.4

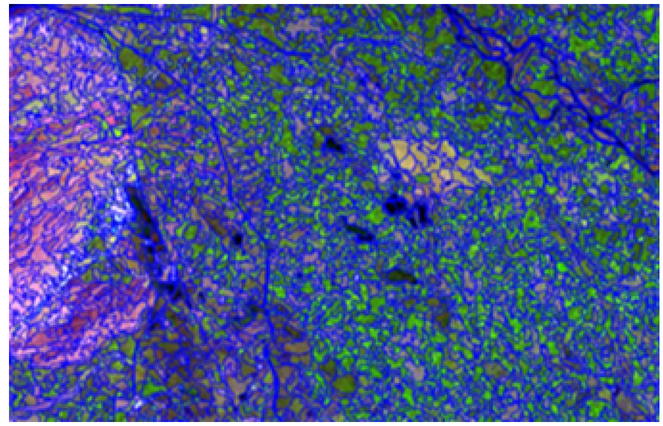

Figure 1: Multiresolution segmentation result for Level1 (SPOT-5 2005)

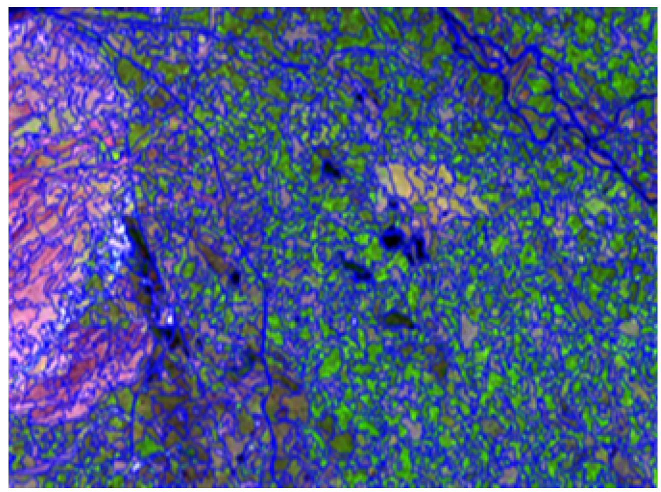

Figure 2: Multiresolution segmentation result for Level2 (SPOT-5 2005)

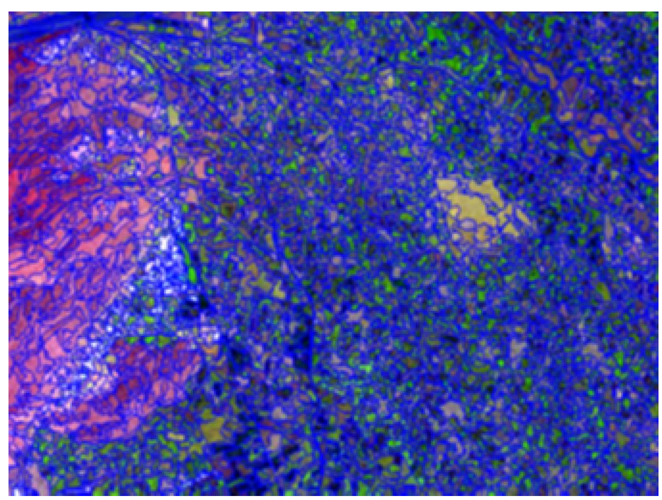

Figure 3: Multiresolution segmentation result for Level1 (SPOT-5 2015)

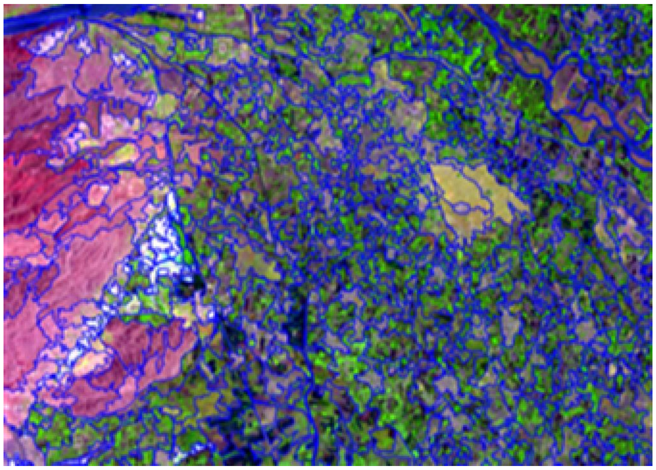

Figure 4: Multiresolution segmentation result for Level2 (SPOT-5 2015)

4.2 Supervised Classifiers

In implementation, the second phase is to classify the segmented images of the first phase into the five land cover classes i.e. urban land, green land, barren hill, bare land and wetland. For classification, two supervised classifiers fuzzy NN and SVM are utilized. NNworks on mean of two neighbors in the entire image [15]. While SVM works on hyperplane and kernel [16].Classification results in figures 5, 6 and figures 7, 8 for 2005 and 2015 of NN and SVM are shown respectively. Urban land is displayed in red, bare land in yellow, barren hill in white, green land in green and wetland in blue color.

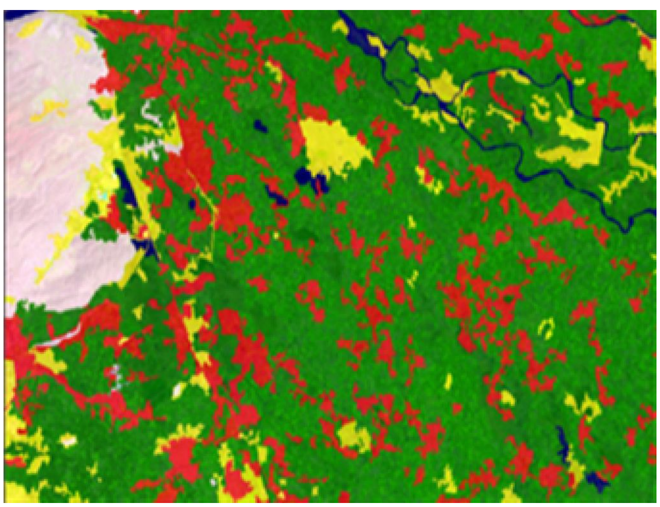

Figure 5: Classification of (SPOT-5 2005) image by Nearest Neighbor

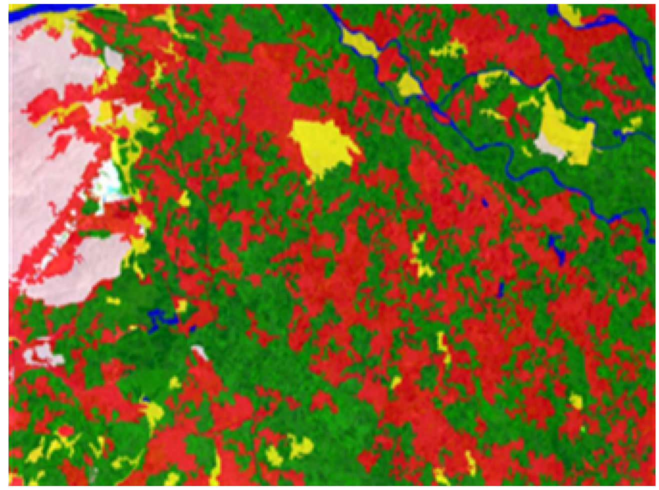

Figure 6: Classification of (SPOT-5 2015) image by Nearest Neighbor

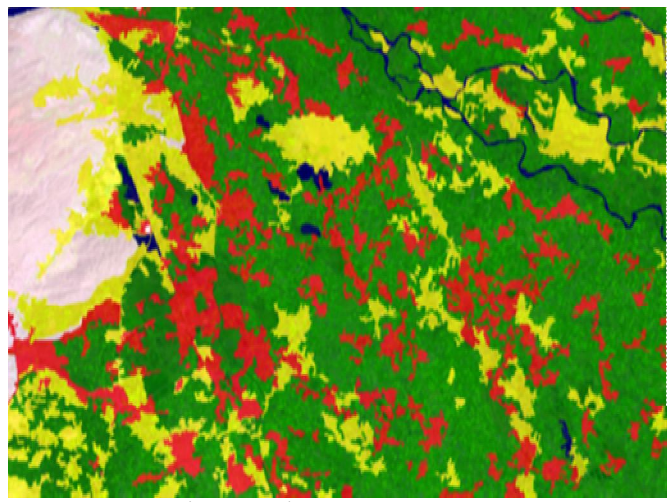

Figure 7: Classification of (SPOT-5 2005) image by Support Vector Machine

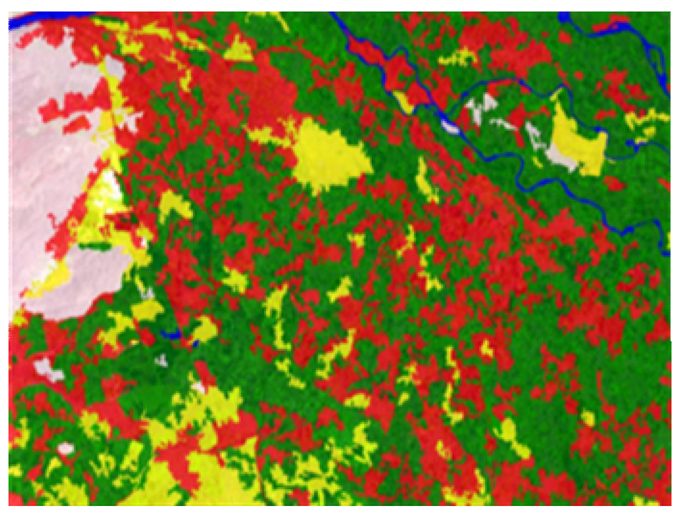

Figure 8: Classification of (SPOT-5 2015) image by Support Vector Machine

5.RESULTS AND ACCURACY CALCULATION

Confusion matrix also known as error matrix and Kappa statisticsalso known as Cohen's kappa are used to calculate the accuracy. The confusion matrices are calculated in every classifier for every image also shown in table 2.The detailed misclassification is also generated on every execution of the classifier, but those misclassifications are removed by incorporating user ground truth experience into sample selection process. Here overall accuracy and kappa statisticsare used to correlate both classifiers. In both classifiers, Wetland feature has extracted normally for any segmentation level. The green land area is expanded, coversa large area in 2005 image, so high SP value will result in large objects. Thus, for extracting expanded objects, high SP values are required which is also shown in figure 5 and 7. In 2015, urban land is expanded, thus in level 2 of 2015, also shown in figure 6 and 8, the urban land is classified in a change profound manner covering large area. Comparing with the ground truth data, the huge change occurred in a decade period in Peshawar, also shown in table 3 and figures 9 and 10. Correlating both classifiers, the SVM values are promising.

Table: 2: Error Matrix (Overall Accuracy and Kappa Statistics of NN and SVM)

Years	2005		2015	
Classes	NN	SVM	NN	SVM
Overall Accuracy	0.962	0.978	0.96	0.983
Kappa Statistic	0.961	0.972	0.96	0.98

Table: 3: Difference in objects with respect to time from 2005 to 2015 (NN and SVM)

Years	B.H		W.L		U.L		B.L		G.L	
	N	S	N	S	N	S	N	S	N	S
2005	66	68	20	21	198	182	144	170	425	413
2015	53	55	18	18	329	289	112	139	287	298
% Difference	-19	-23	-11	-16	+39	+ 35	-28	-22	-48	-38

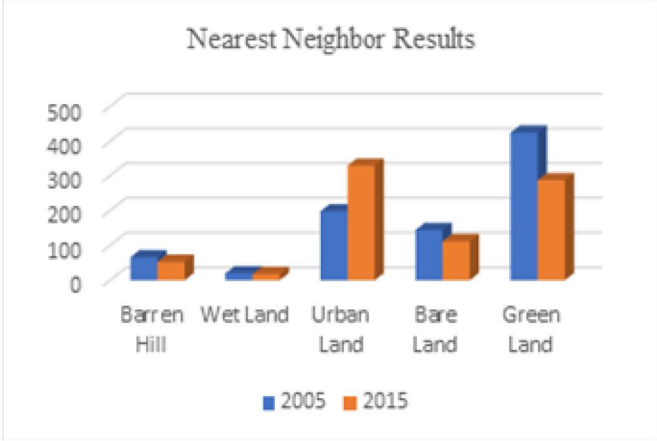

Figure 9: Graphical representation of difference in objects with respect to time from 2005 to 2015 (NN)

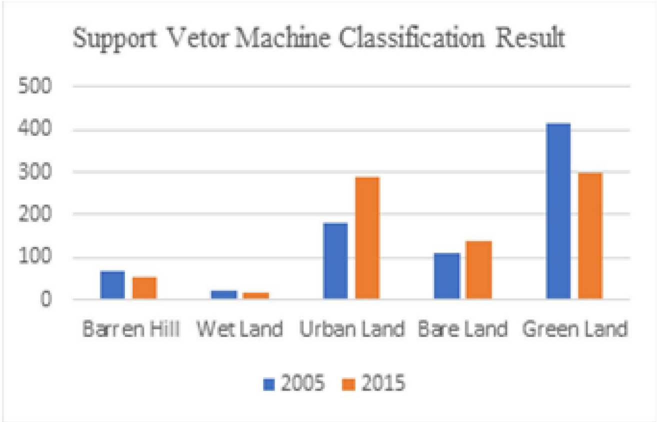

Figure.10: Graphical representation of difference in objects with respect to time from 2005 to 2015(SVM)

6.CONCLUSION

In this research, the object-based classification on the High-resolution imagery has been utilized. The Image segmentation and particularly Multiresolution segmentation has implemented on SPOT-5 Satellite imagery. It is pertinent to note that the image segmentation was worth using for HRI due to the utilization of all its properties in a good manner. Moreover, the image features have a direct connection with the scale parameter of the MRS. And multiple features can be extracted by varying the scale parameter value along with the shape and compactness. Between the two classifiers, SVM performed better, in its execution time and results. The urban land has drastically increased while the green land has decreased.

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