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Evaluation of Object-Oriented and Pixel Based Classification Methods for extracting changes in urban area

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ABSTRACT

This study focuses on the comparison between three image classifications of remote sensing imagery to estimate change detection in urban area (Tabriz, Iran) by Post Classification Comparison (PCC) technique. In order to investigate an appropriate method for extracting changes, pixel-based image classifiers such as: Maximum likelihood Classifier (MLC), Neural Network Classification (NN) and an Object-Oriented (OO) image Classifier were tasted and compered by using Landsat TM and ETM+ image respectively belong to 1990 and 2010. A priori defined five land cover classes in classification scheme were built-up, vegetated area, bare areas, water bodies and roads.

The accuracy of each method was assessed using reference dataset from high resolution satellite image and aerial photograph. The results shows that the MLC method has achieved an overall accuracy of 69% with kappa coefficient of 0.67, NN 92% overall accuracy with a kappa coefficient of 0.90 and object oriented with 94% overall accuracy and 0.92 coefficient kappa. The PCC technique reliably identified area of change was used as the change detection technique for evaluating the three classification method. Different classification methods have their own advantages and disadvantages. Quantitative results shows that, the MLC method is found to be unable to differentiate urban areas such as Built-up, Roads and Barren, the Object-Oriented Classifier has superior performance in classifying Vegetation and Water areas and the Neural Net Classifier also has the best performance in classifying Built-up, Road and Barren areas.

Keywords: Remote Sensing, Change Detection, Classification methods, Tabriz (Iran).

1. Introduction

Land cover plays a pivotal role in impacting and linking many parts of the human and physical Environment (Foody, 1992). Detecting temporal changes by observing surfaces at different times is one of the important applications of satellite sensors because they can provide multidate imagery at short interval on globe scale. In the past few years, there has been a growing interest in the development of change detection technique for the analysis of multitemporal remote sensing imagery. This interest stems from the wide range of application in which change detection methods can be used like environmental and forest monitoring, urban studies and agricultural survey. Changes in land cover and land use in urban areas are dynamic processes, such that transition occur in different location within the constrains, the response to, social, economic and environmental factors.

2. Materials and Method

Post classification comparison (PCC) is the most obvious of detecting changes. It involves the classification of each of the image independently follow by a comparison of the corresponding pixel label to identify areas where change has occurred (Weismiller, 1997).

In this way, it is possible to detect changes and to understand the kinds of transition that have taken place. Furthermore, the classification of multitemporal images avoids the need to normalize for atmospheric condition, sensors differences between the acquisitions. However, the performances of the PCC technique critically depend on the accuracies of the classification (Yuan, 1998). In this study, in order to investigate an appropriate method for extracting changes three classification methods such as two pixel-based classifiers: Maximum likelihood classifier (MLC), Neural Network Classifier (NN) and an object-oriented image classifier (OO) were tasted and compered with each other.

2.1. MLC

Maximum likelihood classifier is one of the most wildly and popular methods in classifying remotely sensed data. The MLC procedure is based on Bayesian probability theory. An unknown pixel X with multispectral values (n bands) will be classified into the class (k) that has the maximum likelihood (max Lk (X)). The likelihood function is given as follows on the assumption that the ground truth data of class k will form the Gaussian (normal) distribution (Richards, 1999)

$$L_k(x) = \frac{1}{(2\pi)^{\frac{n}{2}}|\Sigma_k|^{\frac{1}{2}}} \exp\left[-\frac{1}{2}(x-\mu_k)\sum_k^{-1}(x-\mu_k)\right] \qquad (1\text{-}1)$$

Whereμ_k: mean vector of the ground truth data in class kΣ_k, : variance- covariance matrix of k class produced from the ground data and $|\Sigma_k|$ is determinate of Σ_k.

The MLC is popular because of its robustness and simplicity. But there will be some errors in the results if the number of sample data is not sufficient, the distribution of the population does not follow the Gaussian distribution and/or the classes have much overlap in their distribution resulting in poor Separability.

2.2 NN Classifier

Artificial neural networks, or neural nets, are computational structures inspired by biological networks of densely connected neurons, each of which is capable only of simple computations. Neural nets are able to learn from the presentation of training data, as the free parameters (weights and biases) are adaptively tuned to fit the training data. Neural nets can be used to learn and compute functions for which the analytical relationships between inputs and outputs are unknown and/or computationally complex and are therefore useful for pattern recognition, classification, and function approximation.In the geophysical remote sensing context, Neural Net classifiers can be used for a variety of purposes, including classifying surface types, monitoring of agriculture, forestry, and ecology, and exploring for minerals and petroleum.

Feedforward neural networks propagate the inputs (the input layer) through a set of computational nodes arranged in layers to calculate the network outputs. The output layer is the final layer of the neural network and usually contains linear elements. The layers between the input layer and the output layer are called hidden layers and usually contain nonlinear elements. This network topology is depicted graphically in Figure 1 The various types of feedforward neural networks differ primarily in the nonlinear functions (the so-called activation functions) that are used in the hidden layer nodes and the training algorithms that are used to optimize the free parameters of the network. In general, the connections shown in Figure 1 need not be fully populated (Schiavon, 2004, Schiavo, 2005, Blackwell, 2009). The perceptron is the basic structural element of feedforward multilayer perceptron networks. The inputs to a perceptron are weighted, summed over the n inputs, translated, and passed through an activation function. The perceptron is shown graphically in Figure.2, and the transfer function can be written as follows:

$$y = f\left(\sum_{i=1}^{n} wixi = b\right) \qquad (1\text{-}2)$$

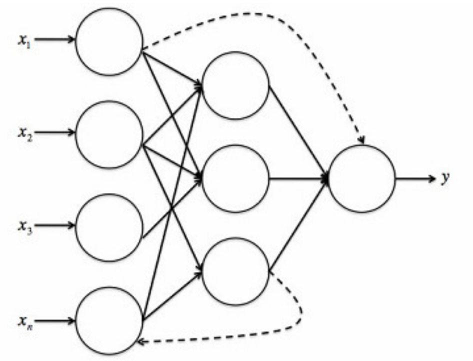


Figure 1: The general structure of a multilayer feedforward neural network

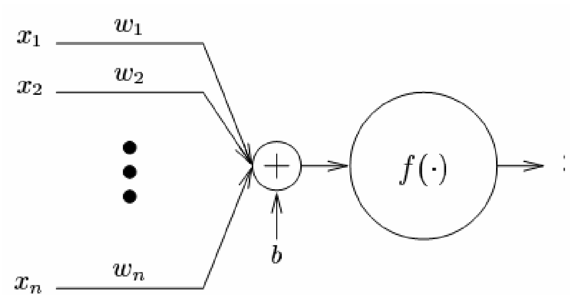


Figure 2: The perceptron weights and sums the inputs, applies a bias, and applies a nonlinear activation function

2.3 Object-oriented classifier

Object-oriented classifier was developed relatively compared to traditional pixel-based image analysis (Burnett, 2003). Object-oriented image analysis is based on information from a set of similar pixels called objects. While pixel-based image analysis is based on the information in each pixel, object-based image analysis is based on information from a set of similar pixels called objects or image objects. More specifically, image objects are groups of pixels that are similar to one another based on a measure of spectral properties (i.e., color), size, shape, and texture, as well as context from a neighborhood surrounding the pixels. Image segmentation seeks to classify objects by partitioning or grouping related region based on shared attributes (Asano, 1996). Standard segmentation can be further augmented by knowledge-based portioning and the construction of sub-object for special classification tasks. Relation-based classification is possible as each object is aware of its neighbor sub-and super-objects. Ensuring a consistent hierarchical structure requires that objects borders of higher levels are inherited by the sub-level and the segmentation process is banded by super object borders (figure1) (Willhoock, 2000).

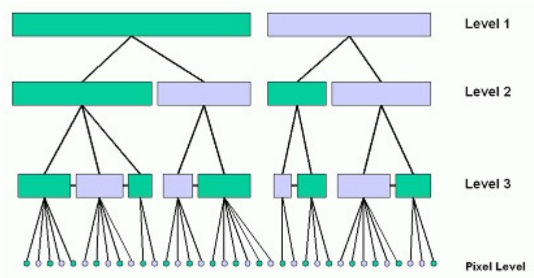


Figure 3: hierarchical network of image objects

Portioning is done via image segmentation techniques such as clustering, boundary detection and region-growing (Mayer, 1993).

2.4 Accuracy assessment

In this study, an overall accuracy and a kappa analysis were used to assess change detection accuracy.

$$OA = \frac{\sum_{i=1}^{c} Eii}{N} \qquad (1\text{-}3)$$

Where c is the number of the classes, N: Number of the certain classes, Eii: error matrix diagonal cell and OA is overall accuracy.

Kappa analysis is a discrete multivariate technique used in accuracy assessments (Congalton,1983, Jensen, 1996)

$$K = \frac{N\sum_{i=1}^{k} nii - \sum_{i=1}^{k} ni + n + i}{N^2 - \sum_{i=1}^{k} ni + n + i} \qquad (1\text{-}4)$$

Where nii is the number of observations in ith row and ith column on the main diagonal, n+1: total number of observations in i_{th} row and i_{th} column and N is total observations.

2.2 Materials properties

The study area covers the city of Tabriz. It is located on the northwest of Iran and covering a total of 26936 ha. The area is bounded by 37°59'30" and 38°12'44" northern latitude and 46°7'14" and 46°28'35" eastern longitude and the maximum and minimum of elevation is about 1298 and 1840 meter. Location of the area is given in the Figure 4.

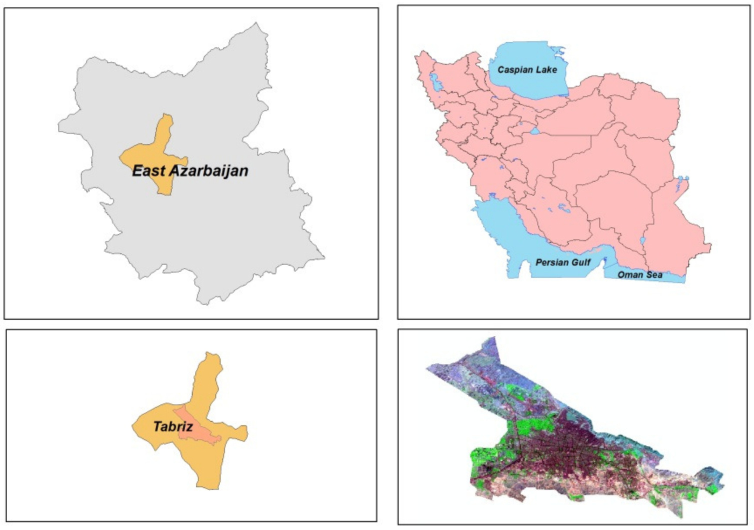


Figure 4: Location of the study area

The data set for this study is comprised satellite images and ancillary data. Landsat TM Ana ETM+ belonged to 25 May 1990 and 17 July 2010 respectively was used to minimize change detection error introduced by seasonal differences. Ancillary data layers, on other hand include 1:25000 scale topographic maps and high-resolution satellite image panchromatic Ikonos (1m). Post-classification comparison with three classification algorithm was done in Tabriz. And Principal procedures of this change analysis were given in the Figure 5.

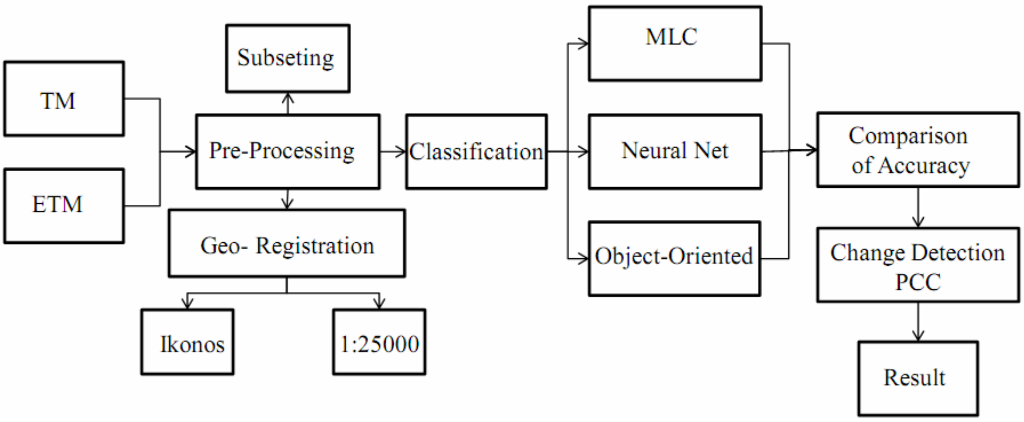


Figure 5: Principal procedure employed for classification and change detection

4. Findings

4.1 Classification

In the area of study defined five land cover classes such as: Built-up, Vegetation, Barren, Water bodies and road.

4.1.1 Pixel-based classification

Pixel-based supervised image classification, Maximum Likelihood and Neural Net, Were performed in Envi 4.7. It is vital that training sample be representative of the class that you are trying to identify. So with the help of field work investigation and Aerial photos, knowledge of the data and of the classes desired, have been acquired before classification.

Also For more accurate classification, signature Separability analysis band 3, 4, and 5 were used. And Logistical method with Training momentum rate 0.9 were used for Neural Net classification, finally Neural Net RMS plot was extracted (Figure 6 and 7).

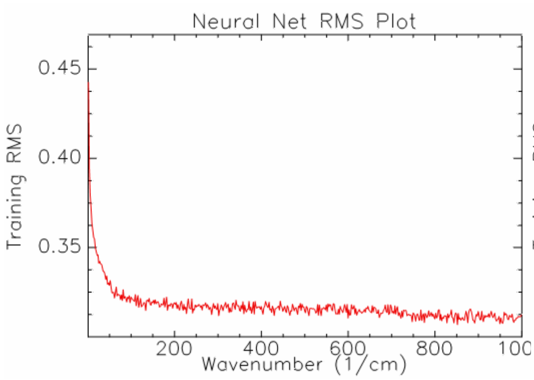


Figure 6: Nureal Net RMS Plot 1990

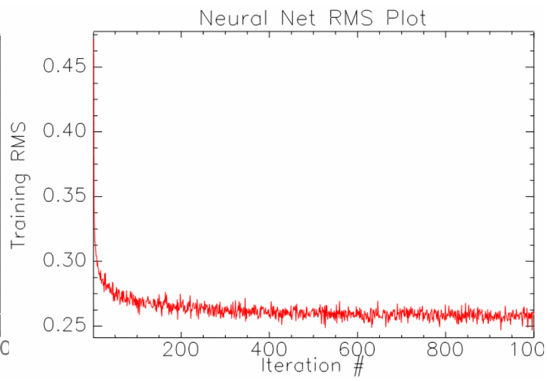


Figure 7: Nureal net RMS plot 2010

4.1.2 Object-oriented Classification

Object-oriented Classification was performed in eCognition V3.0. The choice of segmentation parametrs(Scale, Color, Smoothness, Compatness) was determined using a systematic trial/error approach, validated by visual inspection of the quality of image objects. Once an approprate scale was identified both the color and shape criterion were modified to refine the shape of image objects. So the color certerion was assinged a weight of 0.4, compatness 0.3, smoothness 0.3 and factor shape 5. The classification was performed using the nearset neighbor methods which assigns classess to image objects based on minimum distance measurments(Figure 8).

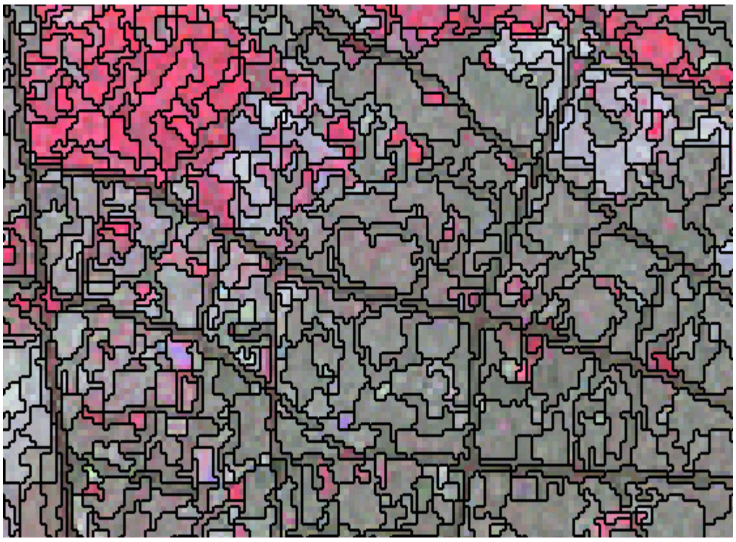


Figure 8: Segmentation of the ETM image at the scale of 5

4.1.3 Accuracy assessment

The accuracy assessment of these there classifiers can be found in table 1.

Table 1: Comparison of the accuracy of there classification algorithm

	MLC		**Neural Net**		**Object-oriented**	
	TM 1990	*ETM 2010*	*TM 1990*	*ETM 2010*	*TM 1990*	*ETM 2010*
Overall Accuracy	67.57	69.41	92.93	94.86	93.61	95.01
Kappa Coefficient	0.65	0.67	0.89	0.91	0.92	0.93

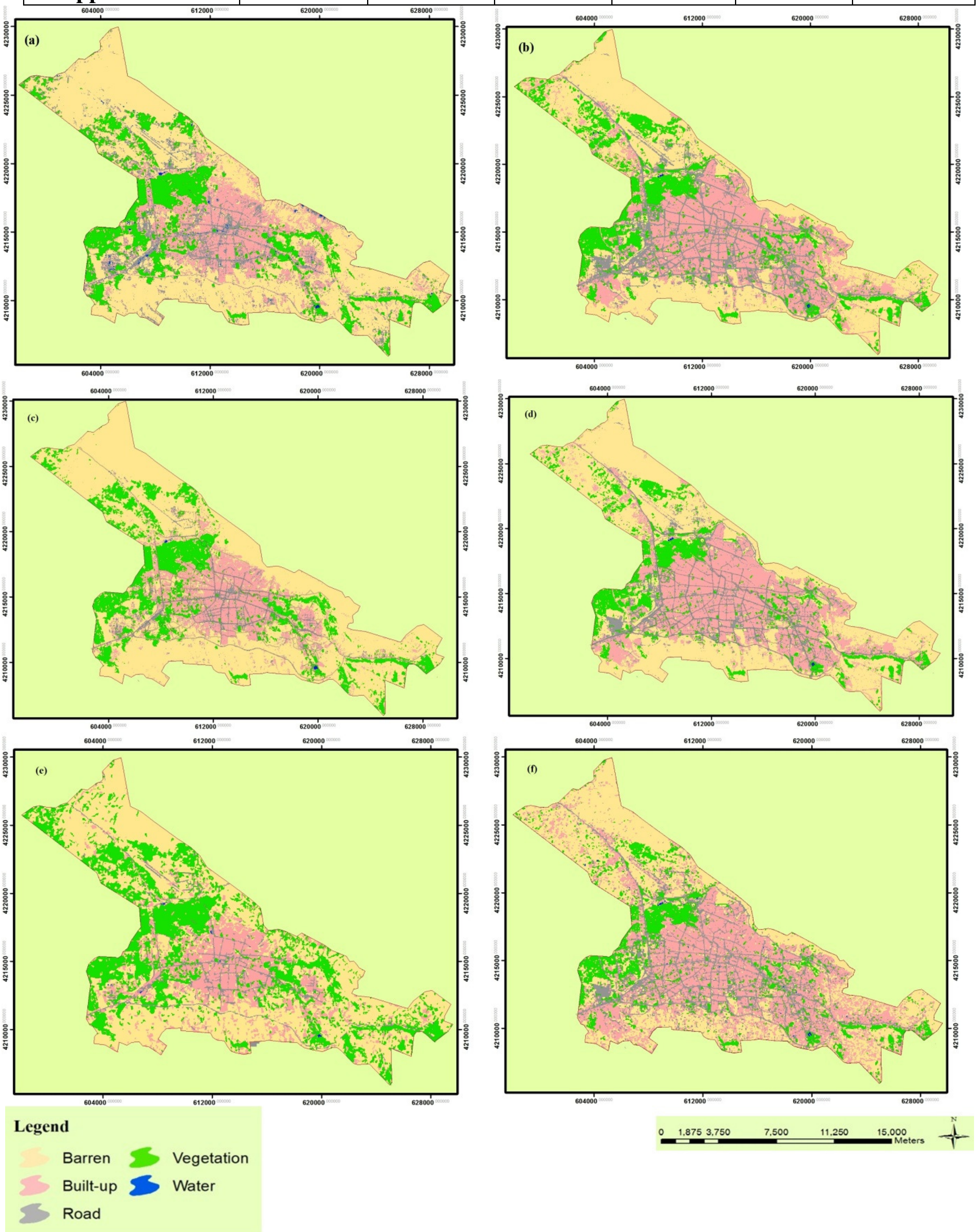


Figure 9: Reference of MLC (a and b), Neural Net (c and d) and Object-Oriented (e and f) 1990 and 2010

The figure 9 shows the land cover classification of images with there classifications methods and the area coverage of land cover categories were summarized in table 2 and figure 10 and 11.

Table 2: Area coverage's (hectares) of the Land Cover categories

	Object-Oriented		MLC		Neural net	
	1990	*2010*	*1990*	*2010*	*1990*	*2010*
Barren	13804	10050	14157	10814	16203	12123
Built-up	4590	9701	4558	8114	4552	8198
Vegetation	5056	3325	4409	4246	4722	3364
Road	3212	3796	3664	3752	2844	3253
Water	31	26	135	11.88	11.1	10

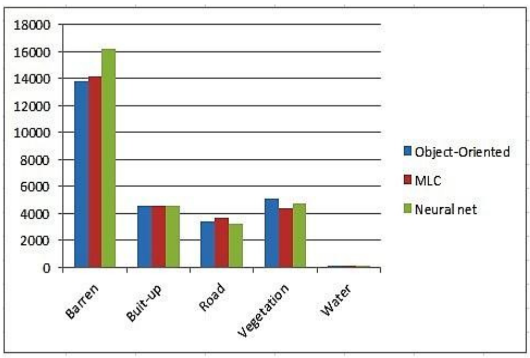


Figure 10: Ratio of land covers 1990

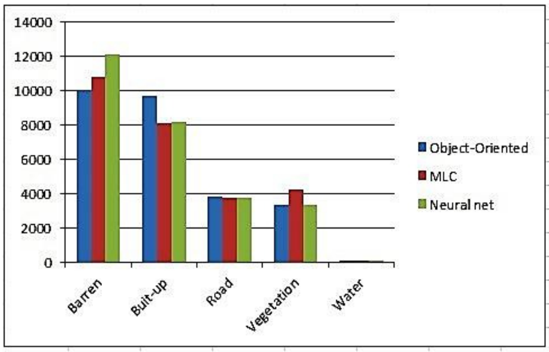
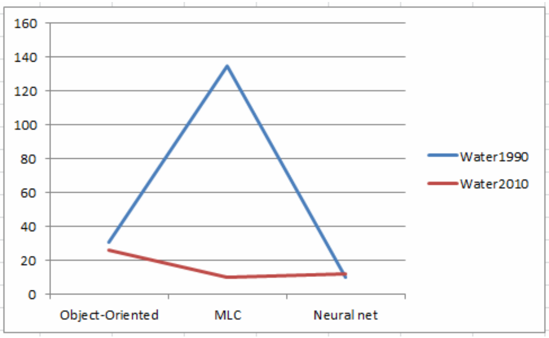


Figure 11: Ratio of Land covers 2010

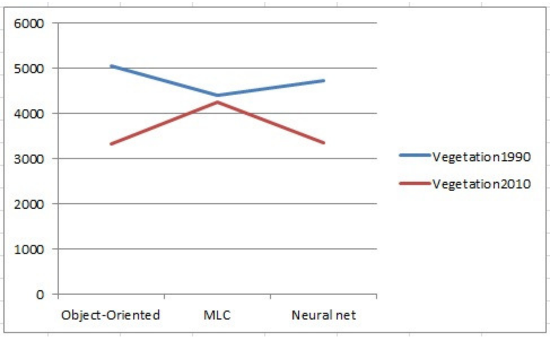
As can be seen from figure 12 (a, b and c), extracted land covers such as water, vegetation and road with MLC method have a considerable different in comparsion with two other methods. It means that MLC method is not able to detect these land covers as efficient as Object-Oriented and Nureal Net methods. figure (a and b) shows that Object-Oriented method has the best result for detecting water and vegitation land covers, on the other hand we can observed from figure 12 (c and d) that road and built-up areas are extracted with more accuracy by Neural Net method. Eventually, Figure 12 (e) shows that three classification methods have a stable procdure in bare areas, but Neural Net is the most precision method for this land cover by using of GCPs.

(a)

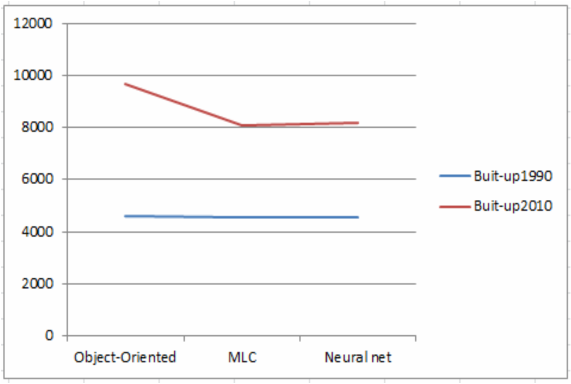


(a)

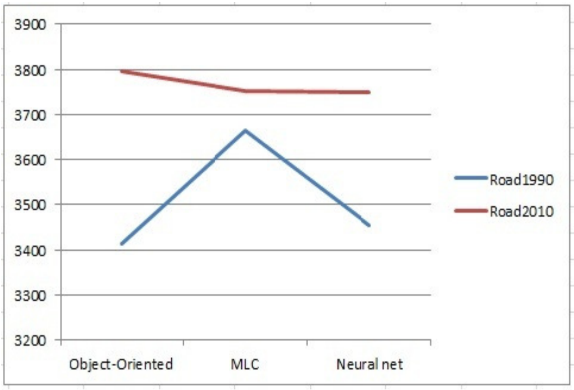
(b)



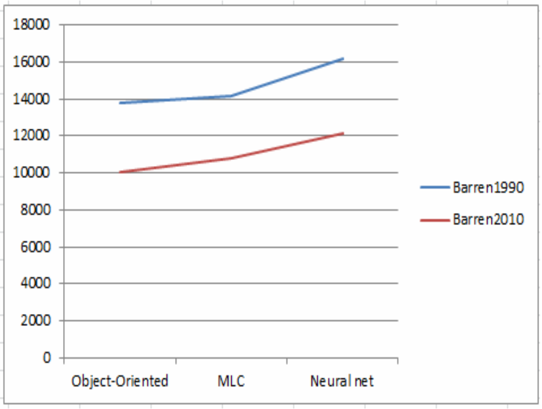
(b)



(c)



(d)



(e)

Figure 12: Comparison of three classification methods on land covers (Water(a), Vegetation (b), Road (c), Built up (d) and Barren(e)) at 1990-2010

As mentiond before, PCC technique critically depend on the accuraciess of the classification results, and from what have been disscuced above, MLC has the lowest accuracy between these three methods. So in the next step only two methods, Object-Oriented and Neural Net, Used for change detection with PCC technique.

4.2 Change Detection

Land cover change detection in this period was analyzed using PCC technique for both classification methods independently (Figure 13). All information about changes between land covers were summrized in table 3 and 4. They shows that urban expansion lead to one of the most obvious land covers change between 1990 and 2010. According to table 3 and 4, the amount of urbanized area was Calculated about 97155 (Squer meter). Invastigating the component of this conversion, the Barren and Vegitation areas were found the most land cover which consumed by urbanization in this period.

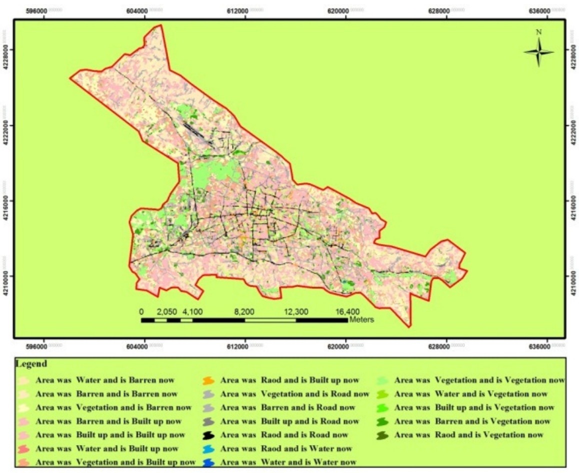


Figure 13 (a): Change Detection with Neural Net Classifier

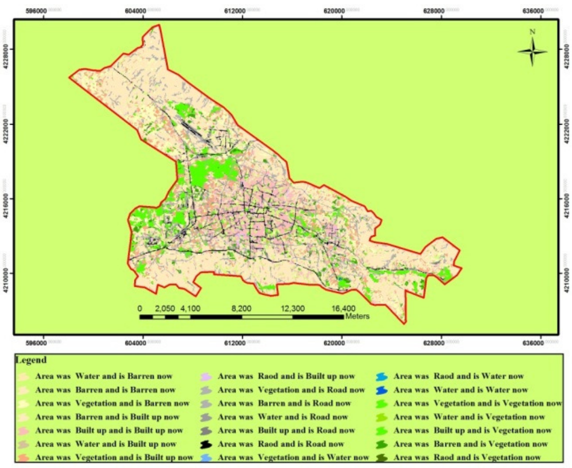


Figure 13 (b): Change Detection with Object-oriented Classifier

Table 3: Land cover changes between 1990-2010 with Object-Oriented Classifier (Square meters)

	Barren	Built-up	Road	Vegetation	Water	2000
Barren	56063	62771	24233	8659	0	151726
Built-up	3463	28826	13367	3336	5	48996
Road	2309	4497	3292	1086	2	11186
Vegetation	24750	29514	15532	29807	11	99615
Water	32	89	73	38	32	264
2010	86617	125697	56497	42926	50	311787

Table 4: Land cover changes between 1990-2010 with Neural Net Classifier (Square meters)

	Barren	Built-up	Road	Vegetation	Water	2000
Barren	56768	65001	25008	8563	2	155342
Built-up	3869	48750	13367	3453	5	69444
Road	2604	4497	3090	1286	10	11487
Vegetation	23670	27814	15834	27807	6	95131
Water	20	89	57	30	29	180
2010	86931	146151	57356	41229	52	311787

4.3 Conclusion

Medium resolution satellite images like Landsat have been used for monitoring land use and land covers from local to regional scales. Change detection and land cover map have increasingly been recognized as one of the most effective tool for urban and environmental resource management. This study showed that the flexibility of the PCC method to use different classification methods made a successful change analysis possible. In this study we have examine three classification methods for extracting changes during 20 years. Quantitative results from this study give a good overview for understanding the advantages and disadvantages of each classification methods. We observed considerable variability in the performance of these methods, which use completely different to perform the task of classifying. The MLC method is found to be unable to differentiate urban areas such as Built-up, Roads and Barren. The Object-Oriented Classifier has superior performance in classifying Vegetation and Water areas. The Object-Oriented classifier has some disadvantages. Classification accuracy depends on the quality of image segmentation and once object is misclassified all pixels in the object will be misclassified. The Neural Net Classifier with an overall accuracy approximately 92% also has the best performance in classifying Built-up, Road and Barren areas. Future studies may include high resolution satellite images for assessing classification methods to extract changes in urban areas.

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