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Evaluation of Land Cover Changes Ysing Remote Sensing Technique (Case study: Hableh Rood Subwatershed of Shahrabad Basin)

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Abstract

The growing population and increasing socio-economic necessities creates a pressure on land use/land cover. Nowadays, land use change detection using remote sensing data provides quantitative and timely information for management and evaluation of natural resources. This study investigates the land use changes in part of Hableh Rood Watershed of Iran using Landsat 7 and 8 (Sensor ETM+ and OLI) images between 2001 and 2013. Supervised classification was used for classification of Landsat images. Four land use classes were delineated including rangeland, irrigated farming and plantations land, and dry farming lands,urban. Visual interpretation, expert knowledge of the study area and ground truth information accumulated with field works to assess the accuracy of the classification results. Overall accuracy of 2001 and 2013 image classification was 81.48 (Kappa coefficient: 0.7340) and 87.04 (Kappa coefficient: 0.7841), respectively. The results showed considerable land cover changes for the given study area. Land cover change detection showed that in a period of 12 years, 277.57 hectares of dry farming lands and 340 hectares of dense range have been lost. But, 341 hectares for low dense range, 280 hectares for semi dense range and 1.4 hectares for urban areas, have been added in area.

Keywords:
Land cover, Land use change, Supervised classification, Remote sensing

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INTRODUCTION

Biophysical materials and anthropogenic features are often subject to rapid changes (Roy *et al*., 1996; Tahir and Hussain, 2008; Podobnikar *et al*., 2009). The land cover changes occur naturally in a progressive and gradual way; however, sometimes it may be rapid and sudden due to anthropogenic activities (Butenuth *et al*., 2007). Thus, analyzing the land cover changes and understanding the subsequent trends of change contribute to present complex dynamics of land cover and are important for policy making, planning and implementation of natural resource management (Ioannis and Meliadis, 2011; Knorr *et al*., 2011; Reddy and Gebreselassie, 2011). In recent years, land use/cover changes in Iran, have occurred increasingly and in some respects unsatisfactorily so that the rate of land degradation has been intensified. So, it is important to know land cover changes across time, while there is not a recent report about land use changes in this area. Nowadays, integration of Geographic Information System (GIS) and remote sensing has provided accurate information about land use changes (Alqurashi and Kumar, 2013; Imam, 2011). Considering the importance of remote sensing and GIS in evaluating the changes in land cover, this technique is used in the present study. There are various classification algorithms for the detection of land use changes by satellite imagery (Aplin and Atkinson, 2004; Lu and 2004; Singh and Khanduri, 2011); however, there is not guarantee to use the best algorithm in all conditions (Srivastava *et al*., 2012; Yang and Lo, 2002). In this study, post classification change analysis was applied. This method provides "from” to “to" transition rules (White *et al*., 2013; Yuan *et al*., 2005). Post classification method is also known to be more appropriate method for change detection (Lillesand *et al*., 2004). In this study, supervised classification has been selected, which are widely used for the classification of remote sensed images for mapping land use changes (Abd Elcavy *et al*., 2011; Jackson *et al*., 2004; Ramadan *et al*., 2004; Shalaby and Tateishi, 2007; Zhang *et al*., 2011). To survey the vegetation canopy, Normalized Difference Vegetation Index (NDVI) was used. Past studies have demonstrated the potential of using NDVI to study vegetation dynamics (Townshend and Justice, 1986; Verhoef *et al.*, 1996). The purpose of this study was to detect land cover changes from 2001 to 2013 using Landsat ETM+/OLI images in the Hableh Rood Subwatershed of Shaharabad Basin of Tehran located in Iran. Maximum Likelihood and Parallelepiped algorithms were used to provide the land use maps in the ERDAS IMAGINE software.

MATERIALS AND METHODS

Study area

The study area with 3128.22 hectares in Hableh Rood Subwatershed of Shaharabad basin of

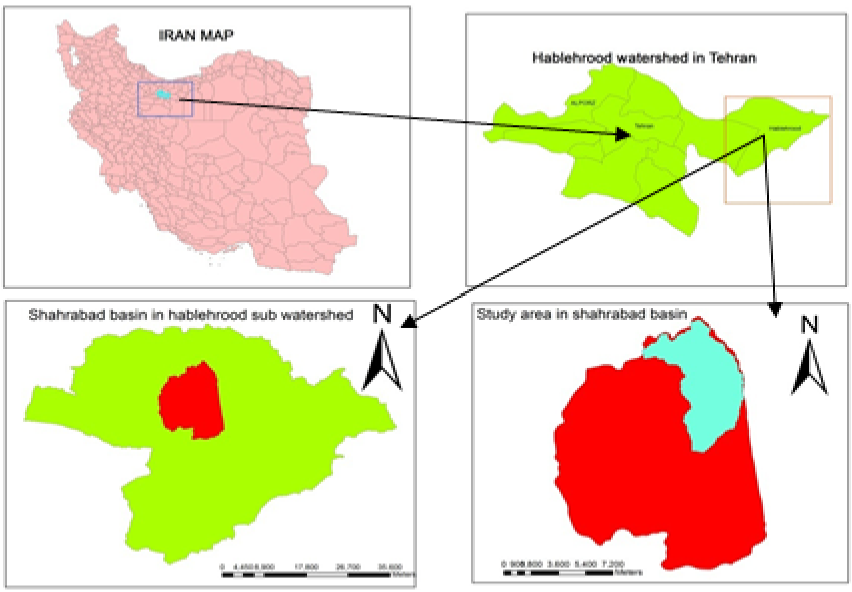

Figure 1: Location of the study area

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Tehran located in Iran. The selected subwatershed lies between 52 º 44' 24" to 52 º35' 10" E longitudes and 35 º43' 06" to 35 º52' 53 " N latitudes (Figure1). It has an average altitude of 2130 meters above sea level and the amount of rainfall is variable in Shahrabad basin, on average, about 354.4 mm. Given the fact that the studied case includes range land, agricultural and rural area, we tried to survey the impacts of droughts on land cover changes in the studied area. This research presented an analytical approach to describe land use changes of the environmentally sensitive Hableh Rood Subwatershed of Shahrabad basin.

Satellite data

The Landsat ETM+ and OLI images used in this study were acquired from www.usgs.gov. The dataset were on 2001 and 2013, with nearly zero percent cloud cover over the region. We tried to select all images almost during the growing seasons for reducing the effect of season on land use change results. The received Landsat images were already geo-referenced with 20 well-distributed ground points using first order (Affine) transformation and nearest neighbor resampling technique. So, the Root Mean Square Error (RMSE) of 0.8 and 0.7 Pixel was estimated for the image 2001 and 2013, respectively.

Methodology

In this study, Erdas Imagine 9.2 and ArcGIS 9.3 were the selected software. Initially, all images were rectified to the UTM coordinate system. Erdas Imagine was used to classify the land uses

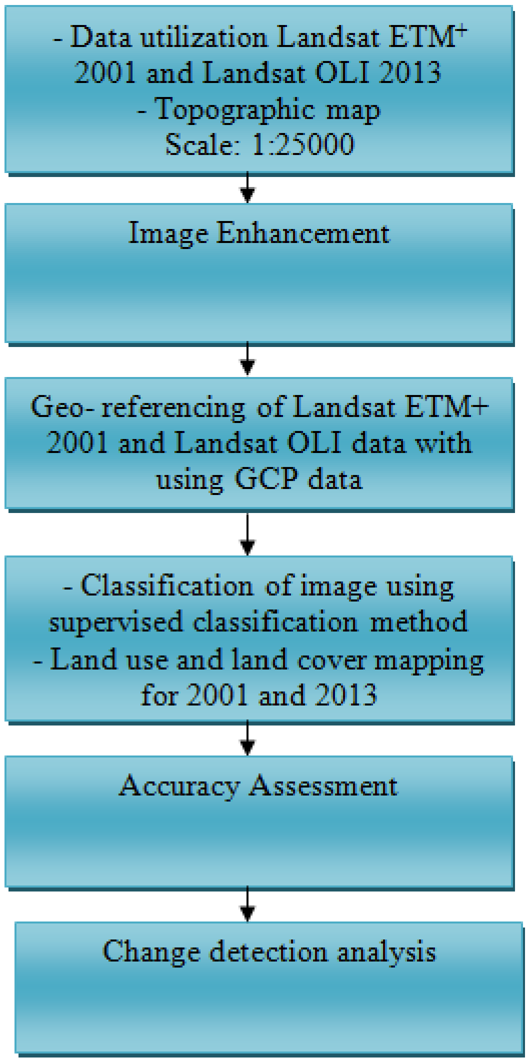

Figure 2: Flow chart showing the major steps research

from the satellite images, after which the raster images were converted to vector maps. The following steps were completed in the ArcGIS environment. An interface was developed in ArcGIS 9.3 environment, which provided the users an efficient and correct area calculation tool. Then, the land use changes were measured and the obtained values were tabulated for all land use changes in the Hableh rood subwatershed of Shahrabad basin. This process was applied for all images. The classification of land cover pattern was one of the prerequisites for analysis. Thus, the initial focus of this study was on classifying the main four types of land use patterns in the Landsat satellite images generated during the time period of 2001-2013. Figure 2 shows the flow chart of this study.

Training site for supervise classification

Selecting training site for supervised classification of remotely sensing images is related to the effective field visit within the local area and collecting exact and useful information (Ahmadizadeh *et al*., 2014). In order to create training sampling points, stratified random algorithm was utilized. Sample points from various classes in the region with suitable numbers were surveyed by GPS and 1:25000 topographic maps. Among these 86 sampling points used for classification of land class, 43 points were used for classification process and the rests were kept for accuracy assessment.

Supervised classification

The Land Use/Land Cover map of the studied area was prepared through digital analysis of satellite data using a non-parametric classification (Parallelepiped) and supervised maximum likelihood classification technique. In the parallelepiped decision rule, the data file values of the candidate pixel are compared to the a priori set higher and lower limits of every signature in every band (Imagine, 2002). Supervised classification is a procedure for identifying areas on an image by identifying 'training' sites of known targets and then extrapolating those spectral signatures to other areas of unknown targets. Supervised classification relies on the prior knowledge of the location and identity of land cover types that are in the image. Training areas, usually small and discrete compared to the full image, are used to "train" the classification algorithm to recognize land cover classes based on their spectral signatures, as found in the image. The classifier then uses the training statistics to compute a probability value of whether it belongs to a particular land cover category class. This allows for within-class spectral variance. In this algorithm, the image analyst uses prior knowledge to weight the probability function. The MLC usually provides the highest classification accuracies (Lellesand and Kiefer, 1994). The NDVI is a standard "greenness" index that has been used for many applications, and has been shown to work well for detecting significant changes in levels of green vegetation (Coppin *et al.*, 2004). This index is one of the most famous, simplest and functional indexes in vegetation studies (Kassa, 1990). It has a simple calculation process and has the highest dynamic power in comparison with other indexes. This index is more sensitive in connection with vegetation changes and is less sensitive to the effects of the climate and soil, except in cases where the vegetation is low (Kogan,1993). Normalized Difference Vegetation Index (NDVI) was used to prepare a rangeland density map. NDVI is a method of measuring and mapping the density of green vegetation. For its measurement scientists use satellite sensors that observe the distinct wavelengths of visible and near-infrared sunlight which is absorbed and reflected by the plants, then the ratio of visible and near-infrared light reflected back up to the sensor is calculated. The ratio gives a number from minus one (−1) to plus one (+1). An NDVI value of zero means no green vegetation and close to +1 (0.8–0.9) indicates the highest possible density of green leaves. The 'normalized difference vegetation index' is calculated by the formula:

$$NDVI = (\rho NIR - \rho Red)/(\rho NIR + \rho Red)$$

where, ρNIR and ρRed are reflectance values of red and near infrared light received at the sensors. The NDVI was first formulated by Rouse *et al.* (1974) and applied to a wide range of practical remote sensing applications in a series of studies by Tucker *et al*. (1985) in the 1970s and 1980s.

RESULTS

Land cover classification

Land cover classification is one of the most studied topics in remote sensing, and land cover maps provide the basis for many applications like modeling of carbon budgets, management of forests, and estimation of crop yield (Wolter *et al*., 1995; Lark and Stafford, 1997; Jung *et al.*, 2006; Rogan *et al.*, 2010). While it is relatively easy to generate a land cover map from remotely sensed data, it is not easy to make it accurate. Using multi-temporal images as inputs is reported to help improve classification accuracy (Wolter *et al.*, 1995; Guerschman *et al*., 2003; Carrao *et al.*, 2008; Zhu and Woodcock, 2012), especially for vegetation because of the unique phonological characteristics of different vegetation types. To achieve higher classification accuracy, most current land cover products are generated using multitemporal images as their inputs (Friedl *et al*., 2010). In this study, four land cover classes were, in total, established as irrigated and plantations land, dry farming, rangeland and urban. Normalized Difference Vegetation Index (NDVI) was used to prepare a rangeland density map categorized into three canopy density classes: dense range, semi dense range and lowly dense range. The classified images of land use/ land cover in Shahrabad basin for 2001 and 2013 are shown in Figures 3 and 4. The Land use/Land cover classification results are summarized in Table 3 for 2001 and 2013.

Accuracy assessment

Accuracy assessment is critical for a map generated from any remote sensing data. For accuracy assessment, error matrices were used with overall accuracy, user's and producer's accuracies, and the Kappa statistic were then derived from the error matrices. The Kappa statistic represents agreement obtained after removing the proportion of agreement that could be expected to occur by chance (Torahi and Chand Rai, 2011). Table (1) provides the separability results achieved for accuracies by supervised classification of the 2001 and 2013 images. According to Table 2, irrigated and plantations land have minimum producer's, 25%, 73.68% for 2001 and 2013 image respectively, and rangeland with another class has maximum producer's, 100% for 2001 and 2013 image.

Change detection

The changes were detected through the post classification by using the gained maps by the aid of supervised classification method. For this propose, the tabulate area order was used in GIS software as confusion matrix. This provides "from" to "to" transition among defined land use classes. Information on existing land use / land cover types and how they change over time is a prerequisite for sustainable resource development planning. In the study area various categories of land use / Land cover were delineated for 2001 and 2013 (Figures 3 and 4). The study area is classified under four land use /

Table 1: Overall accuracy and Kappa coefficient statistics achieved for the supervised classification method

Accuracy	2001	2013
Overall classification	81.48	87.04
Kappa statics	0.73	0.78

Table 2: Summary of accuracies by supervised classification

		Producer's Accuracy%	User's Accuracy%
Land cover 2001	Irrigated and plantations	25	100
	Dry farming	80	84.21
	Rangeland	100	76
Land cover 2013	Irrigated and plantations	73.68	87.50
	Dry farming	92.86	86.67
	Rangeland	100	100

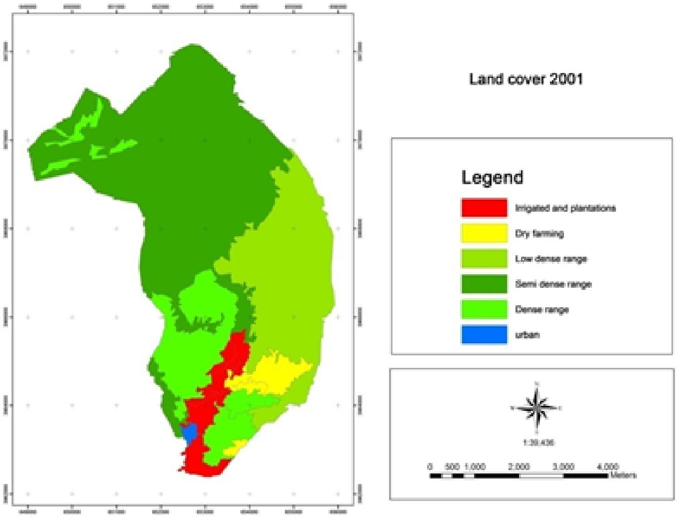

Figure 3: The classification images of land use/ land cover in Shahrabad basin, 2001

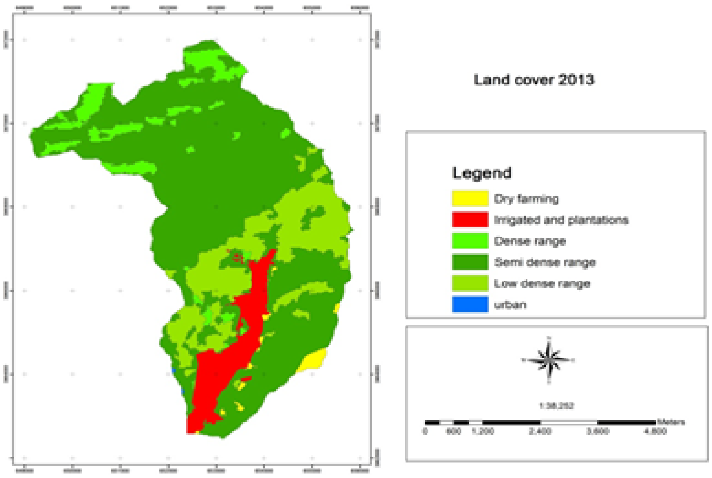

Figure 4: The classification images of land use/ land cover in Shahrabad basin, 2013

Land cover categories. Table 3 shows that 81.05% of the watershed in 2001 and 90.04% in 2013 are covered with rangeland. According to Table 3, the greatest increase was in lowly dense range land about 10.91%, as this class was increased from 203 hectares in the first year (2001) to 544 hectares in final year (2013). Semi dense range class was increased from 1767 hectares in (2001 to 2047 hectares in 2013. Urban class to last 12 years (form 2001 to 2013) has increased about 0.03% (1.04 hectares). Dry farming land was decreased from 412.83 hectares in 2001 to 135.26 hectares in 2013. The largest decrease was observed in dense range land class, nearly 10.87%. The area under irrigated and plantations farming land

Table 3: Summary of Landsat classification area statistics for 2001 and 2013

Land cover class	2001		2013		Relative change	
	Ha	%	Ha	%	Ha	%
Irrigated and plantations	178.03	5.69	174.08	5.56	-3.95	-0.13
Dry farming	412.83	13.19	135.26	4.32	-277.57	-8.82
Dense range	566	18.09	226	7.22	-340	-10.87
Semi dense range	1767	56.48	2047	65.43	280	8.95
Lowly dense range	203	6.48	544	17.39	341	10.91
Urban	1.3	0.04	2.34	0.07	1.04	0.03

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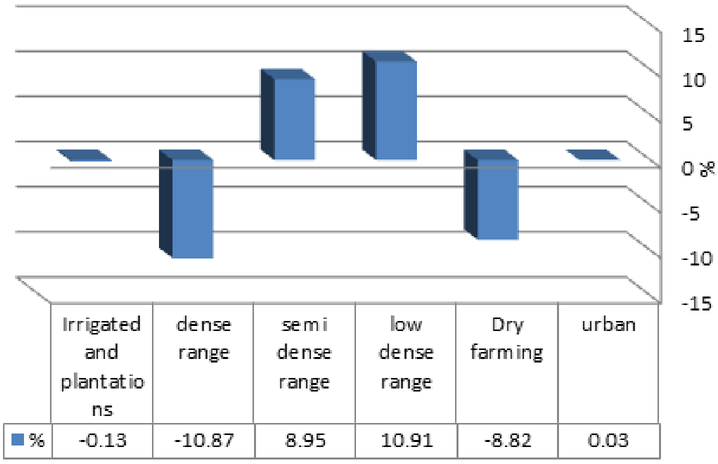

Figure 5: Land use change among 2001 and 2013

was 178.03 hectares in 2001. This class was reduced by about 0.13%; thus, there was little change in the irrigated and plantations farming land from 2001 to 2013. The percentages of land use change between 2001 and 2013 are shown in Figure 5.

DISCUSSION

Regarding the importance of rangelands in the provision of forage for livestock, reliable land use detection is the essential prerequisite and tool for planning these areas.

This study indicated the potential use of remote sensing data in studying land cover/ land use change. GIS techniques integrated in this study proved its undoubted capabilities for spatial analysis. Information from satellite remote sensing can play a useful role in understanding the nature of changes in land cover/use where they are occurring, and projecting possible or likely future changes. Ioannis and Meliadis (2011) used Landsat TM/ETM+ data to monitor the changes in Greece during the period 1999-2008. Nine different land cover/use categories were detected, namely coniferous, broadleaves and mixed forest, agriculture lands, rangelands, grasslands, water bodies, urban areas and others uses. The results showed remote sensing technology in combination with GIS can render reliable information on vegetation cover. The analysis of the spatial extent and temporal change of vegetation cover using remotely sensed data is of critical importance to environmental management.

In this study Landsat images were used satisfactorily for the identification of the four categories. Before using the classification results from satellite images for change detection, it was attempted to assess their validity by testing the results against the reference data or ground truth data. The most common method of performing classification accuracy assessment for any application of remote sensing is creating an error matrix (Foody, 2002). The result of accuracy assessment indicated that the overall accuracy of 2001 and 2013 image classification was 81.48 and 87.04, respectively. It is concluded that supervised classification method can provide acceptable classification accuracy values in this study. Tillmann *et al.* (2012) showed that the supervised classification of multi temporal satellite images is an effective tool to quantify current land use as well as to detect changes in an altering environment. Hence, land use within the test areas could be examined with high accuracy. Shalaby and Tateishi (2007) used supervised classification method to detect land cover changes in the north western coastal zone of Egypt and estimated the change rates. The results showed that coastal zone and cover type were reduced due to agricultural activities and tourist.

Since the drought phenomenon has occurred in the studied area in recent years, dry farming lands have dramatically decreased from 412 hectares to 135 hectares in 2013. As a result, these lands turned into barren agricultural lands. Along with population growth, the urban area has increased from 1.3 hectares to 2.34 hectares in 2013. Increasing population growth in the study area has increased the pressure on rangelands in this area. Ahmadizadeh *et al*. (2014) detected land use changes in Birjand plain and concluded that urban area has increased and dry farming lands has decreased that is similar to the results of this research. Abd El Cavy *et al.* (2011) used supervised classification to detect recent and historical land use/land cover conditions for the western Nile delta. Five land use/land cover categories were identified and mapped. The post-classification comparisons of the classified images indicated that the major change consisted of barren land changing into agricultural land.

A comparative study of the topographic map and satellite imagery of the study area over two time periods revealed that change has been noticed in Hableh Rood subwatershed of Shahrabad basin. Because of the mountainous area and limited irrigated farm land due to lack of slopes between 0-5%, the quantity of this area has not changed dramatically. According to lassifications based on satellite images taken in 2001 and 2013 and according to NDVI index, the quantity of proper rangelands has decreased while rangelands with mediate and weak canopy have increased. According to the taken images and field works, the conditions of canopies in the area clearly reflect overgrazing. Part of the rangeland changes during 2001 and 2013 is due to lower quantity of dry farming lands and their conversion to the low output range. According to the results, dense range class in the area has been decreased from 18.09% in 2001 to 7.22%% in 2013. Semi dense range class has been increased from 56.48% in 2001 to 65.43% in 2013. One reason for the increase is the conversion of barren agricultural lands to rangelands which mostly consist of level 3 rangelands. Lowly dense range has been increased from 6.48% in 2001 to 17.39% in 2013. Because rangelands had been turned into agricultural lands by the villagers in the past, unfortunately, our field works revealed that some of these areas have already been abandoned dry lands. So, the knowledge of the type and percentage of land uses in the watersheds can help the planners in a comprehensive management and sustainable development.

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