INNSPUB

Journal of Biodiversity and Environmental Sciences (JBES)
ISSN: 2220-6663 (Print) 2222-3045 (Online)
Vol. 7, No. 1, p. 543-556, 2015
http://www.innspub.net

RESEARCH PAPER OPEN ACCESS

Identification of land use/cover changes mapping in an urban area using satellite imagery & support vector machine algorithm (case study: Some'esara)

Neda Musavi*

Remote sensing Department, Tabriz University, Tabriz, Iran

Article published on July 30, 2015

Key words: Change detection, Post classification method, Support vector machine (SVM), Some'esara township, Gilan province.

Abstract

Land-use change processes present a variety of trajectories depending on local conditions, the regional context and external influences. This study is an in-depth analysis of spatial and temporal land-use change in a township mountain area for the data period 1989 to 2014 in northwest of Iran. Presently, unplanned changes of land use have become a major problem. Most land use changes occur without a clear and logical planning with little attention to their environmental impact. Since those changes in land use take place in large and extensive areas, so, remote sensing technology is a necessary and valuable tool for land use change detection. Some'esara Township with 1254.543 square kilometer and possible changes are investigated in two times, from 1989 to 2014. For accuracy assessment of this method, after collecting ground truth data, which are carried out through field visiting, Google Earth images and aerial photographs, overall accuracy and Kappa coefficient are used. Overall accuracies of the maps obtained through classification using SVM method for TM, ETM+ images are 93%, 95% respectively, that state high accuracy of this algorithm in classification of satellites images. During 1989 to 2014. The methods enabled four periods to be identified revealing a distinctive evolution in land use, in which urban consolidation is present consistently, together with rotation of the wetland typology e involving marsh degradation, gains from agro-forest land or sparsely vegetated areas and the appearance of urban areas.

***Corresponding Author:** Neda musavi ✉ neda.musavi69@yahoo.com

Introduction

Land cover, land use mapping and assessment are among the core areas of remote sensing data applications (King, 2002; Foody, 2002). Land cover and land use are fundamental variables that impact on and link with many parts of the human and physical environments (Foody, 2002). The change in their use is regarded as a single most important variable of global change affecting ecological systems (Vitousek, 1994) with impacts on the environment that are at least associated with climate change (Skole, 9194). Despite the significant role that land cover and land use information plays in environmental monitoring and understanding, our knowledge about them and their dynamics are still lacking especially in the rural parts of Asia. Remote sensing data has been an is an attractive source in the determination of land cover thematic mapping, providing valuable information for delineating the extent of land cover classes, as well as for performing temporal land cover change analysis and risk analysis at various scales (Kavzoglu & Colkesen, 2009). Such information is also useful in policy decision-making, such as when concerning environmentally or eco-logically protected areas or native habitat mapping and restoration (Council Directive 92/43/EEC, 1992; Fassnacht, Cohen, & Spies, 2006; Sanchez-Hernandez, Boyd, & Foody, 2007).

Thematic maps of land use/cover are also linked to the monitoring desertification and land degradation, key environmental parameters pronounced in areas such as the Mediterranean basin (Castillejo-González *et al.*, 2009). Producing land use/cover mapping thematic maps using remote sensing data is commonly performed by digital image classification (Chintan, Arora, & Pramod, 2004). Lu and Weng (2007) made a recent, comprehensive review of the variety of classification approaches applied to remote sensing data available. Generally, a widely used categorization of classification techniques includes three main groups of approaches, namely: pixel-based, sub-pixel and object-based classification techniques. Pixel-based techniques perform classification by assigning pixels to land cover classes and this be achieved by either supervised or unsupervised classifiers. Unsupervised classifiers group pixels with similar spectral values into unique clusters according to some statistically predefined criteria that the classifier combines and re-assigns the spectral clusters into information classes. On the other, supervised classifiers use samples of known identity for each land cover class, known as "training sites", to classify image pixels of unknown identity (Campbell, 1996). Supervised classifiers are also commonly divided into parametric and non-parametric. In comparison to non-parametric (such as Artificial Neural Networks-ANNs), parametric pixel- based classifiers (e.g. the Maximum Likelihood-ML) require prior knowledge/assumptions regarding the statistical distribution of the data to be classified for the different classes used, information often difficult to attain in practice. Spectral unmixing is a very different classification approach, which is based in defining different surface material fractions within an image pixel. Sub-pixel classification approaches are generally divided into linear and non-linear unmixing, depending on whether it is assumed that the reflectance at each pixel of the image is a linear or a non-linear respectively combination of the reflectance of each material present within the pixel (Plaza, Plaza, Perez, & Martinez, 2005, 2009; Small, 2001). In object-based classification each classi-fication task addresses a certain scale, and image information can be represented in different scales based on the average size of image objects, whereas the same imagery can be segmented into smaller or larger objects.

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The lack of knowledge relating to land cover and land use and its dynamics especially in developing countries can be attributed to: (1) weak government support for mapping agencies and research institutions, (2) expensive software and hardware, (3) insufficient budg *et al.* location for data purchases and (4) resistance to change especially by the traditionalist in the field of mapping, however, the increasing availability of inexpensive or free data such as that provided by the global land cover facility (GLCF), the constant drop in the prices of hardware and software as well as improved awareness about the potential applications of remote sensing technology provide the needed momentum for land cover and land use change assessments in the developing world. The combined use of remote sensing and geographic information system (GIS) will render the essential tools for land cover and land use mapping, storage, analysis and modeling of future scenarios (Geneletti and Gorte, 2003).

Digital change detection is the process of determining and/or describing changes in land cover and land use properties based on co-registered multi-temporal remote sensing data. The basic premise in using remote sensing data for change detection is that the process can identify any change between two or more dates that is uncharacteristic of normal variation. Numerous researchers have addressed the problem of accurately monitoring land-cover and land-use changes in a wide variety of environments (Chan, Chan, & Yeh, 2001; Muchoney & Haack, 1994; Singh, 1989). Many studies have discussed land cover and land use changes in arid, semi-arid and agricultural productive lands. Lambin and Ehrlich (1997) used 10 years of NOAA-AVHRR data to assess and analyze land cover changes in the African continent between 1982 and 1991. The study showed that continuous unidirectional change processes affected less than 4% of Sub-Saharan regions during the study period. Rembold, Carnicelli, Nori, and Ferrari (2000) studied land cover changes in lake regions of central/south Ethiopia using aerial photographs dated from 1972 and 1994 Landsat TM image. Mendoza and Etter (2002) combined black and white aerial photographs with fieldwork and GIS to monitor land cover changes during 56 years (1940–1996) in parts of Bogota, Colombia. Palmer and Van Rooyen (1998) used Landsat TM data to explore the impacts of land management policies on vegetation structure in two study areas in southern Kalahari Desert in South Africa in the period 1989–1994. Ram and Kolarkar (1993) studied land use changes in arid areas in India by visual comparison of satellite imagery, maps and aerial photographs. There are many techniques available to detect and record differences (e.g. image differencing, ratios or correlation) and theses might be attributable to changes (Singh, 1989; Stow, Chen, & Parrott, 1996; Yuan, Elvidge, & Lunetta, 1999). However, the simple detection of change is rarely sufficient in itself: information is generally required about the initial and final land cover or types or land uses, the “from-to” analysis (Khorram *et al.*, 1999). Furthermore, the detection of image differences may be confused with problems in phenology and cropping, and such problems may be exacerbated by limited image availability and poor quality in temperate zones, and difficulties in calibrating poor images.

Post-classification comparisons of derived thematic maps go beyond simple change detection and attempt to quantify the different types of change. The degree of success depends upon the reliability of the maps made by image classification.

In recent years, Support Vector Machine (SVM) is a new learning technique based on Statistical Learning Theory (SLT) which has been introduced for the classification of remote sensing data (Dixon and Candade, 2008; Yao *et al.*, 2008). The SVM methods are used to recognize text in images (to convert documents into computer text), handwritten digital and face recognitions (Vapnik, 1995; Joachims 1998a, b). The results derived from various tests show that the SVM algorithm is capable for comparison with the best classification methods such as artificial neural networks (ANNs), tree classification and so on. SVM's outstanding performance has also been demonstrated in hyper spectral image classification acquired by Visible/Infrared Imaging Spectrometer (AVIRIS) (Gualtieri & Cromp, 1998). Having considered as input, hundreds of variables have been used in the above aforementioned tests but there are fewer of those in remote sensing data acquisition systems such as Landsat, AVHHR and MODIS. Since these sensing systems are the most common instruments used for land cover and land use information, evaluating the performance of the SVM algorithm using images obtained from such systems can have practical applications for land cover classification in this respect.

The SVM algorithm has been used in this study to monitor changes and supervised classification of images related to the years 1988, 2001 and 2007.

The purpose of changes' monitoring is to compare the area over time. The main hypothesis in the application of remote sensing data can be presented for monitoring the changes if the following factors exist: (1) The changes in the target objects are due to changes in the reflection, (2) These changes are caused by some factors apart from those caused by differences in atmospheric conditions, pose angle and soil moisture.

The objectives of this study are to provide a recent perspective for land cover types and land cover changes that have taken place in the last 19 years, to integrate visual interpretation with supervised classification using GIS and to examine the capabilities of integrating remote sensing and GIS in studying the spatial distribution of different land cover changes.

Materials and methods

SVMs classification

This section provides the details concerning the SVMs implementation to the Hyperion hyperspectral imagery for producing a land use/cover thematic map over our studied region. A detailed description of SVMs workings was considered unnecessary to be provided herein, as that can be found elsewhere, for example in Burges (1998) and Foody and Mather (2004).

Classification method

SVMs is a supervised machine learning method that performs classification based on statistical learning theory (Vapnik, 1995). It is a binary classification method that provides a separation of classes by fitting an optimal separating hyperplane to a set of training data that maximizes the separation between the classes. Essentially, the hyperplane is the decision surface on which the optimal class separation takes place. Intuitively, a good separation is achieved by the hyperplane that has the largest distance to the neighboring data points of both classes. Each training example is represented by a feature vector. From a given set of training data, the SVMs classifier calculates an optimal hyperplane characterized by a vector that provides the best separation between the two classes.

The optimal hyperplane is the one that maximizes the distance between the hyperplane and the nearest positive and negative training example, called the margin. To avoid computational overload, this is not done by evaluating all training points, but only a subset, called the "support vectors" of the algorithm. SVMs can be extended to more than two classes by splitting the problem into a series of binary class separations. Also, in order to represent more complex shapes than linear hyperplanes, the classifier may use kernel functions. Commonly used SVMs kernels include polynomial and radial basis function (RBF), and sigmoid kernels. Also, a penalty parameter can be introduced to the SVMs classifier to quantify the misclassification error, providing important information in the case of non-separable training datasets. Last but not least, the binary classification scheme in SVMs can be extended to a larger number of classes N (where N >2).

Choosing between two approaches

This can be done by choosing between two approaches: one against all and oneagainst one (or pair-wise). In the first options, one particular class is being trained against all other classes and this is repeated for all the N SVMs which are developed, whereas in the second option, N(N _ 1)/2 SVMs are produced following a binary tree-like fashion. In the present study, SVMs classification was applied to the Hyperion imagery in ENVI image processing platform (ITT Visual Information Solutions), following a multi-class SVMs pair-wise classification strategy. While the one against all strategy requires less computational time for training, the one-against one (or pair-wise) strategy has shown to yield more desirable results with high dimensional data (Hsu & Lin, 2002 – in Karimi *et al.*, 2006; Petropoulos, Kontoes, & Keramitsoglou, 2011), even if the size of the training data is small (Pal & Mather, 2005).

Thus, the SVMs classification strategy implemented herein allowed creating a binary classifier for each possible pair of classes adopted in our classification key, choosing the class that achieved the highest probability of identification across the series pair-wise comparisons. SVMs was applied at the original Hyperion resolution of 30 m, and the SVMs feature space was defined all the sensor reflective bands which were left after the end of pre-processing (see Section 4.1). The Radial Basis Function (RBF) was selected for performing the pair-wise SVMs classification. The rationale for the selection of this kernel was based on the fact that it requires the definition of only a small amount of parameters to run. Furthermore, it implementation has also shown to produce generally good results in most classification cases (Huang *et al.*, 2008; Petropoulos, Knorr, Scholze, Boschetti, & Karantounias, 2010a; Petropoulos *et al.*, 2011).

Input parameters

The input parameters that needed to be set included the “gamma (c)” and penalty, the number of pyramid levels used and the classification probability threshold value. Generally very littleguidance exists in the literature concerning the criteria to be used in selecting the kernel-specific parameters (e.g. Carrao, Goncalves, & Caetano, 2008; Li and Liu, 2010). Parameterisation of the RBF kernel here was based on performing a number of trials of parameters combinations, using classification accuracy as a measure of quality, as has been done in the past in analogous studies (e.g. Pal & Mather, 2005; Kuemmerle, Chaskovskyy, Knorn, Radeloff, and Kruhlov, 2009). In addition, suggestions provided for the parameterization of these values for the different kernels given in the ENVI User’s Guide (2014) were also taken into account in parameterising each kernel function. As a result, the c parameter was set to a value was equal to the inverse of the number of the spectral bands of the Hyperion imagery used in SVMs (i.e. 0.006), whereas the penalty parameter was set in to its maximum value (i.e. 100), forcing all pixels in the training data to converge to a class. The pyramid parameter was set to a value of zero, meaning that the Hyperion imagery should be processed at full resolution, whereas a classification probability threshold of zero was also applied forcing all image pixels to be classified into one class label and have no unclassified pixels in the imagery.

Study area

Some'esara region in northern Gilan province and between longitudes 49'02^{o} To latitude 49^{o} 32' and 37° 14' to 37° 30' is located. Sowme'eh Sara County is a county in Gilan Province in Iran. Some'esara township from limit from north to township of Bandar Anzali and Rezvanshahr, from south to township of Fuman and the shaft , from the east to Rasht and from west to Masal township. Accordingly Some'esara as center of Some'esara Township at 49 degrees and 18 minutes of eastern longitude to 37 degrees, 18 minutes north latitude with an area of 7.5 square kilometers is located 23 kilometers from the city of Rasht and a height of 6 m above sea level. This township is located on the plain and has a great location to connect with Rasht, Fuman and Bandar Anzali (Planning Deputy of Guilan province, 2007; Molaei Hashtjin & *et al.*, 2014), (Fig. 1).

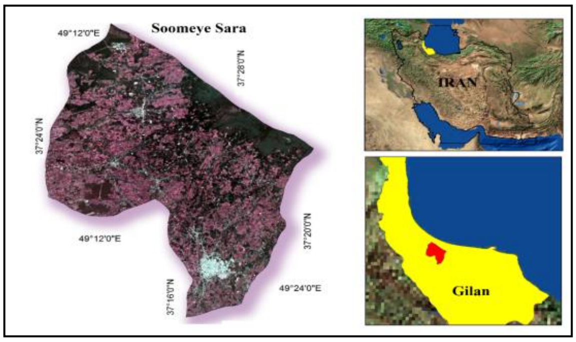

Fig. 1. Location of the study area.

Result and discussion

The satellite images and reference data

Land cover, land use mapping and assessment are among the core areas of remote sensing data applications (King, 2002; Foody, 2002). Land cover and land use are fundamental variables that impact on and link with many parts of the human and physical environments (Foody, 2002). The change in their use is regarded as a single most important variable of global change affecting ecological systems (Vitousek, 1994) with impacts on the environment that are at least associated with climate change (Skole, 9194). Despite the significant role that land cover and land use information plays in environmental monitoring and understanding, our knowledge about them and their dynamics are still lacking especially in the rural parts of Asia.

The choice of an appropriate source of satellite data is determined by the requirement that a long time series of images should be available for the study area, the images being acquired in March (one period), April (two periods in April), to minimize the likelihood of snow cover and preferably in mid-June, at the peak of the growing season. The images are also required to have less than 5% cloud cover. With these criteria, three predominantly cloud free Landsat scenes of the Some'esara region are employed between 1989 and 2014. The first is Landsat TM data obtained in 1989/04/24, the others are Landsat ETM + data in 2014/05/12.

The other data used in this study for reference and analyses mainly include: (1) aerial photographs at a nominal scale of 1:5,0000 from 1994; (2) digitized topographic maps, at scale of 1:50,000 and (3) ground reference data obtained from land survey with hand held GPS to determine the characteristics of sampling points. The existence of ground-truth data is needed for mapping and accuracy measurement in the study area. The ground-truth data for classification and evaluating the accuracy of changes monitoring are obtained by aerial photographs, reports, ground-based observation and visual interpretation of satellite images. ENVI and Idrisi software are used for performing the digital image processing and analyzing such as geometric, radiometric correction and classification. Meanwhile, Arc GIS is also used to compliment the display and to process of the data.

Image preprocessing

Geometric correction

Digitized topographic maps, taken from Army Geographic Organization, at a scale of 1:50,000 are used for geometric corrections. The geometric correction is then performed on images considered as geo-referenced image using image-vector method. To this end, 32 ground control points with appropriate distribution at the intersection of roads are used to find a mathematical model with fewer amounts of errors for unknown coefficients in the equation. The first degree function is used for converting the corrected image coordinates to uncorrected image. The nearest neighbor method is also used for resampling of uncorrected pixel value in this regard. Finally, the landsat image with RMS error equal to 0.29 is considered as earth geo-referenced image. Geometric correction of TM and ETM + images related to 1988 and 2014 are performed respectively using image-to-image method. First, the control points are selected. Then, the points with more errors are excluded from the table. At the end, a 32-control point TM image and a 40-control point ETM + image are corrected by excluding 7 and 9 points of ground control with error equal to 0.30 and 0.36, respectively. The images should have the same pixel dimensions and coordinates in order to determine the changes, whereby all pixel sizes in this study are equal to 28.5 m.

Radiometric Correction

The radiometric correction is performed in case of the multi-temporal images use. There are two types of radiometric corrections, absolute and relative radiometric corrections. Absolute radiometric correction method needs to enter data pertaining to sensor calibration and atmospheric properties. This correction method is often very difficult, especially for old data (Du *et al.*, 2002). On the contrary, the purpose of relative radiometric correction method is to reduce the atmospheric variables as well as the unexpected ones, which may exist in multi- temporal images. Dark Object Subtraction is one of the relative radiometric correction methods in this respect. Dark objects, in an ideal situation, have zero radiation at all wavelengths. It is assumed in this method that the pixels can be found in each band of image having values close to zero or one (such as water). The atmospheric effects of radiation deviation are added to each band of pixels as a constant value. Accordingly, the pixel value of each band should be reduced to the minimum DN of each band in order to eliminate the radiometric error in this respect. The dark-object subtraction method has found one of the oldest and widely used procedures for adjusting digital remote sensing data for effects of atmospheric scattering. It is a simple atmospheric correction method (Chavez and Mackinnon, 1994). The aforementioned method has been used, in this study, for performing radiometric correction.

Training data collection and image classification

Land cover classes are typically mapped from digital remotely sensed data through the process of a supervised digital image classification (Campbell, 1987; Thomas, Benning, & Ching, 1987). The overall objective of the image classification procedure is to categorize automatically all pixels in an image into land cover classes or themes (Lillesand & Kiefer, 1994). The SVM classifier is used for this study as mentioned and described above. Supervised classification is performed using ground checkpoints and digital topographic maps of the study area. In supervised classification, training sites form the basis of classification. Random sampling method is used in this study for data classification. By visiting the area of study, samples are recorded randomly for each group of land cover using GPS. The results derived from field observation and aerial photographs of the area show that there are five classes including forest, rangeland, horticulture, cropland and barren land during 1988 and six classes as lake, forest, rangeland, horticulture, cropland and barren land during 2001 and 2007.

Accuracy assessment of classification

Measuring accuracy is important not only for understanding the results derived but also for using these results for decision making process. The most common parameters for measuring accuracy are total accuracy and kappa coefficient (Lu *et al.*, 2004; Alavi panah, 2005; Bonyad and Hajqaderi, 2007).

Land use/cover change detection

Regardless of the technique used, the success of change detection from imagery depends on both the nature of the change involved, the success of the image pre-processing and classification procedures. In this study, post-classification change detection technique is applied. It is the most obvious method of change detection, which requires the comparison of independently produced classified images. Post-classification comparison proved to be the most effective technique, because data from two dates are separately classified, thereby minimizing the problem of normalizing for atmospheric and sensor differences between two dates. Cross-tabulation analysis is carried out to analyze the spatial distribution of different land cover classes and land cover changes. The CROSSTAB module of IDRISI Selva software is employed for performing crosstabulation analysis, which performs two operations. The first is image cross-tabulation in which the categories of one image are compared with those of a second image and tabulation is kept as the number of cells in each combination. The result of this operation is a table listing the tabulation totals as well as several measures of association between the images.

The second operation that CROSSTAB offers is cross-classification. Crossclassification can be described as a multiple overlay showing all combinations of the logical and operation. The result is a new image that shows the locations of all combination categories in the original images. Crossclassification thus produces a map representation of all non-zero entries in the cross-tabulation table.

Rsults and discussion

The geometric correction of images is performed with a root-mean-square error (RMSE) of 0.36 pixels. The high accuracy of geometric matching operation is confirmed by overlapping the linear layers of streams on the adapted images. The SVM method (radial basis function kernel) is used in the area of this study to monitor changes in land use and land cover during the periods from 1989 to 2014.

The land use and land cover classes are determined in foure classes including wetland, marsh, agriand urban. The training samples are then collected using visual interpretation of satellite images, aerial photographs, and Google Earth image and field observations. The land cover classes, in the next step, are considered in the area of study using image characteristics.

The separatability of classes is also computed using Jefferies- Matusita method. The derived results are shown in Tables 1 and 2. Additionally, the land cover maps are prepared for the three separate years, 1989, 2014, (Fig. 2). The statistical parameters related to accuracy measurement including total accuracy and kappa coefficient are extracted for each map as described in Table 3, after preparing the land cover maps with help of aerial photographs, Google Earth image and performing field operation and random sampling of the area of study using GPS.

Table 1. Separatability amount for land cover map classes derived from TM image (1988).

Land use name	wetland	marsh	agri	urban
wetland	1			
marsh	1.97	1		
agri	1.99	1.87	1	
urban	1.93	2	2	1

Table 2. Separatability amount for land cover map classes derived from ETM image (2014).

Land use name	wetland	marsh	agri	urban
wetland	1			
marsh	1.56	1		
agri	2	1.87	1	
urban	1.93	1.93	1.74	1

Table 3. Accuracy statistics for the classification result during the years 1988, 2014.

Derived maps from images	Overall accuracy	Kappa Coggicient
TM (1989)	95.60	0.94
ETM^+ (2014)	94.40	0.93

Map difference method

One of the results derived from supervised classification maps for the two separate years, 1989, 2014 is the possibility of determining the changes in land use/cover using map difference method. For this purpose, the maps of land use and land cover derived from supervised classification of the first date are subtracted from that of second date. The results derived from this method are shown in Table 4 for class changes.

Table 4. Cross-tabulation of land cover classes between 1989 and 2014 (in percentage).

Land cover name	wetland	marsh	Agri	urban
wetland	78.43	35.50	2.08	11.34
marsh	19.50	98.04	86.33	0
agri	2.05	66.20	12.70	94.35
urban	4.58	2.45	89.60	99
Class change	26.55	38.30	35.60	48.95
Map difference	1.60	4.05	21.80	32.45

Classification Comparison

The areas of foure land cover classes are obtained after preparing the land use and land cover maps for three separate dates. Fig. 3 is depicted in this regard in order to better compare the changes in these three years. It can be seen from this Fig. that there is a lake in the area as a result of dam construction, which appeared during the period from 1988 to 2014. It is also worth mentioning that the urban and wetland have increased during the same period. On the contrary, the agri has decreased and the marsh has almost no change. The agriland has decreased whereas the urban has increased in.

Statistics to monitoring changes

The classes derived from two classification maps are compared one by one in this method. Consequently, there is a possibility to determine comparatively the changes in each class to other classes by this method. A new map is created by crossing of two classified maps during the periods 1989 and 2014 (Fig. 3), which helps to compare the changes in land use and land cover classes during 1989 to that of 2014.

Table 4 includes the results derived from the Fig.. The most positive change (increase) has occurred for urban class due to construction and the most negative change (decrease) for agriland class. In Fig. 2.

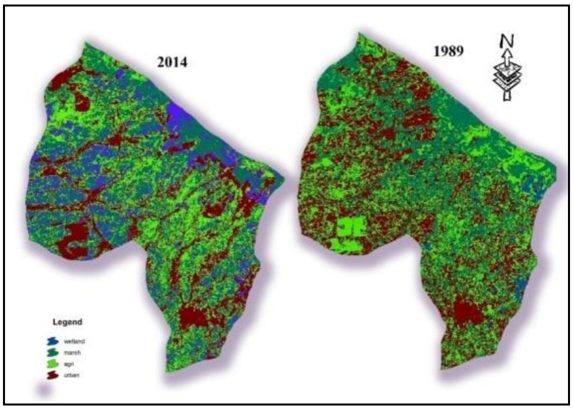

Fig. 2. Land use/ land cover classification map of study area using Landsat 1989 & 2014.

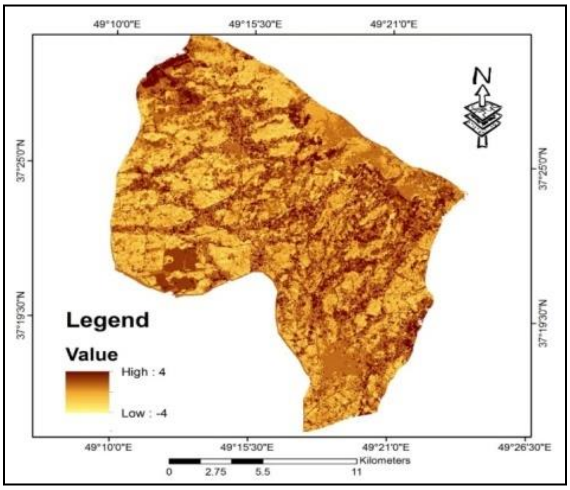

Fig. 3. Change detection map- Differencing between the two classified maps related to 1988 -2014.

Conclusions

The results of this study clearly show how planning instruments, whether sectoral or territorial, influence the dynamics of land-use change in a township area with mountain characteristics. In this study, post-classification comparison method is applied to monitor changes after performing the radiometric and geometric corrections. Since the changes in land use and land cover of Some'esara dam watershed are evident, an attempt is made in this study to detect them using the aforementioned method. Many researchers have shown in their studies that post-classification comparison method is one of the most accurate approaches to monitor the changes in land use and land cover. The land use and land cover information can be extracted from past and present using satellite images. The results can be combined with other data and map information. The effects of land use and land cover development on other uses and changes can be evaluated and determined specially by using the post-classification comparison method and also binary combination of land use maps. One of the objectives of this study is to determine the nature of changes in land use and land cover. However, the traditional classification algorithms such as statistical methods cannot provide the optimum results due to low flexibility and parametric varieties, just like the maximum likelihood method, which is not able to provide optimum results in the absence of normal training data due to its dependence on Gaussian statistics model. In recent years, accordingly, a new technique based on statistical learning theory called Support Vector Machines (SVM) has been devised to classify the remote sensing data. The SVM, in this study, is adopted to classify the land use and land cover of Some'esaratownship during the periods 1998, 2014. Four types of kernels (linear, polynomial, radial and sigmoid) are considered for SVM classifications. Among them, the radial basis function (RBF) kernel is used and the results derived are for the post-classification comparison.

The most positive change (increase), in Some'esara township, has occurred for urban class, during the first period from 1988 to 2014. The percentages of conversion into urban are 40/20%, 30/85%, 9/39%, 5/20% and 29/07%, respectively, for wetland, agriland and marsh. Meanwhile, the most negative change (decrease has occurred for wetland class during the first period. In this period, 65/90 % of wetland has remained unchanged; however, 7/50 % has been converted to urban, 5/08% to marsh, 18/98% to agriland. After all, it can be stated that if the purpose of changes monitoring is to detect the nature of changes (type and direction of changes), then the post-classification comparison is the best method in this regard. The accuracy values of land cover maps derived from satellite data classification by using the support vector machine algorithm are equal to 93%, 95% for TM, ETM+ respectively. This indicates a high accuracy of SVM algorithm in satellite data classification studies. The management of common land, even in an informal way, introduces differences to land-use trajectories, involving the development of wetland and marsh land through the introduction of newspecies and wetland (shore line) maintenance, leading to smaller subdivisions in patterns of land use. Therefore, it is local factors, whether emerging from planning methods or community involvement in land management, which explain land-use change and create greater benefits for the communities, and may also lead to future forms of intervention in this township mountainous community.

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