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RESEARCH ARTICLE

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Automatic Feature Extraction Module for Change Detection in Al Ain, UAE: Analysis by Means of Multi-temporal Remote Sensing Data

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Abstract Monitoring new changes in cities adjacent to dynamic sand dunes requires precise classifier technique. Unlike traditional techniques of supervised classification which use training sites, the integration of image transformation tasseled cap and automatic feature extraction module based on spectral signatures has provided to be sensitive and realistic techniques with time and cost effective. The proposed module was applied to Al Ain district, United Arab Emirates (UAE). The module consists of four steps in terms of segmentation, thresholding and clustering and computing attributes. The obtained greenness and classified maps were then enhanced by applying a 3×3 Sobel filter. The new changes were detected by combining the multi-temporal greenness and classification maps. Accuracy assessment and quantitative analysis were performed using confusion matrix and ground truthing. The results showed significant increasing in urban and agricultural areas from the year from 1990 to 2000 compared with the period of time from the year 2000 to 2006. The image difference showed that the vegetation and building classes had increased 7.58 and 20.28 km^2 respectively. This study showed that image difference and fuzzy logic approach are the most sensitive techniques for detecting new changes in areas adjacent to dynamic sand dunes.

Keywords Al Ain · Landuse · Change detection · UAE · Feature extraction · Tasseled cap

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Introduction

Change detection is an important process in monitoring urban development. It provides quantitative analysis of the spatial distribution of the region of interest (Schmitt and Brisco 2013). The use of remote sensing in updating land use data had little success in urban areas at the parcel level (Zhang et al. 2007) and detecting land cover/ land use using multi-temporal remote sensing data (Chen et al. 2003; Zhang et al. 2007).

In the last two decades, a variety of approaches to detect changes using two-date remote sensing imagery for different methods have been reported. These approaches can be grouped into four general types (Yang et al. 2012): (1) Algebraic methods, which detect changes by implementing algebraic operations between remote-sensing images acquired from the same area at two different dates. (2) Classification methods, which include post-classification comparisons, Sohl (1999); Yang and Lo (2002), and direct two-time classifications, Li and Yeh 1998. In this method, the accuracy of the change-detection result strongly depends on the classification accuracy; (3) Transformation-based change-detection methods, such as principal component analysis (PCA)-based techniques mentioned in Loveland et al. (2002), multivariate alteration detection (MAD) transformation, as well as combined MAD and maximum autocorrelation analysis transformation techniques, (Michalek et al. 1993; Dewindar 2004; Schenk and Csatho 2012; Srivastava et al. 2012); and (4) Visualization change-detection methods, which can be grouped into two general types: temporal compositing techniques, (Zhan et al. 2002) and visual interpretation-based techniques, (Chen et al. 2003) and Fung and Le (1988). Civco et al. (2002) compared different land use and land cover change detection approaches including traditional post-classification cross-tabulation, cross-correlation analysis, neural networks, and knowledge based expert systems with object-oriented change detection. Zhang et al. (2007) used Artificial Neural Network (ANN) to classify multi-temporal vegetation maps. Gamanya et al. (2009) applied a Standardized, Object Oriented, and automatic Classification (SOOAC) method based on fuzzy logic. Ghosh et al. (2010) used fuzzy clustering algorithms for unsupervised change detection in remote sensing images and takes care of spatial correlation between neighboring pixels of the difference image produced by comparing two images acquired in the same geographical area at different times. Veettil (2012) described and compared various urban change detection methods using high spatial resolution images. Maoguo et al. (2014) propped a novel approach based on two multitemporal synthetic aperture radar difference (SAR) images, which are constructed through intensity and texture information,

Locally, Sohl (1999) studied landscape change in the Abu Dhabi Emirate using Landsat Thematic Mapper (TM) data. Yagoup (2004) investigated the development of Al Ain city, in the United Arab Emirates (UAE), between 1976 and 2000, with particular reference to the space–time relationship. Yagoub and Kolan (2006) monitored coastal zone land use and land cover changes of Abu Dhabi using remote sensing. Besides the aforementioned methods, an automatic feature extraction module from multi-temporal data attracts more attention in the field of image processing and classification. The proposed method offers more flexibility in the types of features to be extracted significantly higher accuracy due to its ability to classify the mixed pixels. Additionally, the module offers more flexibility in the types of features to be extracted without training areas that are needed in supervised classification. The main objective of this paper is to monitor the rapid changes in land cover /use in Al Ain district, UAE using multi-temporal Landsat Images.

Study Area

The study area stretches from long 55° 05E and 56° 01E to 23° 29 and 24° 73N in the Eastern region of Abu Dhabi Emirate, UAE (Fig. 1), which is located about 170 km from Abu Dhabi city. It is the fastest changing city in the Arabian Peninsula. It has gone from a desert oasis to a thriving modern city in just over 50 years (Yagoup 2004). It is bound to the east, south and north by Sultanate of Oman. It occupies an area of about 1296 km^2 and extends from Oman Mountain in the east and sand dunes in the west.

According to Menges et al. (1993), four geomorphological features characterize the study area: (i) mountains of exposed bedrock; (ii) Piedmonts, alluvial plains and Piedmonts related to ephemeral streams on the western flank of the Oman Mountains; (iii) a wide alluvial plain and valley near the Al-Ain urban area; and (v) a nearly continuous expanse of Aeolian sand and associated dune landforms divided into the northern and southern dunes area (Fig. 1). Agriculture is intense in the middle of A1 Ain and increases in the south-west direction.

Other areas of the rectangular-shaped planted forests can be found in the sand dunes, desert plain, alluvial plain, Hafeet Mountain, along roads, and wherever adequate ground water is found (Fig. 1).

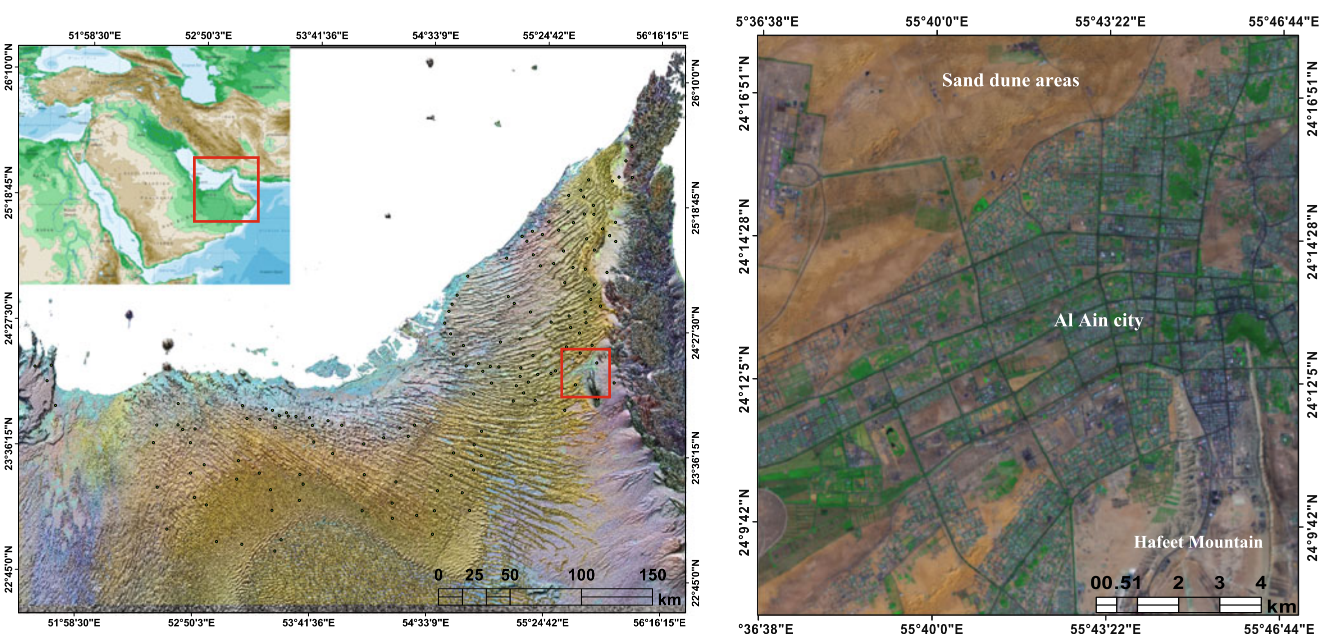

Fig. 1 RGB 742 band combination of Landsat image is draped over DEM showing the location of the study area

Data and Methods

Data

Three remotely sensed datasets were used in this study. The first data set was multispectral images acquired by the Landsat Themtic Mapper (TM) sensor of Landsat-4 satellite in an area of Al Ain, Abu Dhabi on 28 August 1990. The second data set used was a multispectral image acquired by the Landsat Enhanced Thematic Mapper plus (ETM+) sensor of Landsat -7 satellite in Al Ain area, Abu Dhabi, UAE on 23th August 2000. The third data set used was multispectral images acquired by Landsat Enhanced Thematic Mapper plus (ETM+) sensor of the Landsat -7 satellite in Al Ain area, Abu Dhabi, UAE on 25th September 2006. All remotely sensed data are distributed as a geographic (long/lat) projection, with the WGS84 horizontal datum currently available from the Tropical Rain Forest Information Center (TRFIC) database (http://landsat.org/ortho/index.php). We used landsat images due to their temporal and spectral resolution as well as their cost effective.

Methods

Image Transformation

As a first step in feature extraction and classification, the multi-temporal remote sensing data were geometrically corrected using ENVI v. 4.5 software. Then the images were transformed using tasseled cap. This transformation should be applied to calibrate reflectance data rather than applying to raw digital number imagery. In tasseled cap, an orthogonal transformation of the original data into a new four-dimensional space consisting of the soil brightness index (SBI), the green vegetation index (GVI), the yellow stuff index (YVI), and a non-such index (NSI) associated with atmospheric effects (Jensen 1996). Due to the rapidly growing and spreading of green areas in Al Ain city, the green vegetation index (GVI) dimension was chosen to monitor the changes in the vegetation and green areas during the period from 1990 to 2006. The GVI was calculated individually for each image and monitoring changes in GVI was performed. Monitoring changes were performed by overlaying the calculated GVI maps and each map was represented in different color codes. The changes were calculated using change detection statistics tools that implemented in the ENVI v. 4.5 software.

Automatic Feature Extraction

For precise mapping, it is important to employ an automatic algorithm, which classify and automatically extract features of multi-temporal remote sensing data. Feature extraction module, which is implemented in ENVI software has been employed for classifying and extracting features from multi-temporal remote sensing data. The feature extraction module is sensitive and realistic in image classification due to its ability classify the mixed pixels and extract information from high-resolution panchromatic or multi-spectral imagery based on spatial and spectral characteristics with less time understanding processing details and more time interpreting results.

The module consists of four steps: (i) image segmentation, (ii) merging segments, (iii) refining segments and (iv) computing attributes. Segmentation is the process of partitioning an image into segments by grouping neighboring pixels with similar feature values (brightness, texture, color, etc.). The first step called Scale Level, which is a very sensitive parameter, controlling the number and size of segments. It is important to note that good segmentation ensures that classification results are more accurate.

The training of different values of Scale Level shows that the optimal value for image segmentation was 85. It is important to note, a small Scale Level value (20) has led to over-segmented, while a higher Scale Level value (200) has lead to more segments to be defined and delineates the boundaries of features as well as possible. The suitable value of Scale Level was 85. The higher the scale level, the fewer the segments to be defined. The second step was refining segments or thresholding, is a raster operation that works with one band to group adjacent segments based on their brightness or DN value. The value of thresholding ranging from 79 to 207. The best threshold value was 109.

The third step was the compute attributes, is related to spatial, spectral and texture of each object. The attributes were computed automatically based on their spectral signatures, textures and contrasts between objects. Classification errors on 1990 images were independently corrected by adjusting the threshold values at particular problem nodes within the classification hierarchy based on verified field objects (Gamanya et al. 2007). Finally, the resultant classification maps were then enhanced and the high frequencies was amplifies by applying a 3×3 non linear Sobel filter (Gonzalez and Woods 1992).

Post Classification and Change Detection

Post-classification change detection based on class comparison was accomplished using the three classification images of 1990–2000 and 2000–2006 dates. The 1990 and 2000 classification images were combined together, resulting in ten change detection classes. Then, the accuracy assessment was performed on each classified image using confusion matrix and comparing a classification result with ground truth information and land cover of Al Ain city. In each case, an overall accuracy, producer and user accuracies, kappa coefficient, confusion matrix, and errors of commission and omission were reported (Congalton 1991). The classified maps were corrected visually, using high resolution Quickbird images and field survey for selected sites.

Results

Image Transformation and Classification

Figures 2, 3 and 4 show the obtained greenness and classification maps generated from the 1990, 2000 and 2006 images that transformed using tasseled cap into the GVI and

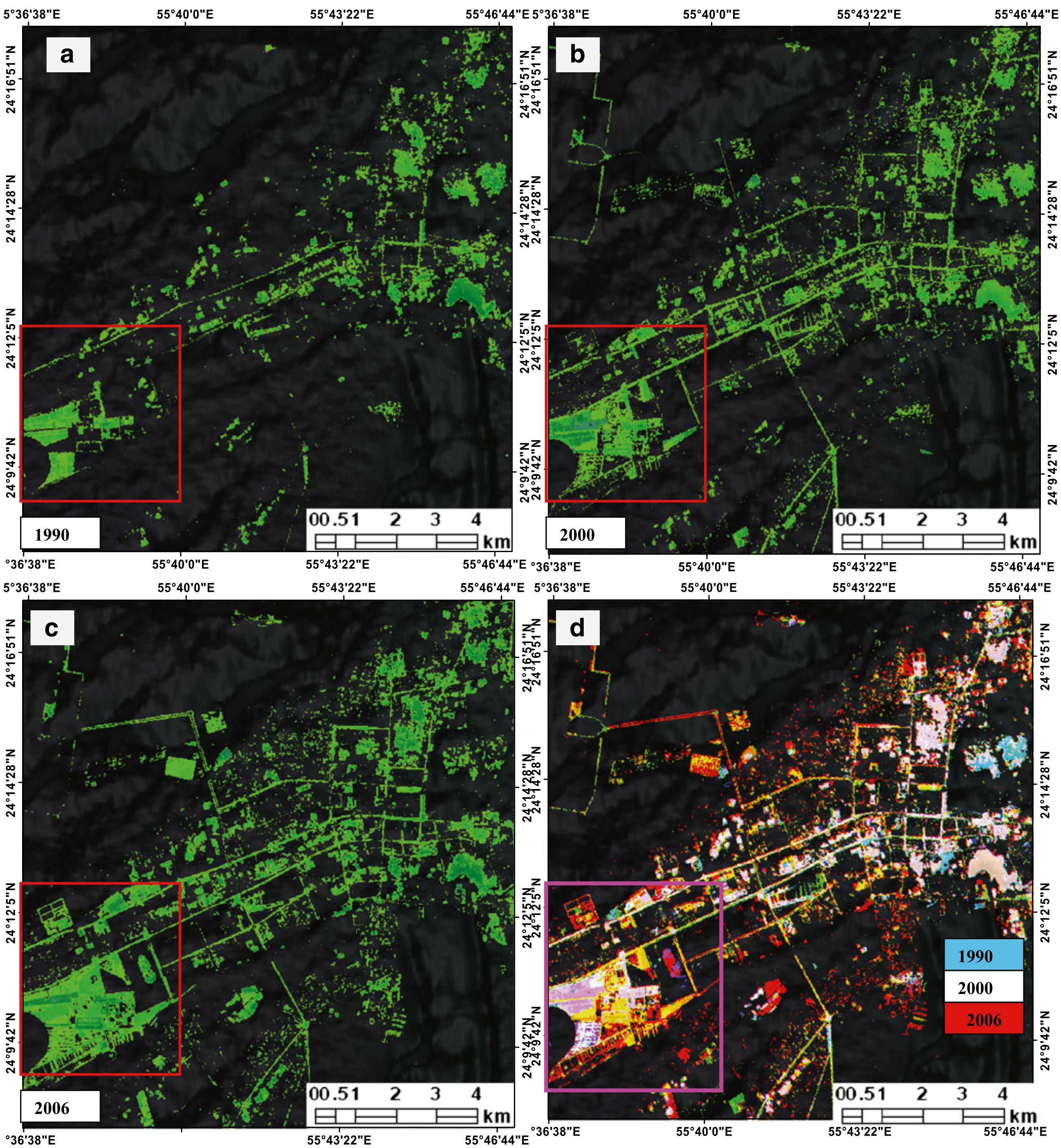

Fig. 2 The 1990, 2000 and 2006 green vegetation index (GVI) maps and RGB combined map (**d**) showing the changes of green areas from 1990–2006 in Al Ain city and its adjacent areas

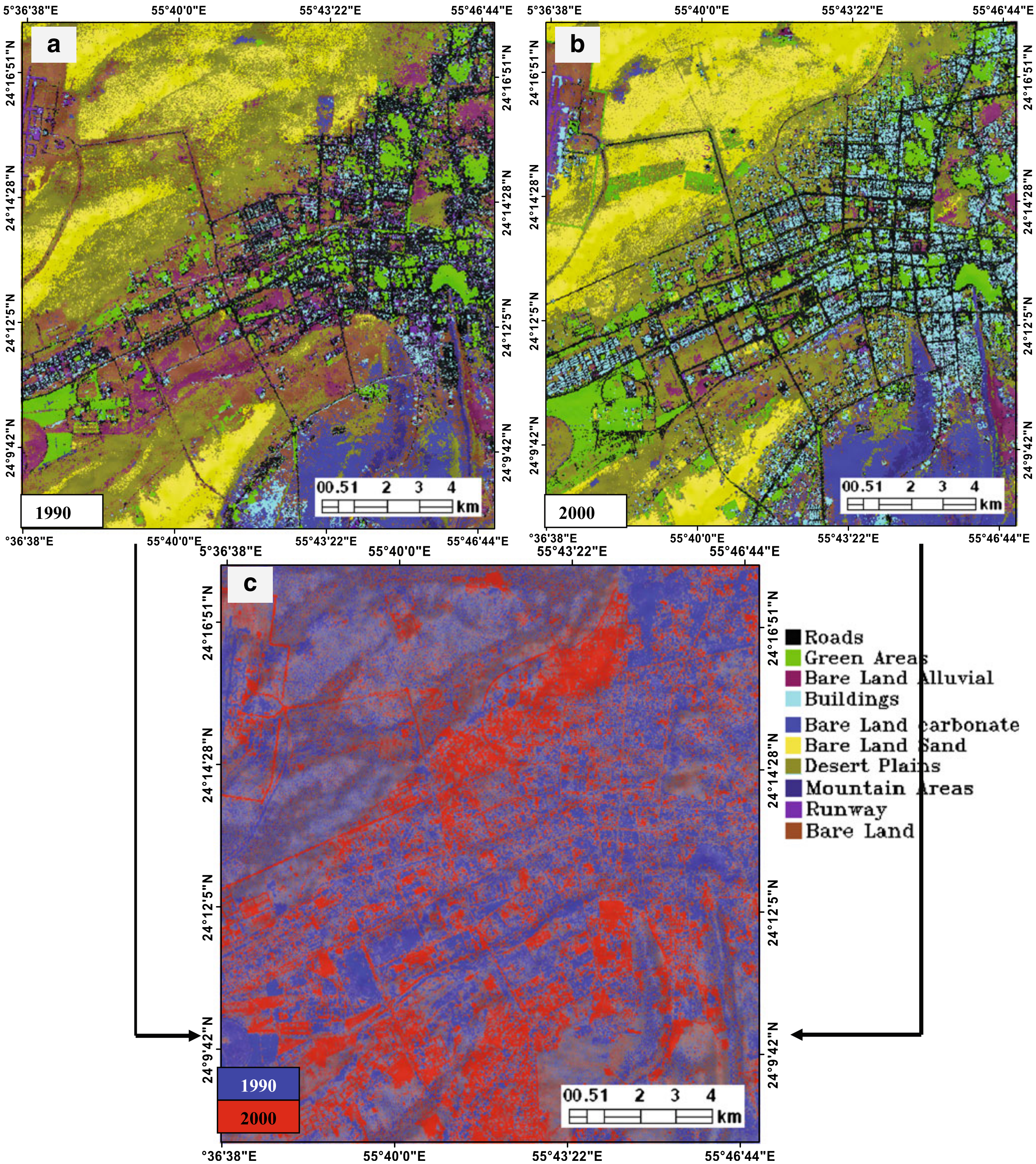

Fig. 3 The 1990 and 2000 classification images derived from multi-temporal remote sensing data **a**, **b** and **c** image difference highlights changes in Al Ain area during the period from 1990 (*blue color*) to 2000 (*red color*) and showing the rapid growth in land cover classes, especially green areas

classification maps. A total of ten classes were produced by the proposed module. The classes were represented in different color codes to facilitate the visual discrimination and highlight on the direction of changes. All classes of the 2000 and 2006 images are in the whole well recognized visually. But, mall building and vegetation types, however, are not well discriminated on landsat images. The urban and agricultural areas within and around Al Ain city were clearly identified, showing the highly cluster within the city center during the period from 1990 to 2006. In the same context, the high density of commercial and residential and urban vegetated areas showed a relative increase in Al Ain city. On the other hands, there was a relative decrease of the bare land of sand dunes, bare land of carbonate rock and bare land of desert plains.

Higher density areas were effectively classified in the LANDASAT images of ETM+ acquired during 2000 and 2006 compared to the images of TM acquired during 1990 due to the high sensitivity and accuracy of later sensors. The discrimination among the different classes performed well in the 2000 and 2006 image compared to 1990 images. On the

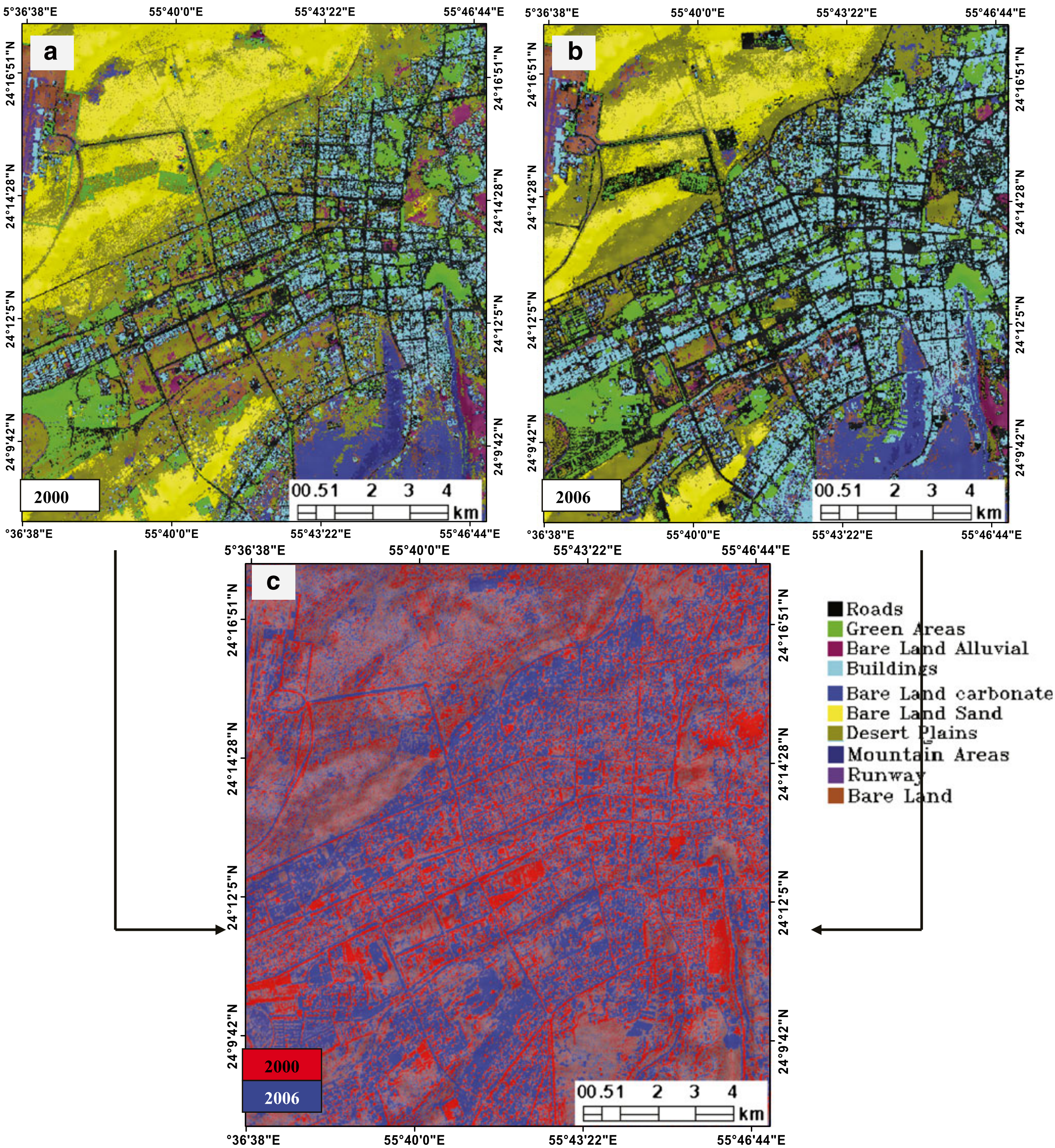

Fig. 4 The 2000 and 2006 classification images derived from multi-temporal remote sensing data using the proposed methods **a**, **b** and **c** difference image highlights changes in Al Ain area during the period from 2000 (*red color*) to 2006 (*blue color*) showing rapid increasing and cover land decreeing in bare lands such as sand dune and carbonate classes

other hands, the low density of residential and commercial areas and green areas were clearly classified and discriminated in 1900 images compared to 2000 and 2006 images due to the selected threshold level performed well with 1990 images. But the threshold level is needed to be adjusted in the 2000 and 2006 images.

Post Classification and Change Detection

Post classification in terms of accuracy assessments was performed using confusion matrix. The result of accuracy assessments is listed in Table 1. The 2006 and 2000 images had a higher accuracy than the 1990 image. The 1990 classification image had the lowest accuracy of 86.68 % and kappa value of 0.83, while the 2006 and 2000 classification image had an overall accuracy of 92.4 and 92.8 % respectively (Table 1). However, the procedure wasn't able to detect the type of vegetation and crops because the low resolution of the data.

The low accuracy of the 1990 classification image could be attributed to the low sensitivity of TM-4 satellite senor and registration and training errors. Post-classification change detection based on class comparison was accomplished using the three transformed images of 1990, 2000 and 2006 dates. Green areas were detected accurately with Tasseled Cap techniques GVI based on ground data. The 1990 and 2000 transformed images were combined together, resulting in ten change detection classes. The subtle differences in the red and green colors corresponding expansion of agricultural activity and those small gardens alignments roads are difficult to discriminate. In the resultant map, red color highlights the change in vegetation during 2006, blue color highlights the change in vegetation during 2000 and green color highlights the changes during 1990.

White color highlights areas that had not experienced any considerable changes (Fig. 2). The most important change that has been noticed in this area is partial decreasing of the existing bare land areas at the southern and southwestern parts of Al Ain district and these portions are identified as development areas. Later these areas have been reutilized as settlement area, aquaculture farm and agricultural land. From Figs. 2, 3 and 4, it was observed that agricultural and farm areas were prevalent in the south and southwestern parts all along desert plains and Wadis. On the other hands, residential and commercial buildings were observed along the NE-SW trending Wadi Al Ain. Scattered villages and agricultural areas were also observed in the barren lands of sand dunes, carbonate rocks and desert plains where groundwater is available. By 2000 and 2006, about 55 km^2 of bare lands have been converted to farms and resorts (Hafeet Mountain) and farms and residential areas (sand dunes and desert plains) as observed from Fig. 3.

The 1990–2000 and 2000–2006 image difference statistics in square kilometer in Tables 2 and 3. The results of image differences showed negative values (decreasing trends) for bare lands and mountain area and positive values (increasing

Table 1 Comparison of the classification accuracies for the change detection

Classification images	Over all accuracy (%)	Kappa coefficient
1990	86.6805	0.8332
2000	92.4161	0.9050
2006	92.8755	0.9067

Table 2 Change detection statistics using the 1990 and 2000 classification images

Class	1990–2000			
	Class changes (%)	Image difference (%)	Class changes (km^2)	Image difference (km^2)
Bare land carbonate	24.266	−2.342	23.31	−2.25
Bare land sand	9.995	−9.224	16.27	−15
Bare land alluvial	19.166	−4.480	15.96	−3.73
Desert Plain	42.855	−11.219	59.52	−15.58
Roads	62	37.644	75.96	46
Green area	43.386	15	21.80	7.58
Building	49.193	83.209	11.99	20.28
Mountain areas	45.265	−27.385	27.24	−16.48
Bare land	70.755	−11.673	21.98	−3.63

Table 3 Change detection statistics using the 2000 and 2006 classification images

Class	2000–2006			
	Class changes (%)	Image difference (%)	Class changes (km^2)	Image difference (km^2)
Bare land carbonate	21.942	−2.272	21.77	−2.12
Bare land sand	7.876	−7.325	13.17	−13
Bare land alluvial	17.166	3.480	14.87	−2.13
Desert Plain	41.733	10.321	52.44	−13.33
Roads	59	33.544	70.55	44
Green area	41.453	14.324	23.67	6.77
Building	46.347	81.409	17.66	19.24
Mountain areas	42.765	−22.457	18.22	−13.32
Bare land	66.844	−9.769	19.77	−3.11

trends) for classes such as green areas (gardens, parks and agricultural areas) and buildings (commercial and residential). For example, bare land of carbonate rocks (Hafeet Mountain) showed decreasing trends of −2.25 km^2 and green area showed increasing trends of 7.58 km^2 during 1990–2000 (Fig. 5).

From the quantitative analysis of this study, it was found that there was an image difference of 7.58 km^2 (15 %) during 1990–2000 and 6.7 km^2 (14.32 %) during 200–2006 (Tables 2 and 3). For example, the residential and commercial building and roads showed image difference of 20.28 km^2 (83.2 %) during the period from 1990 to 2000 and 19.24 km^2 (81.4 %) during the period from 2000 to 2006. In general, green and urban development showed a significant increasing trend during the period from 1990 to 2006. This increasing was found to be expanded in the southwestern and southern parts of Al Ain disdrict. On the other hands, about 13.33 km^2 (10.32 %) of bare land was developed to urban and agricultural areas. All bare lands of carbonate, desert plains and sand dunes showed decline in space and time, especially portions with gentle slope and groundwater availability (Tables 2 and 3). These areas receive most of groundwater from Oman and Hafet Mountains through paleochannels and fault zones under the influence of slope (Al Nuaimi 2003; Samy and Mohamed 2012; Samy and Mohamed 2014). The expansion pattern of urban and green areas is more or less similar for wadis, flow direction, roads and desert plains. Population and farms have played vital role in contraction of bare lands of carbonate areas, desert plains and sand dunes (Figs. 4 and 5) during the period from 1990 to 2006. In the same time the increase in population and agricultural activity has led to the depletion of groundwater quality and quantity (JICA 1996).

Discussion

The main objective of this study was to monitor and detect changes in land use and land cover in Al Ain district using multi-temporal data. Unlike previous studies (Sohl 1999; Yagoup 2004). who used manual screen digitizing calculation and Univariant Image Differencing a small portion, the present study used image transformation tasseled cap and the automatic feature module to detect changes in vegetation and urban areas over regional scale of Al Ain district. The main advantage of the proposed techniques is that the clustering and training sampling is done automatically based on their spectral signatures with time and cost effective. Additionally, they provided different types of spatial information and varied in accuracy.

This study has showed that the use of small value for threshold wasn't able to detect small farms and buildings that distributed in the sand dune fields. To overcome this problem, the threshold value was increased to 65. The proposed module performed well compared with traditional techniques of supervised and unsupervised classification with regard to qualitative descriptions of surface change, primarily due to the types of change that image difference wasn't able to detect and discriminate. It was difficult to detect crop types and discriminate the residential from commercial areas because the bare lands without crop were spectrally similar to other land cover areas.

The proposed method was powerful at depicting areas of urban development and helps to auto-extract a wide variety of features such as buildings, roads, gardens and agricultural areas. The procedure was able to provide a measure of the areas of hectares of new green areas (that is parks, gardens and agricultural areas). The proposed module is designed to work with any type of image data in an optimized and

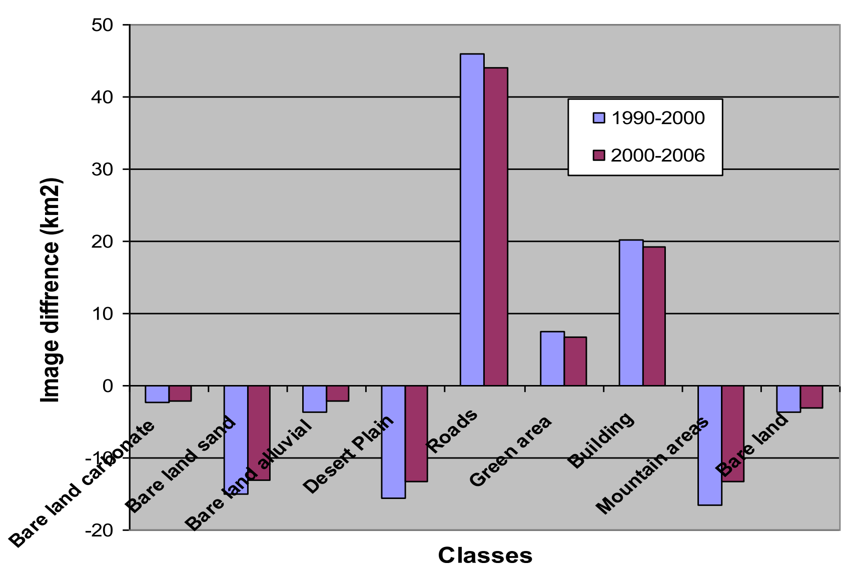

Fig. 5 New changes of land-use classes for August 1990, August 2000 and September 2006

reproducible fashion with less time understanding processing details and more time interpreting results. It provides complete meaningful of land cover and land use changes from 1990 to 2006 which is desirable in change detection and decision making applications. The quantitative analysis using change detection statistic function also provides much spatial and temporal information about area of rapid changes and development.

The obtained maps in conjunction with groundwater data can be used for studying and investigating the influence of intensive farming and urban development on groundwater depletion quantitatively and qualitatively as well as groundwater contamination. Another change detection techniques such as image difference and fuzzy logic techniques in conjunction with field observation and ancillary data can minimize some of classification errors (Congalton et al. 1993; Robb and Russell 1998). For the method to be more generally applied, more land use and land cover data are needed. Future work using high resolution remote sensing data and advanced fuzzy algorithms may be decreased classification errors and increase the accuracy of the post-classification change detection.

Conclusions

This current study has shown that an integration of image transformation using tasseled cap and automatic feature extraction module can be used in change detection from muti-temporal remote sensing data with time and economic effective. The 1990 classification image had the lowest accuracy of 86.68 % and kappa value of 0.83, while the 2006 and 2000 classification image had an overall accuracy of 92.4 and 92.8 % respectively. The result of classification showed that there was an image difference of 7.58 km^2 (15 %) during 1990–2000 and 6.7 km^2 (14.32 %) during 200–2006. The result also showed that urban and land development in Al Ain district were very closely associated with sites with gentle slope and groundwater potential, demonstrating that main activity of the people was in the farming and camel breeding. These areas are distributed in the sand dunes and the desert plains. The result also showed that commercial and residential were concentrated at the foreland of wadi Al Ain where the fresh water is available. The main advantage of the proposed techniques is that the clustering and training sampling is done automatically based on their spectral signatures over large coverage with time and cost effective. Additionally, they provided different types of spatial information and varied in accuracy.

The proposed method wasn't able to detect and determine types of crops and building that distributed in the study area because the low resolution of the data. But it cab used to determine the types of crops and vegetation from high resolution and hyper-spectral sensing data.

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