DETECTION OF LAND USE AND LAND COVER CHANGES IN DIRAB REGION OF SAUDI ARABIA USING REMOTELY SENSED IMAGERIES

[1]Madugundu, R., [1,2]K.A. Al-Gaadi, [1]V.C. Patil and [1]E. Tola

[1]Precision Agriculture Research Chair,
[2]Department of Agricultural Engineering,
College of Food and Agriculture Sciences, King Saud University, Riyadh, Saudi Arabia

ABSTRACT

Knowledge of Land Use and Land Cover (LULC) changes is important for many planning and management activities. It is thought to be an essential element for modeling and understanding the major land forms, especially in arid regions like Saudi Arabia. This study investigates the LULC changes in Dirab region of Saudi Arabia between 1980 and 2010, using Landsat TM/ETM+images. After the geometric correction and radiometric normalization, multi-temporal image data sets were spectrally enhanced separately using Principal Component Analysis (PCA) and Tasseled Cap Transformation (TCT). Each image was then separately subjected to supervised classification and processed to identify and quantify LULC changes (vegetation, barren land and built-up area). Post Classification Comparison (PCC) method was adopted for LULC change detection. Change trajectories ("from-to" classes) and accuracy assessments were made by comparing the detected land use change layers with medium/high resolution images of Google Earth data base. The TCT enhanced procedure gave better identification of the changed areas than PCA based method. The overall accuracy of PCA based change detection was 64.58, 62.68 and 62.12% for 1980-1990, 1990-2000 and 2000-2010 images, respectively. However, the TCT based change detection resulted in higher accuracy of 77.78, 75.62 and 77.92% for 1980-1990, 1990-2000 and 2009-2010, respectively. The results suggested that significant land use changes occurred in Dirab area from 1980 to 2010, which may be related to rapid development of agriculture between 1980 and 2000 and economic development and urban expansion between 2000 and 2010. It was further noted that most changes occurred in cropland areas due to urban encroachment.

Keywords: Principal Component Analysis, Tasseled Cap Transformation, Temporal Changes, Post Classification Comparison, Saudi Arabia

1. INTRODUCTION

Information on land use/land cover change is essential for the selection, planning and implementation of land management schemes to meet the increasing demands for basic human needs and welfare (Reddy and Gebreselassie, 2011). Remotely sensed change detection based on multitemporal, multispectral and multisensor imagery provides this information (Singh, 1989; Othman *et al.*, 2013). LULC studies include, image enhancement, LULC classification and change detection. Principal Component Analysis (PCA) and Tasseled Cap Transformation (TCT) are more commonly used image enhancement methods (Lu *et al.*, 2004). Principal Component Analysis (PCA) transforms a set of correlated image bands in to a new set of uncorrelated image bands that are ordered based on the amount of variance explained in the original data (Eastman and Fulk, 1993). PCA was used for LULC change studies from Landsat TM (Mather, 1999), SPOT (Carr and Matanawi, 1999), IKONOS (Bernardini *et al.*,

Corresponding Author: Madugundu, R., Precision Agriculture Research Chair, College of Food and Agriculture Sciences, King Saud University, Riyadh, Saudi Arabia

2008) and hyperspectral (Licciardi *et al.*, 2012) imagery. Tasseled Cap Transformation (TCT) is another method of enhancing spectral information of satellite data. TCT was first applied to Landsat MSS (Kauth and Thomas, 1976) and further extended to other sensors such as Landsat TM (Crist, 1985), ETM+ (Huang *et al.*, 2002), IKONOS (Horne, 2003), MODIS (Lobser and Cohen, 2007) and CBERS 02B-China and Brazil Earth Resource Satellite (Sheng *et al.*, 2011). In recent years, TCT has been widely used in LULC change detection (Dymond *et al.*, 2002; Han *et al.*, 2007; Liu and Liu, 2010). Supervised and unsupervised classification techniques are two widely used methods of classifying LULC (Lillesand and Kiefer, 2000). Out of several change detection procedures available Post Classification Comparison (PCC) is one of the most widely used methods (Lu *et al.*, 2003). Change detection generally employs one of two basic methods: Pixel-to-pixel comparison and post-classification comparison (Jaiswal *et al.*, 1999). The post classification method compares two or more separately classified images of different dates (Fung and Zhang, 1989). It is considered to be one of the most appropriate and commonly used methods for change detection (Jensen, 2005).

Several LULC change detection studies were reported (Daniel *et al.*, 2002; Lu *et al.*, 2004; Berberoglu and Akin, 2009; Tahir *et al.*, 2013). However, such studies are limited in Saudi Arabia. Example of these studies includes the one conducted by Al-Washe and Bokhari (1993) who assessed the vegetation changes for urban planning in Al-Madina. Al-Rowili *et al.* (2003) assessed changes in the urban areas of Jeddah City between 1988 and 1998. Similar study was conducted by Bagour *et al.* (2006) to evaluate the extent of vegetation changes in north-eastern part of the Kingdom of Saudi Arabia due to the 1991 Gulf War. Agricultural land use changes through the period from 1988 to 2008 was monitored and assessed by Al-Harbi (2010). Also, Al-Gaadi *et al.* (2011) studied the NDVI based temporal land cover changes in Dirab region between 1990 and 2006. Another study was conducted by Hereher *et al.* (2012) to analyze land cover and topography of Hail region, between 1972 and 2000.

Drastic developmental activities are undertaken in the past two decades in Dirab region of Saudi Arabia. As part of this development, structures like Golf club, Arab National Park, KSU research farm, ARABSAT Satellite earth station are being established along with the development of agricultural fields and date palm orchards. In order to assess the impact of these development activities, this study was carried out with the following objectives: (1) to assess Land Use and Land Cover (LULC) changes and their trajectories ("from-to" classes) of Dirab region from 1980 to 2010 and (2) to compare Principal Component Analysis (PCA) and Tasseled Cap Transformation (TCT) of enhanced Landsat TM/ETM+ images for LULC using Post Classification Comparison (PCC) technique.

2. MATERIALS AND METHODS

2.1. Study Area

The study was conducted for Dirab region, which is located about 50 km west of Riyadh and lies between 24°20'35" and 24°20'51" N latitude and between 46°31'41" and 46°45'34" E longitude (**Fig. 1**). Dirab region experienced dry continental climate with hot summer and cold to moderate winters with a mean temperature of 35°C. Geologically, Dirab region is covered with predominant sandstone and subordinate limestone from Mesozoic age. Sedimentary rock formation, which under laid Dirab region, is part of an extremely thick rock bed that dipped easterly into the Arabian shield. The water-bearing sand and limestone beds store substantial volume of water and constitute an important alluvial aquifer. Topographically, Dirab region is steeply undulating terrain dissected by valleys Lida and Al-Awast which are exploited mainly for their high agricultural potential. Wheat and alfalfa are the major crops grown in the region, using centre pivot irrigation system.

2.2. Image Processing

Geo-corrected cloud free Landsat TM and ETM+imageries were downloaded from USGS website (**Table 1**) and geo-referenced to the Universal Transverse Mercator (UTM) coordinate system with WGS1984 as spheroid and datum across the north zone of 39 using a reference image. In this study, Landsat image of 2000 (path: 166/row: 43) was considered as a reference image. A minimum of 25 evenly distributed Ground Control Points (GCPs) were selected from the images. Re-sampling was performed using nearest neighbor algorithm. The transformation had a RMS error of less than 0.5 pixels indicating that the image was accurate within one pixel. These images were radio-metrically (Top of Atmosphere) corrected by applying Radiative transfer model utilizing pre-launch calibration constants of TM and ETM+ (Chander and Markham, 2003). For the SLC-off images (i.e., 7th September 2010), the bad pixels were replaced by the nearest date of acquired image (23rd September 2010) through image mosaic with histogram equalization options.
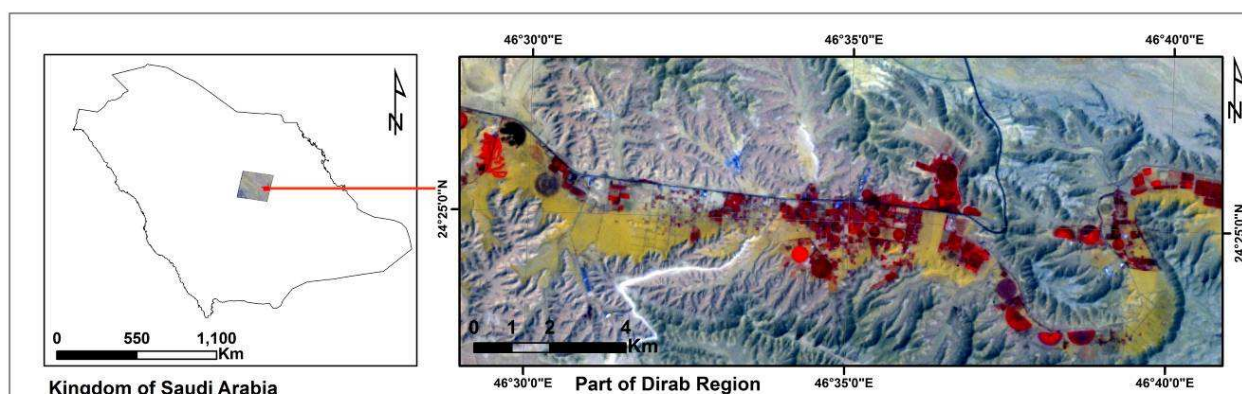
Fig. 1. Location map of dirab region (Study Area)

Table 1. List of remotely sensed data used for the study

Sl. No	Sensor	Path/Row	Date of pass
1	Landsat 4	166/43	14/09/1980
2	Landsat TM	166/43	07/09/1990
3	Landsat ETM+ (SLC on)	166/43	02/09/2000
4	Landsat ETM+ (SLC off)	165/43	07/09/2010
5	Landsat ETM+ (SLC off)	165/43	23/09/2010

After geometric correction and radiometric normalization, multi-temporal image data sets were spectrally enhanced separately using PCA and TCT. Each image was then separately classified by adopting supervised classification method and processed to identify and quantify land use changes.

2.3. Principal Component Analysis

Top of Atmosphere (TOA) corrected Landsat images were subjected to PCA using multivariate algorithm (PCA of ERDAS Imagine software) to generate Eigen images (i.e., PCA outputs). In general, when PCA is applied to data embracing several spectral bands, it concentrates almost all of the information in the first two or three components. The other components generally contain only noise (Deng *et al*., 2008). In this study, a color composite of Eigen images generated from the first three principal components was used for classification and change detection.

2.4. Tasseled Cap Transformation (TCT) Analysis

In this study, the Tasseled Cap Transformation was carried out for TOA corrected Landsat satellite imagery by applying Huang *et al*. (2002) developed band-wise coefficients (**Table 2**) to Equation (1):

$$
\begin{aligned}
TCT_i = {} & (coeff_1 \times band_1) + (coeff_2 \times band_2) \\
& + (coeff_3 \times band_3) + (coeff_4 \times band_4) \\
& + (coeff_5 \times band_5) + (coeff_6 \times band_6) \\
& + (coeff_7 \times band_7)....(1)
\end{aligned}
\tag{1}
$$

where, TCT_i is the calculated tasseled cap transformation index for brightness, greenness and wetness depending on the coefficients used.

The generated PCA and TCT (3 band) images were classified separately using supervised classification technique and processed to assess LULC and its trajectories.

2.5. Change Detection

Post Classification Comparison (PCC) method results in a residual image which represents the change resulting from the subtraction of differently dated images (time 2-time 1). The most widely used change detection algorithm is the PCC which detects changes between hand-labeled region classes (Currit, 2005; Petit *et al*., 2001). This technique provides detailed change trajectories between the two images. Moreover, the independent classification processes reduce the impact of multi-temporal effects due to atmosphere or sensor differences (Lu *et al*., 2004). The changed pixels extracted between the study period (i.e., between 1980 and 2010) were used to define (a) "from-to" land use/land cover class, (b) the area coverage and (c) their trajectories. To determine statistics of the area coverage, outliers were removed by applying 3×3 statistical filter with majority function and only the absolute pixels/classes were used as threshold values for change detection.

Table 2. Coefficients of the "Tasseled Cap Transformation" of Landsat data

Components	Band-1	Band-2	Band-3	Band-4	Band-5	Band-7
Brightness (R)	0.3561	0.3972	0.3904	0.6966	0.2286	0.1596
Greenness (G)	-0.3344	-0.3544	-0.4556	0.6966	-0.0242	-0.2630
Wetness (B)	0.2626	0.2141	0.0926	0.0656	-0.7629	-0.5388

Source: Huang *et al.* (2002)

Trajectories were determined using change matrix generated from the overlaid images.

2.6. Accuracy Assessment

Accuracy assessment including overall accuracy, producer's and user's accuracy was carried out and Kappa coefficient was determined (Berberoglu and Akin, 2009). The LULC changes were verified with medium/high spatial resolution images of Google Earth for the respective study period. Accuracy assessment modules of ERDAS imagine-2010 was used to determine the image classification accuracy. For the images with no ground validation data, the stratified random sampling method (Jensen, 2005) was used to generate 84 reference points for the whole study area. These reference points were generated according to the different strata and overlaid on the Google Earth image to check if the given class falls into the same spectra.

3. RESULTS

3.1. Classification of Images

The data sets pertaining to supervised classification of PCA and TCT enhanced Landsat images are depicted in **Fig. 2 and 3**, respectively and the area statistics are provided in **Table 3**.

3.2. PCA Images

In the year 1980, the area under agriculture/vegetation was 6.34% of the area under study. Other classes such as current fallow and barren area covered 2.14 and 91.52% of the study area. However, there was no representation of built-up area. Over the period, the area under agriculture increased to 9.31 and 10.29 % in the year 1990 and 2000 respectively, which decreased to 7.73% in the year 2010. The built-up area, however, showed a gradually increasing trend with no built up area in 1980 to 0.67% in 1990; to 0.82% in 2000 and to 1.3% in 2010.

3.3. TCT Images

Drastic change was observed in TCT analyzed wetness, brightness and greenness indexes during the study period (**Fig. 4**). There was increased brightness and decreased wetness and greenness witnessing the LULC changes in the study area.

TCA+supervised classified data showed a trajectory changes from vegetation and barren areas to built-up area during 1980-2010. In the year 1980, the area under agriculture/vegetation was occupied by 5.9% of the total area, which gradually increased to 9.01% in 1990; and to 9.81% in 2000. But in the year 2010, it was declined to 7.66%. Other classes such as current fallow and barren area covered 2.02% and 92.08% of the area in 1980. Current fallow area gradually increased through 3.38% (1990) to 4.05% (2000) and declined to 3.75% in 2010. Barren land decreased to 86.72% in 1990 and to 85.02% in 2000. But in the year 2010, the barren increased to 91.54%. There was no representation of built-up area in 1980 which was gradually increased to 0.88% in 1990; to 1.12% in 2000; and to 1.56% in 2010.

3.4. Change Detection Analysis

The results of change detection using Post Classification Comparison (PCC) of PCA and TCT images are shown in **Fig. 5 and 6**. The change detection and trajectory areas are given in **Table 4**. In case of PCA+PCC, about 2.97 and 0.67% of barren area was converted into vegetation/agriculture and built-up area, respectively between 1980 and 1990. Similar trend was observed between 1990 and 2000 with the expansion of agriculture/vegetation (0.98%) and built-up area (0.67%). However, between the years 2000 and 2010, agriculture/vegetation area declined and the barren area increased to 2.56%. However, the expansion of built-up area (0.48%) from barren area was observed between the years 2000 and 2010 (**Table 4**). In case of TCT+PCC, about 3.11% and 0.88% of barren area was converted as vegetation/agriculture and built-up area, respectively between 1980 and 1990. Similar trend was observed between 1990 and 2000 with the expansion of agriculture/vegetation (0.80%) and built-up area (0.24%). On the contrary, agriculture/vegetation area became to barren (2.15%) between the year 2000 and 2010. However, between the years 2000 and 2010, the built-up area was expanded to 0.44%, which was from barren area (**Table 4**).
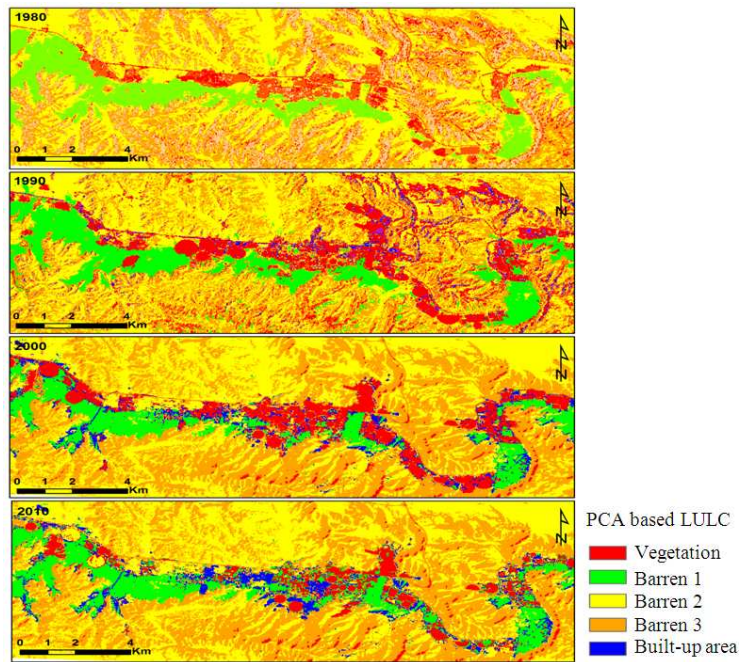
Fig. 2. PCA based classified (supervised) land use land cover map of Dirab region
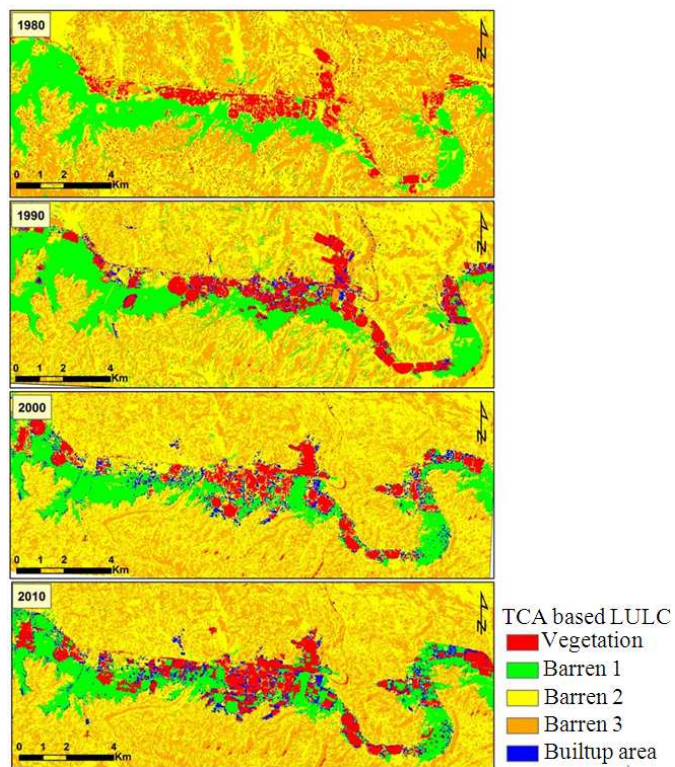

Fig. 3. TCA based classified (supervised) land use land cover map of Dirab region
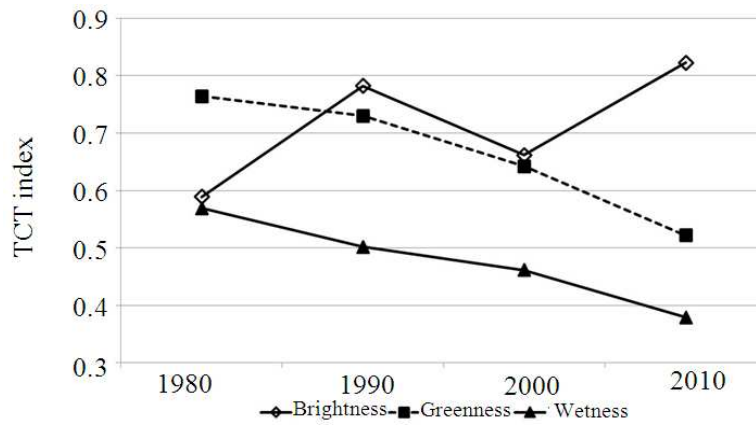
Fig. 4. Temporal variation in tasseled cap transformation index for brightness, greenness and wetness
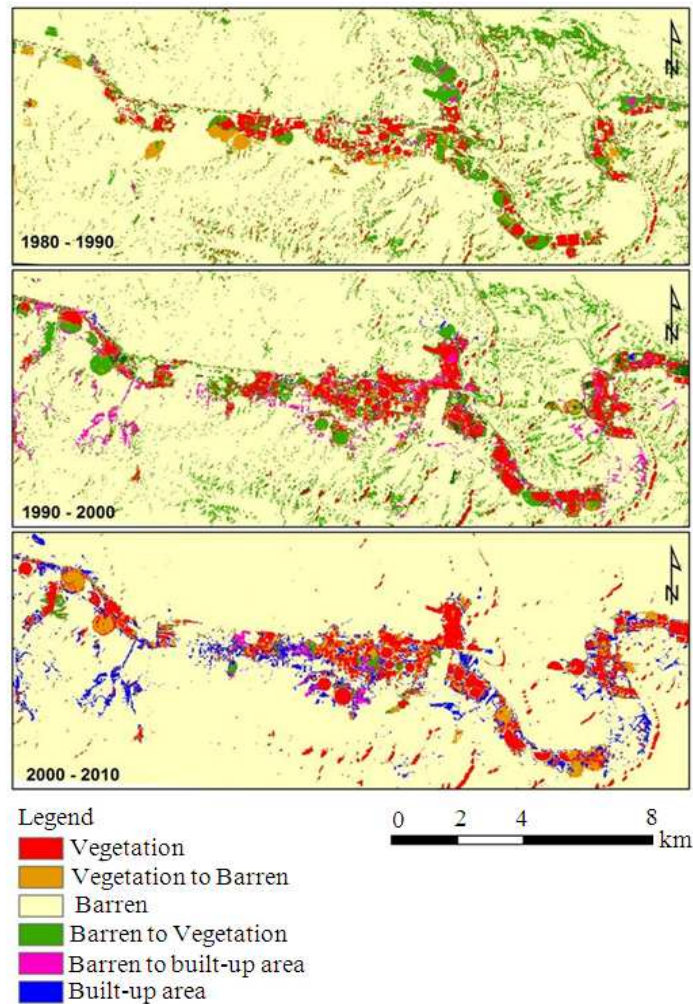

Fig. 5. PCA based trajectories of land use land cover changes during the study period in Dirab region
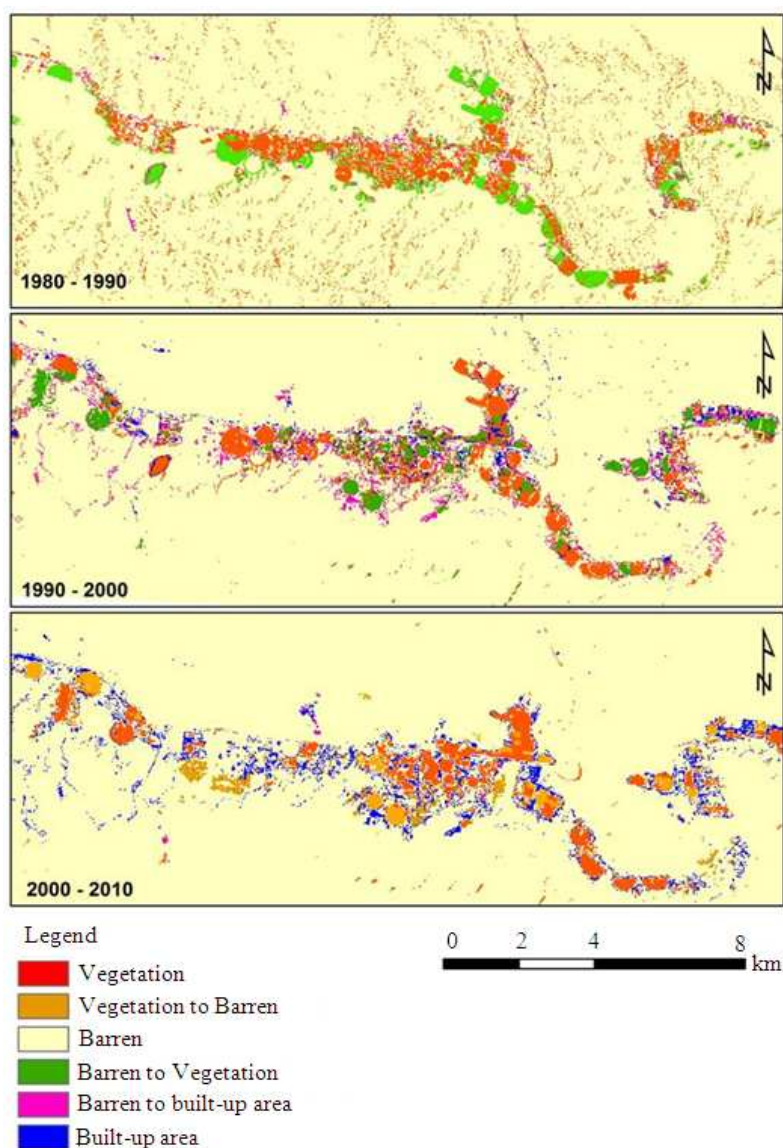
Fig. 6. TCA based trajectories of Land Use Lnd Cover Changes during the study period in Dirab region

Table 3. Land Use Land Cover area (%), parts of Dirab region, Saudi Arabia

LULC	Principle Component Analysis (PCA)				Tassel Cap Transformation (TCT)			
	1980	1990	2000	2010	1980	1990	2000	2010
Agriculture/Vegetation	6.3400	9.3100	10.2900	7.7300	5.9000	9.0100	9.8100	7.6600
Current Fallow	2.1400	3.5400	4.2400	3.8600	2.0200	3.3800	4.0500	3.7400
Barren (plane area) 1	28.0600	23.0200	21.1900	23.6500	28.9600	23.7600	21.6700	23.8500
Barren (valley area) 2	27.8700	27.8700	27.8700	27.8700	29.0700	29.6300	28.2800	28.8300
Barren (valley area) 3	35.5900	35.5900	35.5900	35.5900	34.0500	33.3400	35.0700	34.3600
Built-up	0.0000	0.6700	0.8200	1.3000	0.0000	0.8800	1.1200	1.5600
Kappa	0.6667	0.6861	0.6519	0.6973	0.6978	0.7452	0.7555	0.7524

Table 4. Confusion Matrix of LULC (% of area) over the study period based on image enhancement and PCC techniques

Time 1	Time 2 LULC Class	PCA+PCC			TCT+PCC		
		Agriculture	Barren	Built-up	Agriculture	Barren	Built-up
	1990						
1980	Agriculture	6.34	-	-	5.90	-	-
	Barren	2.97	90.02	0.67	3.11	90.11	-
	Built-up	-	-	-	-	-	0.88
	2000						
1990	Agriculture	9.31	-	-	9.01	-	-
	Barren	0.98	88.89	0.15	0.80	89.07	0.24
	Built-up	-	-	0.67	-	-	0.88
	2010						
2000	Agriculture	7.73	2.56	-	7.66	2.15	-
	Barren	-	88.41	0.48	-	88.63	0.44
	Built-up	-	-	0.82	-	-	1.12

4. DISCUSSION

The accuracy assessment results for the PCA based LULC images showed that the values of Kappa coefficient were 0.6667, 0.6861, 0.6519 and 0.6973 for the years 1980, 1990, 2000 and 2010, respectively. However, the values for the TCT based images were 0.6978, 0.7452, 0.7555 and 7524 for the years 1980, 1990, 2000 and 2010 respectively. Dymond *et al.* (2002) studied TCT indices for LULC studies and found that TCT can improve the accuracy of mapping and land cover classification (**Table 4**).

The overall accuracy of PCA based change detection was 64.58, 62.68 and 62.12% for 1980-1990, 1990-2000 and 2000-2010 images, respectively. However, the TCT based change detection resulted in higher accuracy of 77.78, 75.62 and 77.92% for 1980-1990, 1990-2000 and 2009-2010, respectively (**Table 5**). The results are in close agreement with the findings of Zhou *et al.* (2002) who obtained an overall classification accuracy of 77.8% with TCT method. However, Seto *et al.* (2002) obtained much higher overall accuracy of 93.5% with TCT method. Fung and Ledrew (1987) also used PCA and TCT transformed images to detect land-cover changes from multi-temporal MSS and TM images and concluded that the TCT method seems useful in many change detection applications. Rogan and Yool (2001) compared vegetation indices, PCA and TCT components and found that the TCT approach provided the best detection results of fire-induced vegetation depletion in the Peloncillo Mountains, Arizona and New Mexico, with an overall Kappa of 0.66. The improvement in the accuracy of assessment with TCT over PCA observed in this study was because the TCT transform coefficients are independent of the image scenes, while PCA is dependent on the image scenes.

Table 5. Accuracy Assessment of LULC images drawn against very high resolution images of Google Earth Database

Method	Date of pass	Overall accuracy (%)	Kappa	Kappa variance
PCA+PCC	14/9/1980	72.00	0.6667	0.0004475
	7/9/1990	78.20	0.6861	0.0005164
	2/9/2000	66.10	0.6519	0.0007013
	7/9/2010	58.90	0.6973	0.0007358
TCT+PCC	14/9/1980	66.90	0.6978	0.0006426
	7/9/1990	71.80	0.7452	0.0005911
	2/9/2000	64.40	0.7555	0.0006796
	7/9/2010	69.41	0.7524	0.0006897

This corroborates with the finding of Almutairi and Warner (2010), who observed that PCC does not take into account the dependence existing between two images of the same area acquired at two different times. In this study, urbanized areas were particularly distinct with the high brightness pixels in the brightness component of TCT. Similarly, the biomass areas could be extracted from the brighter portions of greenness component. The results of this study are in agreement with the propositions of Jensen (2005).

In this study, the PCC method resulted in accuracies of 62-65% in PCA and 75-78% in TCT. The higher accuracies observed in TCT method could also be due to higher accuracies of classification. Serra *et al.* (2003) studied PCC based change detection and achieved an accuracy of 85%. Yuan *et al.* (2005) also obtained higher accuracies of 80 to 90% with the PCC method. The results suggested that significant land use changes occurred in Dirab area from 1980 to 2010, may be related to rapid development of agriculture between 1980 and 2000 and economic development and urban expansion between 2000 and 2010. It was further noted

that most changes occurred in cropland areas due to urban encroachment.

5. CONCLUSION

Land use mapping provided detailed information for assessing land use dynamics. Results of the study indicated differences in accuracies between the PCA and TCT based change detection methods. The overall accuracy of PCA based change detection was 64.58, 62.68 and 62.12% for 1980-1990, 1990-2000 and 2000-2010 images, respectively. However, the TCT based change detection resulted in higher accuracy of 77.78, 75.62 and 77.92% for 1980-1990, 1990-2000 and 2009-2010, respectively. TCT based change detection method was found to be more accurate than the PCA approach.

6. ACKNOWLEDGEMENT

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