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

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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 Gebresellassie, 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 into 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., 2004), and Google Earth (Al-Gaadi et al., 2013).
between 1972 and 2000. To analyze land cover and topography of Hail region, unsupervised classification techniques are two widely used methods (Lillesand and Kiefer, 2000). Out of several change detection procedures available 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; 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). Change detection between 1988 and 1998. Similar study was conducted by Hereher et al. (2012) to evaluate the extent of vegetation changes for their high agricultural potential. Wheat and alfalfa are the major crops grown in the region, using centre pivot irrigation system.

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+imagery 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.
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):

\[
\text{TCT}_i = (\text{coeff}_i \times \text{band}_1) + (\text{coeff}_i \times \text{band}_2) + (\text{coeff}_i \times \text{band}_3) + (\text{coeff}_i \times \text{band}_4) + (\text{coeff}_i \times \text{band}_5) + (\text{coeff}_i \times \text{band}_6) + (\text{coeff}_i \times \text{band}_7) \ldots (i)
\]

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 1990 (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 (0.98%) and built-up area (0.67%). 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.
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 |

Fig. 6. TCA based trajectories of Land Use Land Cover Changes during the study period in Dirab region
Table 4. Confusion Matrix of LULC (% of area) over the study period based on image enhancement and PCC techniques

| Time 2 | PCA+PCC | TCT+PCC |
|--------|---------|---------|
| Categorical Class | Agriculture | Barren | Built-up | Agriculture | Barren | Built-up |
| Agriculture | 6.34 | - | - | 5.90 | - | - |
| Barren | 2.97 | 90.02 | 0.67 | 3.11 | 90.11 | - |
| Built-up | - | - | - | - | - | 0.88 |

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 |

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 0.7524 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.

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.

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