

## A Two-Decade Land Use and Cover Change Detection and Land Degradation Monitoring in Central Jordan Using Satellite Images

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### ABSTRACT

This paper describes a suite of techniques used to develop an operational approach for mapping land degradation and change detection purposes in the central parts of Jordan using Landsat (TM) images acquired in March 1987, and February 2009, respectively. The two multi-temporal images were geometrically and radiometrically calibrated to each other and used as input to an automatic change detection procedure. To map changes that had occurred between the two dates six spectral bands of both TM digital data (with the thermal bands being excluded) were individually used as input for supervised classification purpose. Monitoring of the land degradation, particularly in vegetation coverage, had been done using NDVI image differencing. The histogram of difference image showed that unchanged pixels were centered around the mean; the changed pixels were located in the tail regions on either side. The difference image indicated that significant negative changes in land use/cover have occurred between 1987 and 2009. Change detection results of central Jordan revealed that the decline of cultivated areas and green vegetation areas was clearly the result of accelerated expansion through the process of urbanization, which had negative effects on both agricultural lands and water basins, and consequently enhanced land degradation.

**Keywords:** Remote Sensing, Land Degradation, Change Detection, NDVI, Central Jordan, Landsat TM.

### INTRODUCTION

During the last 3 decades, satellite remote sensing has become an important and active useful technique to map land use/cover changes. Changes in the land use/cover particularly in urban areas cannot be understood without a better knowledge of the land use changes that drive them and their links to human causes. The linkage between the human and the biophysical causes or drivers to land use/land cover are not sufficiently understood. Remote sensing technique offers new dimensions, where the importance of this technique was emphasized as a “unique view” of the spatial and temporal dynamics of the processes in urban growth and

land use/cover changes (Herold et al., 2003). Consequently remote sensing already proved useful in mapping urban areas and as data source for analysis and modeling of urban growth and land use/land cover changes (Xio et al., 2006; Grey et al., 2003; Herold et al., 2003; Wilson et al., 2003).

According to the United Nations Convention to Combat Desertification land degradation was defined as (UNEP, 1994):

“Reduction or loss in arid, semi-arid and dry sub-humid areas, of the biological or economic productivity and complexity of rain fed cropland, or range, pasture, forest and woodlands resulting from land uses or from a process or combination of processes, including processes arising from human activities and habitation patterns, such as: soil erosion caused by wind and/or water; deterioration of the physical, chemical and biological or economic properties of soil; and long-term loss of natural vegetation”.

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Most of the changes are highly dependent on the biophysical constraints of the land units (Ridd, 1995; Douglas, 1981). Urbanization has been a major feature of dry lands in the new and old world since World War II and is likely to continue apace (Beaumont, 1989; Warren and Agnew, 1987). Therefore, many urban areas around the world have been responsible for severe damage to the natural environment by the physical expansion of the built land which could lead to land degradation processes. The resultant expansion of urban land has important climatic implications across all scales, since the simultaneous removal of natural land cover and the introduction of urban materials alter the surface energy balance, with a consequent increase in sensible heat flux at the expansion of latent heat flux (Owen et al., 1998). Several authors have also noted the deleterious effect of recreational vehicle use by urban dwellers on the land degradation and desert environment by damaging vegetation and destabilizing soil surface (Cooke et al., 1993).

Jordan's population has grown rapidly during the past two decades. Population had increased by more than 95% between 1987 and 2009. Central part of Jordan is undergoing both a very high rate of urbanization, particularly Amman (the capital city) and Zarqa city, and human-beings induced changes in land cover. Urban land use is the other major land use that is primarily influenced by the activities of the human beings. The growth of the central part of Jordan is gradually encroaching on arable lands, pasture lands, and water basins. Therefore accurate mapping of land use/cover changes in central Jordan (where more than 52% of the total populations of Jordan are residing) for the past 20 years is required to provide the input data needed for urban modeling. In this study the investigation will focus on land use/cover change inside and around both greater Amman and Zarqa cities, where major changes have occurred.

A database needs to be created to show land use/cover change in a particular area at regular intervals

as far back time as possible. Obviously, satellite data, remote sensing and GIS are the most relevant technologies for meeting these needs in the most cost-effective manner (Ridd, 1995; Yang and Lo, 2002). Thus mapping land use/cover and monitoring land degradation between two dates is increasingly interesting and valuable application of remote sensing. In this paper, and by using Landsat TM imagery, and different methods of digital change detection techniques a method for land degradation monitoring had been investigated, as well as land use/land cover changes and environmental changes in the central part of Jordan.

## **2- Study Area**

Encompassing an area of about 90,000 km<sup>2</sup>, Jordan is situated in the western part of Asia. The study area (figure1) is the central part of Jordan, which includes the capital city of Amman and Zarqa city. It lies between the latitudes 31°54'29" and 32°13'04" North and longitudes 35°46'34" and 36°13'38" East. The rapid urban development in this area since 1980s has dramatically enhanced the potential impact that human activities can have on land use/cover and natural resources, which in turn can affect the management needs of the various ecosystem environments.

Jordan's population has rapidly grown during the past two decades. Population had increased by more than 95% between 1987 and 2009. In 1987, the total population was around 3.1 million inhabitants and became around 5.98 million inhabitants in 2009 (DOS, 2010). Amman and Zarqa cities have almost 52% of the total population of Jordan. The annual growth rate in both cities reached 3.5% during the period from 1979 to 1999 and 2.8% between 1999 and 2009 (DOS, 2010). Due to the Gulf crises, more than 300,000 people returned to Jordan in 1991 and 2003 from Gulf countries. Most of those peoples reside in urban areas, especially in cities of Amman and Zarqa, and as a result increasing concentration in these urban areas, where services and job opportunities are available.



Figure 1. Location of the study area.

The climate of the concerned area is hot and dry in summer. The mean annual temperature reaches 29°-35° C in August, but absolute maximum values can exceed 44°C. In winter two distinct climates prevail in the studied area, (i) cold and dry in the eastern parts of the area between the blend of mountainous and desert area. The mean annual of the minimum temperatures decline to as low as 2°-7° C in winter but absolute minimum values can be declined to as low as -8.0° C. Relative humidity is low (between 50-60%) with an average rainfall reaches 150mm (30 years average) (JMD, 2008), and (ii) wet, cold to moderate in the areas close to the desert, in areas of Amman and Zarqa cities. Mean annual minimum temperature declines to as low as 1.5°-8° C in

winter, but absolute minimum values reach less than -8° C, with average annual rainfall reaches more than 450mm (JMD, 2010).

Soil in the studied area is derived from limestone rocks or limestone accompanied with basalt rocks in certain areas. Soil depth decreases as the inclination becomes steeper than 4%; soil rich in calcium carbonates is found in areas of 4-6% inclination. The most important characteristics of this soil are high proportions of silt and calcium carbonates. Salinization and gypsum increase towards eastwards. The low level of organic materials and the formation of the surface cause high rates of erosion by wind and water. The main types of soil prevailing in the areas below an inclination level of 10% are aridsols and entisols in steeper

areas (NSJ, 1991).

### **3- Development of Change Detection Technology**

Change detection and monitoring involve the use of multi-temporal images to evaluate differences in land cover due to environmental conditions and human actions between the acquisition dates of images (Singh, 1989). An adequate understanding of landscape features, imaging systems, and information extraction methodology employed in relation to the aims of analysis are the main factors of the successful use of satellite remote sensing for land use/cover change detection purpose.

Highly heterogeneous surface covers with substantial inter-pixel and intra-pixels changes generally characterize the urban environments. Data used for urban application must meet certain conditions in terms of temporal, spatial, spectral, and radiometric characteristics (Lo, 1986; Yang and Lo, 2002). For urban land use/cover change mapping, finer geometric resolution images are usually preferred. Useful source of satellite data for this type of applications are the images from Landsat MSS, Landsat TM, and SPOT HRV, which have a long period of operation. Since 1982, Landsat TM data has become recently available. The improved spatial, spectral, and radiometric resolution of Landsat TM data allows land use/cover mapping at a higher level of details and finer urban detection Yang and Lo, 2002; Gomasasca et al., 1993; Green et al., 1994). SPOT HRV data have been found to be able to provide significantly more urban land use/cover information compared with Landsat MSS and TM data (Colwell and Poulton, 1985).

Land use/cover change detection using satellite data can be realized through either image-to-image comparison or map-to-map comparison (Green et al., 1994). General reviews of different algorithms under these two categories are given elsewhere (Singh, 1989; Jensen and Cowen, 1999). For urban land use/cover change detection several studies assessed the effectiveness of these techniques (Ridd and Liu, 1998). The image-to-image comparison involves subtraction of two images and is generally accurate, but it cannot

provide detailed information on how various land use/cover categories change. The map-to-map comparison requires that images from two dates are classified, and then the two classified maps are compared. Map-to-map comparison is preferred for many applications as it can detect a full matrix of land use/cover changes (Jensen and Cowen, 1999; Moller, 1990). The effectiveness of the map-to-map comparison technique is highly dependent upon the assumptions and techniques used to produce maps of the same area at different times. For large amounts of data over large study areas, the automated image classification method is preferred; this technique relies mainly upon brightness and spectral elements with limited use of image spatial contents. Consequently, classifiers advocated by this technique generally work well in spectrally homogeneous areas, such as forest, but not in highly heterogeneous regions, such as urban landscapes.

For improving automated classification, many strategies have been developed. Some techniques have demonstrated improved performance, for instance, enhanced classification methods ranging from knowledge-based expert system (Moller, 1990), artificial neural networks (Civco, 1993), fuzzy logic (Ji and Jensen, 1996, to genetic algorithms (Zhou and Civco, 1996). However, few have found their way into routine use because these techniques can vary greatly in terms of their performance with changes in image characteristics, and in circumstances for targeted studies (Campbell, 2006). Opportunely, several less sophisticated techniques or procedures are quite promising because they have been shown experimentally to be not only accurate but also comparatively simple and easy to implement in a conventional image processing platform. Examples include: firstly, the use of pre-classification image transformations and feature-extraction techniques, such as median filtering and various measures of image texture (Yang and Lo, 2002); secondly, the incorporation of spatially referenced, ancillary data into the classification procedure (Ehlers et al., 1990); and thirdly, the application of post-classification spatial processing, ranging from the mode filtering to contextual

reclassification (Booth and Oldfield, 1989; Barnsley and Barr, 1996). However, further efforts will certainly be maintained and will probably intensified in order to adapt these techniques to solving practical problems in a productive environment.

#### 4- Methodology

##### 4-1 Geometric rectification and radiometric calibration

A subset of each of the Landsat TM digital images acquired in March 1987, and February 2009 covering central parts of Jordan including Amman and Zarqa cities (figure1) were used. The digital images were geometrically and radiometrically calibrated to each other to facilitate their comparison. Geometric rectification is critical for producing spatially corrected maps of land use/cover changes through time. The 1987 Landsat TM image, which was supplied by Earth Satellite Corporation, had already been rectified and georeferenced to UTM map projection (Zone 36), and WGS84 ellipsoid. Then, this image was employed as the reference scene to which the second scene (TM of 2009) was registered. Using the image-to-image registration the first-degree polynomial equation was used in image transformation. The resultant root mean square error (RMSE) was less than 0.5 pixels, indicating an excellent registration. The nearest neighbor resampling method was used to avoid altering the original pixel values of the image data.

An important component to the change detection is radiometric calibration and corrections (Chavez and Mackinnon, 1994). Radiometric calibration and corrections can eliminate or reduce image differences introduced as a result of changing atmospheric conditions. Since both images are acquired in same season. A histogram matching provided by PCI software had been used in this study. After this correction, image statistics and histograms from the two periods were found to be similar and comparable.

##### 4-2 Image processing

TM bands 2, 3, and 4 color combination and TM bands 2, 4, and 7 color combination were generated from each image for visual interpretation and analysis purposes. The selection of color combination of TM

bands 2, 4, and 7 combination was done in order to use the information of the three main spectral regions of Landsat imagery (i.e., visible, near-infrared and mid-infrared) regions, TM band-7 (mid-infrared) was used because it gave a better water versus non-water boundary mask.

##### 4-2-1 Image classification

To map changes that had occurred between the two dates, six spectral bands of both TM digital data (with the thermal bands being excluded) were individually used as input for supervised classification purpose. Maximum likelihood algorithm provided by PCI software had been used for land use/cover mapping from Landsat images.

A modified version of Sato-Tateishi Land Cover Guideline (ST-LCG) (Sato and Tateishi, 2002) scheme was adopted and used as a classification scheme design for this study. In total, five land use/cover classes were included in the scheme: (1) urban class, (2) cultivated class, (3) exposed land class, (4) green vegetation, and (5) water class. Detailed definitions for these five categories of land use/cover are summarized in table 1.

**Table 1. Land use and land cover classes and definitions used in this study.**

No	Class	Definitions
1	Urban	Construction materials, e.g. asphalt, concrete, etc.; typically commercial and industrial buildings, residential development including most of single/multiple houses, transportation facilities, e.g. airports, parking lots, highways, and local roads.
2	Cultivated	Plowed areas, and areas of sparse vegetation cover (less than 20%).
3	Green Vegetation	Characterized by high percentages of grasses, other herbaceous vegetation, crops, and

		trees.
4	Exposed land	Consolidated lands, e.g. bare rock areas, gravels, stones and boulders areas, and hardpan areas. Unconsolidated lands, e.g. bare soils areas.
5	Water	All areas of open water, including streams, lakes and dam reservoirs.

#### 4-2-2 Spatial Reclassification

Basically, there are two types of misclassification errors: the boundary error and the confusion in spectral classes representing two or more land use/cover types. These errors can be substantially reduced with the use of spatial reclassification procedures.

(i) Reducing boundary errors: Due to the occurrence of spectral mixing within a pixel boundary error occurs at class boundaries (Booth and Oldfield, 1989). These misclassified areas are often small relative to areas of correct classification. There are also some small areas of anomalous pixels (often in the forms of salt and pepper) representing the noise in the data within the same class. These small areas should be removed and replaced with class values on their surroundings. A contextual classification procedure could be used and it involves two stages (Yang and Lo, 2002; Booth and Oldfield, 1989): Firstly, identification of minimal areas and their subsequent declassification, and secondly, re-labeling of declassification areas on basis of their surrounding pixels. To achieve a fast approximation of these two stages in a one-pass operation, the mode filter had been used.

Mode filter is applied to  $n \times n$  pixel patch, where  $n$  is an odd integer. A histogram of class values in the patch is generated and the value having the highest frequency is returned as the new central value. The center pixel's value thus becomes that of the most commonly occurring class within the patch. In this way, the small (and erroneously classified) pixels are reclassified according to the dominant class within the patch.

The choice of filter size and the number of neighbors

was based on the following considerations (Yang and Lo, 2002; Booth and Oldfield, 1989). First, the filter size should be large enough to allow some important or targeted components to be covered within the patch. Thus, a  $3 \times 3$  mode filter was used here. Second, the mode filter could affect linear features. Most of the linear features found in the studied area are often urban uses and should be preserved. A  $3 \times 3$  mode filter with the four corner cells disabled (i.e. with zero value) can preserve some linear features.

(ii) Resolving spectral confusion: Given that several land use/cover classes have similar spectral response, which is highly dependent upon imaging sensor characteristics (spatial, spectral, and radiometric resolutions) and scene contents, spectral confusion is expected. As image spatial resolution decreases (i.e. larger pixel size), the number of mixed pixels increases, and thus the spectral confusion tends to be more serious. Spectral confusion is the major cause of classification accuracy of a spectrally based classification method (Yang and Lo, 2002; Campbell, 2006; Lillesand and Kiefer, 2003).

Defining spectral confusions requires the use of image spatial and contextual properties. For this purpose, visual interpretation was employed because it allows an integrated use of spectral and spatial contents as well as human wisdom and experience. At present, visual interpretation can be incorporated effectively into a digital classification procedure with the use of on-screen digitizing, multiple zooming, and Area of Interest (AOI) functionality. In addition, several image processing platforms permit advanced tools for spatial modeling through which some "manual" operations can be implemented automatically. With the use of this method, three major types of spectral confusion can be identified in the current study: (1) cultivated class/green vegetation class; (2) green vegetation class/exposed land class; and (3) urban class/exposed land class. These spectrally confused clusters were further split and recorded into their correct land use/cover classes.

#### 4-2-3 NDVI and image differencing generated image

Normalized Difference Vegetation Index (NDVI), an algorithm for monitoring vegetation using satellite data, can be written as (Rouse et al., 1974):

$$NDVI = [(NIR - Red) / (NIR + Red)] \quad (1)$$

where, Near Infra Red (NIR) is band 4 for both TM images, and Red is band 3 for the both images. NDVI images were generated for both dates using equation (1) for land degradation monitoring purpose, and were also used during the classification procedure to differentiate between the cultivated, green vegetation, and exposed land classes. NDVI values were expressed in digital values, and determined as  $(DN = (NDVI * 100) + 100)$ .

Land degradation can be quantified in terms of (Pickup, 1989; Behnke and Scoones, 1994): (i) soil loss; (ii) loss of soil quality, e.g., nutrient loss and/or soil compaction; (iii) a decline in vegetation (forage) production; or (iv) a change in vegetation species composition contrary to management goals (Washington, 1998). Therefore, this study focus on the changes in land use/cover types and on the land degradation monitoring between 1987 and 2009 in the central part of Jordan.

For land degradation monitoring and changes in land cover types, particularly in vegetation coverage, an

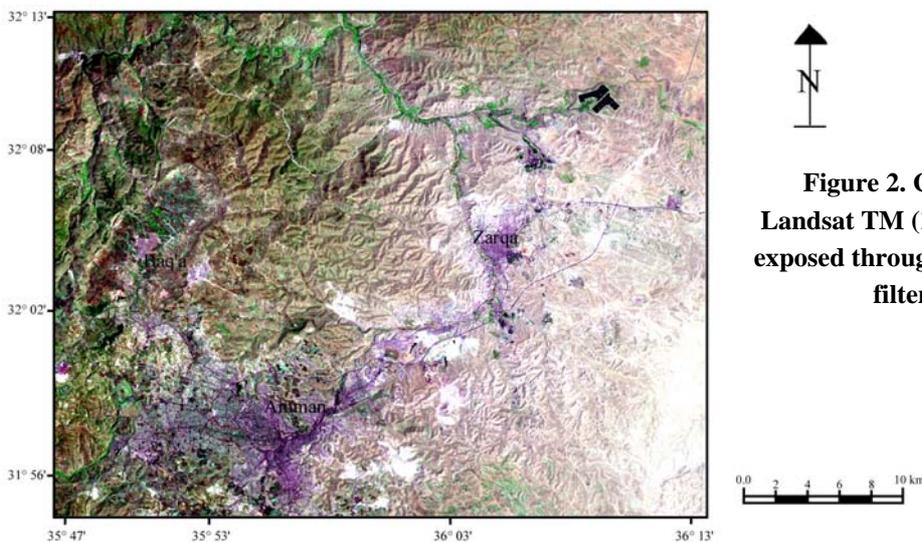
image differencing method was adopted for pixel-by-pixel comparison and was performed on the NDVI generated images of both dates. Image differencing was calculated as:

$$LATER\ IMAGE - FORMER\ IMAGE + 25 \quad (2)$$

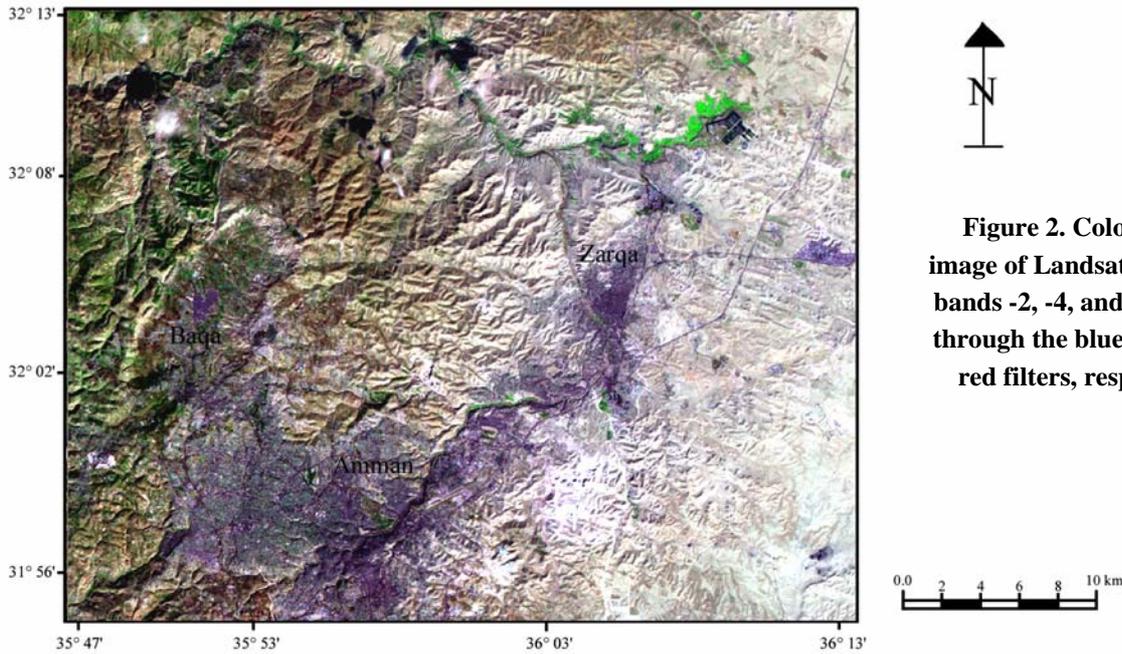
where, 25 is a constant to remove negative values. Subsequently, subtracting NDVI images generated NDVI difference image.

### 5- Results and Discussion

Figures 2 and 3 show the color composites generated from the filtered TM images bands 2, 4, and 7 results using the images acquired in 1987 and 2009, respectively. Urban area is pink color while vegetation is green because the near-infrared band (TM-4), in which vegetation has a high spectral response, was exposed through the green filter. Color products using the bands 2, 3, and 4 combinations were also generated for interpretation and analysis purposes; urban area in this combination is cyan color, plowed areas is green while vegetation is red. The areas that had more mature and/or denser vegetation appear brighter red than areas with less mature and/or less dense vegetation (Kwarteng, 1997).



**Figure 2. Color composite image of Landsat TM (1987) bands -2, -4, and -7 exposed through the blue, green and red filters, respectively.**



**Figure 2. Color composite image of Landsat TM (2009) bands -2, -4, and -7 exposed through the blue, green and red filters, respectively.**

**5-1 Accuracy Assessment**

Figures 4 and 5 show the results of the supervised classification of TM, 1987 and 2009, respectively. Accuracy assessment is necessary for testing the accuracy of the resultant classes from the classification image. There are several methods of performing an accuracy assessment, such as the overall accuracy and the Kappa coefficient (Congalton, 1991). The confusion (or error) matrix, which can be used as a starting point for a series of descriptive and analytical statistical analyses, is used to represent the accuracy assessment (Lillesand and Kiefer, 2003). In order to obtain the confusion matrix, a random sampling was carried out. The columns of the matrix represent the reference data, while the rows indicate the classes generated from the classification process. According to the previous studies, there are many ways to improve the interpretation of the confusion matrix. Among them, the Kappa coefficient is one of the most popular measures for addressing the difference between the actual agreement and the chance agreement (Congalton, 1991).

The Kappa coefficient of agreement was computed as:

$$\hat{k} = \frac{N \sum_{i=1}^r X_{ii} - \sum_{i=1}^r (X_{i+} \times X_{+i})}{N^2 - \sum_{i=1}^r (X_{i+} \times X_{+i})} \tag{3}$$

Where r is number of rows in the confusion matrix,  $X_{ii}$  is number of observations in row i and column i,  $X_{i+}$  is the total number of observation in row i,  $X_{+i}$  is the total number of observation in column i, and  $N$  is the total number of observations included in matrix.

Tables 2 and 3 show the confusion matrices resulting from the classifying digital data. For the 1987 land use/cover map, a total of 527 pixels were selected, which were then checked with reference to 1:50 000 topographic map. The result shows an overall accuracy of 90%. In terms of producer’s accuracy, all classes were over 81%, while in terms of user’s accuracy; all classes were over 86%, and a Kappa index of agreement of 0.860 (table 2). This value indicates that the classification process was avoiding 86.0% of the error.

For the 2009 land use/cover map, a total of 456 pixels were selected. These were checked against an interpretation of the in situ check. The result indicated an overall classification accuracy of about 90.4%. In terms of producer’s accuracy, all classes were over 79%, while

in terms of user's accuracy; all classes were over 79.2%, and a Kappa index of agreement of 0.858 (table 3). This value indicates that the classification process was avoiding 85.8% of the error.

A comparison of table 2 and 3 reveals that the 1987 land use/cover map is compatible in accuracy in every

respect to the 2009 land use/cover map, where the overall accuracy is more than 85%, for both maps, indicating that this is a good evidence that the image processing approach adopted in this study has been effective in producing compatible land use/cover data over time.

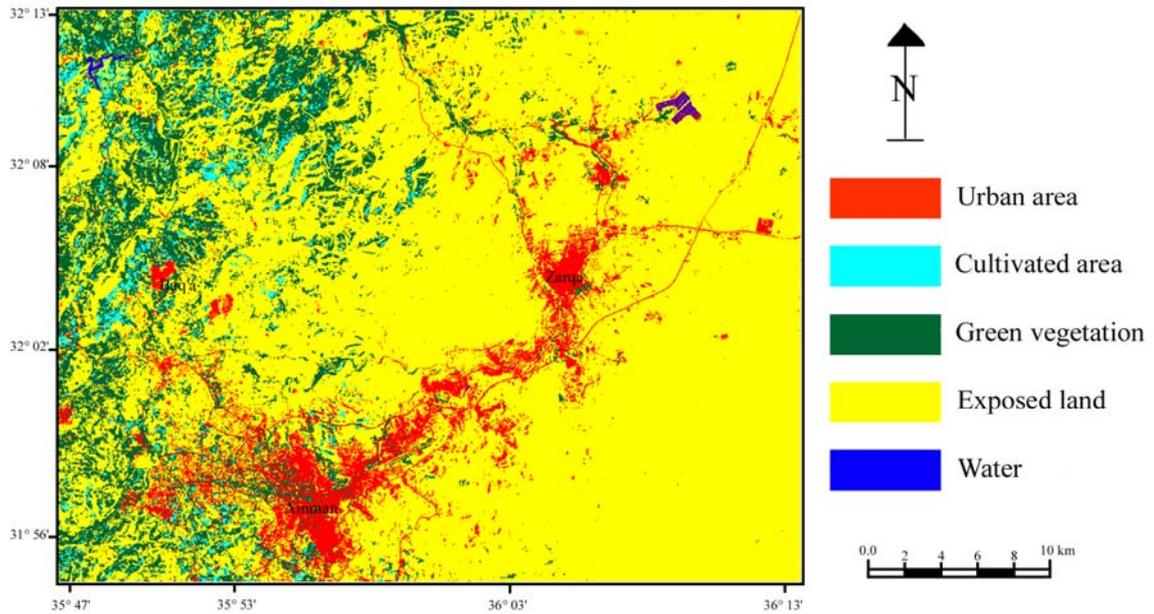


Figure 4. Land use/cover classification map of the central part of Jordan based on analysis of Landsat TM 1987.

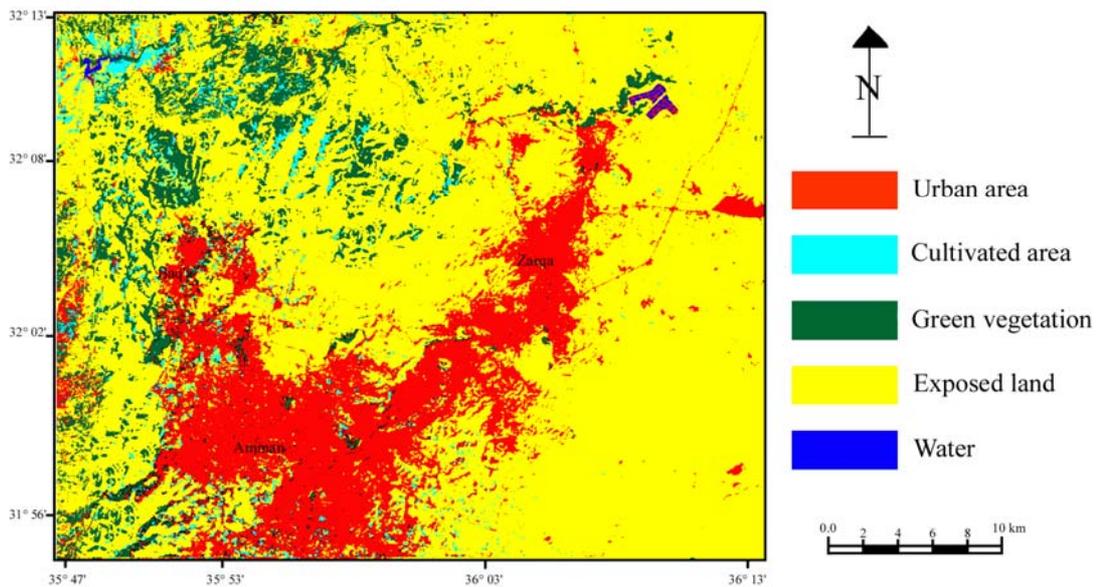


Figure 5. Land use/cover classification map of the central part of Jordan based on analysis of Landsat TM 2009.

**Table 2. Confusion matrix of the signatures derived from supervised training, TM 1987.**

		Reference data					Row total	User accuracy (%)
		1	2	3	4	5		
Classified data								
1		118	2	5	9	2	136	86.76
2		3	63	4	2	0	72	87.50
3		3	1	60	5	0	69	86.96
4		10	0	5	216	0	231	93.51
5		0	0	0	1	18	19	94.74
<b>Column total</b>		134	66	74	233	20	527	<b>overall Kappa index = 0.860</b>
<b>Producer's Accuracy (%)</b>		88.06	95.45	81.08	92.70	90.00		

Note: Number of pixels correctly classified =475; overall classification accuracy = 90.0%; Class 1= Urban; class 2= Cultivated; class 3= Green vegetation; class 4= Exposed land; class 5= Water.

**Table 3. Confusion matrix of the signatures derived from supervised training TM 2009.**

		Reference data					Row total	User accuracy (%)
		1	2	3	4	5		
Classified data								
1		66	3	4	2	2	77	85.71
2		1	34	4	1	0	40	85.00
3		1	2	81	3	0	87	93.10
4		6	4	9	211	0	230	91.74
5		0	0	1	1	20	22	90.90
<b>Column total</b>		74	43	99	218	22	456	<b>overall Kappa index = 0.858</b>
<b>Producer's Accuracy (%)</b>		89.19	79.07	81.82	96.79	90.90		

Note: Number of pixels correctly classified =412; overall classification accuracy = 90.4%; Class 1= Urban; class 2= Cultivated; class 3= Green vegetation; class 4= Exposed land; class 5= Water.

### 5-2 Change Detection

The post-classification comparison change detection approach was employed (Singh, 1989). This method involves comparing two independently produced classified land use/cover maps from images of two different dates. It was found to be an accurate procedure for land use/cover change detection, provided that the two land use/cover maps had been accurately produced, as they were in this study (Singh, 1989; Jensen and Cowen, 1999). There are four major land use/cover classes of interest in the central Jordan: urban, cultivated, exposed land, and green vegetation class. The spatial distribution of these classes were extracted from each of the land use/cover maps of 1987, and 2009, the results are shown in table 4.

**Table 4. Land use/cover change for the studied area as extracted from the digital images.**

Class Name	TM 1987 Area(km <sup>2</sup> ) (%)	TM 2009 Area (km <sup>2</sup> ) (%)	% of increase or decrease over 1987
Urban	127.6 8.7	344.7 23.5	+ 170.1
Cultivated	38.1 2.6	26.4 1.8	- 30.7
Green Vegetation	196.5 13.4	71.9 4.9	- 173.3
Exposed land	1098.5 74.9	1019.9 69.4	- 7.2

Based on figures 2, 3, 4, and 5, the spatial expansion of urban class is clearly visible. In 1987, the urban class was small and was mainly located in the inner parts of Amman and Zarqa cities. The spread of urban class is clearly revealed in 2009 patterns. Amman and Zarqa cities have almost 52% of the total population of Jordan. Between 1987 and 1999 Jordan's population increased by more than 50%. In 1987 the total population was around 3.1 million inhabitants and became around 5.98 million inhabitants in 1999 (DOS, 2010), and as a result

increasing concentration in urban areas, such as northwestern and southwestern parts of Amman city and around Zarqa city had been taken place, where services and job opportunities are available.

In quantitative terms, urban class has increased from 127.6 km<sup>2</sup> (or 8.7%) in 1987 to 344.7 km<sup>2</sup> (or 23.5%) in 2009 for the studied area (table 4), thus representing an increment in the urban area class is more than 2.7 times in land area. Notice the changes of land use/cover of the northwestern and southwestern parts of Amman city and around Zarqa city, where many housing settlements have been established in these areas between 1987 and 2009 (figures 4 and 5). Another significant change is the continuing decline in cultivated class and green vegetation class in the studied area. In 1987, there were 38.1 km<sup>2</sup> of cultivated land (or 2.6%), which declined to 26.4 km<sup>2</sup> (or 1.8%) by 2009. This represents a decrease of 30.7% (table 4). Similarly, green vegetation has declined in area from 196.5 km<sup>2</sup> (or 13.4%) in 1987 to 71.9 km<sup>2</sup> (or 4.9%) in 2009, thus representing a decrease of 63.41% in land area.

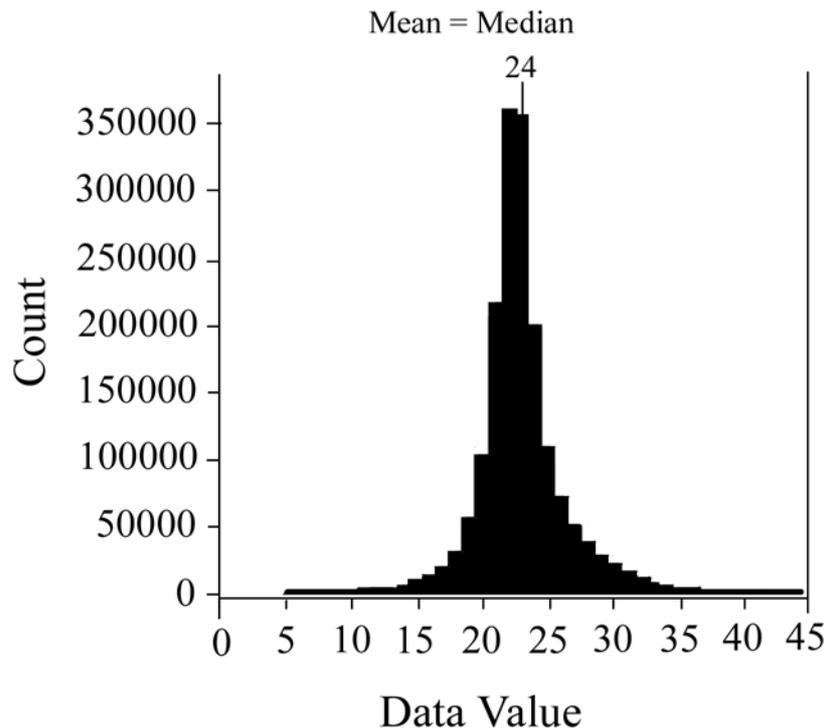
### 5-3 Land Degradation Monitoring Using NDVI Image Differencing

The image differencing procedure was performed on the NDVI generated images using formula (2), where the early image was subtracted from the later image. The resultant NDVI image does not include negative values since a constant (25) was added during the image differencing. Figure 6 shows some of the simple statistics and histogram data plot, which were extracted from the resultant image.

When the difference image is Gaussian in nature, unchanged pixels are centered around the mean while the tail regions on either side of the histogram contain information about the changed area. Misregistration is a major problem in image differencing because it may generate artifact changes during the change detection procedure. This problem can be addressed by statistical methods (Prakash and Gupta, 1998). The standard deviation of the difference image establishes a threshold level at which changes were deduced. To contain any

misregistration, Singh recommended a threshold level of  $\pm \delta$  (standard deviation) around the Mean value (Singh, 1989; Washington et al., 1998; Qong and Igrashi, 1999). For image differencing, unchanged pixels values should be equal to 0 in theory (in this case it should be equal to 25). For this study, the difference image is Gaussian in nature (figure 6), where the Mean value equal the Median value (=24), and one-standard-deviation  $\sigma$  (threshold) had been used (Washington-Allen, 1998;

Qong and Igarashi, 1999),  $\sigma$  value is 1.12. As mentioned above, since many unchanged pixels are centered around the Mean, the Mean  $\pm \sigma$  (standard deviation) threshold level of the difference image was used. All pixels values within the Mean  $\pm \sigma$  (near the Mean) are thus assumed to be unchanged pixels, and tail regions on both sides are assumed to contain information about the positive (gain) and negative (loss) change pixels.



**Figure 6. Histogram for the generated NDVI difference image.**

The difference image was density sliced and color-coded using the above threshold selection method to distinguish unchanged pixels from changed pixels (figure 7). The threshold boundary between changed pixels and unchanged pixels is determined according to the following rules. If:

*Mean  $\pm \sigma$  = DN of the NDVI difference image, then unchanged pixels.*

*Mean +  $\sigma$  < DN of the NDVI difference image, then positively changed pixels (gain).*

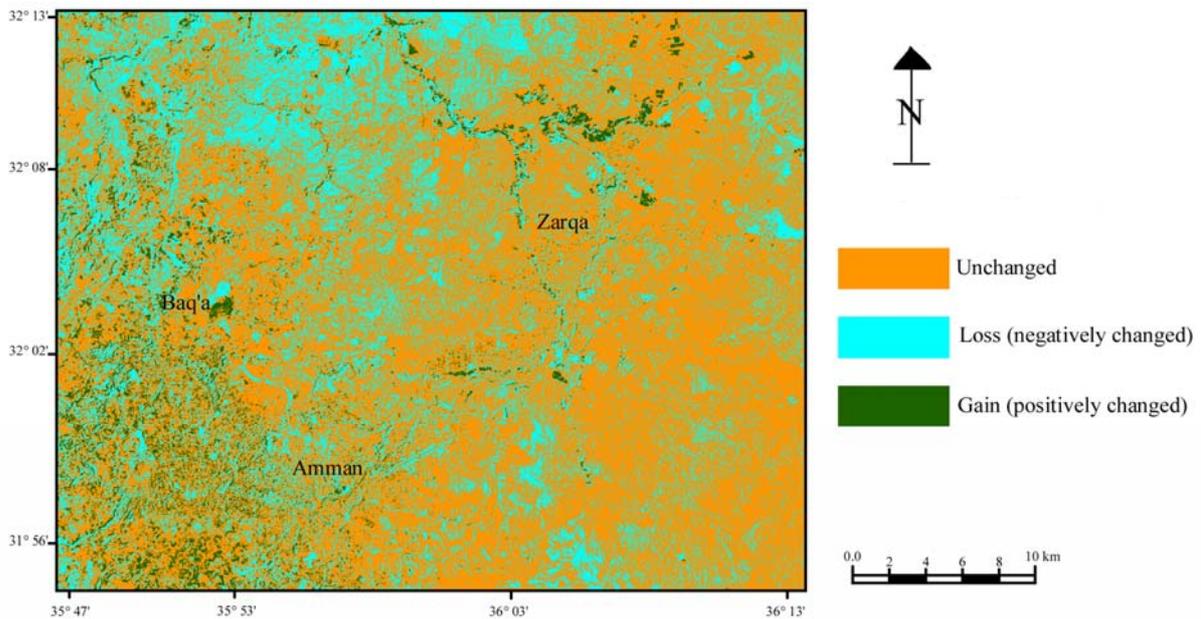
*Mean -  $\sigma$  > DN of the NDVI difference image, then negatively changed pixels (loss).*

The positive changes in the difference image denoted that the NDVI values of the former image were larger than the later one. Similarly, the negatives values denoted that the NDVI value of the former image was smaller than the later one. Positive changes represent an increase in vegetation cover between the two dates. Negative changes represent a decrease in vegetation cover or an increase in lower NDVI values. The

difference image indicated that significant land cover changes have occurred between 1987 and 2009.

The statistical results of the difference image revealed that about 28.10% (412.10 km<sup>2</sup>) of the studied area had negative changes, 3.98% (58.40 km<sup>2</sup>) had positive changes, and the other 67.92% had no changes between the two dates. Negative changes represent an increase in lower NDVI values or a decrease in vegetation cover of the cultivated areas and green vegetation areas. On the other hand change detection results (refer to table 4) showed that the decline of

cultivated areas and green vegetation areas is clearly the result of accelerated expansion through the process of urbanization, such as; northwestern, southwestern and southeastern parts of Amman city and around Zarqa city, these areas have negative changes (figure 7), where many housing settlement have been established in these areas between 1987 and 2009. Both change detection results and NDVI image differencing result indicate that the urbanization process has an increased pressure on agricultural lands, and as a result land degradation has taken place in these areas.



**Figure 7. Density sliced NDVI difference image of the study area.**

Also it worth to notice, that some housing settlements have been established on water basin areas in the studied area, such as, Baq`a Basin to the north of Amman, giving rise to the serious environmental problems (figures 2-5). Such these areas need the attention of the city planners and perhaps to carry out topographical and geological studies for such areas, in order to prevent the expansion of the urban areas into these lands, which do not fit for urbanization from those standpoints.

### 6- Conclusion

Change detection pattern of land use/cover through time

is important not only for a better understanding of the human dimensions of environmental change in specific locations, but also for the management and planning of such areas. The objective of this study was to propose a method for land degradation monitoring, as well as land use/cover changes and environmental changes in the central part of Jordan.

Using different methods of digital change detection techniques, the usefulness of the satellite remote sensing data (Landsat-TM images) for change detection study and land degradation mapping purposes has been

demonstrated. The methodology developed in this study to map land use/cover from Landsat-TM images was based on an adequate understanding of landscape features, and information extraction techniques employed.

A digital change images generated using supervised classification scheme of two dates of both TM digital data, was used for mapping surface changes dealing with five land use/cover classes. To minimize problems of boundary errors caused by spectral confusion in the image classification, a spatial reclassification method was used to break down spectrally clusters to smaller ones for re-labeling. Accuracy assessment confirmed that the image processing procedures were effective in extracting land use/cover maps and statistics of the central part of Jordan from TM image of 1987 which are compatible to those

produced from the TM image of 2009.

NDVI image differencing method was used for land degradation monitoring, particularly in vegetation coverage. The difference image indicated that significant negative changes in land use/cover have occurred between 1987 and 2009. Negative changes represent a decrease in vegetation cover or an increase in lower NDVI values, such as, cultivated class and green vegetation class. Change detection results of central Jordan revealed that the decline of cultivated and green vegetation is clearly the result of accelerated expansion through the process of urbanization, which reflect that there is no doubt that the high concentration of population settlements in urban areas of Amman and Zarqa cities has a negative effects on both agricultural lands and water basins, and is therefore strictly land degradation.

## REFERENCES

- Barnsley, M. J., and Barr, S. L., 1996 Inferring urban land use from satellite sensor images using kernel-based spatial reclassification, *Photogrammetric Engineering and Remote Sensing*, 62, 949-958.
- Beaumont, P., 1999, *Environmental management and development in dry lands*, Routledge, London.
- Behnke, R. H., and Scoones, I., Rethinking range ecology: Implications for rangeland management in Africa. In Behnke R. H., Scoones, I., and Kerven, C., 1994, *Range Ecology at Disequilibrium*, London: Overseas Development Institute, International Institute for Environment and Development, and Commonwealth Secretariat, London, 1-30.
- Booth, D. J., and Oldfield, R. B., 1989, A comparison of classification algorithms in terms of speed and accuracy after the application of a post-classification model filter, *Int. J. Remote Sensing*, 10, 1271-1276, 1989.
- Campbell, J. B., 2006, *Introduction to Remote Sensing*, New-York, Guilford Press.
- Chavez, P. S., JR. and MacKinnon, D., 1994, Automatic detection of vegetation changes in the southwestern United State using remotely sensed images. *Photogrammetric Engineering and Remote Sensing*, 60, 1025-1036.
- Civco, D. L., 1993, Artificial neural networks for land-cover classification and mapping. *Int. J. Geographical Information Systems*, 1, 17-25.
- Colwell, R. N., and Poulton, C., 1985, SPOT simulation imagery for urban monitoring: a comparison with Landsat TM and MSS imagery and with high altitude color infrared photograph. *Photogrammetric Engineering and Remote Sensing*, 51, 1093-1101.
- Congalton, R. G., 1991, A review of assessing the accuracy of remotely sensed data, *Remote Sensing of Environment*, 37, 35-46.
- Cooke, R.U., Warren, A. and Goudie, A.S., 1993, *Desert geomorphology*, London, UCL press.
- Douglas, I., 1981, The city as an ecosystem, *Progress in Physical Geography*, 5, 315-367.
- (DOS), *Jordan in figures*, 2010, Amman, Department of statistics.
- Ehlers, M., Jadcowski, M.A., Howard, R. R., and Brostuen, D. E., 1990, Application of spot data for regional growth and analysis and local planning. *Photogrammetric Engineering and Remote Sensing*,

- 56, 175-180.
- Gomasasca, M. A., Brivio, P. A., Pagnoni, F., and Galli, A., 1993, One century of land use changes in the metropolitan area of Milan (Italy), *Int. J. Remote Sensing*, 14, 211-223.
- Green, K., Kempka, D., and Lackey, L., 1994, Using remote sensing to detect and monitor land-cover and land-use change. *Photogrammetric Engineering and Remote Sensing*, 60, 331-337.
- Grey, W. M. F., Luckman, A. J., Holland, D., 2003, Mapping urban change in the UK using satellite radar interferometry, *Remote sensing of Environment*, 87, 16-22.
- Herold, M., Goldstein, N. C., Clarke, K. C., 2003, The spatiotemporal form of urban growth: measurement, analysis and modeling, *Remote sensing of Environment*, 86, 286-302.
- Jensen, J. R., and Cowen, D. C., 1999, Remote sensing of urban/suburban infrastructure and socio-economic attributes, *Photogrammetric Engineering and Remote Sensing*, vol. 65, 611-622.
- Ji, M., and Jensen, J., 1996, Fuzzy training in supervised image classification. *Int. J. Geographical Information System*, 2, 1-11.
- JMD (Jordan Meteorological Department), 2009, *Climatic data report*, Amman, JMD.
- Kwarteng, A. Y., and Chavez, P. S., JR., 1997, Change detection study of Kuwait City and environs using multi-temporal Landsat Thematic Mapper data. *Int. J. Remote Sensing*, 19, 1651-1662.
- Lillesand, T. M., and Kiefer, R. W., 2003, *Remote sensing and image interpretation*, 3ed, New York, John Wiley & sons, Inc.
- Lo, C. P., 1986, *Applied Remote Sensing*, New York, Longman.
- Miller, A. B., Bryant, E. S., and Birnie, R. W., 1998, Analysis of land cover changes in the northern forest of New England using Landsat MSS data, *Int. J. Remote Sensing*, 19, 245-265.
- Moller-Jensen, L., 1990, Knowledge-based classification of an urban area using texture and context information in Landsat-TM imagery, *Photogrammetric Engineering and Remote Sensing*, 56, 899-904.
- NSJ (*National Strategy for Jordan*), 1991, Amman Ministry of Municipal and Environment.
- Owen, T. W., Carlson T. N. and Gillies R. R., 1998, An assessment of satellite remotely-sensed land cover parameters in quantitatively describing the climatic of urbanization, *Int. J. Remote Sensing*, 19, 1663-1681.
- Pickup, G., 1989, New land degradation survey techniques for arid Australia: Problems and prospects. *Australian Rangeland J.*, 11, 74-82.
- Prakash, A., and Gupta, R. P., 1998, Land-use mapping and change detection in a coal mining area- A case study in the Jharia coalfield, India, *Int. J. Remote Sensing*, 19, 391-410.
- Qong, M., and Igarashi, T., 1999, Environmental changes deduced from satellite data in arid regions- A case study in the lower reaches of the Hotan and YARKANT rivers, China, *Journal of arid land studies*, 9, 153-167.
- Ridd, M. K., 1995, Exploring a V-I-S (vegetation-impervious surface-soil) model for urban ecosystem analysis through remote sensing: comparative anatomy for cities, *Int. J. Remote Sensing*, 16, 2165-2185.
- Ridd, M. K., and Liu, J. J., 1998, A comparison of four algorithms for change detection in urban environment, *Remote Sensing of Environment*, 63, 95-100.
- Rouse, J. W., Haas, R. H., Schell, J. A., and Deering, D. W., 1974, Monitoring vegetation system in the Great Plains with ERTS. 3ed ERTS Symposium, NASA SP-351, NASA, Washington, D. C., 1, 309-317.
- Sato, H. and Tateishi, R., 2002, Proposal for global land cover guideline legend based on FAO's LCCS. *Asian Journal of Geoinformatics*, 3, 35-46.
- Singh, A., 1989, Digital change detection techniques using remotely-sensed data, *Int. J. Remote Sensing*, 10, 989-1003.
- UNEP, 1994, *United Nations Convention to Combat Desertification, Interim Secretariat for the Convention to Combat*, <<http://www.unep.ch/inch.html>>.
- Warren, A. and Agnew, C., 1987, *An assessment of desertification and land degradation in arid and semi-arid areas, Drylands paper 2*, London. International Institute for Environmental and development.

- Washington-Allen, R. A., Ramsey, R. D., Norton, B. E., and West, N. E., 1998, Change detection of the effect of severe drought on subsistence agropastoral communities on the Bolivian Altiplano, *Int. J. Remote Sensing*, 19, 1319-1333.
- Wilson, E. H., Hurd, J. D., Civco, D. L., Prisloe, M. P., Arnold, C., 2003, Development of a geospatial model to quantify, describe and map urban growth, *Remote sensing of Environment*, 86, 275-285.
- Xiao, J., Shen, Y., Ge, J., Tateishi, R., Tang, Ch., Liang, Y., and Huang, Z., 2006, Evaluation urban expansion and land use change in Shijiazhuang, China, by using GIS and remote sensing, *Landscape and Urban Planning*, 75, 69-80.
- Yang, X. and Lo, C. P., 2002, Using a time series of satellite imagery to detect land use and land cover changes in the Atlanta, Georgia metropolitan area. *Int. J. Remote Sensing*, 23, 1775-1798.
- Zhou, J., and Civco, D. L., 1996, Using genetic learning neural networks for spatial decision-making in GIS. *Photogrammetric Engineering and Remote Sensing*, 62, 1287-1295.

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NDVI

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