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Full Length Research Paper

Utilization of Change Vector Analysis for Land Use/ Land Cover Change Detection in a Selected Area in the Northern Delta, Egypt

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Land cover and land use change detection provides valuable data to decision makers especially on the loss of agricultural land and lakes surface areas which is becoming one of the major problems in Egypt. Remote Sensing data are fundamental in providing accurate information regarding land use and land cover changes. The aim of this work is to investigate the use of Change Vector Analysis (CVA) for land use/ land cover change detection in a selected area in the Northern Delta, Egypt. In this paper, a two dimensional CVA using the Normalized Difference Vegetation Index(NDVI) and Bare soil Index (BI) utilized two Landsat image with thirteen year interval from 2001 to 2014. The threshold of change magnitude was applied empirically and revealed that the changed area covered about 6.66% of the studied area. Studying the change direction revealed that classes C1 and C3 representing the expansion of the agriculture and settlement areas covered an area of about 29.1 and 27.4% of the change in the study area, respectively. The major change represented by class C2, which covered about 37.2 % of the changed area, represented the changes in the aquatic vegetation distribution. This class was affected by the changes of the depth and quality of the lake water. The drawback in using this method in the study area was noticed in class C4 this covered only 6.3 % of the change. This class represented the change from wetsoils to fish pond and was underestimated using CVA. It was concluded that even so CVA could be considered a suitable method to monitor the changes in the land use and land cover change in the study area, it is recommended to include a more sensitive water index to overcome its drawback.

Keywords: Change Vector Analysis, land use/ land cover, change detection, El-Northern Delta, Egypt

INTRODUCTION

Change detection is the process of identifying differences in the state ofan objector phenomenon by observing it at different times (Singh, 1989). Timely and accurate change detection of Earth's surface features is extremely important for understanding relationships and interactions between human and natural phenomena in order to promote better decision making(Lu et al., 2004). Change detection techniques using images from different sensors, such as

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satellite imagery, aerial photographs, etc., have proven to be suitable and secure data sources from which updated information can be extracted efficiently, so that changes can also be inventoried and monitored (Molina et al., 2012)with diminishing costs and processing time (Chen et al., 2012).

An array of techniques is available to detect land cover changes from multi-temporal remote sensing data sets. Those different change detection algorithms have their own merits and no single approach is optimal and applicable to all cases (Deer, 1995 and Lu et al., 2004).Change vector analysis (CVA) is a relatively new techniques that have been considered as a valuable technique for land-use/ land-cover change detection (Chen et al., 2003).CVA was used first by Malila (1980) for change detection using multi-temporal Landsat data. The method employs calculation of spectral change vectors from two different dates, prompting its name Change Vector Analysis (Michalek et al., 1993 and Bovolo et al.,2008). CVA has the capability of extracting maximum information in terms of relative magnitude and direction of the change between dates (Lu et al., 2004 and Singh and Talwar, 2013).According to Molina et al. (2012) the main advantage of the CVA method is that any number of spectral bands can be processed, thus generating a single parameter that represents the degree of change between two sets of similar images. One disadvantage of CVA is the difficulty in selecting suitable thresholds to identify the changed areas (Lu et al., 2004 and Chen et al., 2003 and Bovolo et al., 2008)and selecting suitable image bands or vegetation indices (Lu et al., 2004). Michalek et al. (1993)recommended CVA as valuable tool for locating areas of suspected habitat change for the purpose of focusing more intensive field survey techniques and recommended it as a more cost efficient and effective method for detecting changes over large areas than other techniques. On the other hand, Wen and Yang (2009) stated that the threshold of change magnitude and direction of change vector analysis still need further study.In this aspect,Chen et al.(2003) proposed a new method is proposed to improve the determination of the threshold of change magnitude, and direction cosines of the CVA. Carvalho Junior et al. (2011)proposed a new approach to calculate the spectral direction of change using the Spectral Angle Mapper and Spectral Correlation Mapper spectral-similarity measures. Xiaolu and Bo (2011) successfully used a dichotomy search to detect the threshold vector.The aim of this work is to investigate the use of CVA for land use/ land cover change detection in a selected area in the Northern Delta, Egypt.

MATERIALS AND METHODS

Study area

The study area is located in the northern part of the Nile Delta, between longitudes 30º 34' 13" and 31º 6' 25" E and latitudes 31º 18' 26" and 31º 35' 25" N, and covers an area of about 1200 km^2 (Figure 1). The importance for the monitoring of land use/land cover changes along the north part of the Nile delta, Egypt was reported by Dewidar (2004)for the planner, management, governmental and non-governmental organizations and the scientific community for planning and implementing policies to optimize the use of natural resources and accommodate development whilst minimizing the impact on the environment. According to Morgan et al. (2015) the main land use in the study area is agriculture, mostly field crops in the north delta area are rice, barely, beans and clover. Vegetables including tomatoes, potatoes, watermelon and others are cultivated in small scattered areas. Fish ponds are the second dominant land use in the study area. El-Burullus Lake, a shallow brackish lake characterized by a few species of abundant aquatic vegetation, is also located in the study area. The study area is continually subjected to land use/ land cover changes that threaten its ecological balance. Drying parts of the Lake and consequently their conversion into the fish ponds mainly around the southern fringes of the lake is one of the threats. The fast growing of new human settlements and consequently reduced the area of agriculture is another. Additionally, the pollution of the lake water was due to the excessive inflow of agriculture drainage water. Furthermore, the investigated area is suffering from water shortage, thus farmers frequently use drainage water for supplementary irrigation officially or unofficially. Therefore,its vital to have a consistent monitoring strategy to keep track of the changes that is consistently occurring in this area.

Data source

The choice of the temporal images to be analyzed is considered an important factor in change detection. Preferably, images should be selected from the same sensor, acquired under similar illumination geometries, and in a similar environmental condition. Thus, images from the same time of year are often used in multi-temporal studies (Carvalho Junior et al., 2011).

For the purpose of this study we used a cloud free (within the study area) pair of Landsatsurface reflectance images, which have parameters presented in table 1. All the

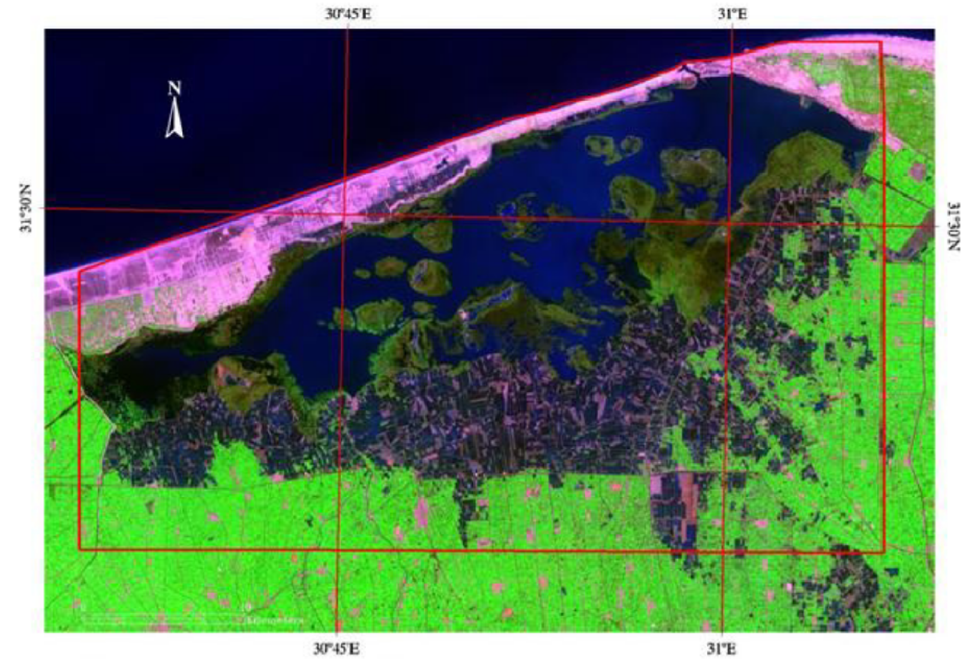


Figure 1: Location map of the study area (Landsat 8, 753 acquired in 5/3/2014)

Table 1.characteristics of the use images

Data	*Date*	*Path/Row*	*Spatial Resolution*	*Used bands*
Landsat 7 ETM$^+$	***22/2/2001***	177/38	***30 m***	***1-5 and 7***
Landsat 8	***5/03/2014***	177/38	***30 m***	***2-7***

satellite images have been delivered geo referenced in UTM projection, datum WGS84, zone 36 Northern Hemisphere.

Data pre-processing

All image processing was performed using ENVI 4.3 software. The bands were delivered separately in Tiff format and were stacked to produce a single multiband image. Because the spatial extent of the two Landsat images is greater than the study area the images were first subsetted to the study area using a bounding rectangle.

Change Vector Analysis

Traditionally, the CVA method is based on two important indices in order to reveal the primary feature of land cover change which can be namely; NDVI and BI (Si et al., 2009 and Duy and Giang, 2012). NDVI is defined as

$$NDVI = \left[\frac{\rho NIR - \rho Red}{\rho NIR + \rho Red}\right]$$

Where ρNIR and ρRed are the reflectance of the NIR and red bands, respectively. The NDVI values, which are unitless, range from –1 to +1, where positive values yield high amounts of vegetation, both deciduous and otherwise, where negative values correspond to sparse or nonexistent vegetation, bare soil and clouds.

On The other hand, BI is defined as

$$BI = \left[\frac{(\rho Red + \rho SWIR) - (\rho NIR + Blue)}{(\rho Red + \rho SWIR) + (\rho NIR + Blue)}\right] + 1$$

where ρRed, ρSWIR, ρNIR, ρ Blue are the reflectance of the red,SWIR, NIR and blue bands, respectively. BI can identify difference between agricultural and non-agricultural vegetation, specifically, the identification of bare soil and fallow lands are enhanced when using the BI index (Duy and Giang 2012).

CVA is a bi-temporal method of change detection that considers the magnitude and direction of change vector(Carvalho Júnior et al., 2011). According to Deer (1995) multi spectral remotely sensed image data can be represented by constructing a vector space with as many axes or dimensions as there are spectral components (bands) associated with each pixel. A particular pixel in an image is plotted as a point in such a space coordinates that correspond to its brightness values in the appropriate spectral components. The data values associated with each pixel thus define a vector in the multi-dimensional space. If a pixel undergoes a change from time t1 to time t2 a vector describing the change can be defined by the subtraction of the vector at t1 from the vector at t2. This is called the spectral change vector. If the magnitude of the computed spectral change vector exceeds some specified threshold criterion, it may be concluded that change has occurred (figure 2).

According to Michaleh et al. (1993) the CVA method computes the total change magnitude per pixel by determining the Euclidean distance between end points through n-dimensional change space. Two approaches have been proposed for calculating the direction component: sector-coding (Michaleh et al. 1993)and calculating vector direction cosines Chen et al.(2003) but in many cases the direction component is disregarded entirely (Xiaolu and Bo, 2011). Michaleh et al. (1993)stated that the change direction for each pixel is specified by whether the change is positive or negative in each band. Thus, there are 2^npossible types of change can be determined per pixel. Because this study used two input bands there were 4 possible types of change that could be detected and illustrated in figure 3 in addition to the codes used with each position in this study.

RESULTS AND DISCUSSION

The NDVI and BI indices were calculated for 2001 and 2014 Landsat images using ENVI's band math (Figure 4).To evaluate the selection of the suitable indices, the correlation between BI and NDVI was calculated

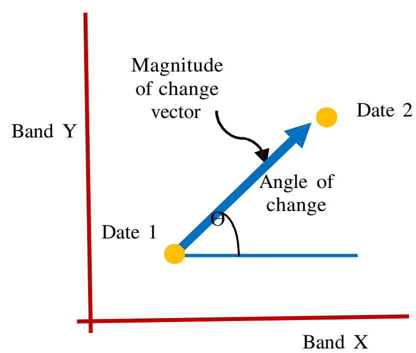


Figure 2: Schematic diagram of the spectral change direction method (modified after Malila, 1980)

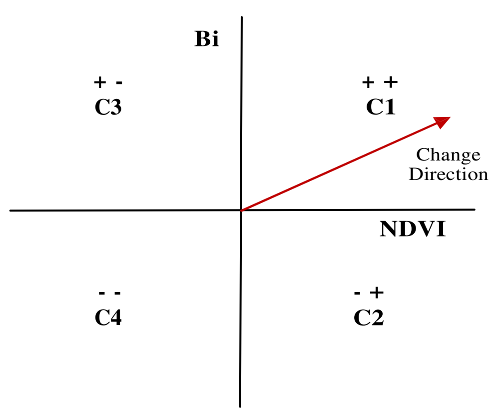


Figure 3. The possible change directions resulting from 2 bands of data and their codes.

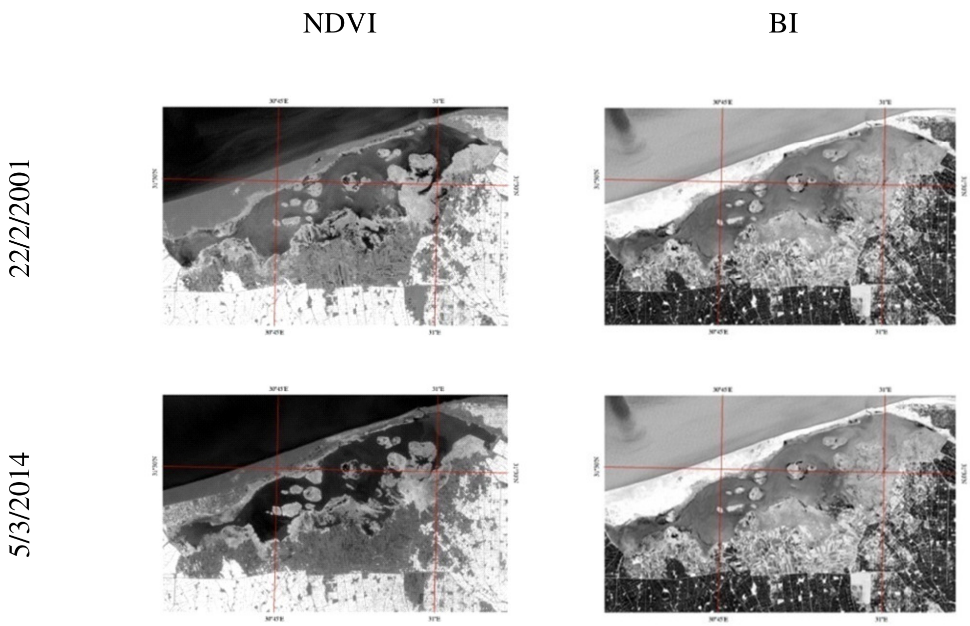


Figure 4. Components of CVA in this study

and reached -0.434. Based on these results, it was concluded that the low correlation between the BI and NDVI validate their use in the change detection studies

CVA Change intensity

Carvalho Junior et al. 2011 defined change magnitude calculated as the Euclidian Distance (ED) between two temporal spectra as the square root of the band-wise sum of the squares of the differences:

$$ED = \sqrt{\sum_{i=1}^{n} (X_2 - X_1)^2}$$

where "X_1" and "X_2" are the date 1 and date 2 pixel values and "i" is the bands. ENVI's band math was also used to calculate the ED (Figure 5).

The greatest challenge to the successful application of the spectral change detection methods is the determination of the threshold of “change” and “no-change” pixels. The threshold of change magnitude is empirically determined and based on the knowledge of the study area. In this

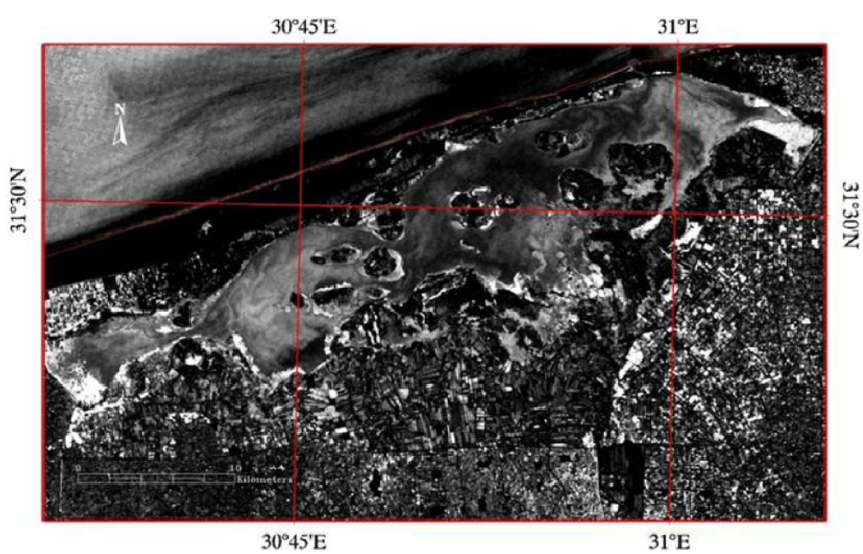


Figure5. Change intensity map of the studied area (the bright areas are changed areas)

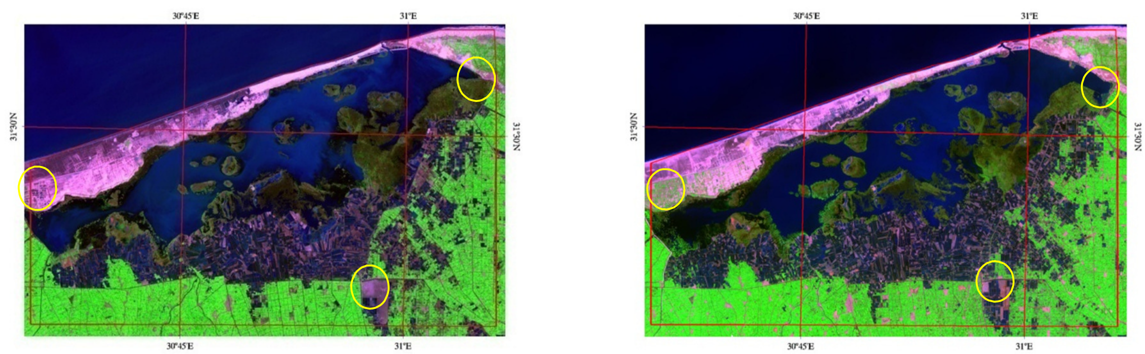
aspect, to detect change or no change threshold the histogram of change intensity image was analyzed and the images of 2001 2014 were examined to look for possible changes and examples of the changes are presented in figure 6.

Applying this approach the area could be classified as change or no-change area (Figure 7), where the changed area represented 6.66% of the studied area covering about 80.74 Km^2. It could also be observed that this method failed to identify the change from bare wet soils to fish pond which could be rendered to insignificant spectral changes that could not be recognized utilizing the two used indices.

CVA Change direction

In this work we used ENVI's Decision Tree (DT) classifier to define the change directions. The Decision Tree (DT) classifier performs multistage classifications by using a series of binary decisions to place pixels into proper classes. Each decision divides the pixels in a set of images into two classes based on an expression. Decision trees are a topic of Artificial Intelligence, which can be applied to a single image or a stack of images (Yacouba et al., 2014). The result is shown in figure 8.

The first two classes CI and C2 represented an increase of NDVI or increase of vegetation covering about 29.1 and



2001 2014

Figure 6. Examples of the possible changes in land use/ land cover in the study area

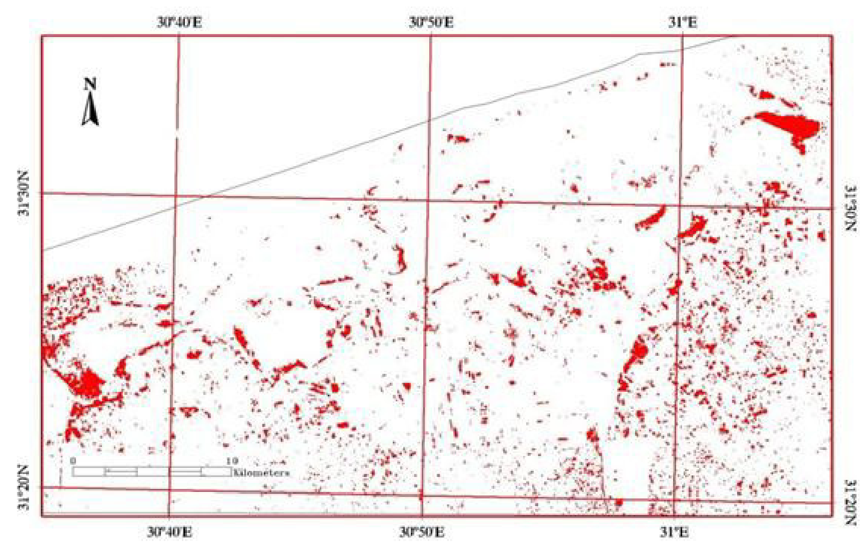


Figure 7: The classified change intensity image after threshold (changed areas marked red)

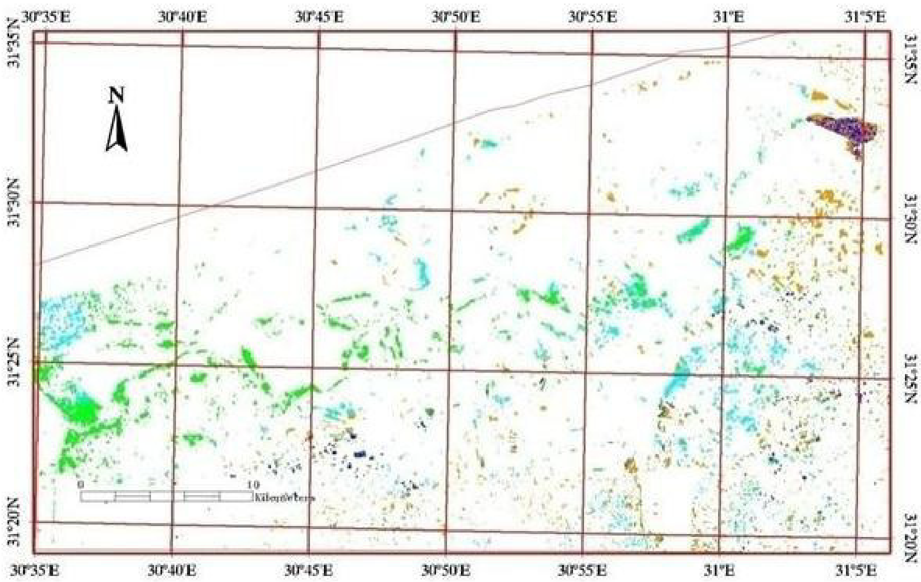


Figure 8. Direction of the change

37.2 % of the total change in the study area respectively. Class C1, was found in the area surrounding El-Burullus Lake and represented mainly the newly reclaimed areas characterized by increase of BI because most of these areas were fish ponds with high water content to the south of the lake or bare sandy wet soils to the northwest of the lake or the small parts of the islands within the lake. On the other hand, class C2 represented a decrease of BI and included the aquatic vegetation located within the lake. Class C3 covered about 27.4 % of the total change with a decrease of NDVI and increase of BI represented the expansion areas of the settlement surrounding the lake and thus reducing the agricultural area or the areas the islands within the lake where the settlements has expanded as well. It also included the fish ponds areas that were dried. Class C4 represented 6.3 % of the change, characterized by decrease in both BI and NDVI and represented the areas that were converted to fish ponds with extremely high water content mostly to the south of the lake or parts of the lake where the aquatic vegetation was removed mostly to the east of the lake.

CONCLUSION

CVA was examined as a potential method for land use and land cover change in the Northern Delta area utilizing Landtsat data acquired in 2001 and 2014. Threshold of change magnitude was the major challenge in identifying the change or no-change area. Based on knowledge of the study area, it was preformed empirically. While most changed areas were recognized by CVA one change pattern was not identified and represented the change from wetsoils to fish farms which could not be recognized using BI and NDVI. Therefore, it is recommended that further studies of CVA in the area should include a more sensitive water index to categorize that change. Examining the direction of change was based on visual interpretation. Classes C1 and C3 represented the two opposites of agriculture and settlement areas expansion and covered about 29.1 and 27.4 % of the change of the area respectively. The major change was located in class C2 and covered about 37.2 % of the change in the area. This class represented the redistribution of the aquatic vegetation within the lake which is subjected to both the quality and depth of the lake. These factors are mostly affected by the quality and quantity of the drainage water that directly discharge their water from the areas surrounding the lake into it. The least area coverage was located in class C4 representing the conversion of bare wet soils into fish ponds and covered about 6.3 % of the change. This was expected because CVA underestimated this class when evaluating the magnitude of change. Overall, CVA offered a good method to study the changes in the land use and land cover change in the study area but further studies is required to increase the sensitivity of the used indices to detect moisture content change in the study area.

REFERENCES

Bovolo F, Bruzzone L, Marconcini M (2008). A Novel Approach to Unsupervised Change Detection Based on a Semi-supervised SVM and a Similarity Measure. IEEE Transactions on Geoscience and Remote Sensing, 46(7):2070-2082.

Carvalho Junior OA, Guimaraes RF, Gillespie AR, Silva NC, Gomes RAT (2011). A New Approach to Change Vector Analysis Using Distance and Similarity Measures. Remote Sensing, 3, 2473-2493.

Chen G, Hay GJ, Carvalho LMT, Wulder MA (2012). Object Based Change Detection. International Journal of Remote Sensing, 33(14): 4434-4457.

Chen J, Gong P, He C, Pu R, Shi P (2003). Land-Use/Land-Cover Change Detection Using Improved Change-Vector Analysis. Photogrammetric Engineering & Remote Sensing 69(4) April 2003, pp. 369–379.

Deer P (1995). Digital Change Detection Techniques in Remote Sensing. DSTO Electronica and Surveillance Research Laboratory. *AR-009-254.*

Dewidar KHM (2004). Detection of land use/land cover changes for the northern part of the Nile delta (Burullus region), Egypt International Journal of Remote Sensing, 25(20):4079-4089

Duy NB, Giang TTH (2012). Study on Vegetation Indices Selection and Changing Detection Thresholds Selection in Land Cover Change Detection Assessment Using Change Vector Analysis. International Environmental Modelling and Software Society (iEMSs), 2012. International Congress on Environmental Modelling and Software. Managing Resources of a Limited Planet: Pathways and Visions under Uncertainty, Sixth Biennial Meeting, Leipzig, Germany, R. Seppelt, A.A. Voinov, S. Lange, D. Bankamp (Eds.).

Lu D, Mausel P, Brondízio E, Moran E (2004). Change Detection Techniques. International Journal of Remote Sensing, 25(12):2365-2401.

Malila WA (1980). Change vector analysis: An Approach for Detecting Forest Changes with Landsat, Proceedings of the 6th Annual Symposium on Machine Processing of Remotely Sensed Data, 03-06 June, Purdue University, West Lafayette, Indiana, pp. 326–335.

Michalek JL, Luczkovich JJ, Stoffle RW (1993). Multispectral Change Vector Analysis for Monitoring Costal Marine Environments. Photogrammetric Engineering & Remote Sensing, 59(3): 381-384.

Molina I, Martinez E, Arquero A, Pajaresand G Sanchez J (2012). Evaluation of a Change Detection Methodology by Means of Binary Thresholding Algorithms and Informational Fusion Processes. Sensors, 12: 3528-3561.

Morgan RS, Rahim IS, Abd El-Hady M (2015). A Comparison of Classification Techniques for the Land Use/ Land Cover Classification in the Northern Delta Area. Global Advanced Research Journal of Agricultural Science (GARJAS) Vol. 4(11): 810-818.

Si ST, Thi LP, Van CP (2009). Land Cover Change Analysis Using Change Vector Analysis Method in DuyTien District, Ha Nam Province in Vietnam. 7th FIG Regional Conference Spatial Data Serving People: Land Governance and the Environment – Building the Capacity, Hanoi, Vietnam, 19-22 October 2009.

Singh A (1989). Review Article Digital Change Detection Techniques Using Remotely-Sensed Data," International Journal of Remote Sensing, Vol. 10(6): 989- 1003.

Singh S, Talwar R (2013). Review on Different Change Vector Analysis Algorithms Based Change Detection Techniques. IEEE Second International Conference on Image Information Processing (ICIIP), 9-11 Dec. 2013 pp136 - 141.

Wen X, Yang X (2009). Change Detection from Remote Sensing Imageries Using Spectral Change Vector Analysis Asia-Pacific Conference on Information Processing,(APCIP), 18-19 July 2009, Shenzhen, 2: 189 - 192.

Xiaolu S, Bo C (2011). Change Detection Using Change Vector Analysis from Landsat TM Images in Wuhan. Procedia Environmental Sciences,11: 238 – 244.

Yacouba D, Xu Y, Hu G, Bokhari AA, Wen X (2014). Change Detection Using Data Stacking and Decision Tree Techniques in Puer-Simao Counties of Yunnan Province, China. Sci-Afric Journal of Scientific Issues, Research and Essays, 2 (11): 491-502.