Ass. Univ. Bull. Environ. Res. Vol. 21 No. 2 October 2018

AUCES

ASSESSMENT, PREDICTION AND FUTURE SIMULATION OF LAND COVER DYNAMICS USING REMOTE SENSING AND GIS TECHNIQUES

Soha A. Mohamed[1] and Mohamed E. El-Raey[2]

Institute of Graduate Studies and Research; University of Alexandria, Egypt

[1]igsr.soha.ahmed@alexu.edu.eg, [2]mohamed.elraey@alexu.edu.eg

ABSTRACT

Mapping land use/land cover (LULC) changes at regional scales is essential for a wide range of environmental hazards and risk, including global warming, earthquakes, landslide, erosion, flooding, etc. These rapid changes adversely affect the environment and have potential economic and social impacts. Thus, detailed accurate information about changes is urgently needed for updating LULC maps, to provide information for policymakers to support sustainable development, and the management of natural resources. The purpose of this paper was to extract reliable land cover information from two Landsat imageries with moderate resolution (Landsat 5 TM and Landsat 8 OLI) over a 15 years period (1999 to 2014) using post-classification change detection analysis. Traditional post-classification change detection approach based on pixel-based classification. However, in this paper, both of pixel based and segment-based classification approaches are deployed and the appropriateness of the classifications to derive accurate land cover maps. Then, Markov model is used to predict and simulate trends of LULC changes during the period of 1999 to 2014 and a future land cover map of the year 2050 are produced. The results showed that image segmentations led to better classification accuracy (86.67% in 1999 and 94.09% in 2014). Vice versa, traditional classification led to poorer accuracy (83.33% in 1999 and 93.33% in 2014).

Keywords: ***Image Classification; Segmentation; Change Detection; Prediction; Markov Chain.***

1. INTRODUCTION

Monitoring and evaluation of environmental changes play major roles in the study of global change. Human/natural modifications have largely resulted in deforestation, biodiversity loss, global warming and increase of natural disaster-flooding (Dwivedi *et al*., 2005; Zhao and Warner, 2004). Moreover, the growing population and increasing socio-economic necessities created a pressure on LULC. These environmental hazards are often related to unplanned and uncontrolled changes in LULC (Seto *et al*., 2002). Therefore, information on LULC changes could provide critical input to decision-making of environmental management and planning for the future (Fan et al., 2007). Consequently, a large and growing literature has focused specifically on the problem of

accurately monitoring land-cover and land-use change in a wide variety of environments change detection methods (Atasoy *et al*., 2006; Shalaby and Tateishi, 2007).

Change detection can be defined as the process of identifying differences in the state of an object or phenomenon by observing it at different times (Singh, 1989). Singh (1989), Coppin and Bauer (1996); Macleod and Congalton (1998), Robb and Congalton (1998); Lu *et al*., (2004); Alqurashi and Kumar (2013) reviewed and summarized a variety of change detection techniques. Other authors developed new change detection techniques. Adams *et al.* (1995) deployed spectral mixture analysis, Macomber and Woodcock, (1994) developed Li–Strahler Canopy Model, Ridd and Liu (1998) applied chi-square transformation, Metternicht (1999 and 2001) used fuzzy sets. Abuelgasim *et al.* (1999) used artificial neural networks (ANN) and Petit and Lambin (2001) integrated multi-data source to detect changes. El-Raey *et al*., (2000) examined using GIS to study changes in Rosetta, Egypt. Almutairi and Warner (2010) compared a change detection approaches based on the image classification. Blaschke (2009) dealt with problems associated with multi-temporal object recognition using a post-classification comparison method and proposed a framework for image object-based change detection. IM *et al*., (2008) introduced object-based change detection using correlation image analysis and image segmentation. Abdu *et al.* (2014) proposed the use of combination of pixel based and segment-based classification for better change detection results as poor classification approach leads to wrong results hence leading to poor change detection results.

Pixel based classification is a traditional method of image classification (Dean and Smith, 2003). Pixel-based classification used multi-spectral classification techniques that assign a pixel to a class by considering the spectral similarities with the class or with other classes (Lu and Weng, 2007). In pixel-based classification, two kinds of traditional classification methods: unsupervised classification and supervised classification were commonly used methods (Dehvari and Heck, 2009). Image segmentation classification is based on image objects which mean a set of similar pixels (Shakelford and Davis, 2003). Image segmentation is the process of partitioning a digital image into multiple segments (Bora and Gupta, 2014). Segmentation employs a watershed delineation approach to partition input imagery based on their variance (Morgan, 2012). A derived variance image is treated as a surface image allocating pixels to particular objects based on variance similarity. Segmentation is a relatively new technique for extracting information from remotely sensed imagery (Blaschke, 2010).

Many studies have been done for LULC change modeling. For this study Markov Chain analysis is used for modeling land use dynamics and projecting future land use. Andrei Andreyevich Markov invented the Markov chain mathematical model in 1906 (Seneta, 1996). It is a stochastic process based on probabilities and the next state depends only on current state (Al-sharif and Pradhan,

2013). The basic assumption in the model was: the state at some point in the future (t+1) could be determined as a function of the current state (t), in other words the future change would be only depend on the existing change, so the transition between two times could be modeled mathematically (Otunga *et al.*, 2014 and Mubea *et al.*, 2010). Markov chain analysis assumed that land cover in a later date could be predicted by the state of land cover in the earlier date, given a matrix of transition probabilities from each land cover class to every other land cover class. The dynamics of land cover transitions are described in context of a Markovian analysis by three items (Luijten, 2003):

- **Transition probability matrix: transition probabilities expressed the likelihood that a pixel of a given class would change to any other class (or stay the same) in the next time.**
- **Transition areas matrix: that expressed the total area (in cells) expected to change in the next time.**
- **Set of conditional probability maps: a map for each land cover class, which presented the probability that each pixel would belong to the designated class in the next time.**

According to Subedi *et al.* (2013), Markov model could be represented mathematically as:

$$L_{(t+1)} = P_{ij} * L_{(t)}$$

and

$$P_{ij} = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1m} \\ P_{21} & P_{22} & \cdots & P_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ P_{m1} & P_{m2} & \cdots & P_{mm} \end{bmatrix} \qquad (1)$$

Where, $L_{(t+1)}$ and $L_{(t)}$ are the land-use status at time "t+1" and "t" respectively. ($0 \leqslant P_{ij} \leqslant 1$ and $\sum_{j=1}^{m} Pij$, (i, j=1, 2…, m)) is the transition probability matrix.

Markov chain is a module called Markov/CA_Markov in the raster GIS IDRISI (Eastman, 2012) and performed in order to estimate the transition matrix between the two past and documented dates (date 1 and date 2) and to estimate probabilities of change for the third date (date 3) to be predicted. This present study examined the land cover changes and the nature of urban sprawl in the city of Alexandria using remotely sensed data for the years 1999 and 2014. It aimed to classify land cover types in each year; detect changes that occurred in each class and finally simulated the situation in the future using Markov Chain.

2. MATERIALS AND METHODS

2.1. STUDY AREA

Alexandria city is the chief port of Egypt and is located approximately between 30°50' to 31°40' north and 29°40' to 32°35' east. The city has a waterfront that extended for 60 km, from Abu-Qir Bay in the east to Sidi Krier in the west. It extended about (32 km) along the coast of the Mediterranean Sea in north-central Egypt as shown in Figure (1).

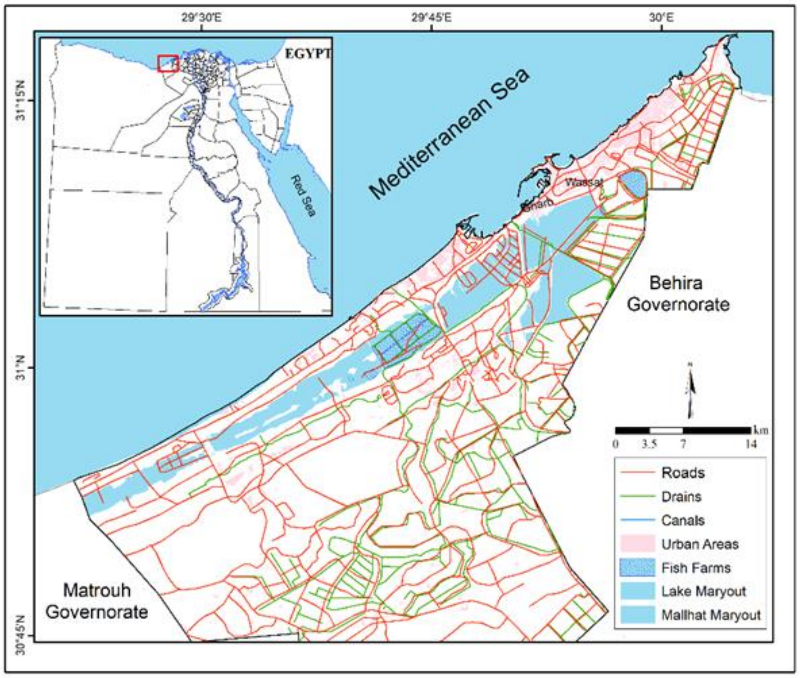


Figure (1). Study area

2.2. REMOTELY SENSED DATA

Two separate Landsat OLI and TM data from 1999 and 2014 covering the study area are acquired freely from the U.S. Geological Survey's (USGS) Earth explorer website (http://earthexplorer.usgs.gov/). Details about the data are given in Table (1).

Table (1). Characteristics of the Landsat datasets used in the study

Acquisition Date	Sensor	Path/Row	Spatial Resolution	Number of Bands	Format
31-1-1999	Landsat-5 TM	178/38 –	30	7	GeoTIFF
23-10-2014	Landsat-8	177/38	30	11	GeoTIFF
	OLI/TIRS	178-38			

2.3. CLASSIFICATION AND ACCURACY ASSESSMENT

The Anderson classification level I scheme is used to identify four land cover categories (water bodies, vegetation, built-up area, and bare soil) as given in Table (2). A pixel-based classification based on hybrid classification (unsupervised classification (ISODATA) and supervised maximum likelihood classification (MLC)) method (using signatures from a total of 90 training sites) is used to classify the Landsat images of the two years (1999 and 2014). Hybrid classification is used to achieve better classification accuracy. Then segment-based classification of the same two images is performed.

Table (2). Land cover classification scheme used in the study

Land Cover Type	Description
Water Bodies	Water areas (sea, lakes, canals, etc.)
Bare Soil	Areas with no vegetation cover, uncultivated agricultural lands, open space and sand
Vegetation	Trees, natural vegetation, gardens, parks and playgrounds, grassland, vegetated
Urban Areas	All types of manmade structures: residential, industrial, agricultural commercial and services; transportation and utilities; mixed urban or built-up.

The classification accuracy is assessed using field trips-ground truth data where 200 locations points are collected and distributed using stratified sampling strategy.

2.4. POST CLASSIFICATION CHANGE DETECTION

The post-classification change detection method is applied by simply comparing two classified images. It resulted in a complete from-to change matrix showing the changes between each class. Post-classification comparison proved to be the most effective technique as the data from two dates are separately classified thereby, minimizing the problem of normalizing for atmospheric and sensor differences between different dates.

2.5. MARKOV CHAIN

After the changes were detected, a simulation for the future has been performed. The produced land cover maps from the previous steps are used to model land cover dynamics quantitatively using Markov Chain analysis through the following steps:

1. The land cover changes for the two dates is provided as two images;
2. The interval of time between the two documented dates (date 1 and date 2) as well as the one between the second date and the date to be predicted (date 2 and date 3) are expressed as regular time steps (iterations);
3. A mask image is introduced in order to limit the development and change to another LULC category due to constraint rules. This modified the transition probability matrix values;
4. A transition probability matrix is produced. It expressed the possibility that a cell of a given land cover category would be changed into any other category;
5. A transition area matrix is derived. It contained the total area (in cells) expected to change in the next time period;
6. Finally, a group of conditional probability images are generated, one image for each category to express the probability that each cell will belong to the designated category in the next time.

3. RESULTS AND DISCUSSION

7. This study revealed the following findings: (1) generate thematic land cover maps for change comparison and dynamics using both of unsupervised and supervised methods. Unsupervised classification was based on ISODATA algorithm with 100 classes with signature file generation. (2) Merging the signature file of land cover classes depending on ground truth

information, topographic maps and google earth. (3) Supervised classification using merged signature file based on maximum likelihood algorithm has been used for classification because the other algorithms result was not satisfactory. (4) Segment based classification of 1999 and 2014 images were performed based on a window width of 3, a weight mean factor of 0.5, a weight variance factor of 0.5, and a similarity tolerance of 30. (5) The last part of the image classification process was the accuracy assessment. (6) Land cover change modeler and a Markov Chain analysis are used to determine present and future land cover trend and its implication in the study area.

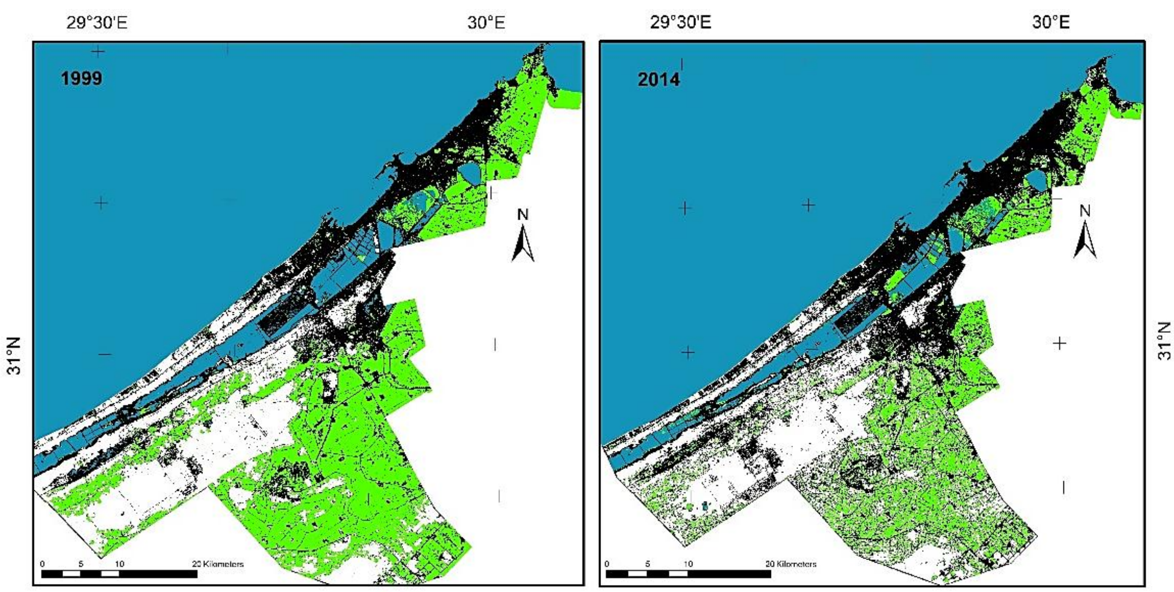
3.1. IMAGE CLASSIFICATION

Hybrid pixel-based classified images that combined unsupervised and supervised classification techniques. Image segmentation was based on a window width of 3, a weight mean factor of 0.5, a weight variance factor of 0.5, and a similarity tolerance of 30. Other similarity variances were also tested. The results of the image classification can be seen in Figures (2).

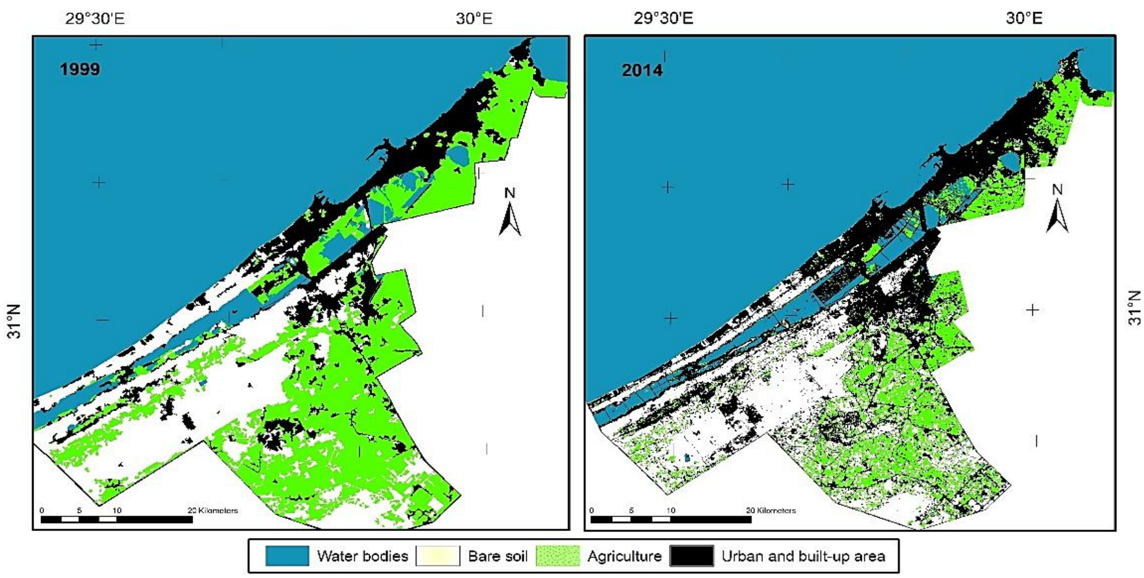
The classified change images were compared to the entire reference change image, generated from the original scene models, to evaluate the accuracy of each change detection method. Accuracy assessment was carried out using 200 points from field data and existing land cover maps. The results of the accuracy analysis were summarized by an overall accuracy percentage as showed in Table (3).

Table (3). Accuracy assessment of Landsat 1999 and 2014 images

	1999	**2014**
Overall pixel-based classification accuracy	83.33%	93.33%
Overall segmentation-based classification accuracy	86.67%	94.09%



a. Pixel-based classification results



b. Segment-based classification results

Figure (2). Classification results

3.2. LAND COVER CHANGE DETECTION

Based on the results of the land cover classification, change analysis for the study periods was performed. The change detection procedure involved classified images for both dates. Change detection results showed an urban expansion from 1999 to 2014. The built-up areas in the study area as shown in Table (4) increased from 306.86 km^2 in the year 1999 to 393.49 km^2 in the year 2014.

Table (4). Pixel-based classification statistic summary for during 1999 and 2014

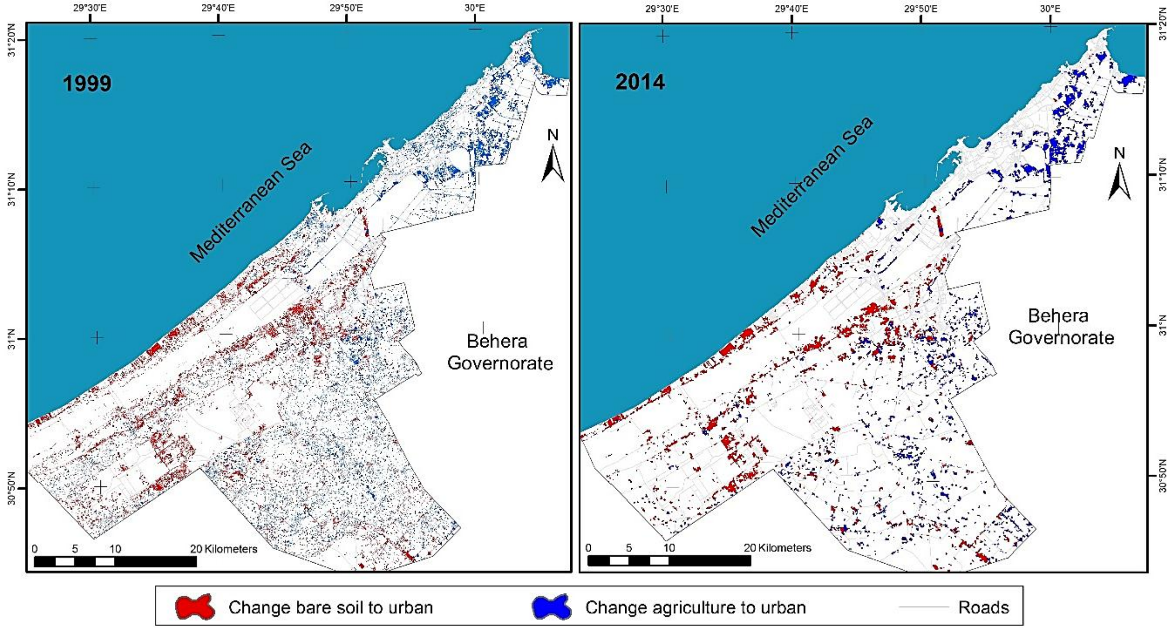
Land Cover Types	Year			
	1999		2014	
	Area (km^2)	Area (%)	Area (km^2)	Area (%)
Water Bodies	2011.37	57%	2044.58	58%
Bare Soil	523.02	15%	579.58	17%
Vegetation	660.52	19%	493.87	14%
Urban Areas	306.86	9%	393.49	11%

Change detection results using segment-based classification are presented in Table (5). It could be observed that there are big losses in agricultural areas resulted mainly from urban encroachment in the agricultural land.

Table (5). Segment-based classification statistic summary for during 1999 and 2014

Land Cover Types	Year			
	1999		2014	
	Area (km^2)	Area (%)	Area (km^2)	Area (%)
Water Bodies	2028.10	58%	2059.69	59%
Bare Soil	525.66	15%	616.04	18%
Vegetation	662.11	19%	477.31	14%
Urban Areas	285.72	8%	359.19	10%

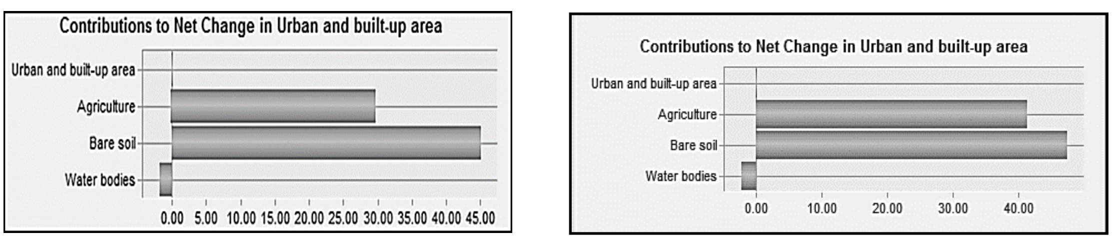
The main change of land cover was the change of agricultural land and urban or built-up land. A lot of agricultural lands are converted into urban or built-up land. The area coverage of bare soil land (unused land) is increased. The cause of increasing bare soil land is due to clearing of agricultural areas. The transition from both agriculture and bare soil to urban area is illustrated in Figure (3) and (4).



a. Segment-based classification b. Pixel-based classification

Figure (3). Transition from other categories to urban (1999-2014)

The contribution to urban area from other classes can be observed from Figure (4).



a. Segment-based classification b. Pixel-based classification

Figure (4). Contribution from other categories to Urban (1999-2014)

3.3. FUTURE PREDICTION

In this study, land cover predictions were based on the state of land cover in 1999 and 2014 using Markov models. The results of the Markov model are; a transition probability matrix, a transition areas matrix, and a set of conditional probability images. A transition matrix contains the probability of each land use/cover category which could change to every other category as presented in Table (6).

Table (6). Markov conditional probability of changing among land cover type

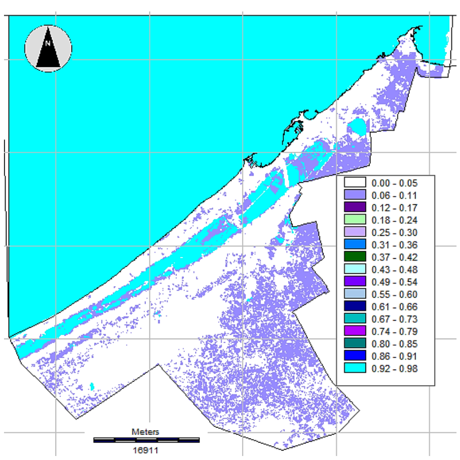
Class	Water Bodies	Bare Soil	Vegetation	Urban Areas
Water Bodies	0.9812	0.0039	0.0099	0.0050
Bare Soil	0.0142	0.5911	0.1469	0.2478
Vegetation	0.0880	0.3959	0.3052	0.2110
Urban Areas	0.0524	0.2429	0.2349	0.4698

Analysis based on the Markov transition probability matrix, it is clear that in the future years, the urban or built-up land will continue increasing, at the same time the agricultural land will continue decreasing. A transition areas matrix contains the number of pixels expected to change from each land cover type to each other land cover type over the specified time period. Table (7) showed the area coverage of different land use and land cover on year 2050 by square kilometers.

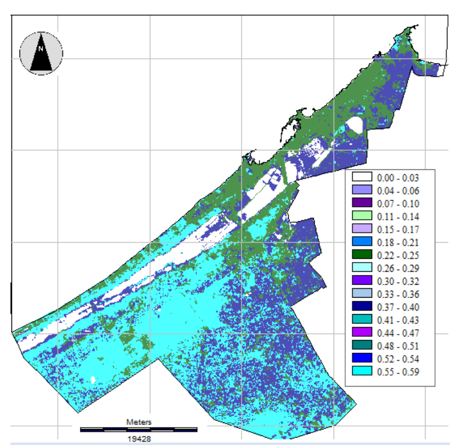
Table (7). Cells expected to be transformed to other classes (in km2) in year 2050

Class	Water Bodies	Bare Soil	Vegetation	Urban Areas
Water Bodies	2011.97	8.02	20.24	10.27
Bare Soil	8.75	364.16	90.47	152.66
Vegetation	41.87	188.44	145.27	100.44
Urban Areas	18.83	87.20	84.31	168.65

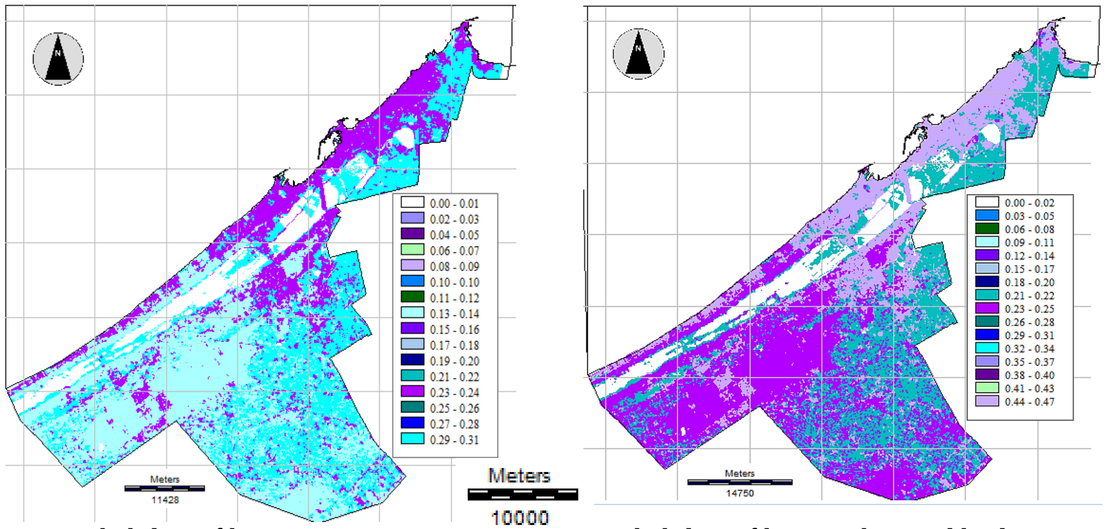
According to the result of simulation, it is expected that; the urban area would increase 263.38 km^2 in total and about 330.76 km^2 losses in agricultural lands and about 100.44 km^2 would be transformed to the urban area if the existing trend continued. Conditional probability images reported the probability that each land cover type would be found at each pixel after the specified time period. As it could be observed from Figure (5) that the probability was in scale of "0-1" and the pink color represented the highest probability which was "1" and the black color represented the lowest probability which is "0".



a. Probability of being water bodies



b. Probability of being bare soil



c. Probability of being vegetation d. Probability of being urban and built-up

Figure (5). The map of future land use and cover of Alexandria in year 2050

4. CONCLUSIONS

Land use/ land cover change analysis are the major information required for planning and decision making. This paper demonstrated techniques and tools for assessing land cover changes in Alexandria city up until 2050. Two kinds of classification approaches are performed to generate reliable and accurate classified maps of land use and land cover. The results indicated that the use of segment-based classification approach enhanced the classification accuracy and the ability to categorize land cover classes. Moreover, Markov model methods are found to have a high accuracy, so that it is used for predicting land cover of the year 2050 over the study area. Regardless of the used classification type, the results showed that urbanized areas increased gradually, while the agricultural areas have been continued to decrease. The observed trends of increasing urban encroachment in agricultural land and built-up areas and decreasing agricultural land in the study area could be explained by:

1. **The population growth forced people in agricultural areas to expand their lands in greater extent than before to cope up with the conditions and to sustain their life.**
2. **Infrastructure expansion on the expense of agriculture land has contributed to the reduction of those land use/ land cover types in the area.**
3. **Lake Mariout and its surrounding land constituted a window for urban growth for the city.**
4. **Building new industrial zones such as Borg El Arab, Om-Zegheow and El-Gharbaneyyat have increased rapidly the urban expansion.**

5. References

1. **Abdu K.K., Alias R.A., Faiza B., 2014. *A* review and analysis of image segmentation approaches in change detection analysis, International Journal of Advancements in Research & Technology, 3, Issue 11.**
2. **Abuelgasim, A. A., Ross, W. D., Gopal, S., and Woodcock, C. E., 1999. Change detection using adaptive fuzzy neural**

networks: environmental damage assessment after the Gulf War. Remote Sens. of Environment, 70, 208–223.

3. Adams, J. B., Sabol, D., Kapos, V., Filho, R. A., Roberts, D. A., Smith, M. O., and Gillespie, A. R., 1995. Classification of multispectral images based on fractions of end members: application to land-cover change in the Brazilian Amazon. Remote Sens. of Environment, 52, 137–154.
4. Almutairi, A. and Warner, T. A., 2010. Change Detection Accuracy and Image Properties: A Study Using Simulated Data, Remote Sens., 2, 1508-1529.
5. Alqurashi, A. F., Kumar L., 2013. Investigating the Use of Remote Sensing and GIS Techniques to Detect Land Use and Land Cover Change: A Review, Advances in Remote Sens., 2, 193-204
6. Al-sharif, A. A. A. and Pradhan, B. 2013. Monitoring and predicting land use change in Tripoli Metropolitan City using an integrated Markov chain and cellular automata models in GIS, Arab J Geosci,
7. Anderson, J.R.; Hardy, E.E.; Roach, J.T.; Witmer, R.E. A Land Use and Land Cover Classification System for Use with Remote Sensor Data; United States Government Printing Office: Washington, DC, USA, 1976.
8. Atasoy, M.; Karslý, F.; Biyik, C.; Demir, O. 2006. Determining Land Use Changes with Digital Photogrammetric Techniques. Env. Engineering Science, 23, 4, 712-721.
9. Blaschke, T., 2009, Object based image analysis for remote sensing, ISPRS Journal of Photogrammetry and Remote Sens., 65, 2-16.
10. Bora, D. J., Gupta, A. K., 2014. A New Approach towards Clustering based Color Image Segmentation, International Journal of Computer Applications (0975 – 8887) 107 –12.
11. Coppin, P. R., and Bauer, M. E., 1996. Digital change detection in forest ecosystems with remote sensing imagery. Remote Sens. Reviews, 13, 207–234.
12. Dehvari A. and Heck R. J., 2009. Comparison of object-based and pixel based infrared airborne image classification methods using DEM thematic layer, Journal of Geography and Regional Planning, 2, 4, 086-096.
13. Dean AM, Smith GM, 2003. An evaluation of per-parcel land covers mapping using maximum likelihood class probabilities. Int. J. Remote Sens. 24:2905–2920.
14. Dwivedi, R.S.; Sreenivas K.; Ramana, K.V. 2005. Land-use/land-cover change analysis in part of Ethiopia using Landsat Thematic Mapper data. Int. J. Remote Sens., 26 (7), 1285-1287.
15. Eastman JR. (2012). *IDRISI Selva Manual.* Worcester, MA: Clark Labs, Clark University. 322p. provided as a PDF with the IDRISI Selva software package.
16. El-Raey, M., Nasr, S., El-Hattab, M., Frihy, O., 1995. Change detection of Rosetta Promontory over the last forty years. Int. J. Remote Sen. 16, 825–834.
17. Fan, F.; Weng, Q.; Wang, Y. 2007, Land use land cover change in Guangzhou, China, from 1998 to 2003, based on Landsat TM/ETM+ imagery. *Sensors,* 7, 1323-1342.
18. IM, J., Jensen, J. R. and Tullis, J. A. 2008, Object-based change detection using correlation image analysis and image segmentation, Int. J. Remote Sens., 29, 2, 399–423

19. Lu, D., Mausel P., Brondi´Zio, E. and Moran, E., 2004. Change detection techniques. Int. J. Remote Sens., 25, 12, 2365–2407.

20. Lu D, Weng Q, 2007. A survey of image classification methods and techniques for improving classification performance. Int. J. Remote Sens. 28: 5,823 -870

21. Macleod, R.; Congalton, R. A., 1998. Quantitative comparison of change detection algorithms for monitoring eelgrass from remotely sensed data. Photogramm. Eng. Remote Sens. 64, 207-216.

22. Macomber, S. A., and Woodcock, C. E., 1994. Mapping and Monitoring Conifer Mortality Using Remote Sensing in the Lake Tahoe Basin. Remote Sens. of Environment, 50, 255–266.

23. Metternicht, G., 1999. Change detection assessment using fuzzy sets and remotely sensed data: an application of topographic map revision. ISPRS Journal of Photogrammetry and Remote Sens., 54, 221–233.

24. Mubea, K. W. Ngigi, T. G. and Mundia, C. N. 2010. Assessing application of Markov chain analysis in predicting land cover change: a case study of Nakuru municipality, JAGST, 12, 2.

25. Otunga, C. J., Odindi, O. Mutanga, 2014. Land Use Land Cover Change in the fringe of eThekwini Municipality: Implications for urban green spaces using remote sensing, South African Journal of Geomatics, 3, 2.

26. Petit, C. C., and Lambin, E. F., 2001, Integration of multi-source remote sensing data for land cover change detection. International Journal of Geographical Information Science, 15, 785–803.

27. Ridd, M. K., and Liu, J., 1998. A comparison of four algorithms for change detection in an urban environment. Remote Sens. of Environment, 63, 95–100.

28. Robb D. M. and Congalton R. G., 1998. A Quantitative Comparison of Change-Detection Algorithms for Monitoring Eelgrass from Remotely Sensed Data, Photogramm. Eng. Remote Sens. 64, 3, 207-216.

29. Seneta, E. 1996. Markov and the birth of chain dependence theory. International Statistical; Review 64, 255–263.

30. Seto, K.C.; Woodcock, C.E.; Song, C.; Huang, X.; Lu, J.; Kaufmann, R.K. Monitoring land use change in the Pearl River Delta using Landsat TM. Int. J. Remote Sens. 2002, 23, (10), 1985-2004.

31. Shakelford AK, Davis CH, 2003. A Combined Fuzzy Pixel-Based and Object-Based Approach for classification of High-Resolution Multispectral Data over Urban Areas. IEEE.Trans. Geosci. Remote Sens. 41, (10).

32. Singh, A. 1989. Digital change detection techniques using remotely sensed data. Int. J. Remote Sens., 10, 989-1003.

33. Subedi, P., Subedi, K., Thapa, B., 2013. Application of a Hybrid Cellular Automaton – Markov (CA-Markov) Model in Land-Use Change Prediction: A Case Study of Saddle Creek Drainage Basin, Florida, Applied Ecology and Environmental Sciences, 1, 6, 126-132.

34. Zhao, G.X. Lin, G.; Warner. 2004. T. Using Thematic Mapper data for change detection and sustainable use of cultivated land: a case study in the Yellow River delta, China. Int. J. Remote Sens. 25 (13), 2509-2522.

التقييم والتنبؤ ومحاكاة التغييرات المستقبلية فى الغلاف الأرضي باستخدام تقنيات الاستشعار عن بعد ونظم المعلومات الجغرافية

سهى أحمد[١]، محمد الراعى[٢]

[١،٢]معهد الدراسات العليا والبحوث – جامعة الاسكندرية

[2]mohamed.elraey@alexu.edu.eg،[1]igsr.soha.ahmed@alexu.edu.eg

الملخص العربي :

تُعد دراسة التغيرات فى الغطاء الأرضي أمرًا أساسيًا للحد من عدد كبير من المخاطر البيئية المحتملة، بما في ذلك التغيرات المناخية والزلازل والانهيارات الأرضية والتعرية والفيضانات وغيرها من المخاطر. إن التغيرات السريعة فى الغطاء الأرضي ومايتبعها من تغيرات فى الغطاء الأرضى لا تؤثر فقط سلبًا على البيئة بل تسبب ايضاً فى خسائر للمجتمع والاقتصاد. وبالتالي، فهناك ضرورة إلى معلومات دقيقة مفصلة عن تلك التغييرات لتحديث الخرائط الطبوغرافية ولتقديم معلومات لصناع القرار لدعم التنمية المستدامة، وإدارة الموارد الطبيعية. الدراسة المقدمة تهدف الى استخراج معلومات حديثة وموثوقة بها عن الغطاء الأرضي والتغيرات به باستخدام صورتان للقمر الصناعى الامريكي لاندسات (Landsat-5 (TM و(Landsat-8 OLI) ذات الدقة المكانية ٣٠ متر والتابع لوكالة ناسا للفضاء على مدى ١٥ عامًا من عام ١٩٩٩ إلى عام ٢٠١٤. تناولت الدراسة تطبيق طريقتان لتصنيف الغطاء الأرضي، الطريقة الاولى تعتمد على التصنيف التقليدي القائم على مستوي البيكسل والثانية تعتمد على تقسيم صورة القمر الصناعى الى اجزاء ومناطق متجانسة. تم استخدام نماذج سلاسل ماركوف للتنبؤ ومحاكاة إنتاج خريطة التغييرات المستقبلية فى الغطاء الأرضي حتى عام ٢٠٥٠. وأظهرت النتائج أن عمليات تصنيف الصورالفضائية بطريقة التقسيم الى مناطق متجانسة أدت إلى دقة تصنيف أفضل فقد كانت ٨٦.٦٧٪ في عام ١٩٩٩ و ٩٤.٠٩٪ في عام ٢٠١٤ فى حين ان التصنيف التقليدي اظهر ضعف فى الدقة حيث ظهرت الدقة ٨٣.٣٣٪ و ٩٣.٣٣٪ في عام ١٩٩٩ و٢٠١٤ على التوالى.