LNCS 11623

Sanjay Misra · Osvaldo Gervasi ·
Beniamino Murgante · Elena Stankova ·
Vladimir Korkhov · Carmelo Torre ·
Ana Maria A. C. Rocha · David Taniar ·
Bernady O. Apduhan · Eufemia Tarantino (Eds.)

Computational Science and Its Applications – ICCSA 2019

19th International Conference
Saint Petersburg, Russia, July 1–4, 2019
Proceedings, Part V

5 Part V

INTERNATIONAL CONFERENCE ON COMPUTATIONAL SCIENCE AND ITS APPLICATIONS
ICCSA 2019

Springer

Lecture Notes in Computer Science **11623**

Commenced Publication in 1973
Founding and Former Series Editors:
Gerhard Goos, Juris Hartmanis, and Jan van Leeuwen

More information about this series at http://www.springer.com/series/7407

Sanjay Misra · Osvaldo Gervasi ·
Beniamino Murgante · Elena Stankova ·
Vladimir Korkhov · Carmelo Torre ·
Ana Maria A. C. Rocha ·
David Taniar · Bernady O. Apduhan ·
Eufemia Tarantino (Eds.)

Computational Science and Its Applications – ICCSA 2019

19th International Conference
Saint Petersburg, Russia, July 1–4, 2019
Proceedings, Part V

Springer

A Comparative Analysis of Temporal Changes in Urban Land Use Resorting to Advanced Remote Sensing and GIS in Karaj, Iran and Luxor, Egypt

Abdelaziz Elfadaly[1,2,3], Beniamino Murgante[4], Mohamad Molaei Qelichi[5(✉)], Rosa Lasaponara[1], and Ali Hosseini[5]

[1] Italian National Research Council, C.da Santa Loja, Potenza, Tito Scalo, Italy
[2] National Authority for Remote Sensing and Space Sciences, Cairo, Egypt
[3] Department of European and Mediterranean Cultures, University of Basilicata, Matera, Italy
[4] School of Engineering, University of Basilicata, Potenza, Italy
beniamino.murgante@unibas.it
[5] Faculty of Geography, University of Tehran, Tehran, Iran
Molaeil@ut.ac.ir

Abstract. As many developing countries, Iranian and Egyptian cities are growing in population and physically expanding at a high rate. The uncontrolled scattered construction causes loss of orchards, agricultural lands as well as spatial chaos, traffic congestion and increasing costs of municipal services. As a consequence, this also induces a loss of identity and social characteristics of neighborhoods, poor quality of life and degradation of natural landscapes, etc. To face with these issues, it is important to quantify trend and the rate of land cover conversion in order to support plan for a rational land use policy. The main purpose of this research is to set up low cost and reliable tools useful for the monitoring of the urban growth. In this paper, multi-temporal satellite data (Landsat TM 1984, Landsat TM 1998 and L8 2016) have been analyzed for investigating and assessing the effects of the urban expansion in Karaj (Iran) and Luxor (Egypt). According to the results obtained from change detection analysis, both of the investigated sites clearly exhibit an increasing trend in urban expansion much more evident in the case of Luxor than Karaj area. The integration between remote sensing and GIS and the joint use of analytical methods for quantitative-qualitative assessment enable the identification of changes and the mapping of new planned and unplanned urban construction. The availability of timely information free available from NASA web site and the data processing herein adopted provide useful information for supporting planning and sustainable developing policies.

Keywords: Urban distribution · Land use changes · Urban growth · Karaj (Iran) · Luxor (Egypt)

S. Misra et al. (Eds.): ICCSA 2019, LNCS 11623, pp. 689–703, 2019.
https://doi.org/10.1007/978-3-030-24308-1_54

1 Introduction

The urbanization is recognized as one of the most irreversible human impacts on environment causing loss of soil, altering hydrological and biogeochemical cycles, modifying energy demand, changing precipitation patterns at scales of hundreds of square kilometers [1] therefore, altering the climate. Moreover, unplanned human settlement consumes land at an alarming rate, fragments habitats reduces biodiversity and produces unsustainable and unlivable city with the lack of open space and arterial grids. This poses serious threats to high-value of urban ecosystems and makes the need for sustainable urban planning and monitoring an urgent priority [2–4]. As in other parts of the world, also in Iran and Egypt, the rapid development of urbanization has been causing critical environmental problems in different areas.

Actually, in Egypt uninhabited lands represent about 95% of the total area. However, the majority of the population is concentrated around the Nile River. This unbalanced distribution causes serious social and economic problems. In particular, the current fast growing of Luxor region is expected to further increase over the next twenty years with at least a doubling in population. The recent completion of a Luxor Bridge and the nearby expansion of a port for the cruise at the south of Luxor City, will favor informal, unplanned development in the southern part of the area. Unplanned urban sprawl will result in negative consequences for the future prosperity of the whole area that is actually one of the biggest and most famous tourist attractions also due to the discovery of the Tutankhamen tomb in 1922. Timely actions to stem this undesirable growth are essential. To this aim, some authors as [5] suggest that a new attractive town can become a magnet for a new planned development in the Luxor region.

Similar critical situations are also present in Iran, as for example in Karaj metropolis whose periphery is involved in an extensive urban expansion and needs to face the relative critical challenges as currently occurring for the whole national territory [6]. This is due to interrelate economic, social and political factors, which induce diffuse changes in lifestyles and drive the evolution of the city so that urban suburbs moved into rural lands involving the conversion of open space into built-up areas.

This current situation and the expected future scenarios impose the need of planning and monitoring. To this aim, the availability of reliable information on the past and current conditions is a critical point for defining and planning potential future scenarios. In this context, satellite data (today also available free of charge) can provide both (i) historical time-series data set and (ii) timely updated information related to the current urban spatial structure and city edges as well as parameters to assess urban effects.

The main purpose of this research is the use of satellite Landsat data for the assessment of urban distribution in both Karaj and Luxor city, respectively in Iran and Egypt, as a comparative analysis. The study is addressed to the investigation of urban growth pattern process for the detection and analysis of changes in urban areas at Karaj and Luxor occurred over the same time period spanning from 1984 to 2016.

2 Study Area

Luxor city is located 600 km (DMS Long 32° 38′ 22.6932″ E, DMS Lat 25° 41′ 14.0748″ N) south of Cairo on the west and east bank of the River Nile [7]. On the Nile‘s west bank, across from Luxor, is Thebes, the capital of Egypt from around 2000 to 1075 B.C.E. (Middle and New Kingdoms). The area is one of richest in antiquity treasures and attractive, but today threatened by urban sprawl and many parts of the Luxor city is lacking infrastructure (Fig. 1).

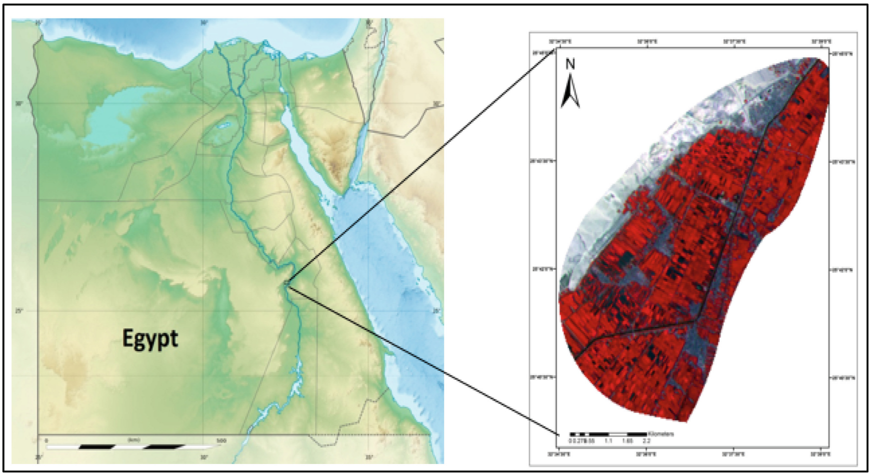

Fig. 1. Study area of Luxor city, Egypt

Karaj is capital of Alborz province in Iran, spanning between latitudes 35° 67′–36° 14 ′N and longitudes 50° 56′–51° 42 ′E and covers a total area of about 141 km^2. [8]. Over the last three decades, Karaj has been experiencing a significantly growing mostly due to its socioeconomic attractions. Past developments and current challenges have led to some instability in various aspects of environmental, socio-cultural, political-security, economic, spatial and etc. [9] (Fig. 2).

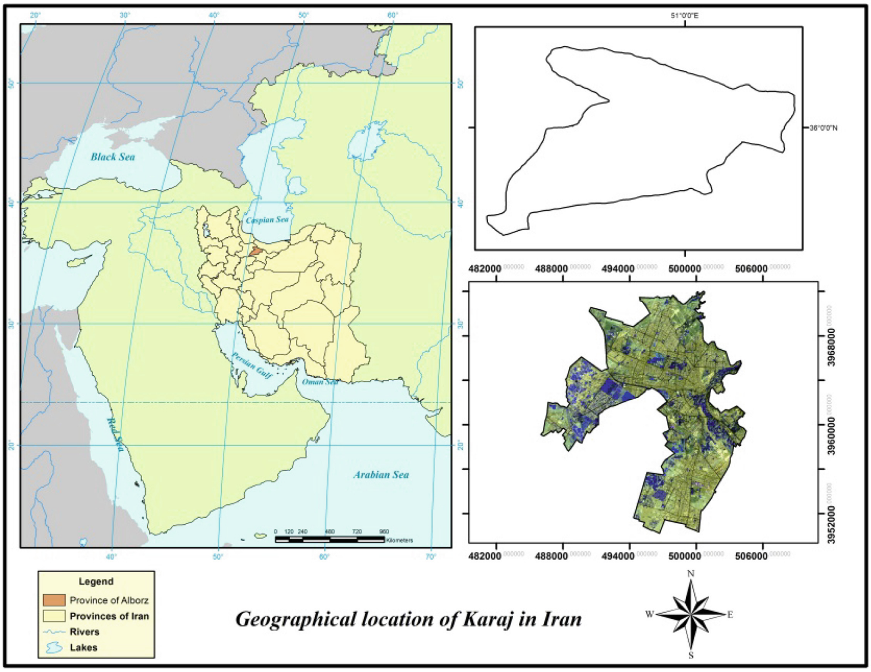

Fig. 2. Study area of Karaj city, Iran [10]

3 Material and Methodology

3.1 Materials

For both of the two study areas, multi-temporal data sets of Landsat TM 1984, 1998 and L8 2016 images were collected free of charge from the USGS and GLCF web sites. Image processing was done using tools available in Arc GIS 10.3 and Envi 5.1 software. The analyses were addressed to detect the changes occurred in the urban areas based on the comparison of the outputs obtained from the classification and geospatial analysis of the past and present data (Table 1).

Table 1. Data collection properties of the study areas (Luxor and Karaj).

Satellite	Sensor	Resolution (M)	Acquisition date
Landsat	TM	30 m	Sep 1984
Landsat	TM	30 m	Oct 1998
Landsat	L8	30 m	Sep 2016

3.2 Methodology

The selected images were geometrically and atmospherically corrected, in order to remove the effect of the atmosphere and make the images of 1984, 1998 and 2016 comparable. To this aim, the dark object subtraction was applied. After the pre-processing, the change detection was made by comparing the results from the classification.

Classification enables the clusterization of similar targets on the basis of the measured reflection values which depend on the local characteristics of the earth surface. In other words, there is a relationship between land cover and measured reflection values using several spectral bands (multi-spectral classification). Land cover types were identified on the basis of their spectral properties, classified and mapped for each study area and each time data set using both unsupervised, supervised classifications, and post supervised classification in order to capture the statistical patterns of the urban distribution.

Unsupervised Classification of Images
Normally there are two types of the algorithm (K-means and ISODATA) to perform the unsupervised classification [11]. In unsupervised classification method, clustering is obtained according to the number of classes required and the digital number exhibited by the processed pixels. Result from un-supervised classified is useful adopted as a reference/preliminary step for understanding the distribution of pixel values. In this research the ISODATA unsupervised classification was used for extracting the urban layer and carry on a preliminary analysis of the statistical distribution pattern.

Supervised Classification of Images
The classification of multi-temporal data set can inform us about the changes occurred over time i.e. quantify the area Involved in land cover change as for example variation from vegetation cover to urban. In supervised classification method, There are different image algorithms such as Parallelepiped, Minimum Distance, Maximum Likelihood, Binary Encoding, etc. [12, 13]. The categorization is done using the training sets (signatures) provided by the user on the basis of field knowledge. In this research, Maximum Likelihood Classification was applied to the spectral bands of each date.

Post Classification of Images
The accuracy of supervised image classification is a function of the consistency between the algorithms and input data [14]. The overall accuracy and Kappa coefficient was calculated for each study area on the basis of the Confusion Matrix (Table 2) which generates random subset of the training sets. The accuracy is generally quite high due to the fact that having an excellent knowledge of the both study areas we can provide reliable training sets related both to urban cover and other areas.

Table 2. Kappa coefficient of ROIs for each period

Year	Luxor		Karaj	
	Kappa coefficient	Overall accuracy	Kappa coefficient	Overall accuracy
1984	0.9974	99.8387%	0.9909	99.4142%
1998	0.9967	99.7976%	0.9938	99.5652%
2016	0.9925	99.5290%	0.9949	99.6606%

Getis-Ord and Hot Spot for Analyzing Spatial Distribution

Spatial autocorrelation in GIS helps understand the degree to which one object is similar to other nearby objects [15]. The process of urban growth associated with the study areas of Karaj and Luxor has analyzed also using spatial autocorrelation analysis to assess the spatial pattern of urban land use [16, 17]. Data derived from satellite images (using ENVI software) have been further processed and analyzed by using Getis-Ord (General G) statistic (in ArcGIS) to assess the degree of clustering by the identification of both "hot spots" and "cold spots". Getis-Ord Gi* statistic is denoted as Eq. 1 [18–22]:

$$\text{Getis}-\text{Ord}\,G_i^* = \frac{\sum_{j=1}^{n} w_{ij}x_j - \bar{X}\sum_{j=1}^{n} w_{ij}}{S\sqrt{\frac{\left[n\sum_{j=1}^{n} w_{ij}^2 - \left(\sum_{j=1}^{n} w_{ij}\right)\right.}{n-1}}} \tag{1}$$

In formula 1, X_j represents the value of attributes to features J. Wij is spatial weight between i and j features and (n) is the number of features: G_i is kind of Z score, so no more calculations are required (Table 3).

Table 3. Classification of Z-Score and P-value in analysing of spatial patterns

Z-Score	p-value	Type of spatial distribution
<−2.58	0.01	High-Clusters
−2.58 – 1.96	0.05	–
−1.96 – 1.65	0.10	Low-Clusters
−1.65 – 1.65	–	Random
1.65 – 1.96	0.10	Low-Clusters
1.96 – 2.58	0.05	–
>2.58	0.01	High-Clusters

NDVI Index

The Normalized Difference Vegetation Index (NDVI) is a numerical indicator that uses the red and near-infrared bands of the electromagnetic spectrum [23] and is one of the most commonly used vegetation index [24]. The NDVI algorithm subtracts the red reflectance values from the near-infrared and divides it by the sum of near-infrared and red bands, as in Eq. 2.

$$[\text{NDVI} = (\text{NIR} - \text{RED})/(\text{NIR} + \text{RED})] \tag{2}$$

4 Results

In this study, satellite images, free downloaded from the NASA web site, have been analyzed in order to detect and quantify urban expansion from 1984 to 2016 in Luxor (Egypt) and Karaj (Iran) area both involved in a rapid urbanization process. The changes have been captured by the differences revealed from supervised classification applied to the scenes acquired at different times for both Luxor and Karaj area. The results obtained from the classification images of the three dates are used to calculate the area of change related to different land covers. In particular, the analysis of Landsat TM and L8 imagery in Luxor revealed that the urban area increased about 955 km^2 from 1984 to 1998; about 2.739 km^2 from 1998 to 2016. In another hand, the urban area in Karaj increased about 13.695 km^2 from 1984 to 1998, and about 5.56 km^2 from 1998 to 2016. (Table 4) (Figs. 3 and 4). As a whole, over time between (1984 to 2016), the urban area clearly increased for both of the two investigated areas (Figs. 5 and 6).

Table 4. Total changes in the urban area by Km^2 in (Luxor and Karaj).

Study area	1984-9	Change detection ($\pm Km^2$)	1998-10	Change detection ($\pm Km^2$)	2016-9
Luxor	10.873 km^2	.955 km^2	11.828 km^2	2.739 km^2	14.567 km^2
Karaj	43.420 km^2	13.695 km^2	57.115 km^2	5.56 km^2	62.675 km^2

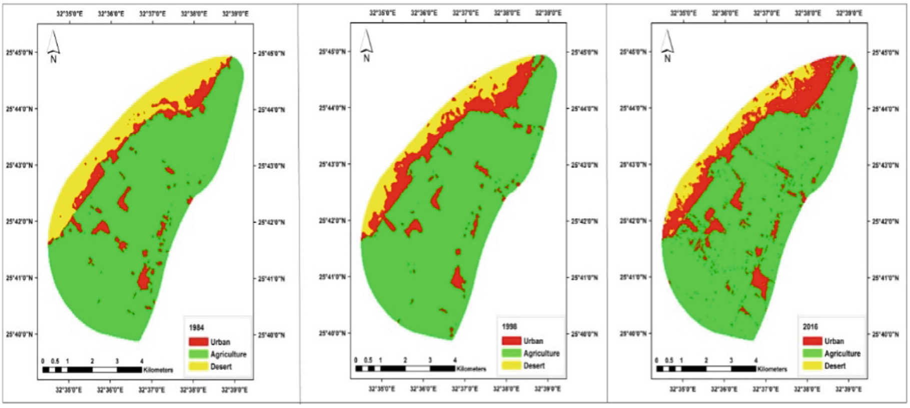

Fig. 3. Supervised classification in study area of Luxor between (1984 to 2016)

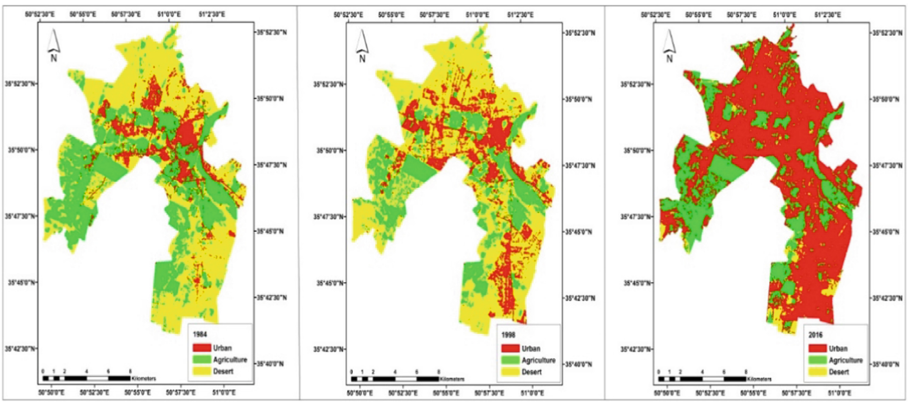

Fig. 4. Supervised classification in the study area of Karaj between (1984 to 2016)

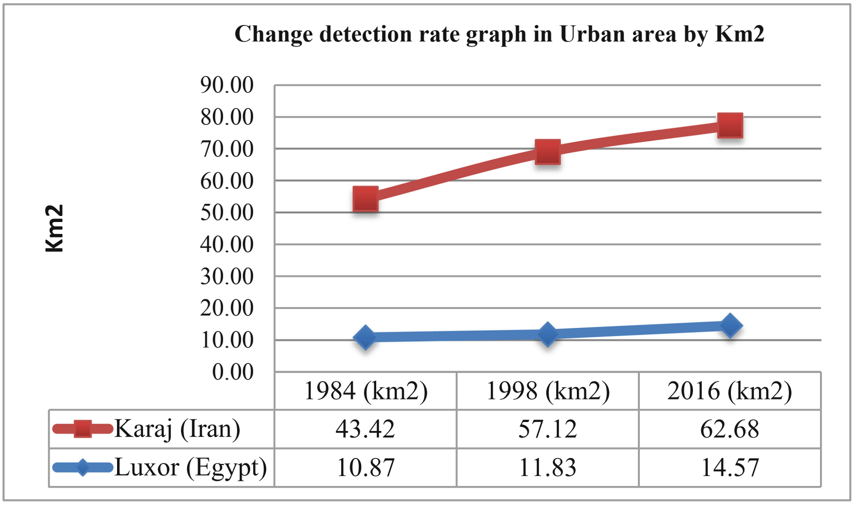

Fig. 5. Graph of the total changes in the urban areas in study area of Karaj and Luxor between (1984 to 2016)

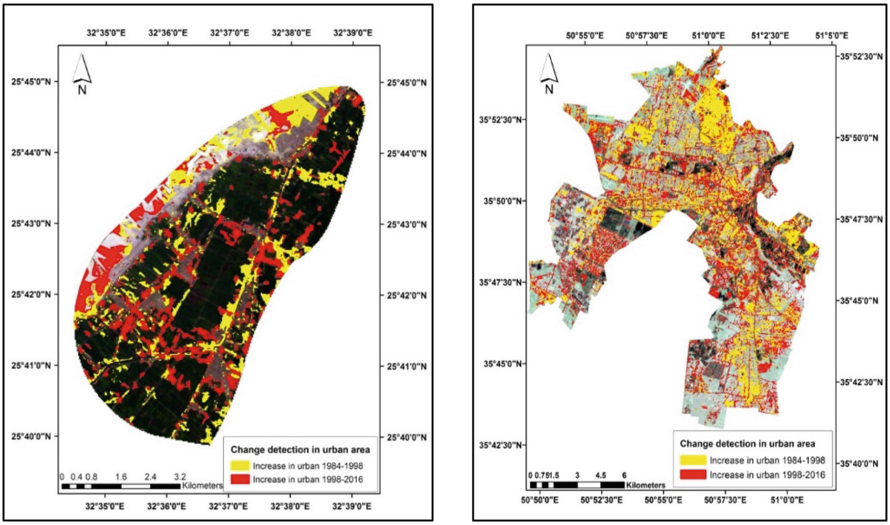

Fig. 6. Total changes in the urban Layers in study area of Luxor and Karaj between (1984 to 2016)

The identified changes have been further analyzed by geospatial investigation made on the NDVI maps computed for the same data set as for the classifications [25, 26]. For calculating the pattern of spatial distribution in urban areas the High/Low Clustering tool was used. Z-Score calculation highlighted the areas with high or low values that are clustered accordingly. The General G in the first period Luxor city at 1984 (Fig. 7) is 0.000258 and statistic Z is approximate −0.293. However, the statistics for the 2nd period 1998 (Fig. 8) is 0.000054 and statistic Z is approximate −1.480. Although the intensity of this concentration is reduced, the changes are minimal. Finally, in the 2016 year (Fig. 9) the G statistic is 0.000040 and Z-Score is −0.0843. In all periods the Z-Score value is negative, this means that low values cluster together. On the other hand, in the case study of Karaj, results show that in the first year 1984 (Fig. 10), the General G is 0.000024 and statistic Z is approximate −1.628. Also, statistics for the 2nd period 1998 (Fig. 11) is 0.000067 and statistic Z is −0.907. Finally, in the 2016 year, the G statistic is 0.000006 and Z-Score are −2.729 (Fig. 12).

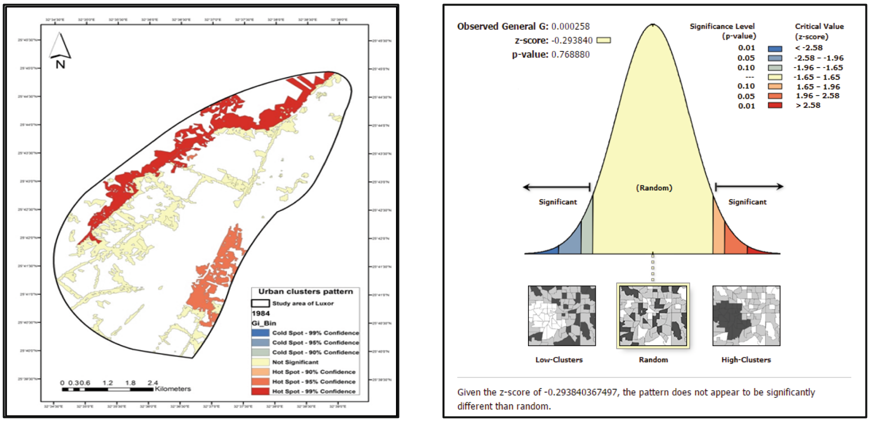

Fig. 7. Spatial Autocorrelation changes in urban clusters in the study area of Luxor in 1984

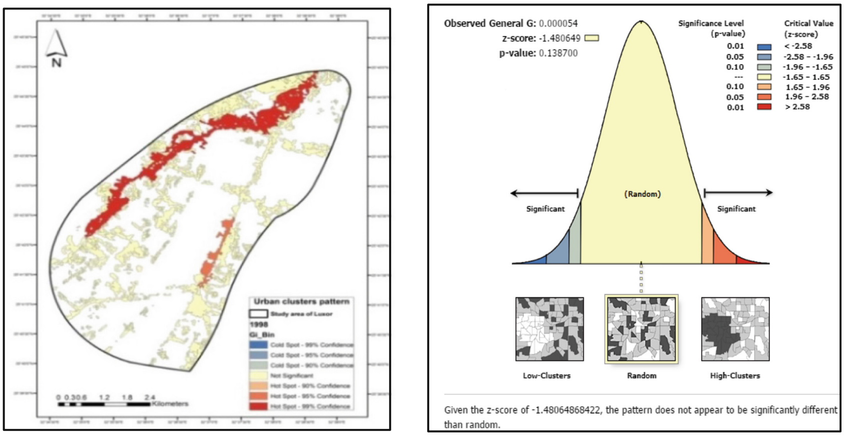

Fig. 8. Spatial Autocorrelation changes in urban clusters in the study area of Luxor in 1998

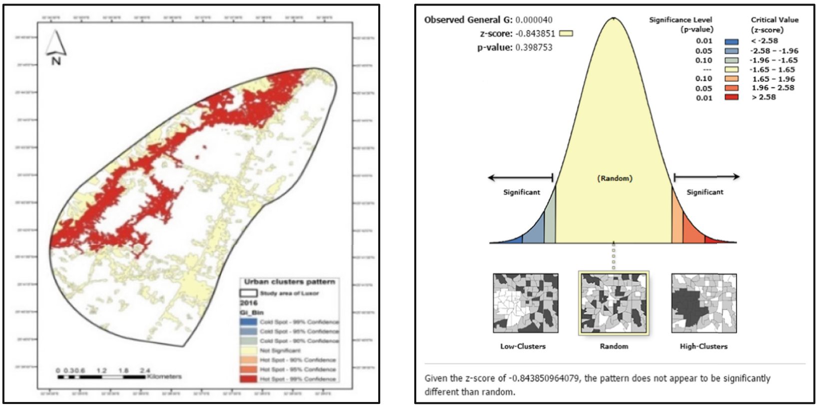

Fig. 9. Spatial Autocorrelation changes in urban clusters in the study area of Luxor in 2016

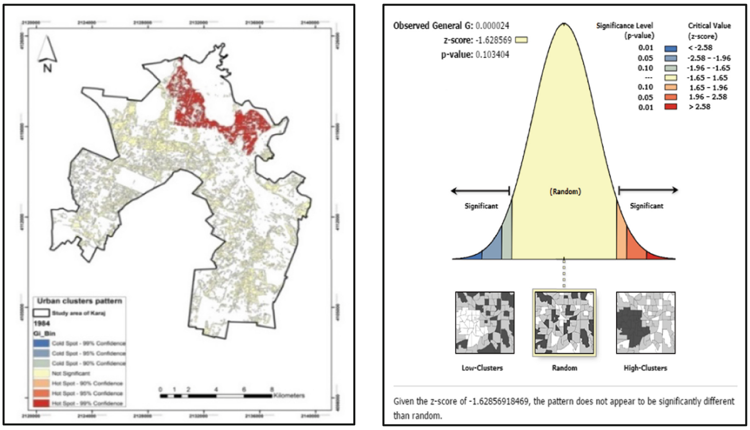

Fig. 10. Spatial Autocorrelation changes in urban clusters in the study area of Karaj in 1984

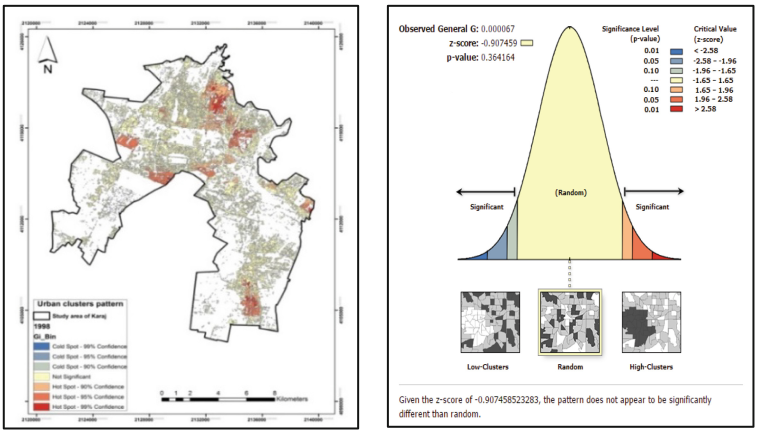

Fig. 11. Spatial Autocorrelation changes in urban clusters in the study area of Karaj in 1998

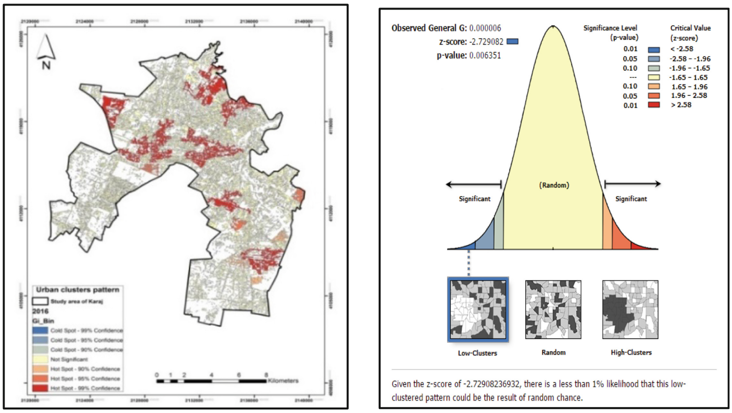

Fig. 12. Spatial Autocorrelation changes in urban clusters in the study area of Karaj in 2016

NDVI analysis was taking place in both of the study areas in order to measure the effects of urban sprawling in the vegetated areas [27]. In Luxor area, the NDVI value highlighted and identified that the change in the vegetation value from 1984 to 2016 was enormous [28]. These effects are very clear in the agricultural land around the urban area in 2016. For Karaj area in the study made during the same period as for Luxor, vegetated areas were "invaded" by urban but less than in Luxor area (Figs. 13 and 14).

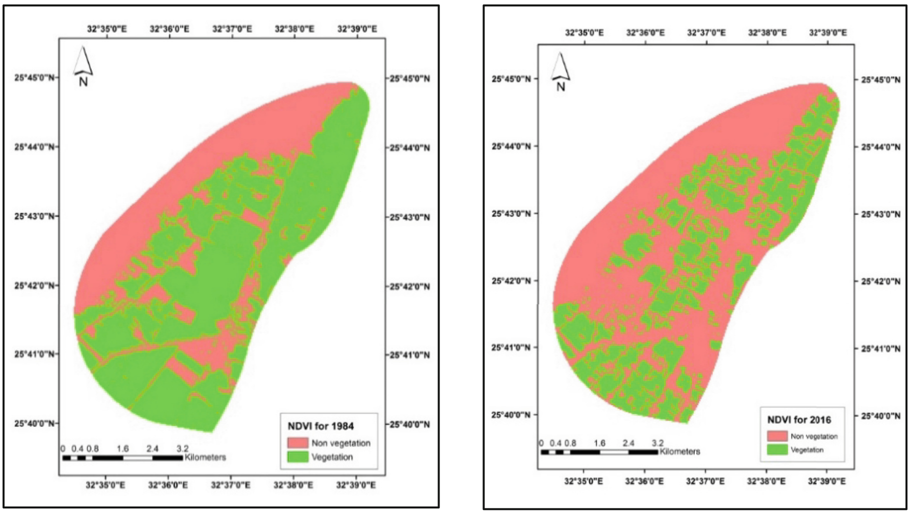

Fig. 13. Changes in vegetation index of NDVI in study area of Luxor

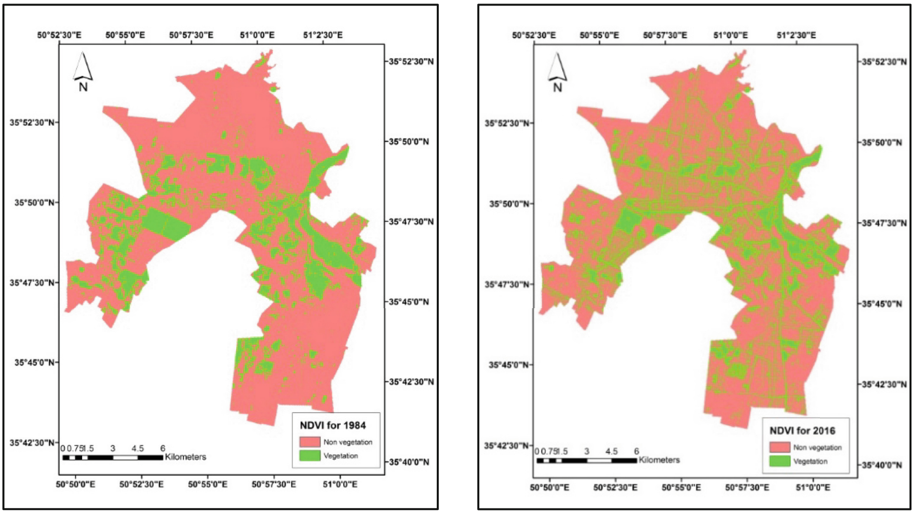

Fig. 14. Changes in vegetation index of NDVI in study area of Karaj

5 Discussions

In this research, Maximum Likelihood Classification was used along with geospatial analysis in order to capture the change from 1984 to 2016 in urban areas and characterize their statistical patterns. Two study areas were selected for a comparative investigation, one located in Egypt (Luxor) and one located in Iran (Karaj). The Luxor area is one of richest in antiquity treasures and attractive, but unfortunately, today threatened by urban sprawl and many parts of the Luxor city is lacking infrastructure [29, 30]. Karaj is the capital of Alborz Province in Iran. Over the last three decades, Karaj has been experiencing a significantly growing mostly due to its socioeconomic attractions [10]. Past developments and current challenge have led to some instability in various aspects of environmental, socio-cultural, political-security, economic, spatial and etc.

Changes in the urban areas for both of the investigated sites have been conducted using supervised and unsupervised classification applied to multi-temporal data. In particular; the ISODATA unsupervised classification was used for extracting the urban layer and carry on a preliminary analysis of the statistical distribution patterns. Successively the supervised classification technique, based on maximum Likelihood algorithm, has been used to improve the results from the unsupervised classification. The final categorization has been done using the training sets (signatures) obtained on the basis of authors' field knowledge. The overall accuracy and Kappa coefficient were calculated to assess the reliability of the classification results.

Results, higher than 99%, were obtained for both Luxor and Karaj. For each study area, the maps of changes were obtained by comparison (subtraction) of the multi-date supervised classification. The change detection analysis revealed that, over time between (1984 to 2016), the urban area clearly increased for both of the two investigated areas (see Figs. 5 and 6). To better characterize these changes captured from the comparison of multi-date and multi-spectral classification we focalized on the multi-temporal pattern variation of NDVI maps. The high clustered pattern in the urban area in Luxor was related by the high numbers of Temples like Medinet Habu, Ramesseum temple, Set I, Hatshepsut temple, and the Valley of the Kings. Many of the people there are depended on the tourism activities, so they prefer to live near to the historical places. In the fact to prevent further urban sprawl and the deleterious effects of unplanned development on the cultural heritage as well as on the population's living conditions, new opportunities for the citizens of the region should be favoured and created also working at the development of the plan for the City of Luxor.

On another hand, also the study area of Karaj has shown similar trends. Its physical development is one of the main critical challenges and caused the loss of orchards and agricultural lands, low level quality in some parts of suburbs and increased the cost of municipal services. Other problems include the scattered construction, traffic congestion, loss of identity and social characteristics of neighborhoods, pollution, loss of natural landscapes, poor quality of life and etc.

NDVI index was used to capture the urban vegetation health, both in urban and non-urban areas because degradation of ecosystem vegetation, or a decrease in green, would be reflected in a decrease in NDVI value. Generally, we can see that the loss of vegetation caused by the urban sprawl in Luxor area is quite high with negative effects, but these effects were less in the area of Karaj which appears in the results of NDVI maps. These effects in Luxor area are a result of population growth in the urban area which included many of archaeological temples. The effects of urban sprawling in Karaj seem to have been a positive phenomenon unlike Luxor area as evident by the development of the trees and parks around the transportation networks.

6 Conclusion

The paper aims to set up low cost and reliable tools useful for the monitoring of the urban growth using multi-temporal satellite data. In this paper, multi-temporal satellite data (Landsat TM 1984, Landsat TM 1998 and L8 2016) have been analyzed for investigating and assessing the effects of the urban expansion in Karaj (Iran) and Luxor (Egypt). According to the results obtained from the multi-spectral and multi-temporal classifications of all the analyzed periods (shown Figs. 3 to 6); both of the investigated areas clearly exhibited an increasing trend in urban expansion actually much more evident in the case of Luxor than Karaj area.

In Luxor, land uses in the north and west regions had a high clustered pattern in the urban layer, but the majority of the areas are characterized by random pattern between 1984 to 2016. Another high clustered area was located at south side of Luxor, but from 1998 to 2016 this clusterization appeared lower.

In the case of Karaj; results showed that in 1984, urban had high clustered areas at the north side of the city, whereas other areas did not show a significant pattern but appeared quite randomly distributed. According to the NDVI index, the vegetation value decreased in both of the two areas from 1984 to 2016 because of urban growth, but different behaviors were observed for the two sites. In the Luxor area most of the "vegetated pixels" were related to agricultural activities. Whereas, in the study area of Karaj most of the "vegetated pixels" were parks and trees around the roads. It means that the urban growth in Karaj has had positive effects unlike in Luxor.

There is a need to suggest areas for further studies. Firstly, it is aimed to develop a research study on the effectiveness of image classification techniques in urban sprawl analysis and modeling. Secondly, it is aimed to gather the satellite data from Sentinel 2 with additional improvement.

References

1. Kaufmann, R.K., Seto, K.C., Schneider, A., Liu, Z., Zhou, L., Wang, W.: Climate response to rapid urban growth: evidence of a human-induced precipitation deficit. J. Clim. **20**(10), 2299–2306 (2007)
2. Amato, F., Maimone, B.A., Martellozzo, F., Nolè, G., Murgante, B.: The effects of urban policies on the development of urban areas. Sustainability **8**, 297 (2016)
3. Romano, B., Zullo, F.: The urban transformation of Italy's Adriatic coastal strip: fifty years of unsustainability. J. Land Use Policy **38**, 26–36 (2014)
4. Romano, B., Zullo, F., Fiorini, L., Ciabò, S., Marucci, A.: Sprinkling: an approach to describe urbanization dynamics in Italy. Sustainability **9**(97), 1–17 (2017)
5. Abraham, G., Bakr, A., Lane, J.: Comprehensive Development Plan for the City of Luxor, Egypt – Investment Project #6, Investment Portfolio for the Creation of an Open Museum and Heritage District in Luxor City, Egypt, December 1999, p. 18 (1999)
6. Darvishi, Y., Masoumi, D.: Role of government in the rapid urban growth in Iran (the Ardebil city instance study). Int. Res. J. Appl. Basic Sci. **7**, 201 (2013)
7. McLane, J., Wust, R.A.J., Porter, B., Rutherford, J.: Flash-flood impacts and protection measure in the valley of the kings, Luxor, Egypt. JSTOR Terms Cond. **34**, 37 (2003)
8. Iranian Statistics Center: Karaj Statistical Yearbook 2012. Tehran, Iran (2012)
9. Sakieh, Y., Amiri, B.J., Danekar, A., Feghhi, J., Dezhkam, S.: Simulating urban expansion and scenario prediction using a cellular automata urban growth model, SLEUTH, through a case study of Karaj City, Iran. J. Hous. Built Environ. **30**(4), 591–611 (2014)
10. Molaei Qelichi, M., Murgante, B., Farhoudi, R., Zanganeh Shahraki, S., Ziari, K., Pourahmad, A.: Analyzing effective factors on urban growth management focusing on remote sensing indices in Karaj, Iran. In: Gervasi, O., et al. (eds.) ICCSA 2017. LNCS, vol. 10407, pp. 469–484. Springer, Cham (2017). https://doi.org/10.1007/978-3-319-62401-3_34
11. Lasaponara, R., Elfadaly, A., Attia, W.: Low cost space technologies for operational change detection monitoring around the archaeological area of Esna-Egypt. In: Gervasi, O., et al. (eds.) ICCSA 2016. LNCS, vol. 9787, pp. 611–621. Springer, Cham (2016). https://doi.org/10.1007/978-3-319-42108-7_48
12. Oruc, M., Marangaoz, M., Buyuksalih, G.: Comparison of pixel-based and object-oriented classification approaches using Landsat-7 ETM spectral bands. In: Society for Photogrammetry and Remote Sensing XXXV:1118–22 (2004)
13. Platt, R.V., Lauren, R.: An evaluation of an object-oriented paradigm for land use/land cover classification. Prof. Geogr. **60**(1), 87–100 (2008)
14. Lasaponara, R., Leuccz, G., Masini, N., Persico, R., Scardozzi, G.: Towards an operative use of remote sensing for exploring the past using satellite data: the case study of Hierapolis (Turkey). Remote Sens. Environ. **174**, 148–164 (2016)

15. Balyani, S., Rointan, S., Qelichi, M.M., Halimi, M., Mohamadi, C.: Evaluating spatial structure of annual rainfall in relation to local factors in Iran. Spat. Inf. Res. **25**(3), 411–420 (2017). https://doi.org/10.1007/s41324-017-0106-6
16. Nolè, G., Lasaponara, R., Lanorte, A., Murgante, B.: Quantifying urban sprawl with spatial autocorrelation techniques using multi-temporal satellite data. Int. J. Agric. Environ. Inf. Syst. (IJAEIS) **5**(2), 19–37 (2014)
17. Lanorte, A., Danese, M., Lasaponara, R., Murgante, B.: Multiscale mapping of burn area and severity using multisensor satellite data and spatial autocorrelation analysis. Int. J. Appl. Earth Obs. Geoinf. **20**, 42–51 (2013)
18. Getis, A., Ord, J.K.: The analysis of spatial association by use of distance statistics. Geogr. Anal. **24**(3), 189–206 (2010)
19. Getis, A., Ord, J.K.: Local spatial autocorrelation statistics: distributional issues and an applications. Geogr. Anal. **27**(4), 189–206 (1995)
20. Getis, A., Ord, J.K.: The analysis of spatial association by use of distance statistics. Geogr. Anal. **24**(3), 189–206 (1992)
21. Ord, J.K., Getis, A.: Testing for local spatial autocorrelation in the presence of global autocorrelation. J. Reg. Sci. **41**, 411–432 (2001)
22. Qelichi, M.M., Murgante, B., Feshki, M.Y., Zarghamfard, M.: Urbanization patterns in Iran visualized through spatial auto-correlation analysis. Spat. Inf. Res. **25**(5), 627–633 (2017). https://doi.org/10.1007/s41324-017-0128-0
23. Holm, A.M., Burnside, D.G., Mitchell, A.A.: The development of a system for monitoring trend in range condition in the arid shrublands of Western Australia. Rangel. J. **9**(1), 14 (1987)
24. Kumari, M., Sarma, K.: Changing trends of land surface temperature in relation to landuse/cover around thermal power plant in Singrauli district, Madhya Pradesh. India. Spat. Inf. Res. **25**(6), 769–777 (2017). https://doi.org/10.1007/s41324-017-0142-2
25. Elfadaly, A., Attia, W., Qelichi, M.M., Murgante, B., Lasaponara, R.: Management of cultural heritage sites using remote sensing indices and spatial analysis techniques. Surv. Geophys. **39**(6), 1347–1377 (2018)
26. Elfadaly, A., Lasaponara, R.: On the use of satellite imagery and GIS tools to detect and characterize the urbanization around heritage sites: the case studies of the Catacombs of Mustafa Kamel in Alexandria, Egypt and the Aragonese Castle in Baia, Italy. Sustainability **11**(7), 2110 (2019)
27. Lasaponara, R., et al.: Spatial open data for monitoring risks and preserving archaeological areas and landscape: case studies at Kom el Shoqafa, Egypt and Shush, Iran. Sustainability **9**(4), 572 (2017)
28. Elfadaly, A., Lasaponara, R., Murgante, B., Qelichi, M.M.: Cultural Heritage management using analysis of satellite images and advanced GIS techniques at East Luxor, Egypt and Kangavar, Iran (A Comparison Case Study). In: Gervasi, O., et al. (eds.) ICCSA 2017. LNCS, vol. 10407, pp. 152–168. Springer, Cham (2017). https://doi.org/10.1007/978-3-319-62401-3_12
29. Elfadaly, A., Wafa, O., Abouarab, M., Guida, A., Spanu, P., Lasaponara, R.: Geo-environmental estimation of land use changes and its effects on Egyptian Temples at Luxor City. ISPRS Int. J. Geo-Inf. **6**(11), 378 (2017)
30. Elfadaly, A., Attia, W., Lasaponara, R.: Monitoring the environmental risks around Medinet Habu and Ramesseum Temple at West Luxor, Egypt, using remote sensing and GIS techniques. J. Archaeol. Meth. Theory **25**(2), 587–610 (2018)