

# Modeling Future Land Use and Land-Cover Change in the Asyut Region Using Markov Chains and Cellular Automata

Hatem Mahmoud and Prasanna Divigalpitiya

**Abstract** The Asyut region in Upper Egypt is often considered as one of the most appealing regions in Upper Egypt for its importance as a medical, educational, and commercial center. As a result of these factors and regarding its location, which is surrounded by agriculture land, the available land area is quickly decreasing. However, the government has established New Asyut city to absorb the urban growth outside the Nile Valley. Yet the region's importance and the increasing population have led to significant urban growth, which has led to increasing loss of agricultural lands within the Nile Valley. Modelling spatially the dynamic change is important for innovative planning strategies. This study's main aims are to characterize the past urban growth process and to investigate a future scenario intended to help decision-makers in redrawing their policies for sustainable development to save the agriculture areas by absorbing the urban sprawl towards the new cities outside the Nile Valley. Satellite-derived Land Use and Land Cover (LULC) maps of the study area from 1990, 2003, and 2015 were processed. The explanatory driving forces were quantified and ordered using an analytical hierarchy process. The outputs were then processed within a framework of the Markov-cellular automata, and a multi-criteria evaluation (MCE) was used to produce the future suitability model. The model was verified using ROC and Kappa statistics. The study concluded that combinations of diversified driving forces exist during different periods. It found that the current urban development process is in a critical stage where urban and rural areas will face unprecedented stress on agriculture areas over the next 15 years. The present policies cannot deal with the future challenges regarding the direction of urban development. However, the study

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suggests that differentiated policies, based on the investigated scenario, should be considered to guide reasonable urban expansion; these have important implications for urban planning and management in Egypt.

**Keywords** Remote sensing · Scenario modelling · Urban development · Land cover land use change · Egypt

## 1 Introduction

### 1.1 Background

Urban sprawl in Egypt is one of the main problems that reduce the limited but highly fertile lands in the Nile Valley of Egypt (Belal and Moghanm 2011). Egypt's uncontrolled population growth and migration into urban areas represents the main reasons for urban sprawl. It suffers from unbalanced distribution of its population, as 95 % of the total area of Egypt is uninhabited land. The majority of the population is concentrated on the banks of the Nile. The encroachment of urban settlements onto agricultural lands may result in dire consequences. The ever-increasing population decreased the agricultural-land area, per capita, from 0.12 ha in 1950 to 0.06 ha in 1990 (Ghar et al. 2004). Rapid urban sprawl has caused agricultural lands to be decreased by 36 % or about 1.5 million acres (6300 million m<sup>2</sup>) (Rageh 2007). Since the 1970s, the Egyptian government has formulated plans and policies to save the agricultural lands and redistribute the population horizontally through establishing new urban settlements across the desert areas outside the Nile Valley; this is intended as a way to reduce the urban pressure on long-standing agricultural land. However, these policies have failed, especially in the Upper Egypt region. Thus decision makers in Egypt face unprecedented challenges with regard to governance, urban planning, and land-use management. As a consequence, knowledge concerning spatial-temporal LULC change and predicted changes that might be occurring have played an important role in the decision-making process. Monitoring growth helps to develop an understanding of past trends and growth patterns, while urban-prediction models provide insights into possible future developments. Both approaches are necessary for implementing appropriate strategies regarding the urban planning decision-making process (Moghadam and Helbich 2013). In this study, the status of LULC of the Asyut region was mapped using multi-temporal data from satellite images, and the future of LULC change was then predicted using Markov-cellular automata (Markov-CA).

Cellular automata (CA) may be defined as discrete models, useful in complexity science, to understand the spatial dynamics of change over time (Vaz 2012). CA, applied to urban growth, relies on the iteration of a given dimensional cell, based on supporting socio-economic and geographical data, to change into urban or non-urban form within a given time frame (Vaz 2012). The simplicity of this model

in dealing with complex variables, has attracted use in many studies in recent years, which employ it as an effective tool to study urban dynamics in rapidly growing cities, to predict urban scenarios for sustainable growth, and as an effective decision-making tool for planners and governments. CA for urban growth usually maintains similar frameworks regarding assembly, testing, validation, and calibration. However, in this study, Markov-CA was used. It is a combination of CA, Markov chain, multi-criteria, and multi-objective land allocation (MOLA) with land cover prediction procedures that add an element of spatial contiguity as well as knowledge of the likely spatial distribution of transitions to Markov-chain analysis. A Markov-CA is capable of simulating temporal and spatial dynamics of LULC change by integrating remote-sensing and GIS-based data with bio-physical and socioeconomic data (Sayemuzzaman and Jha 2014). This technique has not been applied in Egypt. This study is the first study in Egypt to predict future urban sprawl in a region using the CA technique. It aims to characterize the past urban growth process and expects to use the predicted future-growth pattern during the next

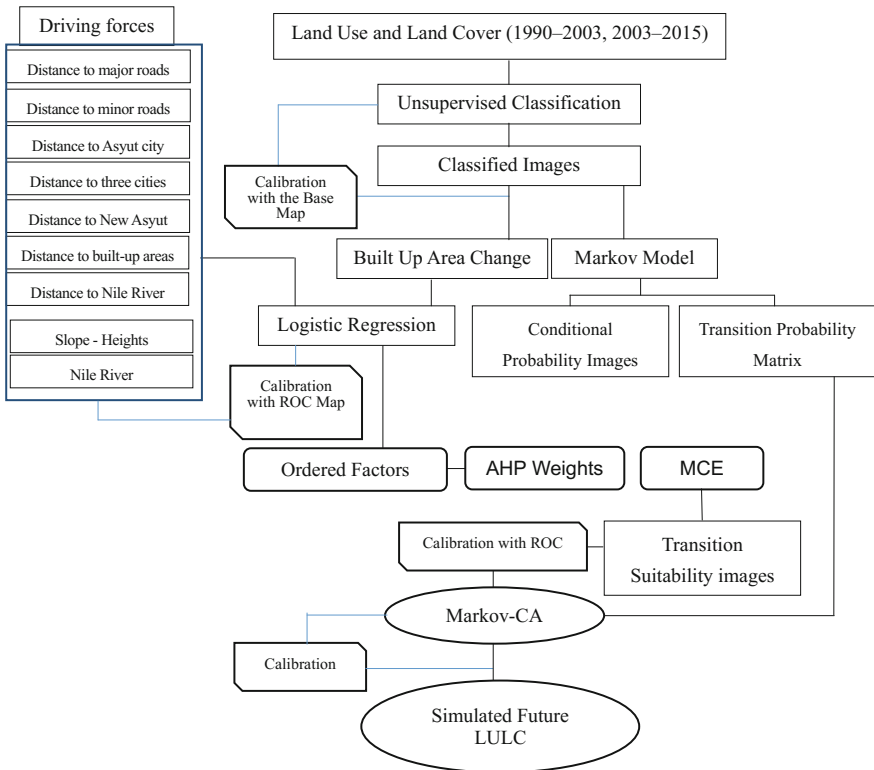


Fig. 1 The study flow chart



Information Center AGIC 2015). As of 2015, the study area had a total population of 1,732,931 and total area of 171,083 acres. It was possible to provide population statistics for the study area for the years 2015, 2004, 1996, and 1986. Based on the population growth ratio in the Asyut governorate in 1986–1996 and 1996–2066, which were 2.24 % (AGIC 2015) and 2.12 % (calculated) respectively, the population in 1990 and 2003 were calculated (see Table 1). The study area coordinates are (Min X 300495, Max X 341745, Min Y 2996895, and Max Y 3026805—reference system UTM 36 N-).

## 2.2 Data and Pre-processing

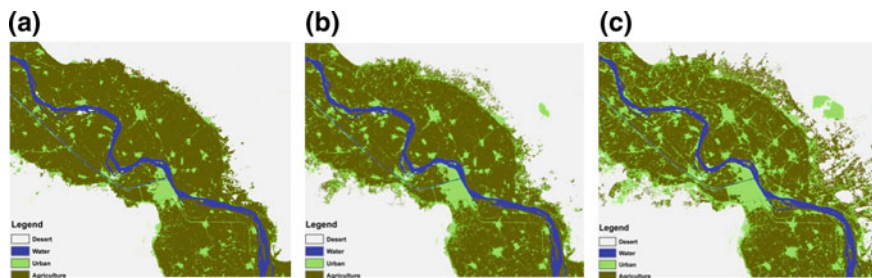
The acquired data of the study area were processed and analyzed using remote sensing, TerrSet software, and GIS techniques to collect information on urban growth from 1990 to 2015. The temporal satellite images were collected for use in the current case study from Landsat satellite imagery (USGS 2015) which was helpful in providing efficient support for the study-area analysis. The following Landsat time stamps were gathered for spatio-temporal mapping: 1990, 2003, and 2015. A projection to the UTM zone 36 North, as well as resampling to a common spatial resolution of 30 m was necessary, to provide a homogenous time series.

## 2.3 Extraction of Land-Use Data for the Model

In order to detect, quantify, and analyze the changes, unsupervised classification ISODATA were used for the years 1990, 2003, and 2015. The LULC was generated (Fig. 3). The factors affecting the urban sprawl in the study area were tested and considered (Mahmoud and Prasanna 2015), which determined the CA-transition rules. The rules for this study are defined as Euclidean distance from major roads, minor roads, existing built-up areas (including the three cities in the

**Table 1** Study area statistics

| Name           | Population 2015 | Area in acres | Area in km <sup>2</sup> | Population in 2003 | Population in 1990 |
|----------------|-----------------|---------------|-------------------------|--------------------|--------------------|
| Asyut center   | 1,007,332       | 53,897        | 218.11                  | 774,525            | 576,489            |
| El Fath center | 302,997         | 38,093.76     | 154.16                  | 231,323            | 145,305            |
| Abnoub center  | 392,602         | 46,293.2      | 187.34                  | 301,863            | 189,616            |
| New Asyut      | 30,000          | 32,800        | 132.74                  | –                  | –                  |
| Total          | 1,732,931       | 171,083.96    | 692.35                  | 1,307,711          | 911,410            |



**Fig. 3** Extracted land use maps **a** 1990, **b** 2003, **c** 2015

study area), Asyut city, New Asyut city, the Nile River, the border between the Nile Valley, and the deserts. For example, the area closer to Asyut city has a higher probability of development, whereas areas farther away from main roads are less prone to development. The transition matrices were constructed from the change/no-change matrices obtained in the change-detection analysis and the modeling processes implemented using algorithms supplied with the TerrSet software. The model calculated the change between 2003 and 2015 and thus predicted the LULC 2015. According to the predicted and generated LULC 2015, the model was validated. Finally, a prediction of LULC 2030 was undertaken using Markov-CA, incorporating the above mentioned parameters.

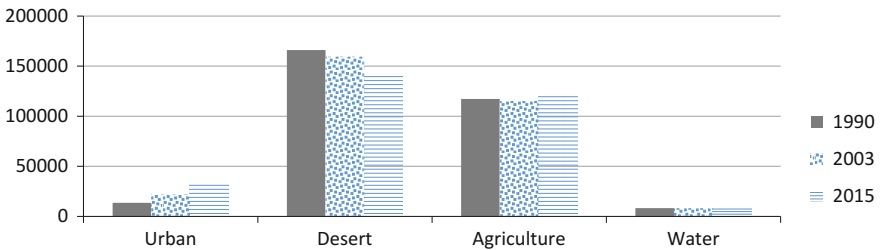
## 2.4 Results

The classification process resulted in three land-use maps that discriminated among the following four land-use categories: desert, water, urban (built-up areas), and agriculture. To assess the results, a file of point locations was also produced. One hundred points were created according to a stratified random-sampling scheme. This scheme works by dividing the area into a rectangular matrix of cells. It then chooses a random location within each cell. The accuracy of the system classification compared to the real LULC was 88 % for the 1990 data; 93 % for the 2003 data; and 84 % for the 2015 data.

In order to understand the changes in LULC, the gains and losses for each class were calculated as described in Table 2 and Fig. 4. In the first period (1990–2003), most land conversion was attributed to the replacement of agricultural lands with urban areas. About 8,428 acres had changed to built-up areas, with 6,125 acres (72.6 %) being former agricultural lands. However, there was partial compensation of agricultural lands; 4,235 acres of desert land were converted to farming. For the period between 2003 and 2015 after the establishment of New Asyut city (NAc) in 2000, a very rapid build-up of development of more than 12,496 acres was observed to have occurred, with approximately 9,020 acres (72.2 %) of the urban sprawl encroaching onto agricultural lands. Moreover, the rate of land development

**Table 2** Urban land expansion in the study area from 1990 to 2015

| Year        | Area (acres) |           | Change rate % |       | 2003      | 2015     | Growth rate % |       |
|-------------|--------------|-----------|---------------|-------|-----------|----------|---------------|-------|
|             | 1990         | 2003      | -             | +     |           |          | -             | +     |
| Urban       | 13482.44     | 21911.1   | 0             | 38.47 | 21911.1   | 34084.06 | 0.22          | 36.46 |
| Desert      | 166062.88    | 159525.04 | 4.18          | 0.25  | 159525.04 | 143009.5 | 11.05         | 0.58  |
| Agriculture | 117156.43    | 115258.70 | 5.58          | 4.03  | 115258.70 | 120280   | 9.46          | 13.21 |
| Water       | 8180.25      | 8185.13   | 0             | 0     | 8185.13   | 7506.38  | 17.95         | 10.54 |



**Fig. 4** Temporal changes of land use classes (in acres)

in the study area outstripped the rate of population growth. Despite the fact that most of the urban sprawl occurred on agricultural land, thus decreasing the latter by 9.46 %, there was an increase in new agricultural land, especially in the eastern desert area, next to the NAc. The increase in agricultural areas more than compensated for the loss due to urban sprawl, even resulting in an increase in the total agricultural areas in this period by encroachment onto agricultural lands; however, the new extensions towards the new city succeeded in creating a good environment for agricultural sprawl.

### 3 Markov Chain Land-Use Simulation

After extracting the land-use model, a Markov chain “MC” model was used to quantify transition probabilities of several land-cover categories for discrete time steps. The model focuses on quantity in predictions for land-use changes, and the model’s spatial parameters are weak (Nejadi et al. 2012). The MC model analyzes a pair of historic land-cover images and outputs a transition probability matrix, a transition area matrix, and conditional probability images for each category of classified land uses (Sayemuzzaman and Jha 2014). The first step in applying the MC model is comparing the historic land-use maps for two periods: from 1990 to 2003, and from 2003 to 2015, to produce images for the categorical pattern of changes between the maps of the two dates in each period (Fig. 5). The transition

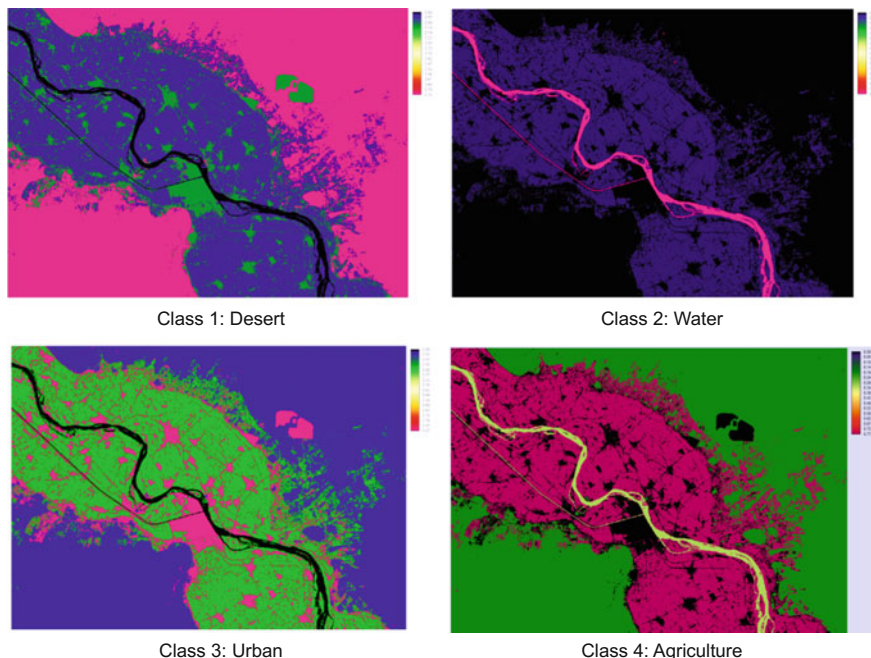


Fig. 5 Conditional probability images based on projection date 2030

Table 3 Markov transition probability

|             | 1990–2003 |        |        |             | 2003–2015 |        |        |             |
|-------------|-----------|--------|--------|-------------|-----------|--------|--------|-------------|
|             | Desert    | Water  | Urban  | Agriculture | Desert    | Water  | Urban  | Agriculture |
| Desert      | 0.8364    | 0.0000 | 0.0540 | 0.1096      | 0.7509    | 0.0001 | 0.0460 | 0.2029      |
| Water       | 0.0000    | 0.8700 | 0.0000 | 0.1300      | 0.0000    | 0.6769 | 0.0008 | 0.3222      |
| Urban       | 0.1300    | 0.0000 | 0.8700 | 0.0000      | 0.1318    | 0.0000 | 0.8676 | 0.0006      |
| Agriculture | 0.0109    | 0.0002 | 0.1639 | 0.8251      | 0.0236    | 0.0165 | 0.1919 | 0.7680      |

probability matrix is then calculated according to the projection date 2015 for the first period and 2030 for the second period (Table 3). The predicted image for 2015 was compared with the base map of 2015 for validation.

### 3.1 Standardization and Weighting of Main Driving Forces

The evaluation of the driving forces that shape urban expansion and affect land use transition probabilities was executed within the Analytical-Hierarchy-Process (AHP) framework. The relative importance of each criterion was determined by applying the logistic regression model on them in a previous study (Mahmoud and



Prasanna 2015). The individual weights are listed in Table 4. Driving forces with higher weights are statistically more important. The consistency ratio was calculated to verify the logical consistency of the selected weights. The suitability of the defined weighting schema was confirmed, because the value was 0.03 which is below the critical value of 0.1 (Malczewski 1999).

### 3.2 Predicting Future Urban Expansion

The multi-criteria evaluation (MCE) (Eastman 1995) and extracted weights of urban driving forces that cover the natural and socioeconomic variables were used to generate the group of suitability images for 2015 and 2030 (Figs. 6 and 7). The suitability images for each land cover establish the inherent suitability of each pixel for each land-cover type in a specified time period (Eastman 2006). The suitability images for urban change for 1990–2003 were validated using the relative operating characteristic (ROC) test (Swets 1986), an excellent instrument to evaluate the degree of certainty of the transition suitability images. ROC values range from 0 to 1, where 1 indicates a perfect fit and 0.5 indicates a random fit. In our study, the initial result within 10 % of the sampling test. It was performed by comparing the suitability image of 1990–2003 (to predict 2015) with the image derived from the actual 2015 map. The value of ROC was 0.9168.

Although probabilities of land-use transition are provided on a per-class basis by the MC model, the spatial distribution of occurrences within each land-use class was lacking in the analysis (Belal and Moghanm 2011). Thus, the integration of cellular automata by using the Markov-CA model is required. For validation purposes, the transition probabilities for the period 1990–2003 and its suitability image were used in the model to predict the known map for 2015. Validation was conducted to ensure accuracy and an applicable simulation that represented effective predictions. The predicted image for 2015 was compared with the classified satellite-derived image on the Kappa statistic. The Markov-CA's overall simulation

**Table 4** Extracted weights based on AHP

| No. | Driving force name         | Relative weights |           |
|-----|----------------------------|------------------|-----------|
|     |                            | 1990–2003        | 2003–2015 |
| 1   | Distance to New Asyut city | 0.3313           | 0.3337    |
| 2   | Distance to urban heart    | 0.2307           | 0.2302    |
| 3   | Distance to border         | 0.1572           | 0.1568    |
| 4   | Distance to minor roads    | 0.0509           | 0.1056    |
| 5   | Distance to water          | 0.0327           | 0.0707    |
| 6   | Distance to three cities   | 0.0477           | 0.0475    |
| 7   | Distance to Asyut city     | 0.1059           | 0.0326    |
| 8   | Distance to major roads    | 0.0236           | 0.0230    |

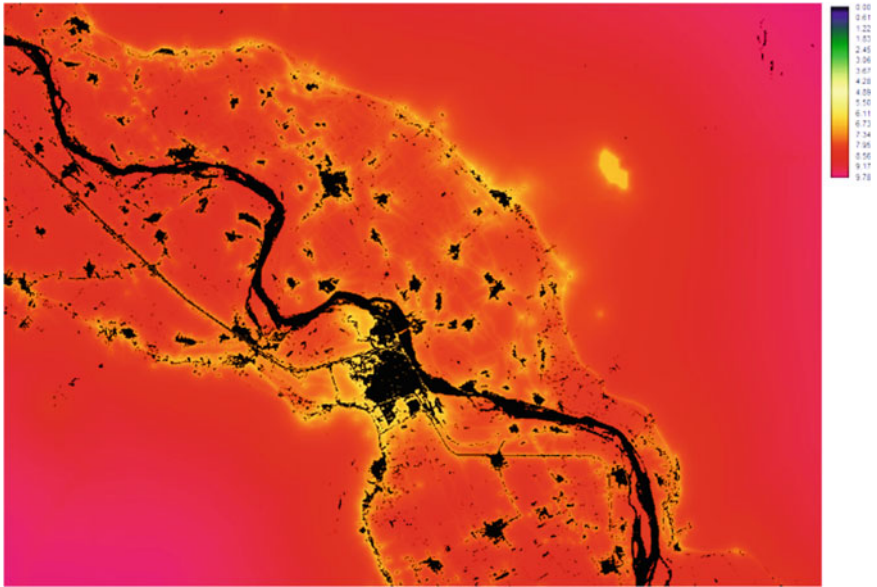


Fig. 6 The suitability images 1990–2003 to predict 2015

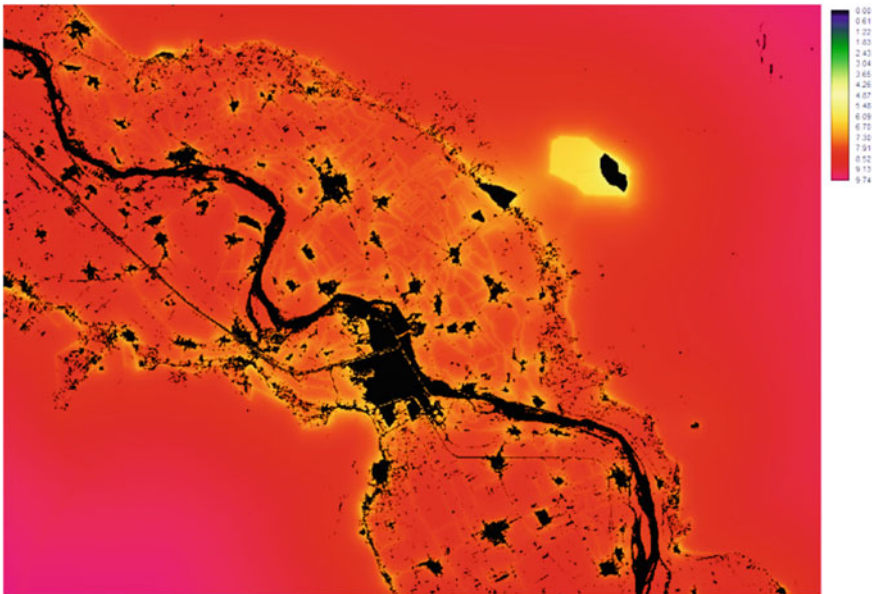


Fig. 7 The suitability image 2003–2015 to predict 2030



**Fig. 8** 2015 base map

success is 77.235 % which means a “substantial” degree in the level of agreement (Landis and Koch 1977). It was difficult to increase the simulation success due to the nature of the study area as most of the growth is informal growth. For the simulation of the 2030 LULC map, a similar procedure described for the 2015 simulated map was carried out, specifying 15 cellular automata iterations based on (1) the 2015 LULC base map (Fig. 8), (2) the 2015 transition potential maps, and (3) the 2003–2015 transition area matrix.

### 3.3 *The Results*

After extracting the simulated LULC for the year 2030 (Fig. 9), the changes in LULC, the expected gains, and the losses for each class were calculated. According to Table 5, Figs. 10, and 11, most land conversion will be attributed to the replacement of agricultural lands with urban areas. About 22,137 acres from agricultural lands will change to built-up areas. Thus the net growth rate of built-up areas is expected to be about 42.16 %. Despite the fact that the main aim for building New Asyut city was to absorb the urban sprawl from the agricultural lands, most of the urban sprawl will occur on agricultural land, thus agricultural lands may lose 18 % of their current extent. However, there was an increase in new agricultural land, especially in the eastern desert area, next to NAc. The increase in agricultural areas is more than compensated for by the loss due to urban sprawl, and even results in a very small increase in the total agricultural areas of 2.33 %.



Fig. 9 Simulated LULC change for the year 2030

Table 5 Urban land expansion in the study area from 2015 to 2030

| Year        | 2015     | 2030      | Growth rate % |       |
|-------------|----------|-----------|---------------|-------|
|             |          |           | -             | +     |
| Urban       | 34084.06 | 59240.18  | -0.72         | 42.88 |
| Desert      | 143009.5 | 114738.29 | -19.94        | 0.72  |
| Agriculture | 120280   | 123821.69 | -18.44        | 20.77 |
| Water       | 7506.38  | 7079.82   | -6.17         | 0.52  |

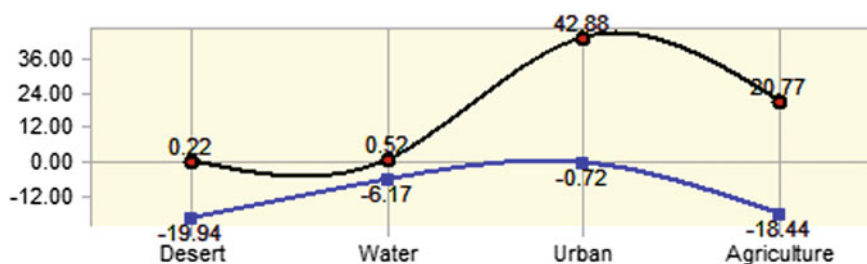
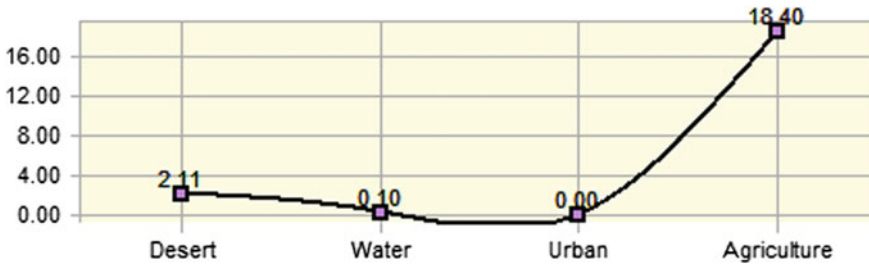


Fig. 10 Gains (red) and losses (blue) in land-use classes 2015–2030 (percentages %)

Looking at the spatial patterns of land change in the future, the evidence shows that the rate of conversions from non-built to built-up areas is quite rapid, with scattered patches of urban development in agricultural areas characterizing the urban sprawl in the Nile valley. The simulated future LULC changes indicate



**Fig. 11** Contributions of each land-use class in urban growth 2015–2030 (% change)

increasing pressure on agricultural lands (one of the most important resources in Egypt). Socioeconomic conditions and the roads network have played important roles in producing these spatial patterns. Spatial diffusion of built areas spreads outward from the core of existing built-up areas along with the roadways. This is mainly because of road expansion and weak regulation over increasing the population; citizens have no strong motivations to move outside the valley towards the new city.

#### 4 Conclusion

The urban growth of Asyut region make it one of the fastest growing urban regions in Egypt, and this growth has unprecedented effects on LULC changes. However, no research had previously addressed the simulation of future urban growth of the Asyut region. In this respect, the Markov-CA model in combination with socio-economic and natural urban driving forces was used to predict the future LULC changes during the next 15 years (until 2030).

Strong evidence suggests that urban expansion will continue to occur in the Asyut region throughout the next 15 years. The temporal mapping of built-up areas and simulation models for the next 15 years indicate that the projected urban expansion will be directed mainly near to New Asyut city, existing built-up areas, and the agricultural-lands border. The main swap in land use will occur between urban and agricultural lands; however, it should occur between urban and desert lands. This problem is mainly because of (a) the relative location of these agricultural lands being near to existing built-up boundaries, (b) the lack of regulations that ensure protecting the agricultural lands, and (c) New Asyut city is not able to absorb all of the urban expansion. Thus, it is clear that the decision-makers should act strongly on other urban development driving forces than are used in this study, whether natural or socioeconomic, to control future urban growth.

The outcome of the LULC study investigated here will provide decision-makers and urban planners with the basic information necessary for the integrated assessment and management of future urban growth in the study area. It will inform

them of the extent of growth that can be expected so that they can adapt their policies to the expected situation.

Urban areas are responsible for the majority of resource consumption, thus instigating an increasing need to create smarter management for the future, which provides greener and more sustainable urban dynamics. In this study, the combined approach, using remote sensing and future modeling, is a powerful and productive direction for achieving improved understanding, and representing future urban data; such an approach will help in better planning the future and conserving natural resources, because it is vital to ensure cities are made greener and more sustainable.

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