Modeling of built-up lands expansion in Gaza Strip, Palestine using Landsat data and CA-Markov model

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Abstract. In Gaza Strip, Built-up lands expansion have reached critical level due to speed in population growth and high demand for new houses especially since the establishment of the Palestinian national authority (PNA) in 1994. In this context, more agricultural and arable lands have been transformed to built-up areas. Thus, monitoring and modelling this expansion is a fundamental task for sustainable management of available resources and long-term urban planning purposes. Against this background, the primary objective of this research is modelling and predicting the future expansion of built-up lands that would take place in the study area by the year 2036. The research was conducted based on times series satellite images that taken in (1992, 2003, 2014) by Landsat and Cellular Automata Markov (CA_Markov) model integrated with GIS and multi criteria evaluation technique. In this research, land cover maps have been prepared based on the satellite images and the post classification change detection technique has been employed for quantitative analysing of the past land cover changes among the study area. Then, CA_Markov model has been implemented and validated. Later, the land cover map for the year 2036 has been predicted. The results illustrate that if the trend of change in the future period continue as the same the built-up lands would cover 45.3% of the total area in Gaza Strip by 2036. Moreover, the expansion of the built-up lands occurred at the expense of the agricultural and arable lands. In conclusion, this research demonstrated that Gaza Strip face serious crisis if the same pattern followed. Therefore, focus on urban planning is essential to control the expansion of built-up lands and minimize the negative impacts of urbanization in Gaza Strip.

1. Introduction
Built-up lands expansion are dynamic spatial issues. Thus, monitoring this expansion is fundamental task for sustainable development. Because of the speed in population growth in the Gaza Strip, a demand for new houses increase, which mean more agricultural lands transforms to built-up area. Thus, for sustainable management of land resources in the study area, these transformations need to be planned and under continuous observation. Landsat data is appropriate for land cover analysis and modelling. Since these data is available to all users at no charge and cloud-free since 1972. Moreover, in terms of spatial resolution, Landsat supplies images with moderate resolution, 30 meter, which is suitable for land cover analysis and modelling.
In various studies, to predict land cover changes; included built-up lands class, a number of methods and models, which employ different techniques, were applied. In general, the selection of an appropriate and useful model depends on many factors such as the available data for a study area, assumptions, number of classes, decision rules, data format, etc [10]. In this research, the land cover map of Gaza Strip for the year 2036 were predicted using CA-Markov model, the classified land cover images of the study area for the years 1992 and 2003 had used to predict the land cover map of 2014. Then the model was validated by comparing the classified and predicted land cover image of 2014. The kappa statistics were used to estimate the validation parameters of the CA-Markov model. Lastly, the land cover map of the study area for the year 2036 were predicted.

1.1 Study Area
Gaza Strip is a part of the Palestinian occupied territories as shown in ‘Figure 1’. It is a narrow strip located on the north east of Egypt on the eastern coast of the Mediterranean Sea. It locates at longitude 34.20 degrees east and latitude 31.25 degrees north. It is about 41 km long and between 6 and 12 km wide with total area of 365 square kilometers [1]. In Gaza Strip the total Palestinian population was estimated by the mid-year of 2016 to 1,881,135 Capita with a population density of 5,153 capita per square kilometer [2]. Therefore, Gaza Strip is one of the densest populated areas of the world [3].

![Figure 1. Gaza Strip, the location of the study area.](image)

2. Methodology and Data
In this research, ‘figure 2’ outlines the phases and the features of research methodology and the data used to achieve the research objectives. The details of data and methodology are explained in the next sections.

2.1 Data
For the purpose of this research, different data have been collected. Three multispectral Landsat images for the years 1992, 2003, and 2014 that cover the study area have been obtained. Other data included shape files for road network, international boundaries and governorates for Gaza Strip have been obtained. Moreover, existent Land use maps for the study area for 1991 and 2005 and Google Earth images are used as reference data to perform accuracy assessment on classified satellite images.

2.2 Methodology
For this research, as outlines in ‘Figure 2’, the following four stages have been executed to achieve the research objectives. The four stages are image pre-processing, image classification, change detection analysis and land cover modelling. In an Image pre-processing stage, the study area has been clipped and band combinations were performed many times in order to obtain visual of interpretation of classes and other information.

2.2.1 Image Classification
In this stage, an object-based classification method has been applied to prepare these maps for the years 1992, 2003 and 2014 using the Landsat satellite images. Object-based classification method is based on the segmenting an image into objects by grouping neighbouring pixels with common values [11]. While pixel-based classification method is based on the properties of each pixel. In an object-based classification method, there are two steps to generate the land cover map. The steps are image segmentation and image classification [12]. In this research, ENVI 5.0 software was used to perform image segmentation step. The final output of segmentation step is a multispectral image which shows the objects defined by segmentation and then incorporated into the classification step. ERDAS software was used to perform an unsupervised classification, ISODATA algorithm, on these segmented images (i.e. the classification was applied on objects, rather than on single pixels). The classification process was performed to defined land cover classes in the study area by assigning 50 classes and then the similar class was merged based on a visual interpretation. Then, generalization technique was adopted to derive a final classification maps with three main LULC classes, ‘Figure 3’.

**Figure 2.** Flow Chart of Methodology.
2.2.2 Accuracy Assessment
In order to estimate the quality of classified images, two statistical tools, an Error Matrix (EM) and Cohen’s kappa (K) analysis, were performed using ERDAS software using 204 test points that has been distributed randomly among the three land cover class according to the proportion of each class. The results, in (table 1), indicates that the overall accuracy and Kappa values was in perfect level, above 90% and above 0.81 respectively.

Table 1. Classification Accuracy assessment results for classified maps.

| Land cover type | 1992       | 2003       | 2014       |
|----------------|------------|------------|------------|
|                | PA(%)      | UA(%)      | PA(%)      | UA(%)      | PA(%)      | UA(%)      |
| Built-up lands | 95.83%     | 95.83%     | 100.00%    | 94.12%     | 98.15%     | 92.98%     |
| Agriculture    | 87.18%     | 73.91%     | 86.27%     | 89.80%     | 78.26%     | 97.30%     |
| Soil lands     | 90.78%     | 95.52%     | 95.87%     | 95.87%     | 100.00%    | 94.55%     |
| Overall accuracy | 90.69%   | %94.12    | %94.61    |            |            |            |
| Overall Kappa  | 0.81       | 0.90       | 0.91       |            |            |            |

PA = Producer’s Accuracy , UA = User’s Accuracy

2.2.3 Change Detection Analysis
The change detection analysis has been applied using post-classification method. The total actual gain and losses as well net transitions from each category to built-up lands that took place in the study area have been calculated by performing change detection analysis using the Land Chang Modeler (LCM) embedded in the TerrSet software. For this research, three possible analyses for change detection over time were performed. These are change between 1992 and 2003, 2003-2014 and 1992-2014. The quantity of gains and losses in each class can be observed in (Table 2) that shows the built-up lands has increased over the years without losses - the small losses in built-up lands, -77 and -59 hectares, might be resulted due to misclassified - what means the previously existed built-up lands have expanded, while some lands of the previously existed agriculture class have converted to some other land cover classes, what means losses. The transitions from other categories to built-up lands can be observed in (Table 3). The land cover categories in each classified images (1992, 2003 and 2014) were quantified and
expressed as a percentage of the total area of the study area in (Table 4). The change detection analysis shows that the expansion of built-up lands in the study area have been took place mainly around to the existing built-up areas.

Table 2. Area (ha) of gains and losses in each class

| Category  | (1992 - 2003) | 2003-2014 | 1992-2014 |
|-----------|---------------|-----------|-----------|
|           | losses | gain   | losses | gain   | losses | gain   |
| Built_Up  | -0     | 1821   | -77    | 3981   | -59    | 5744   |
| Agriculture| -3835  | 4250   | -5459  | 3357   | -5331  | 3688   |
| Soil      | -5295  | 3060   | -5772  | 3970   | -7395  | 3353   |

Table 3. Transition from other categories to Built-Up Lands

| Transition      | Area (ha) | 2003-2014 | 1992-2014 |
|-----------------|-----------|-----------|-----------|
| Agriculture to Built-Up | 776       | 1413      | 1920      |
| Soil to Built-Up      | 1045      | 2491      | 3766      |
| Total (ha)            | 1821      | 3904      | 5686      |

Table 4. Percentage of land cover types in Gaza Strip (1992, 2003 and 2014)

| Interval | 1992 | 2003 | 2014 |
|----------|------|------|------|
|          | Area (%) | Area (%) | Area (%) |
| Built-Up | 11.86 | 16.83 | 27.69 |
| Agriculture | 22.69 | 23.83 | 18.23 |
| Soil      | 65.45 | 59.34 | 54.08 |

2.2.4 Land Cover Modeling.

In this phase, the CA-Markov model integrates both the cellular automata (CA) and Markov models. The advantage of combining the two models is that the Markov chain has inadequate spatial knowledge while CA-model has a good spatial sense. Therefore, the (CA-Markov) model has the capability to convert the quantitative results of the Markov chain into spatially explicit outcomes by means of a CA function in addition to its capability to model a number of categories at the same time [13].

For any system, the Markov chain is a stochastic process (i.e. based on probabilities not certainties) in which the probability to observe a state y at a time point (t+1) is completely depend on the existing state x at time t) [14]. This means that the next state depends only on the current state, not on previous states (i.e. do not depends on the sequence). All landscape spatial transition models can be expressed in a simple matrix equation as follows [16]:

\[ N_{n+1} = N_t \times P \]  

where, \( N_{n+1} \) is the distribution of land uses among the different types at the end of the projection period (at time t + 1), \( N_t \) is the distribution of land uses among the different types at the beginning of the period (time t) and \( P \) is the transition probability matrix.

In this research, a CA-Markov model was implemented using the TerrSet software. The first step was producing the transition suitability images which are constructed with multi-criteria evaluation based on the factors that have impacts on dynamics of the study area. Then, in order to calibrate the model and simulate land cover change for the year 2014, the land cover images of the years 1992 and 2003 were used. After that, in order to validate the model, the agreement between the predictive model output for the year 2014 image and a “real” land cover map for the year 2014 was measured. Finally,
the land cover map for the year 2036 was simulated using the same procedures. The methodology applied to calibrate, simulate and validate the model is illustrated in ‘Figure 4’.

Figure 4: Methodology applied to calibrate, simulate and validate the model

3. Results and analysis

3.1 Model Calibration

The calibration of CA_Markov requires different dataset including transition probability matrix, land cover data and suitability maps. The transition probability matrix was computed using CA_Markov model that embedded in the TerrSet software, (table 5). The land cover maps for the years (1992 and 2003) was prepared as mentioned in (figure 3) and the suitability map were also prepared using raster calculation function in ArcMap software (figure 5).

The suitability maps define the pixels that would change from each land cover category to other categories according to the largest suitability [7]. For this research, the suitability analysis was done only for built-up lands category and two types of criteria (constraints and factors) were used in construction of multi-criteria suitability maps. The existing built-up lands and the security zone along the north and east borders of Gaza Strip were considered as constraints (the locations which are restricted the built-up development) ‘figure 7’. While the distance from Build-up lands and the distance from road network considered as factors. For this research purpose, the factors were standardized to a continuous scale of suitability, from 0 to 255 (the most suitable) then a weights for each factor were established using raster calculation function in ArcMap software. The standardization formula is:

\[ R_i = \frac{X_i - R_{\text{min}}}{R_{\text{max}} - R_{\text{min}}} \times \text{Standardized Range} \]  

where \( R \) = raw score. The Weighted Linear Combination (WLC) combine the standardized factors and constraints. With a WLC, each standardized factor image is multiplied by its weight, then the results are summed and then multiplied by the product of the constraints to have the final suitability map. The formula of the Suitability according to WLC-MCE is:

\[ S = \left( \sum W_i X_i \right) \prod C_i \]  

where: \( S \) :Suitability, \( W \) :weight of factor i, \( X_i \) :criterion score of factor i, \( C \) : criterion score of constraint j, \( \sum \) :Sum, \( \prod \) :Product.

The final suitability map for built-up expansion in the future across the study area ‘figure 5’, and the included standardized factors were given equal weights. The white color represents the high suitability and the black represents the low suitability. Constraints are illustrated as black because in these areas built-up expansion was restricted.
Table 5. The transition probability matrices (1992 - 2003).

| Cells in | Built_Up | Agriculture | Soil |
|----------|----------|-------------|------|
| Built-Up | 1.0000   | 0.0000      | 0.0000 |
| Agriculture | 0.0925   | 0.5438      | 0.3637 |
| Soil     | 0.0434   | 0.1788      | 0.7778 |

3.2 Model implementation and validation

As an initial step, in model implementation, the land cover maps for the years 1992 and 2003 were used to “predict” the land cover map for the year 2014. Then, the validation process was carried out to determine the quality of 2014’s predicted map in relation to 2014’s land cover map (the map of reality). Validation is a method to measure agreement between two categorical images [17].

![Final suitability map for built-up](image)

Figure 5. Final suitability map for built-up

In this research, the VALIDATE model in the TerrSet software was used to measure the validation. The results states that the predictive power of the model by computing the standard Kappa index of agreement (i.e. overall accuracy of a prediction that was 0.8179. According to [17], Kno value should be used to evaluate the overall success of the module in simulation process. Since Kno value was 0.8956, the CA-Markov model in the present research was succeeded in predict the land cover for the year 2014. Therefore, this model will use to predict the future changes in land cover changes.

3.3 Land cover prediction for the year 2036

The process of prediction of the land cover for the year 2036 followed the same steps in the prediction of the land cover for the year 2014. The prediction was carried out using the key inputs which are land cover maps for the years 1992 and 2014, the transition areas matrix, a contiguity filter and the transition suitability image. The projected land cover image for the year 2036 is presented in ‘Figure 6’.

The results of the modeling, indicate that if the trend of change in the future time period continue as the same, 45.3%...
of the total area in Gaza Strip will be occupied by built-up by the year 2036, after this percentage was 27.7% in 2014. In contrast 5.6% from agriculture lands will transformed to built-up lands, decrease from 18.2% in 2014 to 12.5% in 2036. Also, the soil lands class will also face a 11.7% decrease in 2036, decrease from 54.1% in 2014 to 42.2% in 2036. As shown in ‘Figure 7’, the growth in built-up lands among Gaza Strip will also take place mainly in the area surrounding the existing built-up regions and main roads.

4. Conclusion
The results of modelling the expansion of built-up lands in Gaza Strip, indicated that, if the trend of change continue as the same, 45.3% of the total area in Gaza Strip will be occupied by built-up lands in the year 2036. Moreover, this research pointed out that, the expansion of built-up lands in the study area occurred at the expense of the agricultural and arable lands, which mean that Gaza Strip face serious crisis. Therefore, focus on urban planning is essential to control the expansion of built-up lands and minimize the negative impacts of urbanization in Gaza Strip. Lastly, Since the agreement between the “actual” and “predicted” land cover maps for the year 2014 was 0.8956, we can say that the Landsat data and CA_Markov model integrated with GIS and multi criteria evaluation technique was found to be successful to achieve the aims of this research in the study area.

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