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RESEARCH PAPER

# Using CA-Markov Model to Predict Land Use/Land Cover Changes in Bayer and al-Bassit region, Latakia, Syria

Ola Ali Merhej[1*], Mahmoud Kamel Ali[2], Ali Thabeet[3]

# استخدام نموذج CA-Markov للتنبؤ بتغيرات استعمالات الأراضي/الغطاء الأرضي في منطقة الباير والبسيط، اللاذقية، سورية

علا علي مرهج[١*]، محمود كامل علي[٢]، علي ثابت[٣]

**ABSTRACT.** Recently, land use change models have become important tools to support the analysis of land use dynamics. This research was aimed at the evaluating and predicting the land use/land cover change dynamics in Bayer and al-Bassit region of northwestern Latakia, Syria. In this paper, we used Cellular Automata and Markov Chain models to predict the LULC changes that are likely to occur by 2030 in Bayer and al-Bassit region. Three Landsat images acquired in the years of 1992, 2005, and 2018 were classified using Maximum Likelihood Classification algorithm and used as the input data for CA-Markov models. Kappa index was used to validate the model, and the overall accuracy recorded 79.34%. Based on a transition area matrix and transition rules a LULC map for the year 2030 were predicted. Compared to the LULC status of the reference year 2018, a significant reduction is likely to occur in 2030 in the forest area. This reduction might be in favor of the growth of agricultural land and urban area. The result shows CA-Markov model ability to predict future LULC changes in Bayer and al-Bassit region, and its importance for planners and land use managers.

**KEYWORDS:** CA-Markov, IDRISI, Land Use Change, Remote Sensing, Satellite Images, Syria.

**الملخص:** مؤخراً، أصبحت نماذج تغير استعمالات الأراضي أداة مهمة لدعم تحليل ديناميكيات استعمالات الأراضي. هدف هذا البحث إلى تقييم ديناميكيات تغير استعمالات الأراضي/ الغطاء الأرضي والتنبؤ بها في منطقة الباير والبسيط الواقعة شمال غرب اللاذقية، سورية. في هذه الدراسة، تم استخدام كل من نموذج الأتوماتا الخلوية وسلسلة ماركوف للتنبؤ بتغيرات LULC التي من المحتمل أن تحدث في عام ٢٠٣٠ في منطقة الباير والبسيط. تم تصنيف ثلاث صور لاندسات مُلتقطة في أعوام ١٩٩٢ و٢٠٠٥ و٢٠١٨ باستخدام خوارزمية الاحتمالية القصوى، واستخدمت الخرائط الناتجة كبيانات إدخال لنموذج CA-Markov. استخدم مؤشر كابا للتحقق من صحة النموذج، وسجلت الدقة الإجمالية ٧٩,٣٤ ٪. استناداً إلى مصفوفة منطقة الانتقال وقواعد الانتقال، تم التنبؤ بخريطة LULC لعام ٢٠٣٠.مقارنة بحالة LULC للسنة المرجعية ٢٠١٨، من المرجح أن يحدث انخفاض كبير في مساحة الغابات في عام ٢٠٣٠. قد يكون هذا الانخفاض لصالح النمو في الأراضي الزراعية والمناطق الحضرية. الخلاصة. تُظهر النتيجة قدرة نموذج CA-Markov على التنبؤ بالتغيرات المستقبلية في LULC في منطقة الباير والبسيط، وأهميته للمخططين ومديري استعمالات الأراضي.

**الكلمات المفتاحية:** نموذج CA- Markov، ادريسي، تغير استعمالات الأراضي، الاستشعار عن بعد، صور الأقمار الصناعية، سورية.

## Introduction

The changes of land use/land cover (LULC) are modifications of the Earth's surface made by human activities (Roy et al., 2015). These changes are huge land surface transformations (Meles, 2008) and they are critical factors for ecological degradation of environment (Hamad et al., 2018). LULC changes in all life sides happen because of many natural and human factors or variables (Ali, 2009). Moreover, human activities and natural processes influence the LULC changes and cause a large modification and even conversion of land use. This may create problems that can affect the environment (Singh et al., 2015). Because of its importance to understanding the Earth's interactions, LULC changes research has occupied an important place in the internationally active fields of study (Lambin et al., 2003).

Remote sensing and geographic information systems are important tools to analyze and simulate the LULC changes (Roy et al., 2015). They are extensively utilized for understanding LULC changes by determining the past and the present status (Ozturk, 2015). Multi-temporal satellite images were used to monitor vegetation cover changes through prepared LULC maps (Palmer and Fortescue, 2003). Multiple satellite images of the same study area, which gained on different dates. These provide planners with the opportunity to monitor land cover changes by utilizing alternative parameters, such as vegetation indices.

In addition, within an RS–GIS environment, many spatial modeling techniques have been used for understanding the land use dynamics (Li and Yeh, 2000; He et

Ola Ali Merhej[1,*](✉) olamerhej@gmail.com, [1]General Organization of Remote Sensing, [2]Forestry and Ecology Department- Agriculture Faculty- Tishreen University- Syria, [3]Natural resources Department- Agriculture Faculty- Aleppo University- Syria.

al., 2008). This is needed to provide valuable information for decision-makers to support sustainable development (Fan et al., 2007). LULC models are used to improve better understand the land use changes caused by human activities (Brown et al., 2012).

Many types of spatial and statistical models have been used to analyze and predict LULC changes, including multinomial logistic regression models (Millington et al., 2007), Markov model (Hathout, 1988), Cellular Automata (CA) (Clarke and Gaydos, 1998), Empirical-statistical Models (Veldkamp and Fresco, 1996) and others (Ren et al., 2019). CA and Markov modeling have widely used in the fields of spatial and geographic, where they have given sufficiently accurate results especially in the changes of land use (Al-shalabi et al., 2013; Zadbagher et al., 2018; Hamad et al., 2018); and urban growth simulation (Siddiqu et al., 2018; Nasehi et al., 2019).

In Syria, negligible real study was done to predict land use/land cover changes. This research attempts at evaluating and simulating the dynamics of spatio-temporal land use/land cover changes in Bayer and al-Bassit region of northwestern Latakia, Syria. The main objectives were to: (a) map and assess the LULC changes under different categories using Landsat images acquired in 1992, 2005, and 2018; and (b) predict the future LULC map in 2030 using CA-Markov model.

# Materials and Methods

## Study Area

Bayer and al-Bassit region extends between longitudes ($35^0$ 47’ 49.2”, $36^0$ 15’ 57.44” E) and latitudes ($35^0$ 57’ 0.6”, $35^0$ 35’ 42.7” N) and encompasses an area of 7300 $km^2$. It lies in the northwestern part of the coastal mountains in north and north-west Latakia, Syria (Figure 1). A Mediterranean climate type with a rainy winter and a long dry summer characterizes the study area. Brown Mediterranean Soil is the main type of soils, formed on hard calcium rocks, in the study area, which is highly washed, well-structured, rich in organic matter and iron oxides (Verheye and de la Rosa, 2005). The altitude above sea level is between 300 and 1400 meters, and the average rainfall ranges between 800 and 1200 mm/year.

Forest cover, covering more than 70% of the area, characterizes the area. Bayer and al-Bassit forests are the best and most important forests in terms of area and diversity in Syria, consisting mainly of conifers, oaks and many other species. Villages are located in the western and southern parts of area, the majority of people living there depend on agriculture in their livelihoods, so agricultural land is mostly concentrated around the villages.

## Data collection and processing

Three Landsat images were used in this study: 1992, 2005 and 2018, and downloaded freely from the United State Geological Survey (USGS, 2018). Table 1 presents the characteristic of these images. The preprocessing of the images including Geometric, Radiometric and Topographic corrections was applied to the images as in Ali et al. (2018) using ERDAS imagine software (v.15).

The maximum likelihood algorithm (MLC) which falls under supervised classification was used for the image classification process (Gong and Howarth, 1992; Richards and Xiuping, 1999). LULC classes were categorized into four classes: water, urban, agriculture and forest. Classification accuracy assessment was performed for each LULC map by calculating Kappa statistics for the accuracy assessment and the overall accuracy (Congalton and Green 2008). These use maps used for land were then exported by ArcMap v. 10.3 software into ASCII files in order to predict land use change in IDRISI

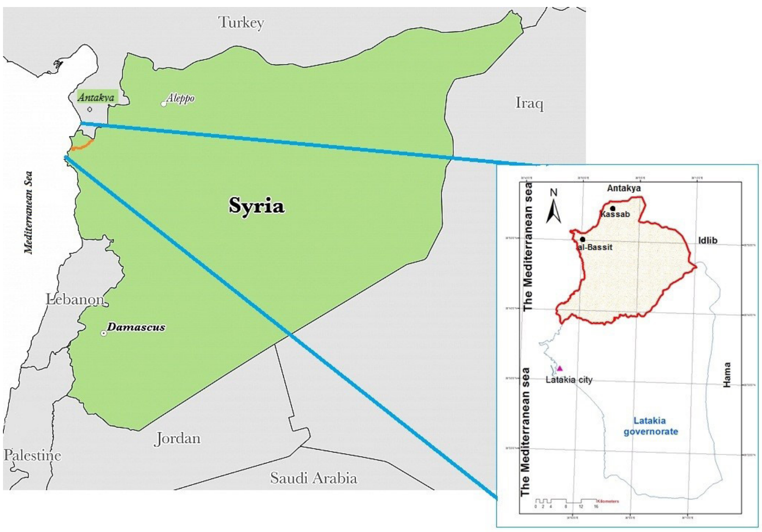


**Figure 1.** Geographic position of the Study area, Bayer and al-Bassit region, Latakia, Syria.

Selva (v 17.0). In IDRISI Selva, the modules "MARKOV, CA-MARKOV, and VALIDATE" were used for projecting the 2018 land use map for Bayer and al-Bassit.

## Data Analysis

**Table 1.** Characteristics of the Landsat images used in this study.

| Landsat Sensor | Path/Row | Date Acquired | Spatial Resolution |
|---|---|---|---|
| Landsat 5 TM | 174/035 | 12/09/1992 | 30 m |
| Landsat 5 TM | 174/035 | 16/09/2005 | 30 m |
| Landsat 8 OLI | 174/035 | 06/10/2018 | 30 m |

Classification Accuracy Assessment: To validate LULC Maps resulted from image, the "ACCURACY ASSESSMENT" tool in Erdas Imagine was used as in Merhej et al. (2020). This tool compares a set of points distributed within each map with what they are in reality, calculates the overall accuracy and Kappa statistics (for calculations see Jensen 2003). Google Earth maps and more than 200 Ground Control Points (GCP) distributed throughout the study area were used in the assessment process. The coordinates of these points were recorded using "GARMIN eTrex" GPS, then we arranged them with the type of land cover for each point within Excel. By ArcMap v. 10.3, the excel file was imported and converted to shape file, which was used in accuracy assessment process.

Percentage of Land use Change: To achieve the percentage of land use changes, firstly, a table contains the area and the percentage of change for each LULC class was developed, then the trend of change, which is percentage change, was calculated using the following equation:

$$\text{Trend} = (\text{Observed change}/\text{Total change})\times 100 \qquad (1)$$

To obtain an annual rate of change, the trend was divided by 100 and multiplied by the number of study years: 1992 – 2005 (13 years), 2005 – 2018 (13 years).

Markov Model: Markov model is often used in researches of change in ecosystems, whether in monitoring, analyzing or quantifying this change (Subedi et al. 2013). It is also used to predict the amount of land use change and the state stability of land development in the future (Parsa et al. 2016; Weng 2002), and it can be represented mathematically as Equation 2:

$$S(t,t+1)=Pij\times s(t) \qquad (2)$$

where S(t) is the system status at time of t; S(t+ 1) is the system status at time of t+1; and $P_{ij}$: the transition probability matrix in a state which was calculated as Equations 3 and 4:

$$= \|P_{ij}\| = \begin{Vmatrix} P_{1,1} & P_{1,2} & \dots & P_{1,N} \\ P_{2,1} & P_{2,2} & .. & P_{2,N} \\ \dots & \dots & \dots & \dots \\ P_{N,1} & P_{N,2} & \dots & P_{N,N} \end{Vmatrix} \qquad (3)$$

$$(0\le P_{ij}\le 1) \qquad (4)$$

where P is the transition probability; Pij is the probability of converting from current state i to another one j in next time; and PN is the state probability of any time (Kumar et al., 2014). To predict how a specific variable changes over time, Markov took the past states of the variable into consideration. Markov model has the ability to determine the amount of conversion between land use classes and the rate of conversion among land use classes, which makes the model optimistic in land use change modeling. IDRISI Selva was used to present Markov model.

CA-Markov Model: To simulate the change of land cover over time, the spatial contiguity and probable spatial transitions (i.e. place in a specific area) were defined (Subedi et al., 2013). The combination of Markov model and cellular automata "CA-Markov" were calculated from Equation 5 (Sang et al., 2011):

$$S\ (t,t+1)=f\,(S(t),) \qquad (5)$$

where S (t,t + 1) is the state of the system at time t and t+1, operating according to the principle that the state was the likely to occur at any time (N). Transition probability and transition area matrices were created by applying MARKOV and CA_MARKOV modules in IDRISI Selva. While the transition probability matrix assessed, the change probability of a pixel in a land use category into another one during a period was determined. The transition area matrix contained the expected number of changed pixels during the same period (for more details see Zadbagher et al., 2018). In order to predict

**Table 2.** Land Use Land Cover Distribution (1992, 2005, 2018).

| Land Cover | 1992 | | 2005 | | 2018 | |
|---|---|---|---|---|---|---|
| | Area (km$^2$) | % | Area (km$^2$) | % | Area (km$^2$) | % |
| Water | 11.39 | *1.58* | 11.55 | 1.60 | 12.48 | 1.73 |
| Urban | 41.97 | *5.80* | 41.11 | 5.69 | 61.44 | 8.51 |
| Agriculture | 326.96 | *45.22* | 328.67 | 45.45 | 407.14 | 56.30 |
| Forest | 342.74 | *47.40* | 341.81 | 47.27 | 242.05 | 33.47 |
| Total | 723.1 | *100* | 723.1 | 100 | 723.1 | 100 |

the 2018 LULC map, which was generated to evaluate the model accuracy, a transition probability matrix was created using 1992 and 2005 land use maps. The iteration number in CA-Markov depended on the number of years between the base and projected LULC maps, and the default contiguity filtered of a kernel size of 5 5 pixels was used (Subedi et al. 2013).

### Model Accuracy Assessment

Kappa indices used to validate CA Markov prediction for the spatial patterns of future change (Lambin et al., 2003). Kappa statistics were suggested by Pontius (2002) for testing accuracy in terms of change location (Kappa for location) and number of correct cells (Kappa for quantity). The validation was applied by comparing the actual land use map with a predicting map (Al-sharif and Pradhan, 2013).

LULC maps of 1992 and 2005, which were derived from Landsat images classification to predict 2018 LULC (Projected, 2018), then it was compared with actual 2018 LULC (actual 2018) (Yang et al., 2008; Al-sharif and Pradhan, 2013). Because of Kappa statistics' drawback (i.e. wrong or high values of accuracy) (Wu et al., 2015) and confusion of the accuracy assessment (Ahmed et al. 2013), cross-tabulation were used (Pontius and Millones, 2011). Therefore, the overall Kappa Coefficient and Kappa Index of Agreement (KIA) were performed using cross-tabulation for respective LULC categories. When reasonable result and a good level of confidence were achieved, the 2030 LULC map was predicted.

## Results and Discussion

### Land Use/Land Cover status

Table 2 clarifies the static land use/land cover distribution in square kilometers derived from LULC maps for the years 1992, 2005 and 2018. Figure 2 shows LULC maps derived from Landsat image classification as used the years in this study. Figure 2 also shows that forest cover followed by agricultural areas, occupied the most of the study area. The 2005 map shows the decline of forest concentrates in al-Bassit region due to the large fire that occurred at the end of 2004. In the 2018 map, the decline of forests in favor of agriculture was clearly indicated by the excessive deforestation during the years of war (2011 and thereafter), it was achieved with the purpose of heating on the one hand, and switching to agricultural use on the other.

That is confirmed in Table 2, where vegetation covered (forests and agriculture) during the study period (1992 to 2018) the most of Bayer and al-Bassit region.

In 1992, the vegetation covered accounts for 92.62% of the total area of Bayer and al-Bassit region, distributed to 326.96 km$^2$ of agriculture and 342.74 km$^2$ of forests. The other land use types covered 53.36 km2, of which 11.39 km$^2$ was water and 41.97 km$^2$ was urban (Figure 2). Within this thirteen years' gap (1992 –2005), vegetation cover maintained a good stability (92.72%), because of the afforestation projects implemented during the 1990s. On the other hand, around 99.76 km$^2$ of forest land had been lost and converted to agriculture and other human induced land uses (78.47 km$^2$) between 2005 and 2018. Thus, it was found that in 2018, forest area was reduced to 33.47% (242.05 km$^2$) of the total area, while there was a sharp increase in agriculture land sharing almost 10.85% (407.14 km$^2$ of the total area of Bayer and al-Bassit). There was also a steady increase in urban during 2005 –2018 periods.

### Accuracy Assessment of MLC

The "ACCURACY ASSESSMENT" tool was used to evaluate the classification accuracy on each LULC map. GCP were used to validate the 2018 map, while Google Earth images were used for the 1992 and 2005 maps. The results showed that the overall accuracy values were 89.23%, 89.38% and 88.28%, respectively. On the same hand, Kappa index values were recorded 0.85, 0.86 and 0.84, respectively. The values were close and consistent, and gave excellent confidence to the LULC mapping.

### Land Use/Land Cover Change

Rate and Trend: The study period used in this project was divided into two partial periods. The first period was between 1992 and 2005, while the second was between 2005 and 2018. The positive change means that an object has increased its existence and the negative change, on the opposite, decreased its existence. Both the positive and negative changes in the second period (2005- 2018) showed a significant increase as compared to the first period (1992- 2005). The total changes in the first period were about 4 km$^2$, while in the second period were

**Table 3.** LULC change of Bayer & al-Bassit and its environs: 1992, 2005 and 2018.

| Change | 1992-2005 | | 2005-2018 | | Annual Rate % | |
|---|---|---|---|---|---|---|
| LULC | Area (km$^2$) | Trend % | Area (km$^2$) | Trend % | 1992-2005 | 2005-2018 |
| Water | 0.16 | 4.32 | 0.93 | 0.47 | 0.56 | 0.06 |
| Urban | -0.86 | -23.37 | 20.43 | 10.24 | -3.04 | 1.33 |
| Agriculture | 1.72 | 46.79 | 78.46 | 39.31 | 6.08 | 5.11 |
| Forest | -0.94 | -25.52 | -99.76 | -49.98 | -3.32 | -6.50 |

**Table 4.** The table of transitional Probability derived from applying Markov model using the LULC map of 1992 and 2018.

| LULC | 92-05_transition_probabilities | | | |
|---|---|---|---|---|
| | 2005 | | | |
| 1992 | Water | Urban | Agriculture | Forest |
| Water | 0.8698 | 0.0344 | 0.0006 | 0.0952 |
| Urban | 0.0018 | 0.5145 | 0.3951 | 0.0886 |
| Agriculture | 0.0001 | 0.0725 | 0.9461 | 0.0464 |
| Forest | 0.0008 | 0.0068 | 0.3888 | 0.5386 |

about 200 km². This indicated that rapid changes had happened as loss and gain trends, due to the impacts of the war crisis on this area (Merhej et al., 2019).

From Table 3, there seems to be a reduction (a negative change) in urban area in the first period and a sharp increase in the second one. Whereas urban area decreased by 23.37% between 1992 and 2005 and increased by 10.24% between 2005 and 2018. This may be a result of the shift towards housing rather than farming, confirming the increase of agricultural area so, as it rose by 46.79% in the first period, this expansion fell to 39.31% in the second period.

Furthermore, water class showed an increase of 4.32% in the first period (1992- 2005) due to the good precipitation in that period. This agrees with results reported in neighboring Antakya (in Turkey) which has climatic conditions similar to those of this study region. The period of 1990-2004 was characterized as a wet period except the dry season of 1990-2000 (Karabulut, 2015). In the second period (2005- 2018), there was a slight difference in the water category at the study area due to the disastrous drought as recorded between 2005 and 2010 (Mohammed et al., 2019), followed by a wet period between 2010 and 2018.

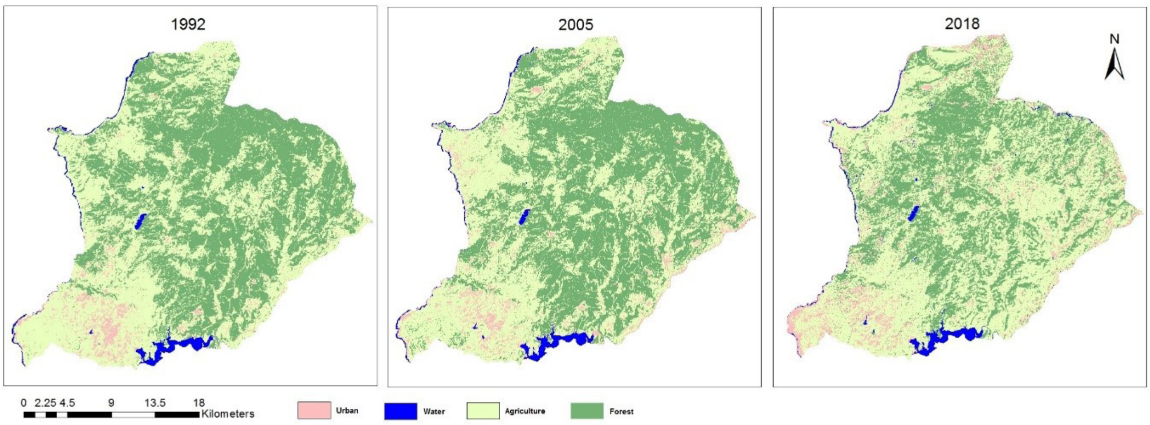


**Figure 2.** LULC maps for the Bayer and al-Bassit region

The entire period of this study has witnessed a sharp decline in the proportion of forests, where the distribution of forests can be worrying. The forest category fell by -25.52% in the first period and continued to decline rapidly between 2005 and 2018 by -49.98%. This decline in forest area was due to a number of causes, such as overcutting, forest fires, as well as land fragmentation and conversion to agriculture land.

Forest decline was evident throughout the whole study period and the annual decline rate reached 3.32% in the first period and 6.5% in the second period. According to Rajab (2008) forest decreased in Latakia by 32.2% between 1991 and 2004, and converted to agricul-

**Table 5.** The validation analysis: agreement/ disagreement components.

| Agreement | | | | Kappa Indices | |
|---|---|---|---|---|---|
| AgreeGridCell | 0.5 | DisagreeGridCell | 0.0991 | Kstandard | 0.7934 |
| AgreeQuantity | 0.18 | DisagreeQuantity | 0.0295 | Kno | 0.8392 |
| AgreeChance | 0.2 | | | Klocation | 0.8329 |
| | | | | KlocationStrata | 0.8329 |

**Table 6.** The expected area of the LULC categories in the projected maps for 2018 and 2030 for Bayer and al-Bassit region.

| LULC Categories | LULC areas in 2018 projected map (km²) | LULC areas in 2030 projected map (km²) |
|---|---|---|
| Water | 10.1655 | 7.80 |
| Urban | 30.2058 | 38.2034 |
| Agriculture Land | 181.4467 | 203.1873 |
| Forests | 501.7235 | 474.3433 |
| Total | 723.5415 | 723.5415 |

ture lands and urban and other human uses. In addition, about 8 km$^2$ converted to agriculture lands in al-Bassit after the fire in 2004 (Kassas, 2008).

## Transition Probability Matrix

In order to simulate the future LULC changes, Markov model was applied for the period of 1992–2005 to calculate both the transition probability matrix and the transition area matrix. The raw classes represented the land cover types in 1992 map, while the 2005 land cover types were represented in the column classes (Table 4). The used iteration number was 13, which was the years number between the base map (2005) and projected map in 2018 (Figure 3a).

As seen from Table 4, agriculture during the study shows a high probability of remaining as agriculture in 2005 with a value of 0.9461, which signifies a high level of stability. As well, water class showed a probability as high as 0.8698 to stay as water in 2005. Urban and forest classes, on the other hand, could likely change to other land use classes in this period with a high level of instability. While the probability of changing from urban class to agriculture was 0.3951, the urban stability value was 0.5145. This might be a false projection of this class if we made the drought events in the region (Karabulut, 2015) as an exception. Indeed, forest class showed a 0.5386 probability of remaining as forest and a 0.3888 probability of converting to agriculture class. This, therefore, showd an undesirable change (reduction).

## Model Validation

CA-Markov model was validated using *validate* tool in GIS Modeling in IDRISI. This statistical method differentiated between error and agreement by elements due to the specification of quantity and location. Table 5 clarifies Kappa statistics for quantity and location derived from comparing the 2018 predicted LULC map to the 2018 actual LULC map.

The results of Kappa statistics for location show that $K_{no}$ was 0.8392, $K_{location}$ was 0.8329, $K_{location\ Strata}$ was 0.8329 and $K_{standard}$ was 0.7934. According to Mondal et al. (2016), these results indicated that CA Markov model had a high ability to define the location of future change on a grid cell level (the perfect $K_{location}$ value is 1).

Table 5 also shows that there is an excellent agreement between the simulated and actual LULC maps of 2018 where the $K_{standard}$ is more than 0.75 (Fleiss et al., 2003). The correct agreement of grid cell, agreement of quantity and agreement due to chance represented by 50, 18 and 20%, respectively. On the opposite, the model was with the disagreement grid cell (i.e. 9.91%) and disagreement quantity (i.e. 2.95%). These results agreed with those by

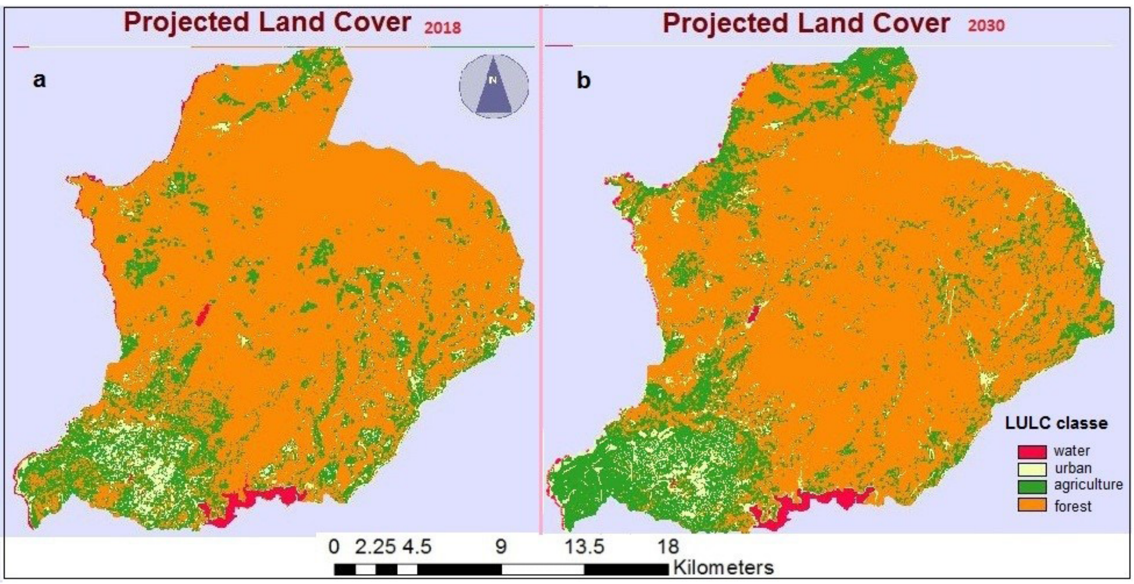


**Figure 3.** The projected LULC maps for the year of 2018 (a), and 2030 (b)

Halmy et al. (2015) and indicated that CA Markov could be used successfully in the LULC changes prediction.

### Simulation of future changes in 2030

After evaluating the accuracy of the applied model and gaining good values of reliability, CA-Markov model was used to obtain the 2030 LULC map, shown in Figure 3b. Figure 3 shows the expected spatial distribution of land use categories in the years of 2018 and 2030 in the study area, and Table 6 clarifies the expected areas for each LULC category. The agricultural areas can expand at the expense of forests in several patches in Bayer and al-Bassit region, continued their existence and expansion in the years 2005 and 2018, especially in the northern parts. The expected decreased area of forests in 2030 was 27.38 km$^2$ (3.78% of the study area) corresponding to an expected increase in the area of agricultural land in 2030 by 21.74 km$^2$ (3%) (Table 3). The urban areas are concentrated and expanded in the south western part of the study area, and we can notice that the northern border of the study area can be converted from forest category to Urban in 2030 (Figure 3).

On the other hand, a decrease in the water category by a small percentage, amounting to 0.32% was noted (Table 6), and it can be explained that it may be a reflection of the drought periods that passed in the period 2005-2018 and appeared in the transition probability matrix, and this was confirmed by what appears when comparing the maps for the years 2018 and 2030.

## Conclusion

In summary, it was found that the forest area decreased significantly during the period 1992-2018 mainly in favor of agricultural lands and urban areas. The CA Markov model showed very good results of agreement between the actual and predicted LULC maps on the level of location and quantity. CA Markov can be improved by adding many factors that affect the land use changes like topographic, social and economic factors. Therefore, the CA Markov would be a suitable model to predict future land use change in the Bayer and al-Bassit region.

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