



# Application of modified cellular automata Markov chain model: forecasting land use pattern in Lebanon

Walid Al-Shaar<sup>1,2</sup> · Jocelyne Adjizian Gérard<sup>1</sup> · Nabil Nehme<sup>3</sup> · Hassan Lakiss<sup>2</sup> · Liliane Bucciante Barakat<sup>1</sup>

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## Abstract

This article modifies the use of the Cellular Automata Markov Chain Model to predict future land use pattern in Lebanon, and compares it to the current developed model. LandSat images of years 2000, 2009 and 2018 are used to generate land use maps within the geographic information system. Current developed model was generated by integrating Population density data with land use classification maps to decompose the built-up development to three sub-classes: High, Medium and Low-density built-up land uses. Simulations of future land use pattern over the year 2018 based on these two prediction models reveal that the Modified Cellular Automata Markov Chain Modelling technique is more accurate than the Extended Markov Chain model. Spatial effects of built-up densities are validated in this study. Consequently, the extension of the Cellular Automata Markov Chain Model represents an innovative tool for regional and urban planning to forecast potential locative distribution of old and new urban agglomeration. The sequential shift of the urban areas among different density classes in addition to the interactions of urban agglomerations should be employed as a guiding tool for decision-makers and planners during the phase of developing new population and economic strategies, new urban Masterplan and during the process of enacting/developing new land-use policies. In the final part of the study, a simulation of land use pattern for the year 2036 is generated using TerrSet v.18 software and an analysis of the outcome for the forecasted map is discussed.

**Keywords** Markov chain · Cellular automata · Land use · GIS · Lebanon

## Introduction

Previous applications of Cellular Automata—Markov Chain model (CAMCM) and Markov Chain Model (MCM) in addition to a brief introduction of the models used in the study are presented in this section. Moreover, the selection and the background of the study area are also reported.

Relationship of land use dynamics and Cellular Automata—Markov Chain Modelling; and preceding applications.

The simulation of Land Use (LU) dynamics is an essential technique to evaluate the future LU pattern, urban sprawl and landscape structure. The MCM is considered as an effective method to be employed to predict the future LU transitions (Al-Shaar et al. 2020; Chakir and Parent 2009; Wang and Kockelman 2009). The CAMCM provides an efficient tool for the modelling of LU changes by integrating the location-based interactions between LU with the temporal dimension expressed as the historical LU transformations and their spatial interactions (Houet and Hubert-Moy 2006; Ozturk 2015; Ghosh et al. 2017). The following part

✉ Walid Al-Shaar  
walid.al-shaar@net.usj.edu.lb

Jocelyne Adjizian Gérard  
jocelyne.gerard@usj.edu.lb

Nabil Nehme  
nabil.nehme01@lau.edu.lb

Hassan Lakiss  
hassanlakiss@yahoo.com

Liliane Bucciante Barakat  
lbarakat@usj.edu.lb

<sup>1</sup> Doctoral School of Human and Society Sciences, Geography Department, CREEMO (Centre de Recherche en Environnement-Espace Méditerranée Orientale) Geography Department, Saint Joseph University, Campus des sciences humaines, Rue de Damas, B.P. 17-5208, Mar Mikhael, Beirut, Lebanon

<sup>2</sup> Doctoral School of Science and Technology (Civil Engineering), Lebanese University, Badaro, Museum, P.O. Box 6573/14, Beirut, Lebanon

<sup>3</sup> School of Engineering, Lebanese American University, Chouran, P.O. Box 13-5053, Beirut, Lebanon

discusses several case studies where the integrated CAMCM was implemented.

The CAMCM model was employed as a land-use forecasting model in recent studies as the study conducted by Ackom et al. (2020) on land degradation in the Odaw River Basin in Ghana; and the study of Kabite et al. (2020) intended to identify the land cover transformations in the Dhidhessa River Basin in Ethiopia and the driving forces behind these changes. The SLEUTH model which is derived from the Cellular Automata (CA) model was employed by Akin and Erdoğan (2020) to predict the future urban sprawl and land degradation in Bursa city in Turkey. A new urban planning simulation model was developed by Falah et al. (2019) by integrating the analytical hierarchy process into the modelling technique of cellular automata. The land use data of Qazvin city in years 1996 and 2016 were used in the model's validation process. A study on the dynamics of LU in Halgurd-Sakran zone in Kurdistan, Iraq was conducted by Hamad et al. (2018) on the basis of CAMCM and the Remote Sensing Technology. The model was used to simulate LU for the year 2023 under two distinct situations. The first situation is a temporal period where Iraq was under the United Nations sanctions, satellite images for years 1993, 1998 and 2003 were used. The second situation is after the end of the United Nations sanctions against Iraq, satellite images for years 2003, 2008 and 2017 were used. Results indicated that the cultivated zones are affected significantly by the United Nations sanctions (Hamad et al. 2018). The CAMCM was also applied by Hua (2017) to foresee the changes of LU in the watershed zone of Malacca River in Malaysia between the years 2015 and 2029. Historical data of LU were obtained from maps generated in ArcGIS 10.0 and ENVI 4.0 softwares where the Landsat images for years 2001, 2009 and 2015 represent the input data. Simulation of LU map for the year 2015 was processed within IDRISI Selva v.17 software and validated using Kappa statistics test. Then, a simulation of LU for the year 2029 using CAMCM was conducted. Outcomes indicate a degradation of vegetation and open space areas in addition to a significant reduction in water bodies generated from the increased development of farming, industrial and non-industrial areas associated with increased pollution of Malacca River. The land-use scenarios of Shannon River's watershed in Ireland for years 2020, 2050 and 2080 were simulated by Gharbia et al. (2016) by using the integrated Cellular Automata-GIS model based on land use maps and digital elevation models of the study area. Vázquez-Quintero et al. (2016) forecasted a reduction in the areas of pine forests of Pueblo Nuevo region in Mexico through a land-use CAMCM simulation for the year 2028. A new LU prediction model integrating CA, logistic regression and MCM was developed by Arsanjani et al. (2013) to investigate the increase of suburban areas in Tehran metropolitan zone, Iran. Socio-Economic

and Environmental factors involved in the urban expansion were taken into consideration during the phase of formulating the Probability Transition Map for spatiotemporal states of urban LU in years 2006, 2016 and 2026. The model and its calibration were validated through cross comparison of simulated LU maps to actual maps. Subsequently, the calibrated model was employed to simulate the LU for the year 2016 and 2026. Simulation results showed an induced urban development in the western metropolitan neighborhood of Tehran. The concept of spatial evolution of the CAMCM was adopted by Houet and Hubert-Moy (2006) to forecast future LU and LandCover evolution in Coët-Dan watershed which is an intensive cultivated zone in Central Brittany, France. Historical LU data and landscape features were extracted from aerial photos and satellite imagery for the period between 1950 and 2003. The authors considered that spatial evolution is occurring due to observed landscape features, biophysical and socio-economic driving factors. CAMCM simulations were applied to forecast the future LU change for the years 2015 and 2030. Two scenarios were conducted throughout these simulations: with and without taking into account the landscape features of the studied watersheds. The model that includes the landscape features simulates more accurately the LU changes than the one that excludes these features. Findings depict that considering landscape features will enhance the accuracy of simulations for future LU states.

### Markov chain model

The study of chance progression as a new theory of predictive probability was first introduced in 1907 by the mathematician Andrei Markov. This study showed the interdependence between the results of future experiments and the outcomes of historical chance processes; this theory is known as the Markov Chain (Ching and Ng 2006; Grinstead and Snell 2006; Gagniuc 2017). Markov Chain Model (MCM) was considered as practical predictive in different scientific fields as the study and the prediction of LU dynamics (Al-Shaar et al. 2020; Iacono et al. 2017). Baker (1989) as cited in (Iacono et al. 2017) indicated that a row vector describing the LU distribution at the time  $(t + 1)$ :

$$V_{t+1} = P \times V_t \quad (1)$$

Iacono et al. (2017) assumed that the transition probability matrix will remain constant at following future periods and a row vector " $V_{t+y}$ " at time " $t+y$ " could be obtained by multiplying the current LU row vector " $V_t$ " by the matrix " $P$ " raised to the power " $y$ " ( $P^y$ ):

$$V_{t+y} = P^y \times V_t \quad (2)$$

More info about the Markov Chain mathematical equations are explained in the following references:

(Hamad et al. 2018; Iacono et al. 2017; Rozario et al. 2017; Gagniuć 2017; Parsa et al. 2016; Han et al. 2015; Subedi et al. 2013; Takada et al. 2010; Grinstead and Snell 2006; Ching and Ng 2006; Levinson and Chen 2005; Weng 2002; Muller and Middleton 1994).

### Cellular automaton (CA) model

The Cellular Automata concept was initially presented by John Von Neumann and Stanislaw Ulam between 1940 and the early 1950s (Wolfram 2002). The concept indicates that the state of a group of cells is governed by its previous state, previous states of its surrounding/ neighboring cells in addition to local rules that govern this array of all cells (Wolfram 2002; Alkheder et al. 2006; Houet and Hubert-Moy 2006; Koomen and Borsboom-van Beurden 2011; He et al. 2013; Ozturk 2015; Mishra and Rai 2016; Parsa et al. 2016; Hua 2017; Hamad et al. 2018). The cellular Automata model relates the time with space interactions.

The following equation depicts the general algorithm of Cellular Automata model (Alkheder et al. 2006; Hamad et al. 2018):

$$S^{t+1}(\alpha) = f(S^t(\alpha), S^t(\pi)), \quad (3)$$

where:

$\alpha$ : Group of studies cells.

$S^{t+1}(\alpha)$ : the state of cell  $\alpha$  at time  $(t + 1)$ ,

$S^t(\alpha)$ : the state of cell  $\alpha$  at time  $(t)$ ,

$S^t(\pi)$ : the state of cell  $\pi$  at time  $(t)$ ,

### Local transition rules: spatial interactions among cells

The literature indicates that the Cellular Automata models represent a powerful tool that could forecast the future LU dynamics on the basis of the spatial interactions known also as the neighboring effects (Alkheder et al. 2006; Houet and Hubert-Moy 2006; Arsanjani et al. 2013; Halmy et al. 2015 and Parsa et al. 2016).

### CA-Markov chain model

CAMCM represents an efficient tool that intends to describe future LU dynamics on the basis of integrating historical dynamics data with the spatial interactions effects. The CAMCM uses the outputs of MCM represented by the “Transition” data in the application of a “Contiguity Filter” to simulate the future LU changes. Through a predefined contiguity filter weighting factors are associated to neighboring LU cells (Eastman 2012; Arsanjani et al. 2013; Subedi

et al. 2013; Halmy et al. 2015; Ozturk 2015; Mishra and Rai 2016; Parsa et al. 2016; Hua 2017; Ghosh et al., 2017 and Hamad et al. 2018).

A previous study by Al-Shaar et al. (2020) considered and validated the applicability of the extended MCM (EMCM) in forecasting future land use pattern in Lebanon. The authors indicated in their study that the Extension of Markov Model was explained as the integration of population density within the built-up land uses. An expansion of this previous study is conducted in this paper by modifying the CAMCM by the way of integrating the population densities with the built LUs. The extended model is denoted as ECAMCM. A comparison of two LU simulation models: ECAMCM and EMCM are carried out to determine which model has the greater accuracy and the better realistic representation of the LU change. Simulations to the year 2018 were conducted and the produced LU maps were compared to actual one based on the Frobenius Matrix Norm. It is hypothesized that the ECAMCM is the most accurate model since it generally takes the spatial effects of land use distribution during the simulation process and specifically the spatial distribution of population densities. Used data in this study are: (i) maps of Lebanon LU over years 2000, 2009 and 2018 which were generated using the Landsat images, (ii) projected population density maps (with reference to the available density map of the year 2004) using ArcGIS 10.6.1 software. This research provides an innovative methodological concept (ECAMCM) within the techniques of future land use forecasting models. The structure of this article is depicted as follows, next section comprises a simple background of the case study. The second section depicts the adopted research methodology, the collected data and the treatment of these data. The third section represents the simulations of LU for the year 2018 using the two models and for the year 2036 using the CAMCM. The fourth section highlights the analysis of actual and simulated LU transitions, respectively, between the period 2000–2018 and the period 2018–2036. The fifth section concludes the paper and highlights the robustness of the developed model for future LU simulation.

### Background and case study

This paper considers Lebanon country as the case study zone since its LU are intensively changing.

A degradation of water bodies, natural areas and agricultural zones has occurred and it is currently occurring in Lebanon. These uncontrolled LU dynamics represents a major national problem. Reasons behind these changes could be explained in the lack of appropriate LU planning policies in addition to the non-existence of a nationwide LU Masterplan and a centralized governmental entity responsible for planning and coordination of landscape and LU dynamics

(FAO 2012). A study of the LU dynamics in Lebanon for the period from 1963 to 1998 was conducted by Masri et al. (2002). The study was processed using the Agro statistics map for the year 1963 in addition to the remote sensing satellite images for the year 1998 and Geographic Information System tools (GIS) by which the LU map of the year 1998 was produced. The results showed an increase in the areas of bare soil lands and urban development at the expense of reduced Forests and Agricultural lands. The vertical and horizontal urban sprawl of Lebanese cities is expanding in a chaotic pattern without relying on consistent planning strategies. The population growth increases the need for housing as well as for secondary houses as chalets and mountain retreats (Stephan 2010 as cited in FAO 2012). These urban developments are diminishing the natural areas, bare soils and agricultural zones (Zurayk and El Moubayid 1994 and FAO 2012). Fawaz (2011) reported that the quality of LU in Lebanon is deteriorating and the degraded agriculture zones along the coastline and natural zones in addition to old classical buildings could not be restored again. The research directed by Al-Shaar et al. (2020) indicated that the land use simulation under the Extended Markov Chain Model (EMCM) shows an estimated decrease in the areas of water bodies and agriculture zones in addition to an increase in high-density development and bare soil lands in the year 2036. In this study, and after comparing the outputs accuracy of the ECAMCM and the EMC, a simulation of future LU (for the year 2036) is conducted. The outcomes are considered as guidelines for policymakers during the stage of taking proactive decisions to appropriately manage the LU pattern and to protect the landscape.

## Materials and methods

### Research methodology

This research proposes the development of a new land-use forecasting model by modifying the CAMCM to include spatial effects of built-up densities in urban areas. The methodology comprises stages of collecting and merging data, simulation of EMCM and ECAMCM models, validation and accuracy tests. The data processing phase comprises first the collection of data for the available population density map and the Landsat Satellite imagery for the study area over years 2000, 2009 and 2018. The second stage consists of processing the supervised LU classification of the collected satellite images; and the generation of density maps over years 2000, 2009 and 2018 at the basis of the projection and back-projection of the available population density map. The third stage is presented by integrating the generated density maps into the produced LU maps to decompose the

built-up land use to three sub-classes characterized by: High, Medium and Low built-up densities. The fourth and fifth stages are, respectively, described as the computation of the Extended Markov matrix of transition for the period between 2000 and 2009 and the use of this matrix in the application of the ECAMCM to generate the simulated LU map of the year 2018. These two processes are conducted using TerrSet v.18 software. The MCM is not adequate to conduct a realistic spatial simulation due to lack of neighboring effects as an input (Arsanjani et al. 2013; Houet and Hubert-Moy 2006). As indicated by Ozturk (2015), the neighboring effects represent one of the main spatial modelling component. These effects could be explained as the tendency of an area to be transformed to another LU class corresponding to its adjacent and surrounding zones. The hybrid CAMCM combines the Markov change process with the neighboring effects by employing a Cellular Automata filter (Eastman 2012 and Houet and Hubert-Moy 2006). This filter develops a space-based contiguity-weighting factor through a contiguity matrix by which the Cellular Automata model assess the contiguity pattern where the contiguity matrix indicates that the closest cells have higher effects on the considered center pixel than the far ones (Hamad et al. 2018). Using this model, the state's change of a cell will not be based only on its historical dynamics but further on the states of its neighbors, and the neighboring effects are considered in the modelling process. This Cellular Automata filter was applied to maps to determine the contiguity of the pixels in each LU class. The standard Cellular Automata contiguity filter is a five by five pixels matrix, this means that each cell in the map will be surrounded by a matrix space of 5 × 5 cells as indicated in the next matrix (Eastman 2012; Ozturk 2015; Hamad et al. 2018).

$$\text{Contiguity filter} = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}.$$

Nevertheless, the contiguity filter could be edited and tailored depending on the objective of the study (Eastman 2012 and Houet and Hubert-Moy 2006). At this stage, the simulated LU map for the year 2018 is generated and compared to the actual map to validate the simulation. The Validation process is based on the “Kappa Statistics test” which compares the simulated and actual LU states based on a defined calculation. After validating the simulation, a second simulation process is performed by calculating the Extended Markov transition matrix for the period between 2000 and 2018. This matrix is employed within the ECAMCM to generate the simulated LU map of the year 2036. Figure 1 illustrates the flowchart of followed research processes in this paper.

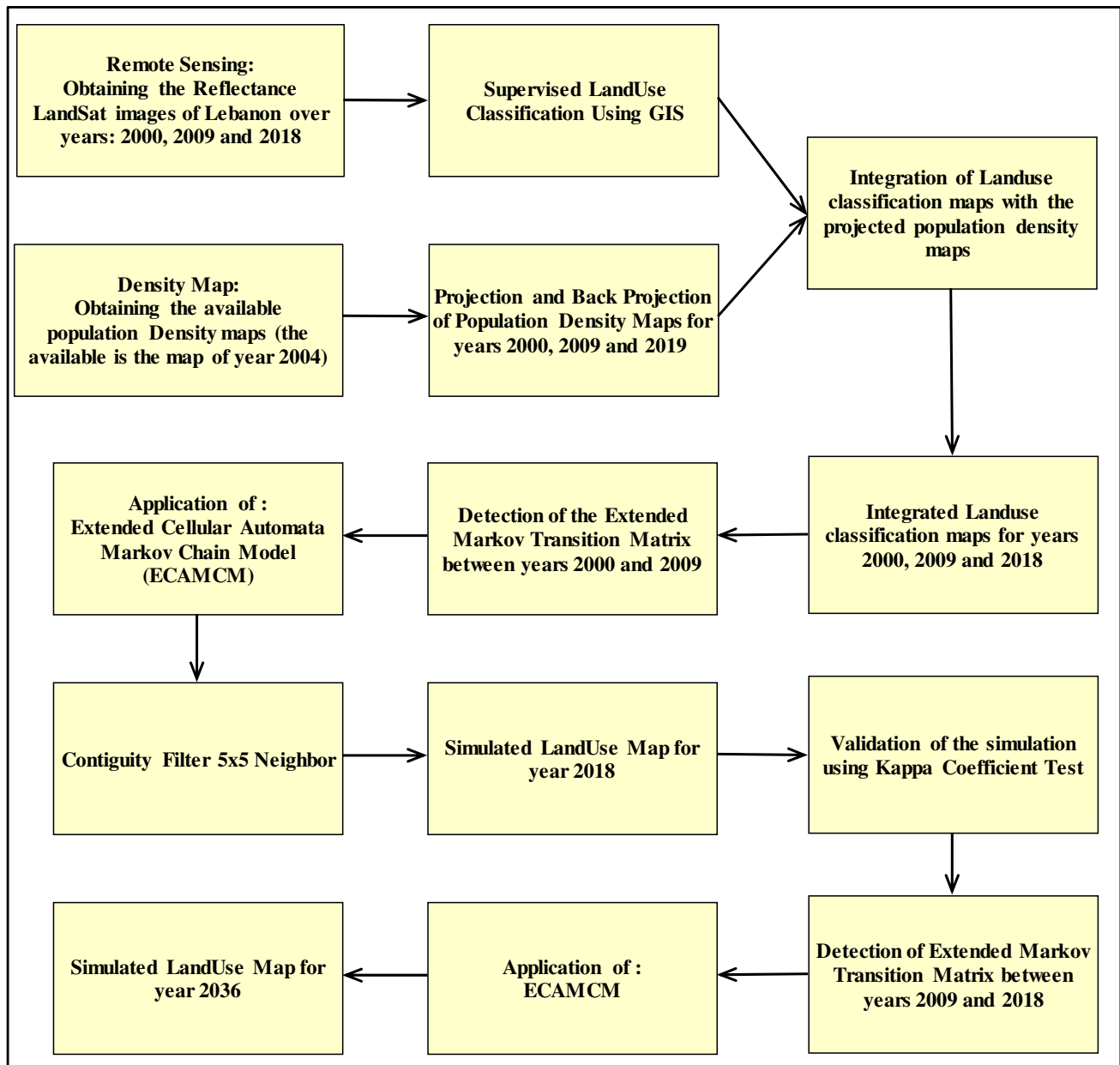


Fig. 1 Flowchart of followed research processes

**Data collection**

The data needed in this study are the LU and population density maps. Population density and LU maps over years: 2000, 2009 and 2018 are not available; however, these data are the same data input used in the study conducted by Al-Shaar et al. (2020) which validated the suitability of a modified Markov Model (Extended MCM) to be used in predicting the future land-use changes in Lebanon. Next sections provide a detailed description of data collected and the treatment process of these data.

**Landsat images**

Three multispectral satellite images (surface reflectance) with 30 m’ resolution for years 2000, 2009 and 2018 were downloaded from USGS Earth explorer (EarthExplorer 2019). The image of the year 2000 was taken by the Landsat 4–5—C1 Level 2 satellite, the image of the year 2009 was the Landsat 7—C1 Level 2 satellite and the image of the year 2018 was taken by the Landsat 8—C1 Level 2 satellite. It worth noting that Lebanon is located into two international UTM zones: 36 N and 37 N; therefore, a single image



of Lebanon for any defined year could not be downloaded from (EarthExplorer 2019) since it provides two separate images located in the two UTM zones indicated above. In this research, these separate images were merged to obtain a single and full satellite image of Lebanon for each of the years 2000, 2009 and 2018.

### Lebanon density maps

Maps of Population density in Lebanon over years 2018, 2009 and 2000 are not available. Projected and Back-projected density maps (for 2000, 2009 and 2018) were generated based on the available Lebanon density map for the year 2004 (Localiban 2016) and on the population data given by (WorldPopulationReview 2019) assuming that density and population's growth rates are uniform across all areas illustrated within the density map of the year 2004. The data of WorldPopulationReview (2019) have been estimated based on United Nations (2019) data which were in turn based on the statistics of the Lebanese Central Administration for Statistics (CAS) over the year 2004. Densities' intervals as tabulated in Table 1 are classified by Low, Medium and High population densities.

**Table 1** Defined density intervals of built-up areas' classes

Categories of built-up areas	Density intervals
Low population density	$< 250$ person/km <sup>2</sup>
Medium population density	$250 \leq$ person/km <sup>2</sup> and $< 5000$ person/km <sup>2</sup>
High population density	$5000 \leq$ person/km <sup>2</sup>

The generated Lebanon density maps over years 2000, 2009 and 2018 are illustrated in Fig. 2.

### Treatment of data

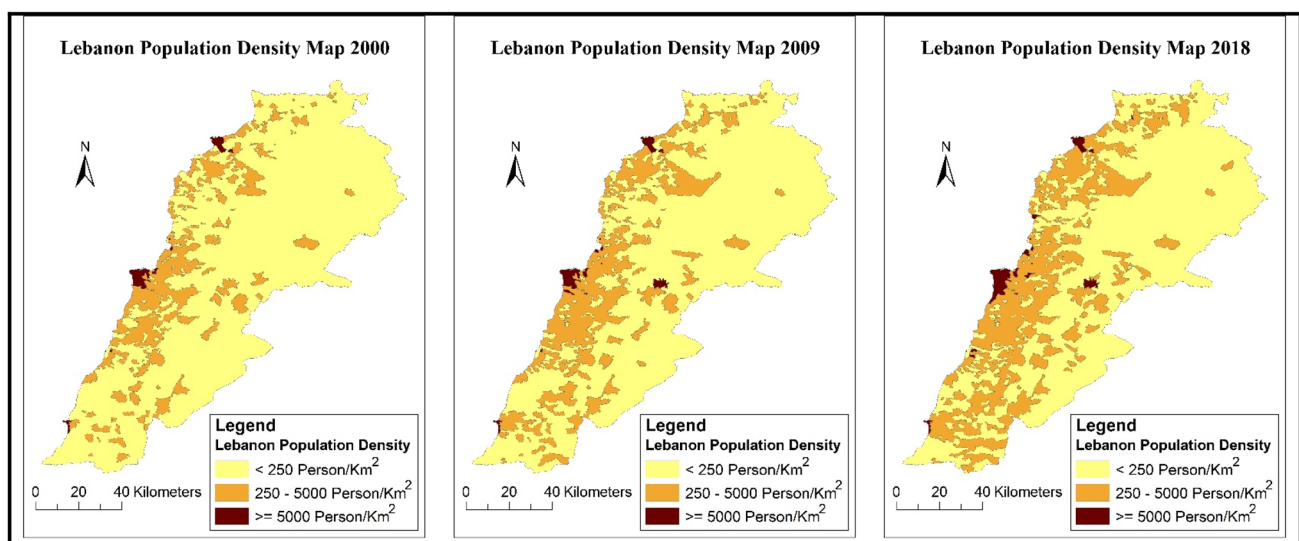
#### Classification of land use

The process of "Supervised classification" was conducted using the software ArcGIS 10.6.1.

The LU classes defined to classify the images are Built-up, Bare Soil, Forest and Agriculture areas in addition Water Bodies. The built-up LU was decomposed by referring to the projected Lebanon population density maps to three further sub-classes: High, Medium and Low built-up density lands. This integration is implemented in ArcGIS 10.6.1 software through the use of Raster Calculator module by adding the pixel values of the original LU classified rasters to the ones of population density maps converted to rasters. The areas of LU classes were compiled in ArcMap software through the "Zonal Statistics as Table" module.

The LU classification for years 2000, 2009 and 2018 was validated via the accuracy assessment test. This test comprises the accuracy assessment process conducted in ArcGIS and the computation of a confusion matrix which indicates the kappa value of the classification and the percentage of its accuracy.

The percentages of accuracy for LU classifications over years 2000, 2009 and 2018 are 88, 89 and 92, respectively. The corresponding kappa statistics' values are 0.83, 0.85 and 0.89, respectively. All percentages are above 85% which, as stated by Weng (2010), is a good accuracy percentage of classification. In addition, all kappa values are above 0.8



**Fig. 2** Maps of Lebanese population density over years: 2000, 2009 and 2018 (Al-Shaar et al. 2020)

indicating that the classification has a strong to perfect accuracy as indicated by Ozturk (2015).

Figure 3 illustrates the generated actual Lebanon LU maps over the years 2000, 2009 and 2018.

### Maps simulation

#### Simulation of land use map for the year 2018

The LU classification raster maps of years 2000 and 2009 were imported to TerrSet software to simulate the LU map for the year 2018. The TerrSet software calculates the Extended Markov transition matrix for the period between 2000 and 2009 and it uses this matrix in the application of the ECAMCM to simulate LU map for the year 2018.

#### Validation

A comparison of simulated and actual LU maps for the year 2018 was conducted in addition to a simulation’s validity test using “Kappa Statistics”. Subedi et al. (2013) and Parsa et al. (2016) stated that the “Kappa Index of Agreement” is an effective test to be used for the validation of LU dynamics predictions.

Kappa test provides a numerical value of the accuracy degree of the simulation; it calculates the accuracy value

according to the difference between actual and predicted states known respectively as the “Observed Agreement” and “Expected Agreement” (Tang et al. 2015; Viera and Garrett 2005; Landis and Koch 1977; Cohen 1960). Kappa statistics is a standardized measure of the difference among Observed and Expected Agreements; the next equation depicts how Kappa Value could be calculated:

$$K(Kappa) = \frac{P_o - P_c}{1 - P_c} \tag{4}$$

where “ $P_o$ ” represents the Observed Agreements and “ $P_c$ ” represents the Expected Agreement or Agreement by Chance.

Kappa value indicates the level of accuracy of the simulation as indicated Table 2.

We used the software TerrSet v.18 to conduct the kappa validation test based on 10 iterations; the calculated Kappa values are: 0.8041, 0.8529, 0.8529, and 0.6996 as indicted in Table 3.

All calculated Kappa values are within [0.7–0.85] range which verify the accuracy of the ECAMCM Simulation in forecasting the future LU change in Lebanon.

The following section shows a comparison between the predicted LU transition matrix from 2009 to 2018 using the EMCM and the simulated transition matrix using the ECAMCM for the same time period.

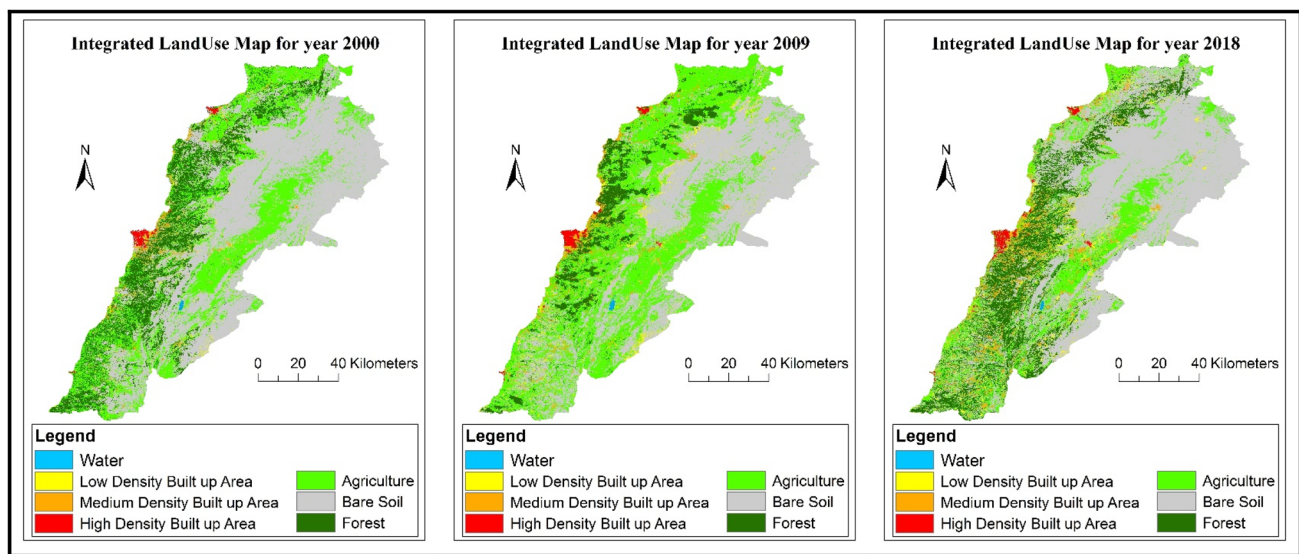


Fig. 3 Generated maps of Lebanese land use over years: 2000, 2009 and 2018 (Al-Shaar et al. 2020)

Table 2 Interpretive kappa values (Viera and Garrett 2005)

Kappa	Poor	Slight	Fair	Moderate	Substantial	Almost perfect
	0.0	0.20	0.40	0.60	0.80	1.0

**Table 3** Values of calculated kappa

Type of kappa	Value
Kappa for no information (Kno)	0.8041
Kappa of grid cells level location (Klocation)	0.8529
Kappa of stratum level location (KlocationStrata)	0.8529
Overall kappa (Kstandard)	0.6996

Figure 4 illustrates the actual and simulated LU maps of the year 2018.

Comparison of Extended Cellular Automata Markov Chain (ECAMCM) and Extended Markov Chain Models (EMCM).

A comparison between the EMCM and the ECAMCM was conducted in this section to determine which of these two models is more accurate in forecasting future LU.

The matrix of actual LU transition between years 2000 and 2018 is used as the base for this comparison and denoted as Matrix A, as shown in Table 4. The predicted transition matrix between 2000 and 2018 denoted

as Matrix X, as shown in Table 5, was calculated on the basis of Extended Markov Chain modelling technique using the actual 2000–2009 Probability Matrix as indicated in Table 6.

The simulated transition matrix using the ECAMCM between 2000 and 2018, denoted as Matrix Y and tabulated in Table 7, was computed by TerrSet software using the simulated LU map of the year 2018 and the actual map of the year 2000.

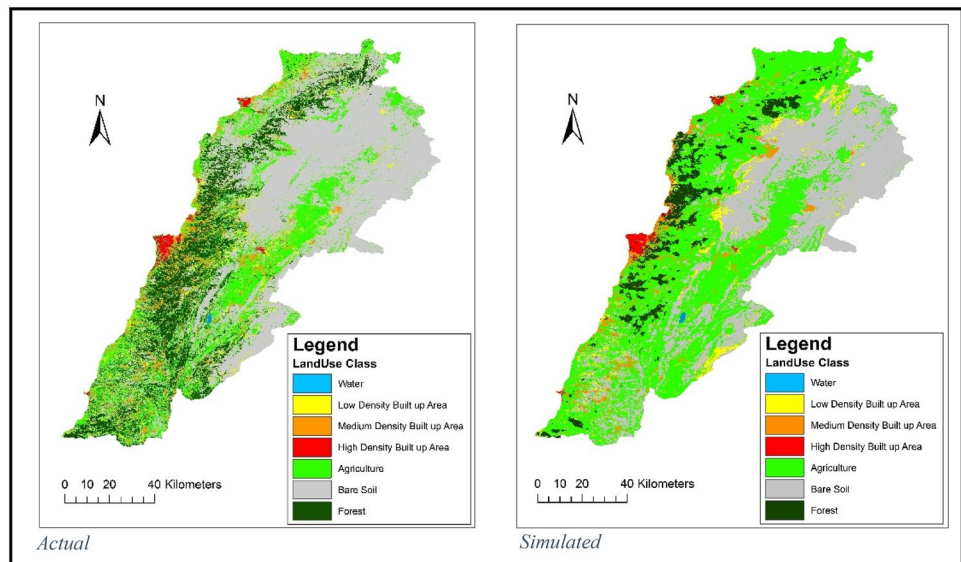
The comparison process is based on assessing and comparing the Frobenius norm of these Matrices. The Frobenius norm of a matrix is calculated as the square root of the sum of all its elements (Ford 2015 and Rencher 2002). The following equation depict the calculation processes:

$$\text{Frobenius Norm} = \sqrt{\sum_i \sum_j (x_{ij})^2} \tag{5}$$

where  $x_{ij}$  represents the elements of the matrix and  $1 \leq i, j \leq 7$  (7 is the number of LU classes represented by the matrix).

The Frobenius norms of the above-indicated matrices are depicted in Table 8.

**Fig. 4** Actual and simulated Lebanon land use maps of year 2018



**Table 4** Matrix A: actual 2000–2018 matrix of land use transition (Al-Shaar et al. 2020)

	Water	Low density built-up area	Medium density built-up area	High density built-up area	Agriculture	Bare soil	Forest
Water	5,404,155	463,666	330,247	116,247	6,038,228	758,246	99,074
Low density built-up Area	0	40,918,088	25,853,300	0	15,791,475	49,316,917	7,867,788
Medium density built-up area	0	0	81,034,206	17,386,650	17,138,269	32,925,968	6,752,851
High density built-up area	0	0	0	38,138,141	6,601,522	6,222,242	292,148
Agriculture	0	116,995,843	150,160,019	7,676,893	1,206,193,366	1,047,128,151	542,909,845
Bare soil	0	150,194,984	171,578,677	16,292,337	682,241,623	3,699,887,966	370,650,673
Forest	0	41,243,110	84,400,457	5,046,625	316,371,198	340,038,130	953,116,089



**Table 5** Actual matrix of transition for years 2000 and 2009 (Al-Shaar et al. 2020)

	Water	Low density built-up area	Medium density built-up area	High density built-up area	Agriculture	Bare soil	Forest
Water	6,289,215	354,024	208,716	413,469	5,744,969	157,197	42,272
Low density built-up area	125,773	55,633,507	13,737,186	0	55,675,431	12,926,650	1,662,996
Medium density built-up area	15,524	0	94,602,002	5,930,089	40,051,389	9,857,609	4,781,329
High density built-up area	0	0	0	44,278,376	3,229,005	1,886,149	1,860,522
Agriculture	1,535,532	80,154,773	76,776,603	5,835,022	2,043,486,063	634,174,740	229,101,383
Bare soil	3,054,508	233,160,759	118,616,718	13,745,285	1,329,219,958	3,337,049,723	57,017,478
Forest	0	20,882,587	26,777,256	1,914,237	996,447,457	115,550,316	579,317,776

**Table 6** Predicted 2000–2018 transition matrix on the basis of the extended Markov chain model (Matrix X)

	Water	Low density built-up area	Medium density built-up area	High density built-up area	Agriculture	Bare soil	Forest
Water	2,997,602	467,139	409,287	573,407	6,844,072	1,428,244	490,183
Low density built-up area	146,918	24,216,195	15,560,390	671,212	67,137,093	26,100,726	5,937,324
Medium density built-up area	42,791	1,554,612	58,953,871	8,845,259	56,749,469	21,275,394	7,818,997
High density built-up area	2,746	192,989	152,766	38,265,364	6,495,926	3,656,143	2,488,682
Agriculture	2,213,132	117,080,174	124,013,991	13,868,711	1,709,279,538	865,416,379	239,349,954
Bare soil	4,342,797	281,116,887	207,097,713	28,099,588	1,914,103,569	2,495,347,682	162,452,620
Forest	588,976	46,564,654	54,417,325	5,499,986	1,040,143,436	323,647,022	269,611,361

**Table 7** Predicted 2000–2018 transition matrix on the basis of ECAMCM (Matrix Y)

	Water	Low density built-up area	Medium density built-up area	High density built-up area	Agriculture	Bare soil	Forest
Water	5,734,401	339,493	221,926	462,345	6,351,302	79,259	23,778
Low density built-up area	55,899	47,989,315	26,440,240	69,874	60,356,975	3,619,462	1,201,829
Medium density built-up area	0	15,524	96,014,668	14,623,414	38,654,248	1,350,570	4,563,996
High density built-up area	0	0	30,752	43,842,717	2,834,349	1,629,879	2,916,356
Agriculture	614,213	92,131,924	131,134,438	6,756,341	2,128,247,433	517,781,410	194,398,359
Bare soil	1,018,169	367,559,100	196,506,666	13,745,285	1,430,018,714	3,049,416,909	32,581,416
Forest	0	24,885,083	42,809,304	2,088,259	1,138,623,072	80,920,026	450,715,842

**Table 8** Calculated Frobenius norms

Matrix	Frobenius norm
Actual 2000–2018 transition matrix (Matrix A)	4,286,569,065
Predicted 2000–2018 transition matrix based on EMC (Matrix X)	3,882,814,361
Predicted 2000–2018 transition matrix based on ECAMCM (Matrix Y)	4,231,802,773

The Calculated Frobenius norms of these three matrices indicated that the norm of the simulated 2000–2018 transition matrix by ECAMCM is closer to the actual one than the one predicted by EMC and as a result the simulation of ECAMCM is more accurate.

### Simulated land use map of the year 2036

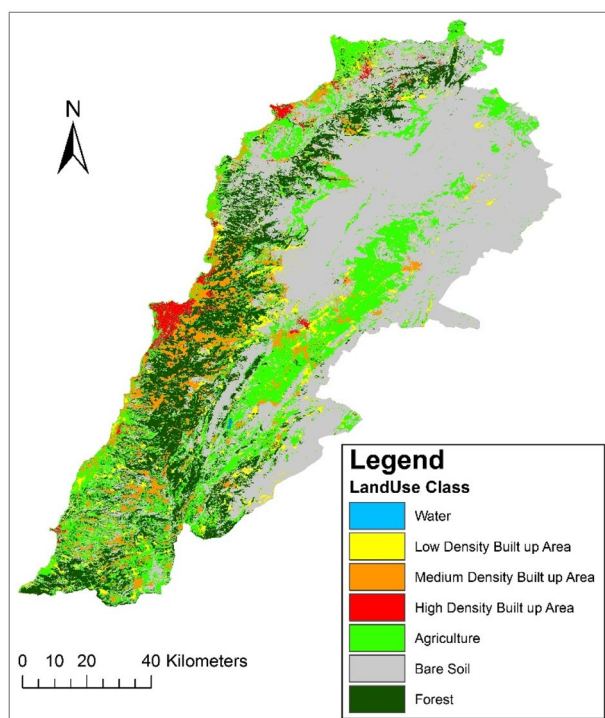
The produced LU maps of years 2018 and 2000 were used in TerrSet software as input to simulate the LU map for the year 2036. The TerrSet software calculates the Extended Markov

transition matrix for the period between 2000 and 2018 and utilizes this matrix in the application of the ECAMCM to produce the simulated LU map for the year 2018. Figure 5 illustrates the simulated LU map for the year 2036.

## Analysis and discussion

The comparison of the simulated and actual land use maps shows that the types of urban development, categorized by their development densities, have spatial effects that could be considered in the CAMCM. This type of model extension, discretized by the insertion of urban development density zones as parts of land use classes, could add a new concept of urban and regional planning. New conceptions of urban planning dynamics could be monitored and measured by taking into account (i) population growth, (ii) locative distribution, (iii) types of potential urban agglomeration, (iv) interactions between urban agglomerations (differed by their urban densities), and (v) sequential shift of the urban areas among different density classes.

The actual 2000–2018 transition matrices by areas and probabilities of LU dynamics was computed by TerrSet software using the Extended Markov transition matrix module which compares the actual LU maps of the year 2000 with the actual map of the year 2018 as shown in Table 9. This table depicts the conversion rate of Actual



**Fig. 5** Simulated Lebanon land use maps of the year 2036

LU areas in the year 2000 to other LU over the year 2018. As for example, the Agriculture LU was transformed to Low-Density Built-up LU by 3.8%, to Medium-Density Built-up LU by 4.9%, to Forest by 17.7%, to bare soil by 34.1%, and it maintains 43.6% of its total area of the year 2000. It is noted that Low and Medium Density urban settlements were converted, respectively, to Medium and High-Density urban development by 18.5% and 11.2%. Moreover, High-Density Built-up lands have not been converted at all to urban settlements Medium and Low built up Densities as well as Medium Density Built-up lands were not changed to Low-Density urban development. The forested areas are changed by 2.4% to lands with Low Built-up Density, 4.9% to lands with Medium Built-up Density, 0.3% to lands with High Built-up Density, 18% to agricultural areas, 20% to Bare Soil and retained 55% of their lands. The table shows the conversion of Actual LU areas of the year 2000 (in square meters) into other LU classes over the year 2018. As an example, the Agriculture LU has been transformed to low-Density Built-up LU by 116,995,843 square meters, to Medium Density Built-up LU by 150,160,019 square meters, to High-Density Built-up LU by 7,676,893 square meters, to Forest by 542,909,845 square meters, to bare soil by 1,047,128,151 square meters, and it maintained 1,206,193,366 square meters of its total area of the year 2000.

The predicted transition matrices by areas and probabilities of LU dynamics between years 2018 and 2036 was computed by TerrSet software using the Extended Markov transition matrix module which compares the actual LU map of the year 2018 with the simulated map of the year 2036 as indicated in Table 10. This table summarizes the conversion rate of forecasted LU areas to other LU between the years 2018 and 2036.

For example, the Agriculture LU was transformed to Low-Density urban settlements by 3.3%, to Medium-Density urban settlements by 4.1%, to Forest by 7.3%, to bare soil by 10.9%, and it maintains 74.5% of its total area of the year 2018. It is noted that Low and Medium-Density Built-up lands will convert respectively to Medium and High-Density urban settlements by 24% and 20%.

These rates of conversion are considered elevated in comparison to the ones observed at the period between 2000 and 2018. Thus, the urban development is oriented toward more condensed development.

High-Density Built-up lands are not expected to convert at all to Medium- and Low-Density Built zones. Likewise, Medium-Density Built-up lands are not expected to convert to Low-Density Built-up zones.

The forested areas are expected to convert by 2.5% to Low-Density Built lands, 7.4% to Medium-Density Built lands, 6.4% to agricultural areas, 2.6% to Bare Soil and expected to maintain 81% of their lands.

**Table 9** Actual 2000–2018 land use transition matrix (Al-Shaar et al. 2020)

		Water bodies	Built-up (low density)	Built-up (medium density)	Built-up (high density)	Agriculture	Bare soil	Forest	Sum of areas over the year 2000
Water bodies	Probability	0.4091	0.0351	0.0250	0.0088	0.4571	0.0574	0.0075	–
	Area (m <sup>2</sup> )	5,404,155	463,666	330,247	116,247	6,038,228	758,246	99,074	13,209,862
Low-density built-up	Probability	0	0.2928	0.1850	0	0.1130	0.3529	0.0563	–
	Area (m <sup>2</sup> )	0	40,918,088	25,853,300	0	15,791,475	49,316,917	7,867,788	139,747,568
Medium-density built-up	Probability	0	0	0.5220	0.1120	0.1104	0.2121	0.0435	–
	Area (m <sup>2</sup> )	0	0	81,034,206	17,386,650	17,138,269	32,925,968	6,752,851	155,237,943
High-density built-up	Probability	0	0	0	0.7441	0.1288	0.1214	0.0057	–
	Area (m <sup>2</sup> )	0	0	0	38,138,141	6,601,522	6,222,242	292,148	51,254,053
Agriculture	Probability	0	0.0381	0.0489	0.0025	0.3928	0.3410	0.1768	–
	Area (m <sup>2</sup> )	0	116,995,843	150,160,019	7,676,893	1,206,193,366	1,047,128,151	542,909,845	3,071,064,117
Bare soil	Probability	0	0.0295	0.0337	0.0032	0.1340	0.7267	0.0728	–
	Area (m <sup>2</sup> )	0	150,194,984	171,578,677	16,292,337	682,241,623	3,699,887,966	370,650,673	5,090,846,259
Forest	Probability	0	0.0237	0.0485	0.0029	0.1818	0.1954	0.5477	–
	Area (m <sup>2</sup> )	0	41,243,110	84,400,457	5,046,625	316,371,198	340,038,130	953,116,089	1,740,215,608
Sum of areas over the year 2018		5,404,155	349,815,691	513,356,906	84,656,892	2,250,375,680	5,176,277,619	1,881,688,467	–

The table shows as well the expected conversion of LU areas of the year 2000 (in square meters) into other LU classes over the year 2036.

For example, the Agriculture LU will be transformed to Low-Density Built LU by 73,587,285 square meters, to Medium-Density Built-up LU by 92,265,403 square meters, to Forest by 163,827,350 square meters, to bare soil by 244,165,761 square meters, and it will maintain 1,676,304,844 square meters of its total area of the year 2018.

The net changes of LU areas among the 2000–2018 and 2018–2036 periods are shown in Tables 11 and 12, respectively.

A reduction in the areas of agriculture zones and water bodies is illustrated in Fig. 6. The rate of reduction has diminished from the period between 2000 and 2018 to the period between 2018 and 2036.

The rate of reduction in agriculture areas has diminished from – 820,688,436 to – 71,379,366 square meters.

The rate of reduction in water bodies areas has diminished from – 7,805,707 to – 3,288,968 square meters. An expansion in the lands of Forests and Bare Soil was observed in period between 2000 and 2018 as the total area of forests will increase by 141,472,859 square meters and the one of Bare Soil will increase by 85,431,359 square meters. However, a reduction in the lands of Forests and Bare Soil is expected to occur in the period between 2018 and 2036 as the total area of forests will decrease by 55,855,578 square meters and the one of Bare Soil will decrease by 536,013,417 square meters. The actual and predicted LU transition matrices respectively for periods: 2000 to 2018 and 2018 to 2036 show clearly that the orientation of built-up LU are heading towards more compact urban development. Furthermore, the period from 2018 to 2036 shows an increased rate of conversion from low to medium and from Medium to High-density built-up lands in comparison to the period from 2000 to 2018.

**Table 10** Matrix of the predicted land use transition among years 2018 and 2036

		Water bodies	Built-up (low density)	Built-up (medium density)	Built-up (high density)	Agriculture	Bare soil	Forest	Sum of areas over the year 2018
Water bodies	Probability	0.3915	0.0100	0.0043	0	0.5881	0.0062	0	–
	Area (m <sup>2</sup> )	2,115,727	54,042	23,238	0	3,178,183	33,506	0	5,404,155
Low-density built-up	Probability	0	0.7366	0.2368	0	0	0.0266	0	–
	Area (m <sup>2</sup> )	0	257,674,238	82,836,356	0	0	9,305,097	0	349,815,691
Medium-density built-up	Probability	0	0	0.7932	0.2012	0.0016	0.0038	0.0002	–
	Area (m <sup>2</sup> )	0	0	407,194,698	103,287,409	821,371	1,950,756	102,671	513,356,906
High-density built-up	Probability	0	0	0	0.8568	0.1432	0	0	–
	Area (m <sup>2</sup> )	0	0	0	72,534,025	12,122,867	0	0	84,656,892
Agriculture	Probability	0	0.0327	0.0410	0	0.7449	0.1085	0.0728	–
	Area (m <sup>2</sup> )	0	73,587,285	92,265,403	0	1,676,304,844	244,165,761	163,827,350	2,250,375,680
Bare soil	Probability	0	0.0255	0.0399	0.0002	0.0708	0.8375	0.0261	–
	Area (m <sup>2</sup> )	0	131,995,079	206,533,477	1,035,256	366,480,455	4,335,132,506	135,100,846	5,176,277,619
Forest	Probability	0	0.0249	0.0736	0	0.0637	0.0264	0.8114	–
	Area (m <sup>2</sup> )	0	46,854,043	138,492,271	0	119,863,555	49,676,576	1,526,802,022	1,881,688,467
Sum of areas over the year 2036		2,115,727	510,164,687	927,345,442	176,856,690	2,178,771,276	4,640,264,202	1,825,832,889	–

**Table 11** Actual net changes (Gains and Losses) in the areas of land use (in square meters) among years 2000 and 2018

Type of land use	2000–2018		
	Loosed areas	Gained areas	Net change
Water bodies	– 7,805,707	0	– 7,805,707
Low density built-up area	– 98,829,480	308,897,603	210,068,123
Medium density built-up area	– 74,203,737	432,322,700	358,118,963
High density built-up area	– 13,115,912	46,518,752	33,402,839
Agriculture	– 1,864,870,751	1,044,182,315	– 820,688,436
Bare soil	– 1,390,958,294	1,476,389,653	85,431,359
Forest	– 787,099,519	928,572,378	141,472,859
Total	– 4,236,883,401	4,236,883,401	–

Moreover, the rate of expansion of Low-density built-up areas has diminished between the two periods 2000 to 2018 and 2018 to 2036. Thus, the urban fabric will come to be more condensed during the period between 2018 and 2036. The increase in the areas of built-up zones, bare soil and forests between years 2000 and 2018 is justified by the

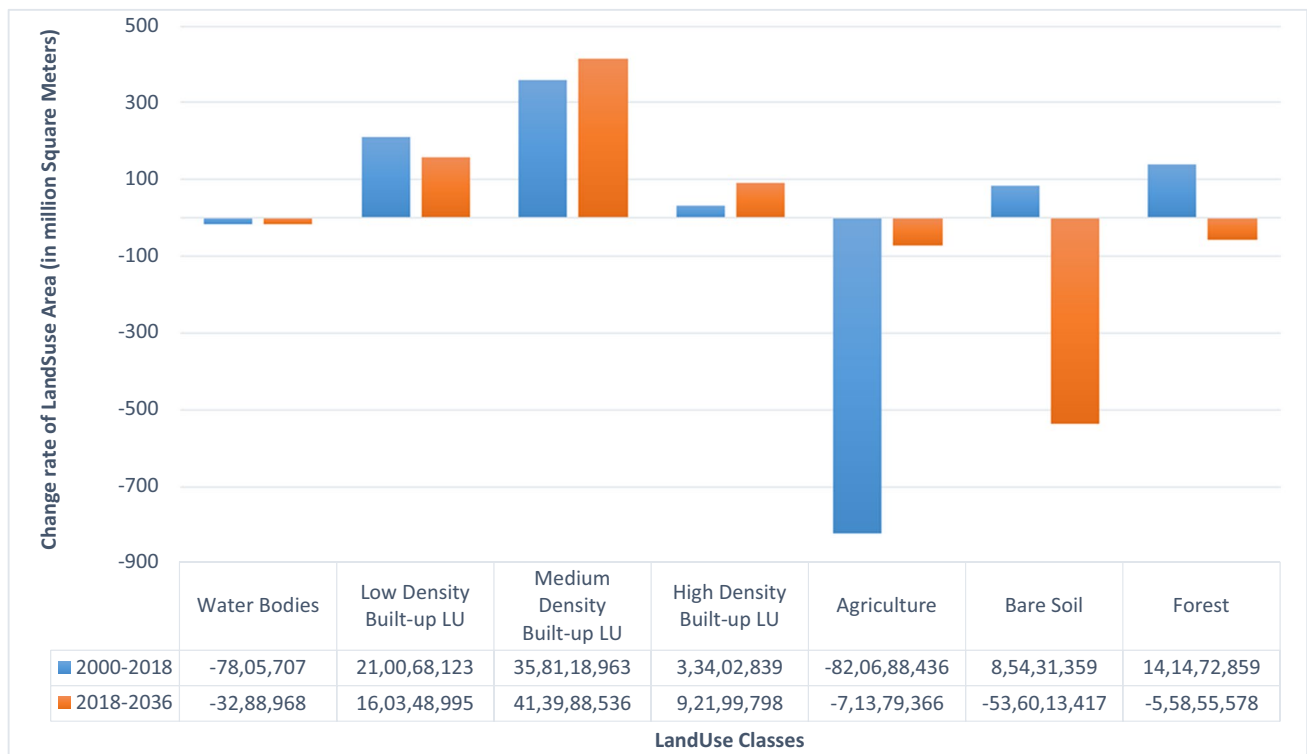
diminishing of Agriculture areas. However, the increase in the areas of built-up zones between the years 2018 and 2036 is explained by the decrease of Agriculture, Bare Soil and forest areas.

Figure 6 illustrates a comparison of the variations in LU areas between 2000–2018 and 2018–2036.



**Table 12** Predicted net changes (Gains and Losses) in the areas of land use (in square meters) among years 2018 and 2036

Type of land use	2018–2036		
	Loosed areas	Gained areas	Net change
Water bodies	– 3,288,968	0	– 3,288,968
low density built-up area	– 92,141,453	252,490,448	160,348,995
Medium density built-up area	– 106,162,208	520,150,745	413,988,536
High density built-up area	– 12,122,867	104,322,665	92,199,798
Agriculture	– 573,845,798	502,466,432	– 71,379,366
Bare soil	– 841,145,113	305,131,696	– 536,013,417
Forest	– 354,886,445	299,030,867	– 55,855,578
Total	– 1,983,592,853	1,983,592,853	–



**Fig. 6** Observed and simulated land use evolutions among the periods 2000–2018 and 2018–2036

### Conclusion

This paper validates the spatial effects of urban densities within built-up zones by comparing two models intended to forecast the LU variation in Lebanon. The two models compared are the Extended Markov Chain (EMCM) and the Extended Cellular Automata Markov Chain Model (ECAMCM). The accuracy of applying the ECAMCM to predict the LU dynamics was conducted using the Cohen’s Kappa statistics test. A comparison between these two models in reference to actual LU data for the year 2018 using Frobenius norm indicates that the forecasted data

by ECAMCM are the best data representing the actual LU dynamics. Effects of contiguity was taken into consideration within the Extended Cellular Automata—Markov Chain Model to be merged with historical changes’ data of the studied LU. The neighboring effects could be presented as the Cellular-Automaton modelling integrated with Extended Markov Chain technique.

However, both models are lacking the effects of transport implementations, policies, strategies, plans and socio-economic effects. Transport-Land Use interactions such as gravity models need to be integrated into ECAMCM to study the impact of transportation in changing the urban fabric. The LU projection under ECAMCM to the year

2036 indicated a reduction in the areas of Bare Soil lands, Forests, Agriculture and water bodies.

This reduction was associated with an expansion in urban settlements with Low, Medium and High built up Densities. Between 2018 and 2036 the forecasted decreasing rate of cultivated zones is less than the rate of the period 2000–2018. Furthermore, the forecasted increasing rate in low urban development between 2018 and 2036 is less than the rate corresponding to 2000–2018's time frame; while the forecasted increasing rate for High and Medium-density built-up zones among years 2018 and 2036 is higher than the rate corresponding to the preceding time frame. These results indicate that a shift in urban development orientation is occurring in favor of increasing the High and Medium-density Built-up zones.

This paper provides a guiding tool for decision-makers and planners to develop new urban masterplans in addition to population, economic and land-use strategies by monitoring and assessing potential variations in densities of new and old urban sprawl.

More studies focusing on changes of lifestyles and socio-economic capacities in addition to climatic changes and pollution are needed to explain the decrease in Agriculture, Bare Soil, forests and water bodies' areas in favor of the sprawl of urban development. The degradation of natural areas in addition to agricultural zones as depicted in the findings impose the critical necessity for enacting updated appropriate LU enforcing policies and planning regulations. Moreover, developing a national Masterplan in addition to establishing a central governmental entity that superintends and forecast activities, plans or coordinates the evolution of LU patterns and Lebanese landscape is considered to be on the top of priorities of national requirements.

**Author contribution** All authors contributed to the study: Conceptualization, Methodology, Analysis and Validation. Resources, Data curation, Software, Writing—Original draft preparation were performed by WAS. Supervision, Writing—Reviewing and Editing were performed by JAG, NN, HL, LBB.

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**Data availability** Available upon request.

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## Compliance with ethical standards

**Conflict of interest** The authors declare that they have no conflict of interest.

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