

Measuring and predicting urban growth patterns and trends in Putrajaya, Malaysia

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Abstract. Spatio-temporal measurement and prediction of urban growth patterns are the main challenges that face researchers, planners, decision makers, and local authorities when building a realistic sustainable urban planning model. This study aims to apply spatio-temporal data, methods, and models to generate a realistic measurement and prediction of the urban growth issue. Three Landsat TM5 and OLI images of 1997, 2007, and 2017 were used to create urban growth maps. Land-use maps were used to measure change in urban area during the periods 1997 to 2017. A CA-Markov model was used to predict the urban growth trends of 2027 and 2037. The results of the study confirm that urban area increased and continued to cover most of the city area of Putrajaya. The urban development process has greatly affected the Putrajaya green lands between 1997 and 2017. This impact is expected to increase in the future based on the prediction results, which in turn will lead to an increased need for new policy development to protect the ecosystem in Putrajaya.

1. Introduction

Urban growth has become a significant issue that influences land-use and land-cover systems due to several reasons such as population and economic growth [1]. Several types of driving forces of urban growth were identified such as environmental, socio-economic, and physical forces that lead to a rapid increase in urban growth trends [2]. Many types of GIS and remote sensing methods, techniques, and models were used to measure urban growth patterns such as land-use change detection and landscape matrices [2]. These methods, techniques, and models are commonly used to develop an urban planning system for future sustainable development. Geospatial technology has become an effective way to understand the historical and future trends of the urban growth phenomenon [1-4].

Moreover, the simulation of future urban growth trends has become one significant application in urban studies involving spatial modeling. Many models were used to improve the simulation capability of urban growth such as the Cellular Automata (CA), Land Transformation Model (LTM), and Logistics Regression (LR) models [5].



In addition, many models were integrated with each other to improve simulation accuracy such as the Cellular Automata based on Artificial Neural Network (CA-ANN), CA-LR, and CA based on the Analytical Hierarchy Process (AHP) [5]. The main key to creating a realistic simulation process is to integrate the main driving forces of urban growth into the simulation process. The CA-Markov model is a common model used in the last five years due to its simplicity and it can be easily integrated with other models [5, 6]. This study aims to create a realistic and accurate evaluation and simulation process of urban growth using geospatial technology.

2. Materials and Method

2.1. Study Area

Putrajaya is located 25 km east of Kuala Lumpur city, and contains 20 blocks. The study area is located between the longitudes (101°37' 50" E and 101°43' 20" E) and latitudes (2°53' 20" N and 2°57' 55" N). The wild area of Putrajaya allows this research to obtain more accurate results from different parts of the study area, as shown in (Figure 1). Putrajaya is considered as the administrative capital of Malaysia.

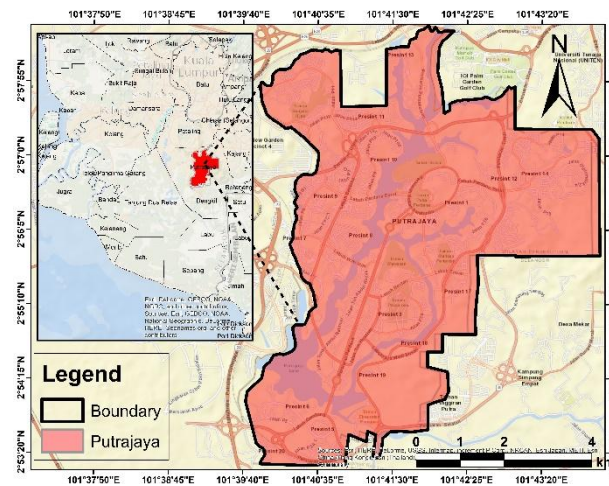


Figure 1. Location of the study area

2.2. Data Collection and Preparation

Landsat TM and LOI of 1997, 2007, and 2017 were used to generate urban growth maps. Enhancement methods were applied in the GIS environment to generate accurate classification. Subsequently, a Maximum Likelihood technique was used to classify Landsat images into three classes, which are urban area, green lands, and surface water. For accuracy assessment purposes, Google Earth was used to observe whether or not the land-use classification is acceptable. The acceptable values should be more than 0.85 based on Anderson's scheme [7]. Overall accuracy and Kappa coefficient techniques were applied to validate the land-use map classification (Equations 1 and 2) [8]:

$$\text{Overall accuracy} = \frac{\text{total correct}}{\text{total number of pixels in the error matrix}} \quad 1$$

$$K_{\text{hat}} = \frac{N \sum_{i=1}^r x_{ii} - \sum_{i=1}^r (x_i + * x + i)}{N^2 - \sum_{i=1}^r (x_i + * x + i)}$$

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2.3. Measuring Urban Growth Patterns

The methodology to measure urban growth patterns in Putrajaya is presented in Figure 2. The method used is the measurement of urban growth using two different techniques. The first technique visually shows historical urban growth, while the statistical values of historical growth of the urban area was generated from land-use maps [9, 10].

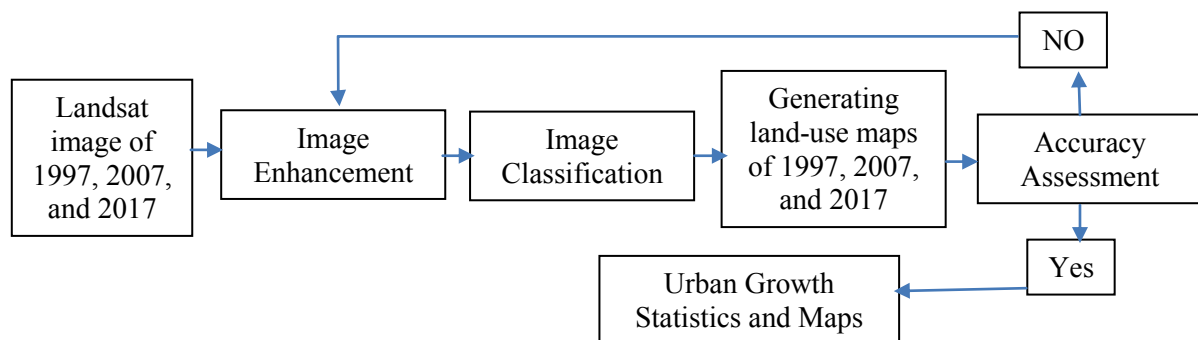


Figure 2. Methodology for measuring urban growth patterns

2.4. Simulation of Urban Growth using the CA-Markov Model

The Markov chain, also known as the Markov model or the Markov process, is a concept developed within the theory of probability and statistics that establishes a strong dependence between the occurrence of an event and a previous event. Its main contribution is in the behavioral analysis of stochastic processes [11]. This model is commonly used to simulate urban growth because it does not need rich data [12]. This model is also used to compute the probabilities of transition areas from one status of land use to another status, as presented in Fig. 3. In this study, urban and non-urban classes were used as input data for the model. Then, a transition area probabilities matrix and a probability map for specified periods in time were generated using this model. The prediction of urban growth was computed according to a conditional probability formula outlined by Equations 3, 4, and 5:

$$S(t+1) = P_{ij} \times S(t) \quad (3)$$

$$P_{ij} = \begin{bmatrix} P_{11} & P_{12} & P_{n1} \\ P_{21} & P_{22} & P_{n2} \\ P_{n1} & P_{n2} & P_{nn} \end{bmatrix} \quad (4)$$

$$\left(0 \leq P_{ij} < 1 \text{ and } \sum_{i=1}^N P_{ij} = 1, (i, j = 1, 2, \dots, n) \right) \quad (5)$$

where: $S(t)$ is the state of the system at time t , $S(t+1)$ is the state of the system at time $(t+1)$, and P_{ij} is the matrix of transition probability in a state.

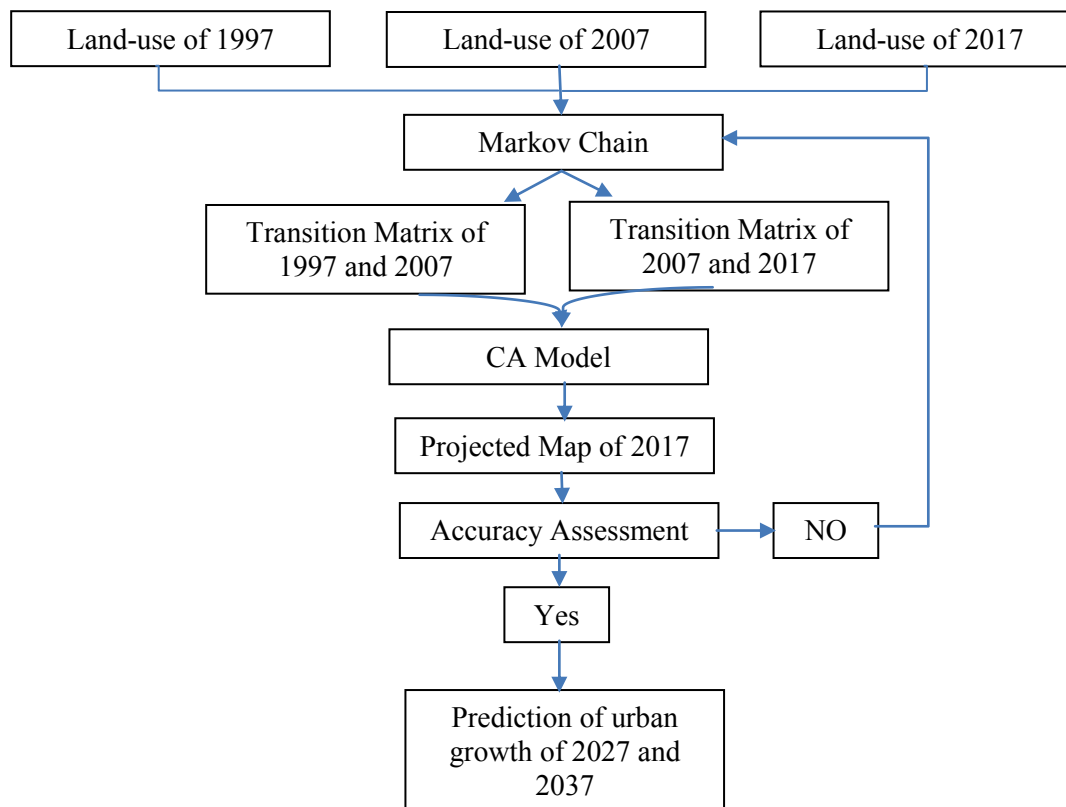


Figure 3. Stepwise CA-Markov model

3. Results and Discussion

Table 1 shows the accuracy assessment of the classification process of the land-use maps, which show an acceptable overall accuracy assessment. The values of accuracy for the land-use maps of 1997, 2007, and 2017 have reached acceptable levels, which are 90.77, 92.31, and 90.77, respectively. Land-use classification was compared with high quality Google Images to observe the accuracy of the classification of Landsat 5 and 8 images. The availability, free cost, and simplicity of processing are the main advantages of using Landsat 5 and 8 in this study.

Table 2 shows the land-use changes over the period 1997–2017. The urban area increased rapidly over the period 1997–2007 by 16.03% compared to 2.83% for the period 2007–2017. The green lands decreased by -7.8% for the period 1997-2007 compared to an annual rate of growth of -5.84 for the period 2007–2017. Water areas underwent an exceptional increase with an annual rate of growth of 54.7% over the period 1997–2007, which is due to the establishment of an industrial lake within the study area; meanwhile, the annual rate of growth for the period 2007–2017 is 0.28%.

The growth patterns in Putrajaya from 1997 to 2017 are shown in Table 3 and Figure 4. The obtained result from the land-use change analysis shows an increase in urban area from 5.36 km² in 1997 to 23.7 km² in 2007, and to 31.34 km² in 2017. In contrast, the land-use change analysis shows a decrease in green lands from 38.54 km² in 1997 to 17.1 km² in 2007, and to 9.37 km² in 2017. Meanwhile, the water increased from 0.04 km² in 1997 to 3.14 km² in 2007, and to 3.23 km² in 2017. In brief, the overall average changes for the period 1997 to 2017 show an average increase in urban area equal to 25.98 km², an average decrease in green lands equal to -29.17 km², and an average increase in water equal to 3.19 km².

Table 1. Accuracy assessment values for land-use maps.

1997				
Classification	Green	Urban	Water	Row total
Green	29	1	0	30
Urban	4	21	0	25
Water	0	1	9	10
Total Correct	29	21	9	65
Accuracy	90.76			
2007				
Classification	Green	Urban	Water	Row total
Green	27	3	0	30
Urban	2	23	0	25
Water	0	0	10	10
Total Correct	27	23	10	
Accuracy	92.30			
2017				
Classification	Green	Urban	Water	Row total
Green	28	2	0	30
Urban	3	22	0	25
Water	0	1	9	10
Total Correct	28	22	9	
Accuracy	90.76			

Table 2. Annual Rate of Growth of land-use changes observed.

	Urban Area	Green Lands	Water
1997	5.36	38.54	0.04
2007	23.7	17.1	3.14
2017	31.34	9.37	3.23
Annual Rate of Growth (1997-2007)	16.03%	-7.80%	54.70%
Annual Rate of Growth (2007-2017)	2.83%	-5.84%	0.28%

Table 3. Changes in Land use of 1997-2017.

	1997		2007		2017		LULC 1997-2017
	Km ²	%	Km ²	%	Km ²	%	
Green	38.54	87.71	17.1	38.91	9.37	21.32	-29.17
Urban	5.36	12.19	23.7	53.93	31.34	71.32	25.98
Water	0.04	0.09	3.14	7.14	3.23	7.35	3.19
Total	43.94	100	43.94	100	43.94	100	

The Markov chain model was used to calculate the transition probabilities matrix, as presented in (Table 4). In addition, future potential percentages of change in land use in the time periods 1997–2007, 2007–2017, and 2017–2027 are also ascertained using the transition probabilities matrix. The change in transition in land-cover categories from a later date to the predicted one, according to a projection of the transition probabilities into the future is observed, and a transition probabilities matrix generated (Table 4).

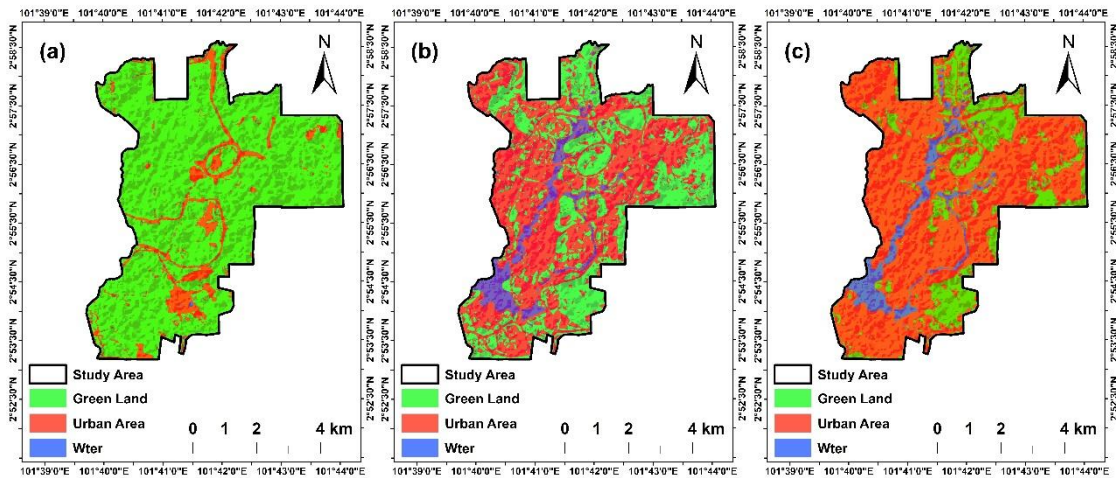


Figure 4. Figure 4. Land-use changes from 1997 to 2017

Table 4. Transition Probability Matrix of Periods: 1997–2007, 2007–2017, and 2017–2027.

Land-use Type		Urban Area	Green Lands	Water
1997-2007	Urban Area	0.4512	0.5087	0.0401
	Green Lands	0.5886	0.3290	0.0824
	Water	0.4000	0.6000	0.0000
2007-2017	Urban Area	0.7396	0.1981	0.0623
	Green Lands	0.8475	0.1342	0.0183
	Water	0.2490	0.0287	0.7223
2017-2017	Urban Area	0.8396	0.0981	0.0623
	Green Lands	0.9475	0.0342	0.0183
	Water	0.2490	0.0287	0.7223

Figures 5 and 6 show the observed and simulated land-use maps of 2017, respectively, where map (a) shows the observed map of Putrajaya area in 2017 based on the actual changes over the period 1997–2017, while map (b) shows the simulated map of Putrajaya area in 2017. The results of the accuracy assessment confirm that there is a disagreement between the observed and simulated results. Figure 7 shows the results of the accuracy of the projected map of 2017 via comparison of observed and projected land-use maps of 2017, which are used to calculate the Kappa index of accuracy. This result confirms almost perfect accuracy as $k = 0.88$, k location = 0.96, and k standard = 0.96.

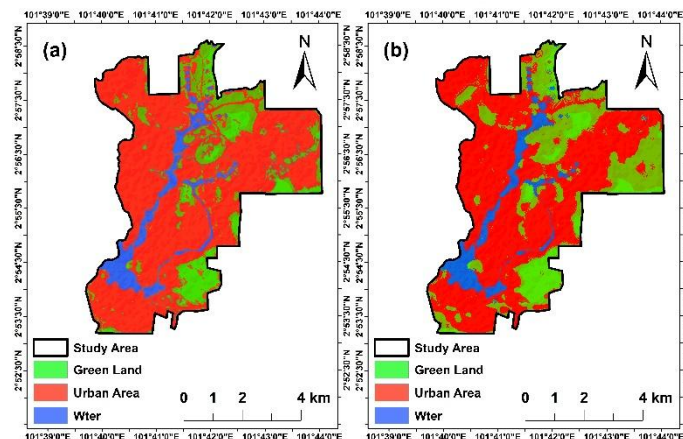


Figure 5. Observed and Simulated Land-use maps of 2017: (a) Observed 2017; and (b) Simulated 2017

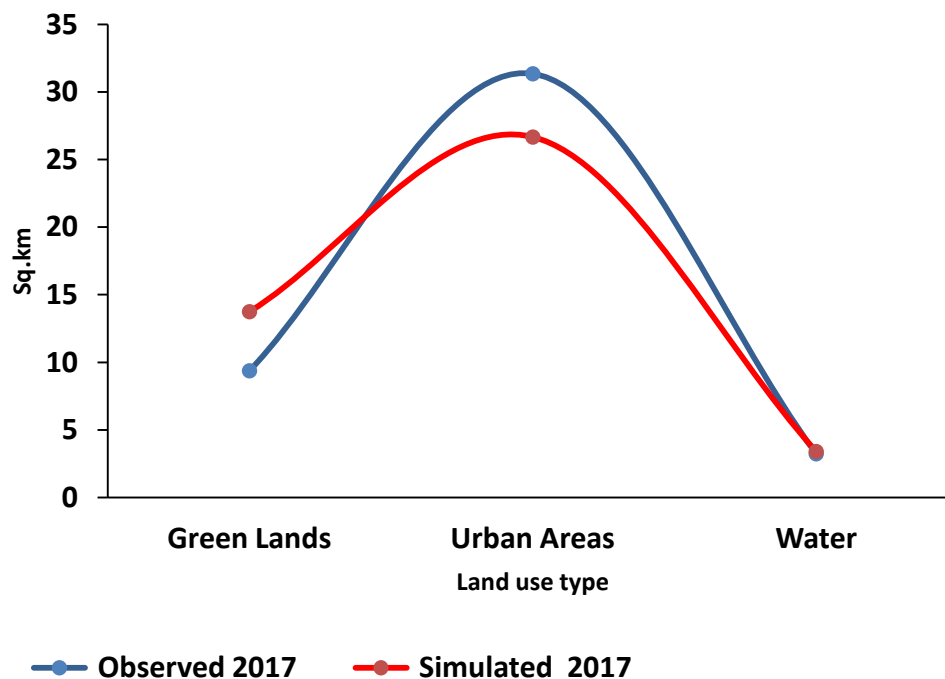


Figure 6. A comparison of Land-use types between the Observed and Simulated maps for 2017

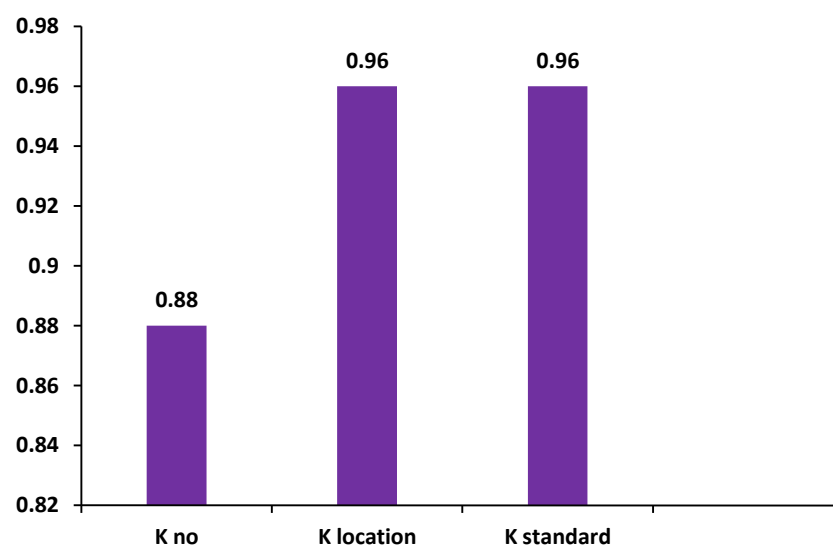


Figure 7. Accuracy Assessment for the Observed and Simulated 2017 Maps

Figure 8 shows that the urban growth in 2027 and 2037 will increase in all directions in Putrajaya unless the urban planning institutions in the City take into account sustainable urban forms in future urban planning processes. There are several types of sustainable urban forms that can be considered in Putrajaya, which could decrease the impact of urban areas on the green lands such as the compactness urban form, green urban form, etc. Figure 9 shows the future trend for each type of land-use, which confirms the increase in urban area due to socio-economic factors. The overall results of the study confirm that the need for creating sustainable rules to protect the ecosystem in Putrajaya will remain the main challenge in the next few decades.

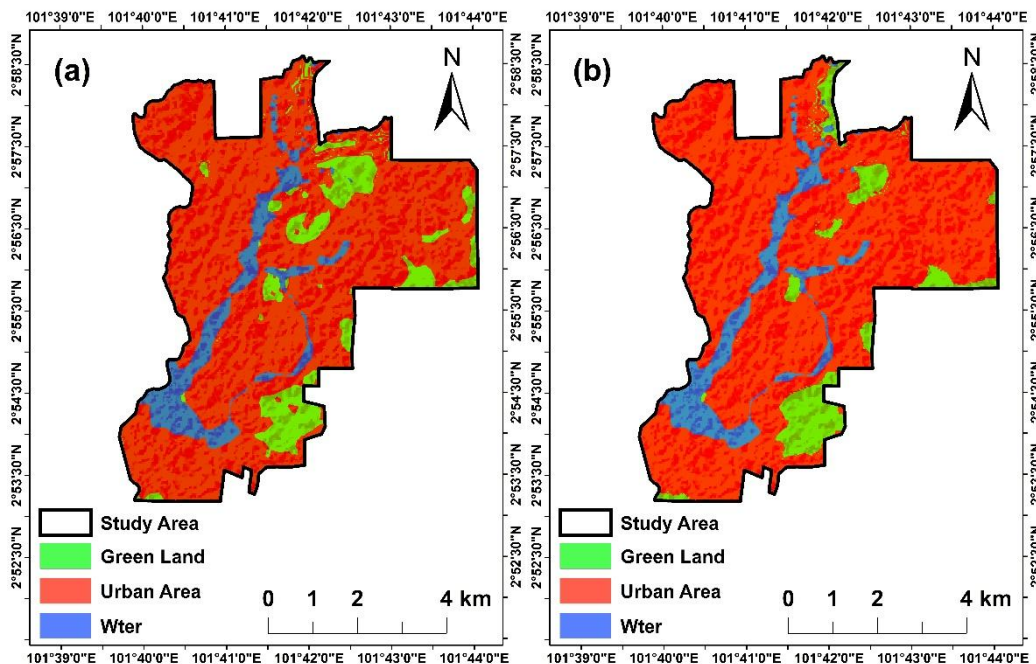


Figure 8. Predicted Maps of Urban Growth In Putrajaya: (a) 2027; (b) 2037

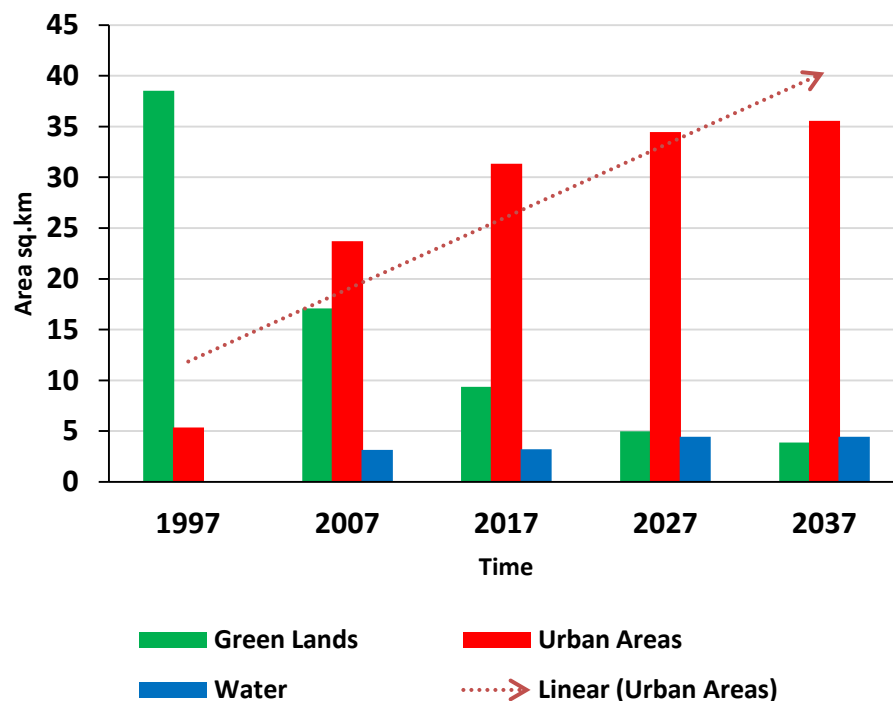


Figure 9. Quantity of previous and predicted land use change in square kilometres

4. Conclusion

It can be concluded that the green lands in Putrajaya are strongly undergoing an urban development process. This impact from urban development will continue to cover most green lands in the future. The impact of urban areas on green lands will affect the surrounding areas as well. The status of Putrajaya as the administrative capital city is the main reason behind the rapid urban growth in the

area. Therefore, urban growth in Putrajaya can be controlled via the actions of high-level administrative institutions and decision-makers in the city. The simulation process can be improved by including the significant driving forces of land-use change in the prediction model. These driving forces could be integrated with a CA-Markov model by generating land suitability maps using different methods such as AHP and ANN techniques.

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