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Applicability of the CA-Markov Model in Land-use/ Land cover Change Prediction for Urban Sprawling in Batticaloa Municipal Council, Sri Lanka

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Abstract. Rapid urbanization is leading to sprawling development around the world today, which is becoming a concerning issue for researchers and planners. Urban sprawl depends on the dynamics of land use, mainly on the built-up growth in this area. The study aims to apply and test the applicability of the CA-Markov model in the land use/ land cover change prediction for urban sprawling in Batticaloa Municipal Council, Sri Lanka. The secondary data were used, which are Landsat images for years 1990, 2000, 2010, and 2020. The Supervised Maximum Likelihood classification, the Markovian transition estimate, and the CA-Markov chain analysis were employed with ArcGIS 10.6.1, IDRISI 17.0, and MS-Excel 2013. The result revealed that the existing and simulated maps for the years 2000, 2010, and 2020 showed an almost equal probability of changes. The simulation for 2030 is credible for the future prediction, which showed that a significant estimate occurs. Therefore, the CA-Markov model is appropriate for land use/land cover predictions.

1. Introduction

Urban sprawl has received the attention of researchers today, due to the rapid growth of cities in the world. This growth directly caused an increase in the urban sprawl of a city. Cities are home to more than half of the world's population, which is unevenly distributed worldwide [1]. This distribution involves the sprawling growth in a city, which is identified in many countries such as Sri Lanka, India, and China. For example, more than 1,500 km^2 of built-up areas expanded in Chinese cities from 1992 to 2013, with average annual growth rates of almost 5.6% [2]. Knowledge and technological growths are the essential reason that resulted in a large scale of changes in land use/ land cover.

Land Use / Land Cover (LULC) dynamics is vital to a sustainable urban environment and development that has been understood in different terminologies. Land use refers to land used by humans for a functional role as economic activities, while the land cover is the distribution of biophysical features on the earth surface, such as vegetation, water, and soil. These two are more related to the sustainable economic development of a city [3]. The growth of advanced technologies, such as remote sensing, the Geographic Information System, uses high-resolution images to monitor and evaluate LULC dynamics in recent decades [4]. These technologies are integrated with spatial models that allow the user to simulate the transformation of land use.

LULC changes are identified with different analytical models [5], such as Markov models, cellular models, hybrid models, multi-agent models, statistical models, and evolutionary models [3]. The Markov model is a theory, which is the formation of Markov random process systems for prediction. This empirical application in urban analysis emerged in the 1960s, which became the dynamics of land use in the 1970s used on a large scale for urban simulations in land use [6]. This model can be used to produce a matrix of a transition probability in two different periods with LULC maps. This matrix allows the evaluation of the LULC probability, which has any conversion to another class or sustain in the same class [2]. Cellular Automata is known as discrete dynamic systems used to simulate local and global changes in computations. Today, this model is increasingly used for urban growth analysis because it can adapt to an intricate spatial pattern [7]. Besides, this model considers the interaction between micro-phenomena, such as cell state changes, to simulate macro-phenomena, such as changes in land use, by way of a top-down approach [8].

However, the CA-Markov model is a hybrid dynamic model for predicting urban change [9]. Because the CA-Markov model is the effective combination of Cellar Automata and the Markov model, it has the ability to simulate long-term predictions of spatial variations of any intricate pattern [2][3][10]. This mixed model has facilitated for simple calibration, highly efficient, and the ability to simulate multiple changing patterns. Many researchers have successfully used this model for land-use change and prediction [3][4][5].

Batticaloa area is significant for analyzing the dynamics of the land use/ land cover changes because the rapid urban growth and sprawling development have been identified in recent decades. However, future projections of the urban land use/ land cover are still rarely reported to this area due to the limited researches [11][12]. The projection of LULC will be favourable to minimize the sprawling growth in the city. Therefore, this study aims to apply the CA-Markov model in the land use/ land cover change prediction for urban sprawling in Batticaloa Municipal Council, Sri Lanka.

2. Methodology

2.1. *The Study Area*

Batticaloa is one of the cities in Sri Lanka located in the East coast (Figure 1). The average elevation of this city is 8.523m, and it lays with five (5) separated plots with the inland water bodies. The total number of population of this area is 94,604 [13]. This clustered city is connected with the bridges for transportation and contains several sectors of economic activities such as fisheries, agriculture, small industries, and commercial. Each land plots have different land use category and some mixed categories such as commercial, recreational and settlements. Rapid urban development and ongoing projects change a lot in the city. Therefore, this area is significantly experiencing land use/ land cover changes and suitable to be tested using CA Markov Model.

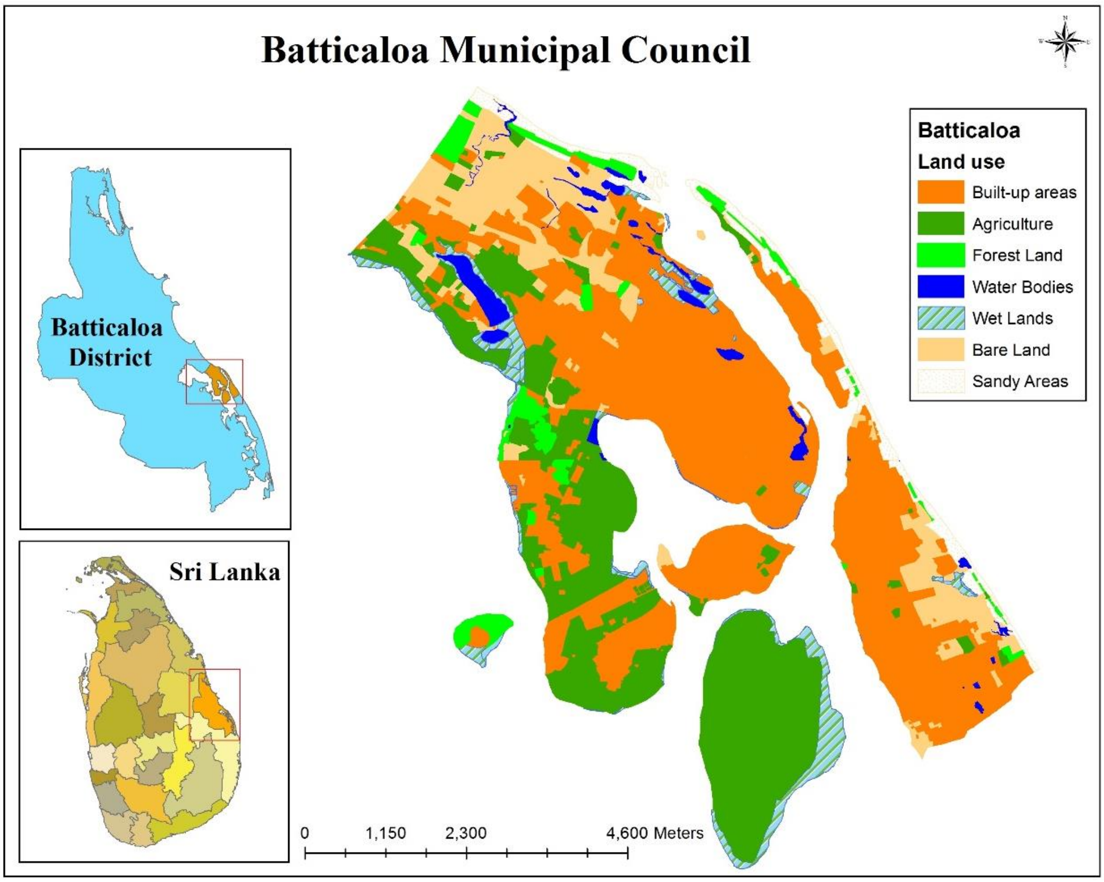

Figure 1. The Study Area – Batticaloa Municipal Council Modified from the Batticaloa MC Profile, (2020)

2.2. Data Source

The study was conducted using secondary data, which is remote sensing data to generate the maps. Satellite datasets, which are Landsat images, were downloaded from Earth Explorer, the US Geological Survey (Table 1). These datasets for 1990, 2000, 2010, and 2020 were used to develop land use maps to identify built-up changes.

Table 1. Details of satellite imagery

Type of Satellite	Image ID	Acquisition Date	Resolution
Landsat TM (1990)	Landsat_TM_140_55_19900525	25-MAY-90	30m
Landsat ETM+ (2000)	LE07_L1TP_140055_20000928_20170209_01_T1	28-SEP-00	30m
Landsat TM (2010)	LT05_L1TP_140055_20100924_20161212_01_T1	24-SEP-10	30m
Landsat 8 (2020)	LC08_L1TP_140055_20200303_20200314_01_T1	03-MAR-20	30m, Pan - 15m

Source: Earth Explorer, 2020

2.3. *Data Processing*

Landsat image layers were composite with composite bands tool and converted to false colour image. These images were geo-referenced to World Geodetic System 84 (WGS84), which is projected to the Kandawala Sri Lanka coordinate system. Image analysis tools such as sharpen, blur, and smoothing were used to enhance the quality of the images. A shapefile for the Batticaloa Municipal council area was digitized using the existing map to delineate the study area. Landsat images for the year 1990, 2000, 2010, and 2020 were clipped using the Batticaloa municipality boundary layer. These images were classified using Supervised Maximum Likelihood classifier to identify the land-use changes. These areas were categorized into five (5) classes, which are built-up, agriculture, forest, water bodies, and vacant land (Table 2) based on the training samples. A total of 193 random ground points were obtained at specific locations of this area by Google Earth Pro. The classified images were validated with the Kappa index accuracy technique. The values of Kappa calculation are understood as poor agreement = less than 0.20, fair agreement = 0.20 to 0.40, moderate agreement = 0.40 to 0.60, good agreement = 0.60 to 0.80 and very good agreement = 0.80 to 1.00. The accuracy for all classified images was found by the confusion matrix to acquire the level of precision.

Table 2. Land use categories

Code	Land use class	Description
1	Built-up	Houses, Shops, Banks, Administration
2	Agriculture	Paddy cultivation, Home garden, Crop field
3	Forest	Scrubland, Grassland, Wetland, Mangroves, Trees
4	Water bodies	Reservoirs, River, Lake
5	Vacant land	Abandon land, Sandy areas

The classified images were used to predict future land use by 2030. Prediction of land use from one period to another is possible using the Markov chain model, which is generally used for monitoring, simulating the changes, and predicting future land use. A transition probability matrix for land-use change was developed using the Markovian transition estimator from time one to two. The nature of this change serves as a basis for projection to a later time. The calculation of land use prediction, which is followed by;

$$S\,(t,\, t+1) = Pij \times S\,(t) \tag{1}$$

Where S (t) is the system status at the time of t, S (t + 1) is the system status at the time of t + 1; Pij is the transition probability matrix in a state which is calculated as follows:

$$= \|P_{ij}\| = \begin{Vmatrix} P_{1,1} & P_{1,2} & \ldots\ldots & P_{1,N} \\ P_{2,1} & P_{2,2} & \ldots\ldots & P_{2,N} \\ \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots \\ P_{N,2} & P_{N,2} & \ldots\ldots & P_{N,N} \end{Vmatrix}$$
$$(0 \leq P_{ij} \leq 1) \tag{2}$$

P is the transition probability; Pij represents the probability of converting from the current state i to another state j in next time; PN is the state's probability for any time. The low transition has a probability close to ‘0’, and the high transition has probabilities close to ‘1’ [1][3][4][5][10][14].

The transition probability matrix was calculated for the periods 1990–2000, 2000–2010, and 2010–2020 to predict the probability of land use pattern by 2030. This matrix was produced by the cross-tabulation of two periods with land use images. A dynamic process model is known as Cellular Automata, familiar for land use analysis combined with the Markov chain model. This CA-Markov chain model allows it possible to simulate a two-way transition and predict the transition between any numbers of categories [14]. The expression of the CA model followed by;

$$S\ (t,\ t+1) = f(S\ (t),\ N)\ (4) \tag{3}$$

where S (t + 1) is the status of the system at the time of (t, t + 1); operated by the probability of the state at all times (N).

The images were employed with the standard contiguity filter of 5 × 5 pixels to determine the neighbourhoods of each cell of land-use class. The center of each cellular, which made up of 5 × 5 cells, is enclosed by a matrix space to have a significant influence on the cell center. The 5 × 5 spatial filter causes a category's gain to occur close to where already existed category [14].

Three parameters, Kno, Kstandard, and Klocation are highly recommended for the evaluation of simulated maps. The value equal to 1 is satisfactory of the simulation, which is equivalent to 0 unsatisfactory [14]. Kappa for no ability (kno), Kappa for standard (Kstandard) and Kappa for location (Klocation) were used to validate the predicted land use images. The overall accuracy of simulation was obtained with Kappa for no ability (kno), and the quantity and location were achieved between existing and simulated images by Kappa for standard (Kstandard) and Kappa for location (Klocation).

Finally, ArcGIS 10.6.1 software was used to generate various thematic layers, such as land use maps using satellite imagery, and municipal boundary maps of Batticaloa. IDRISI 17.0 was used to predict the image and calculate parameters for 2030. MS-Excel 2013 was used to create the charts, and Google Earth Pro was used to collect the ground samples.

3. Results and Discussion

3.1. Land use/ land cover pattern

Land use patterns were classified to understand the urban sprawling growth in Batticaloa Municipality. Five (5) categories, such as built-up, agriculture, forest, water bodies and vacant land, were derived during the analysis for the year 1990, 2000, 2010, and 2020 (Figure 2). Of these, built-up is the dominant category today, which occupied with the highest proportion of land use. The next dominant class is agricultural land having massive land for the cultivation. Built-up land was occupied by 31.5% in 1990, which increased to 48.0% in 2020. However, agriculture area stood at 35.6% in 1990, which decreased to 31.7% in 2020. People from the neighbour village areas were moved to the city due to the civil war conditions, education, and standard life. Vacant land and forest area fell strongly during these periods, which caused the built-up growth (Table 3).

Table 3. Land use/ land cover from 1990 to 2020 (in hectares)

LULC	1990	2000	2010	2020
Built-up	1308.06	1340.4	1697.5	1998.8
Agriculture	1479.16	1136.1	1086.1	1319.7
Forest	373.34	601.1	576.2	325.7
Water bodies	15.99	40.8	94.2	32.4
Vacant Land	991.88	1050.5	713.8	485.7

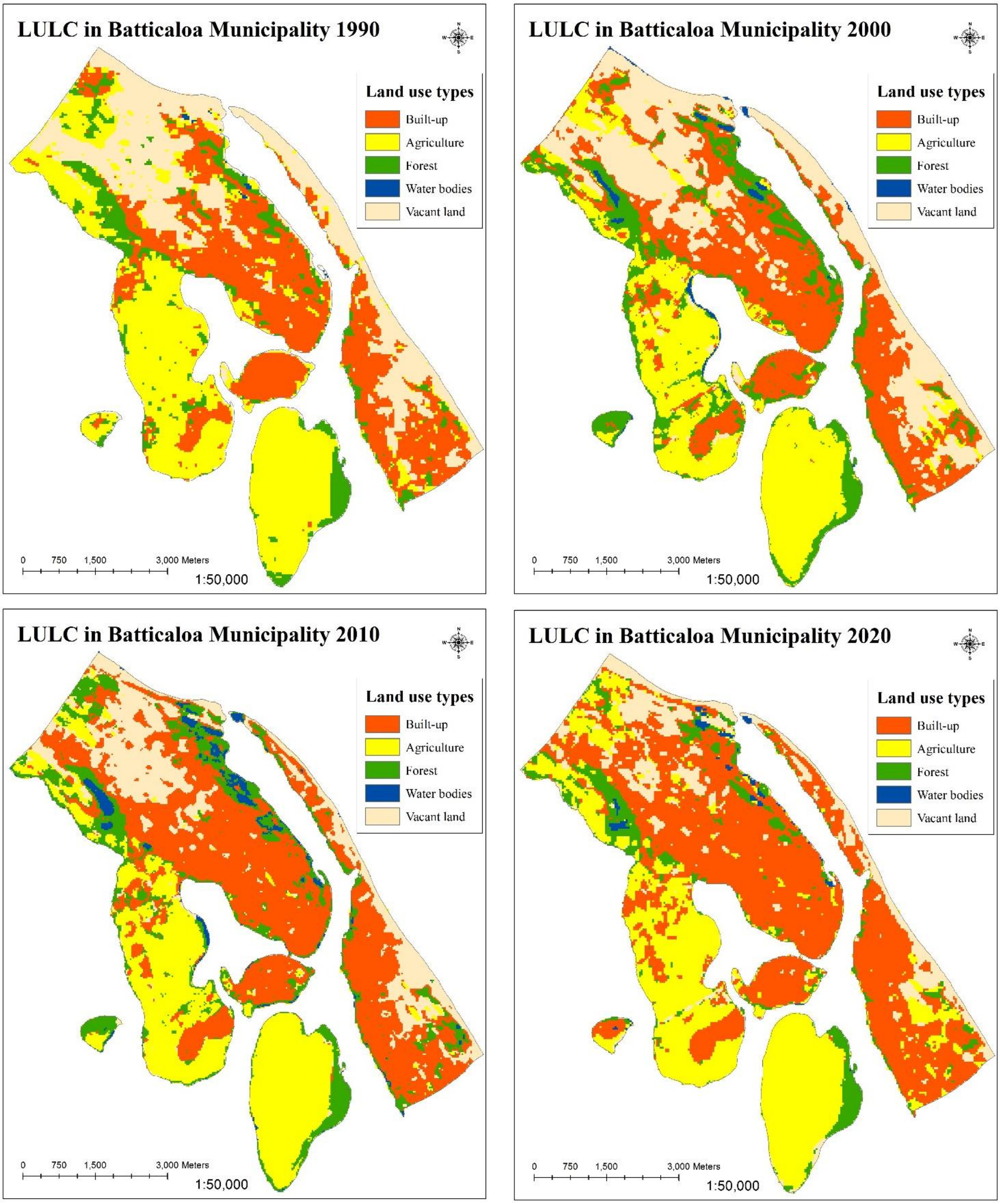

Figure 2. Land use/ Land cover pattern in Batticaloa Municipal Council from 1990 to 2020

Overall accuracy and Kappa index accuracy were calculated to the classified land use/land cover images (Table 4). The overall accuracy for each period was above 80%, which is a very good precision of the analysis and Kappa index accuracy also showed a very good agreement of the selected periods except the year 1990. However, this level showed a good agreement, which is almost reliable.

Table 4. The accuracy level of land use/ land cover from 1990 to 2020

	1990	**2000**	**2010**	**2020**
Overall Accuracy	80%	88.75%	95%	92.5%
Kappa Index Accuracy	0.74946	0.85827	0.93632	0.90367

Table 5 shows a summary of the probability matrix for major land-use conversions for all classes that took place between 1990 and 2020. Row categories characterized land use classes in 1990, while column categories typed classes of 2020. The probability of changing the land use class by 2020, and the gain and loss of these categories were displayed. Built-up land was achieved the highest gain at 77.92% during this period while forest and vacant land loss its land 45.88% and 45.07% respectively. The probability of change for built-up to built-up during this period is 75.89%, while the probability of future change of built-up to agriculture is 11.44% and so on for other land use classes. The agriculture was 71.96% while the future change of agriculture to built-up 14.86% and rest per cent to other types. The agricultural land was lost 28.04% of the land use. Approximately 42.77% of vacant land was converted to the built-up area, which reasonably established by the analysis.

Table 5. Transitional probability matrix between 1990 and 2020

		Probability of Changing by 2020 to:						
		Built-up	Agriculture	Forest	Water bodies	Vacant land	Total	**Loss**
Land use 1990 Changing from:	Built-up	0.7589	0.1144	0.0518	0.0000	0.0749	1.0	**0.2411**
	Agriculture	0.1486	0.7196	0.0807	0.0023	0.0488	1.0	**0.2804**
	Forest	0.1982	0.2218	0.5412	0.0304	0.0084	1.0	**0.4588**
	Water bodies	0.0047	0.1273	0.1588	0.6955	0.0137	1.0	**0.3045**
	Vacant land	0.4277	0.0143	0.0000	0.0087	0.5493	1.0	**0.4507**
	Total	1.5381	1.1974	0.8325	0.7369	0.6951	5.0	
	Gain	**0.7792**	**0.4778**	**0.2913**	**0.0414**	**0.1458**		

3.2. Simulated Land Use Change

The land use prediction was simulated using the CA-Markov chain model that showed slight differences between some categories and the same probability between some categories. Figure 3 illustrates the areas for existing and simulated land-use change in 2000. The reference and simulated maps for the year 2000 was similar to forest nearly 601.1 hectares. The reference and simulated maps for the year 2000 were slightly deference in built-up, agriculture, water bodies and vacant land, while the water bodies were almost similar between simulated and existing maps.

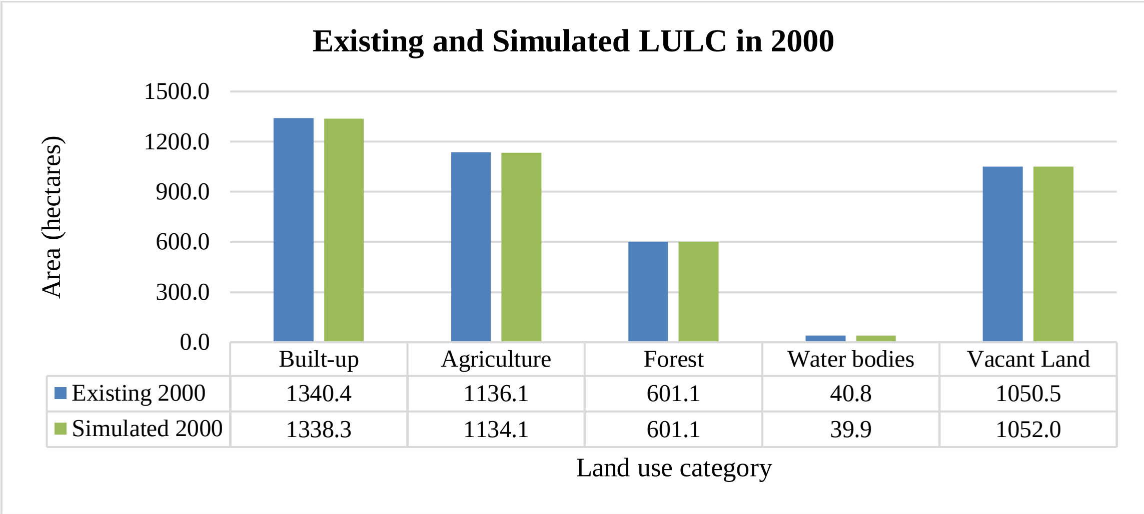

Figure 3. Comparison of existing and simulated land use/ land cover in Batticaloa Municipal Council - 2000

As shown in Figure 4, the areas for existing and simulated land-use classes show similarities and differences between the maps in 2010. The reference and simulated maps for the year 2010 was almost similar to the forest. The reference and simulated maps were reasonably identical to built-up and agriculture, while for the rest land use categories were almost slight differences, which are water bodies and vacant land.

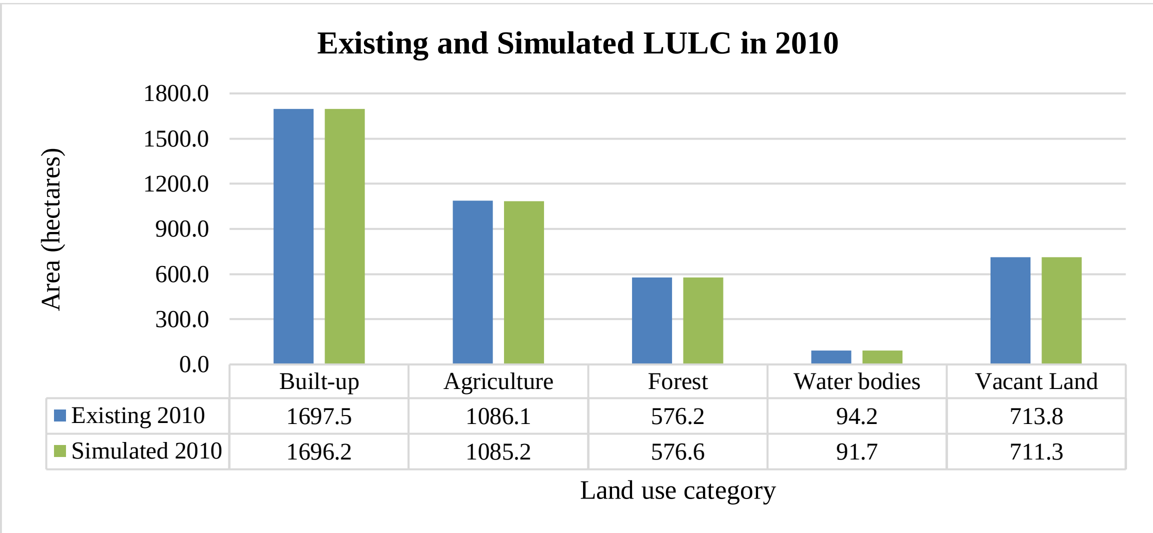

Figure 4. Comparison of existing and simulated land use/ land cover in Batticaloa Municipal Council - 2010

Figure 5 displays the areas for existing and simulated land use classes in 2020. The reference and simulated maps were similar to water bodies. Agriculture and forest are reasonably similar range in both. Although built-up and vacant land had almost slight differences between simulated and existing maps. According to the complete analysis of Markov, the prediction for the future land use of the Batticaloa Municipality can relatively be given the reliable output.

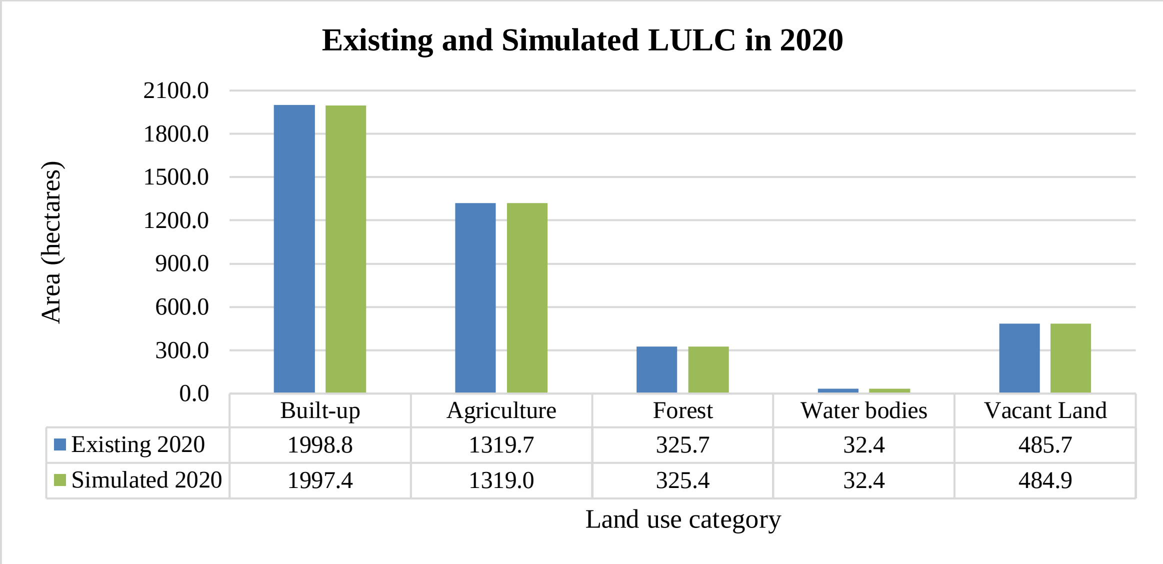

Figure 5. Comparison of existing and simulated land use/ land cover in Batticaloa Municipal Council – 2020

3.3. Projected Land use Pattern

The land use pattern for 2030 has projected based on the CA-Markov chain model, which has been used one iteration for the projection. According to Table 6, the transitional matrix for land use probability between 2020 and 2030 was analyzed using Markovian transition estimator. Row categories of the table entered land use classes in 2020, while column categories indicated land use classes for 2030.

Table 6 shows the matrix of the probability of changing the land use class by 2030 and the gain and loss of these categories. Built-up land will be achieved the highest gain at 83.38% during this period while water bodies will be lost its land by 85.09%. The probability of change for built-up to built-up during this period is 64.80%, while the probability of future change of built-up to agriculture and vacant land are 11.45%, 18.41% respectively. The agricultural land will be expected to be at 75.88% while the future changes in agriculture to forest and built-up are 11.02% and 4.39% respectively. The agricultural land will be lost 24.12% of the land use. Probably 10.77% of vacant land will be expected to convert to built-up land, which revealed the predicted map during the analysis.

Table 6. Transitional probability matrix between 2020 and 2030

		Probability of Changing by 2030 to:						
		Built-up	Agriculture	Forest	Water bodies	Vacant land	Total	**Loss**
Land use 2020 Changing from:	Built-up	0.6480	0.1145	0.0529	0.0005	0.1841	1.0	**0.3520**
	Agriculture	0.0439	0.7588	0.1102	0.0016	0.0855	1.0	**0.2412**
	Forest	0.0000	0.1812	0.7424	0.0056	0.0708	1.0	**0.2576**
	Water bodies	0.0342	0.1467	0.4255	0.1491	0.2445	1.0	**0.8509**
	Vacant land	0.1077	0.1108	0.0423	0.0006	0.7386	1.0	**0.2614**
	Total	0.8338	1.312	1.3733	0.1574	1.3235	5.0	
	Gain	**0.1858**	**0.5532**	**0.6309**	**0.0084**	**0.5849**		

Figure 6 displays the future land use for 2030 by the prediction of CA-Markov chain analysis. According to this map, increases in built-up land should be a challenge for sustainable urban growth, which leads to sprawling developments. Thus, this predicted map will aid to develop future planning for built-up development reduces the sprawling growth.

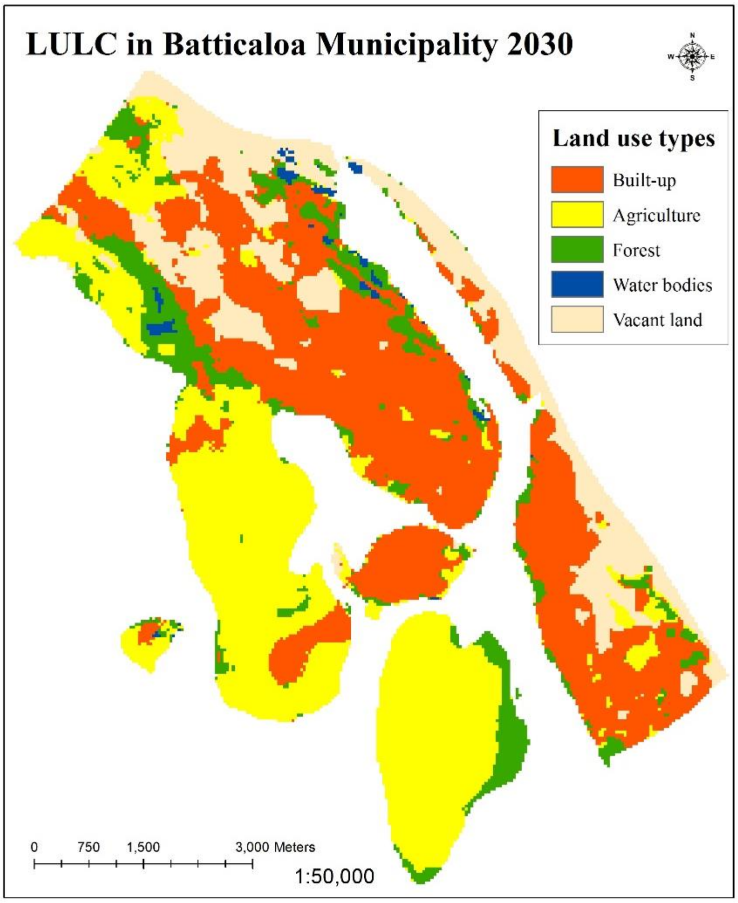

Figure 6. Predicted land use/ land cover in Batticaloa Municipal Council - 2030

According to Figure 6, the land use/land cover was predicted by 2030 that shows the estimated land area for built-up is 1607.5 hectares. Agriculture, forest, water bodies and vacant land are 1430.9 hectares, 420.2 hectares, 30.8 hectares and 711.2 hectares respectively in the Batticaloa Municipal Council area. This prediction was achieved with 0.15% errors, which provide almost reliable information on the land use/ land cover.

3.4. Model Validation

The predicted model by 2030 has validated concerning with existing land use map 2020. Kappa for no ability (kno), Kappa for standard (Kstandard) and Kappa for location (Klocation) were derived using model validation tool. The statistics revealed that Kappa overall accuracy for the predicted map is 0.9103, which is very good agreement of precision. Kstandard and Klocation are 0.8690, and 0.9371 respectively, which are also very good agreement during the analysis. The accuracy level above 0.80 is acceptable and credible for making future predictions [14]. All Kappa index values exceed the minimum acceptable standard, and all were greater than 80%, showing good agreement of predicted land use map.

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Numerous researches have studied using CA-Markov model, which were achieved the reliable outputs [7][8][9][10]. The land-use dynamics using Monte Carlo Markov chain (MCMC) method, which was only used the alphanumerical analysis [15]. This model needs a large number of unknown parameters for the analysis that is a barrier to in-depth study. Nevertheless, the CA-Markov model was not provided with an accurate simulation of land-use dynamics [5]. Because this study was used the three-dimensional analysis, which can have errors in the allocation of land use. However, this model recommended for land use/ land cover change prediction [9]. This model is also appropriate to the complex urban system. Therefore, the projected map can be identical to 2030, when current growth is the same, or if planners adopt modern technology in the future, it can change.

4. Conclusions

Urban sprawl is the expansion of urban physical growth due to socioeconomic development. This development leads to a complex process of transformation and structure of the land. Anthropogenic activities, such as housing development, commercial and other infrastructure development, affect the land use pattern. However, the projection provides almost a precise amount of land use, which is confirmed by the probability prediction of Markov analysis. Based on these results, the projected map for 2030 will be the genuine prospect for land use, but sometimes development techniques can even slightly change the pattern, such as vertical development. This projected map for 2030 will aid to develop a suitability modelling to the built-up development, which was enormously growing from 1990 to 2020. Therefore, adequate planning must be implemented in the area that can reduce future effects.

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