SPATIAL-TEMPORAL ANALYSIS OF PATTERN CHANGES AND PREDICTION IN PENANG ISLAND, MALAYSIA USING LULC AND CA-MARKOV MODEL

HUA, A. K.

Department of Environmental Sciences, Faculty of Environmental Studies, Universiti Putra Malaysia (UPM), 43400 Serdang, Selangor, Malaysia
e-mail: angkeanhua@yahoo.com

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Abstract. Penang Island has witnessed rapid urban development and economic growth in recent years. With the ambitious vision to become a developed country by 2020, planners and policy-makers need to know the most likely direction of future urban development without compromising on the forest landscape. In this study, remotely sensed data combined with cellular automata models were used to predict the land use land cover change in Penang Island, Malaysia. Cellular Automata (CA)-Markov models were applied in 1990 and 2006 to predict the land cover in 2016. Land use land cover maps for the study area were derived from 1990, 2006, and 2016 Landsat Images (MSS, TM, and OLI). The accuracy of models is above 80%. A Markov model was applied in 2006 and 2016 to predict the land cover in 2042. The results indicate that the built-up area had expanded more in the east towards the north and south, and also towards the centre of the island and moving upwards to the north. The models suggest limiting urban development in the centre of the island to protect forest landscapes. This study serves as guidelines for other studies which attempt to project land use land cover change in forest landscape while experiencing similar land use changes.
Keywords: *Penang Island, CA-Markov, land use land cover change, accuracy, future land use*

Introduction

Environmentalists and landscape planners who are knowledgeable about land use and land cover (LULC) change are concerned that LULC can affect the global environment (Guan et al., 2011). Majority of the causes leading to biodiversity loss is due to changes in land use which are associated with habitat loss and fragmentation (Sala et al., 2000). Deforestation, urbanisation, agriculture intensification, as well as overgrazing and subsequent land degradation are all classified as land use changes in anthropogenic origin. The existence of nature, viz: slope and elevation are also involved in the change (Lambin, 1997), thus making the dynamics of land use a complex process. This complication which caused the LULC dynamics to change originates from economics, politics, culture and society as well as other legal aspects (Lambin, 1997). However, the main causes of land and forest degradation are severe changes made to urbanisation and agriculture. Such decline in natural resources which affects the environment quality through air pollution (Wu et al., 2012), water pollution (Hua, 2017), and can influence the climate are man-made changes (Angelsen and Kaimowitz, 1999). Therefore, having a good knowledge of land use land cover will be useful in providing information when decision making for using and managing the land use resources (Lu et al., 2004).

A sudden growth in distant senses data in temporal, spatial and spectral resolutions appears to be beneficial as it provides essential tools for identifying changes on the Earth’s surface at different scales (Wu et al., 2006; Rogan and Chen, 2004). Several suitable approaches that have been used to model the land use land cover changes by

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using remotely senses data are; statistical models (regression and structure equation model), mathematical models (linear and static), systems model (stock and flow), agent based models cellular models (Cellular Automata (CA) and Markov Chains), and evolutionary models (neural networks) (Parker et al., 2003; Agarwal et al., 2002). Roger and Chen (2004) cited that digital change detection is defined as the process of determining and describing the changes in land use characteristic based on co-registered multi-temporal remote sensing data. These techniques used for assessing change are numerous including both statistical and rule-based methods (Coppin et al., 2004; Rogen and Chen, 2004; Lu et al., 2004).

Modeling LULC change

To detect changes that have happened or are about to take place, LULC change models are used (Veldkamp and Lambin, 2001). These change models involve analysing historical land use data where the past land transformation and transition are evaluated. The transition trend which has been identified is amalgamated with environmental variables to provide an estimate of future land use (Eastman, 2009; Pijanowski et al., 2002). Having an understanding of the factors of change (i.e population growth, soil type, distance to road or other facilities), the models have the ability to provide a probabilistic prediction of where the changes may happen (Overmars et al., 2003). LULC model which was designed to evaluate the cumulative impact of land use change and develop future activities (Veldkamp and Lambin, 2001) which are essential in helping and supporting decision making of land use planning (Guan et al., 2011). In particular, LULC change have been forecasted to be important for understanding and highlighting of potential modifications and alterations that might happen over landscapes in the future. LULC changes have been applied in different situations viz; rural development and urban growth (Kityuttachai et al., 2013), selecting conservation priority areas and setting alternative conservation measures (Adhikari and Southworth, 2012) and simulating rangeland dynamics under different climate change scenarios (Halmy et al., 2015; Freier et al., 2011).

To understand better the dynamics of land use change at different angles, the Markov chain analysis has been extensively used (Baker, 1989; Muller and Middleton, 1994). This chain analysis works on the probability of a system being in a certain state at a certain time can be determined, if the state at an earlier time is known (Bell and Hinojosa, 1977). To put it simply, this method develops a transition probability matrix of land use change between two different dates by providing an estimation of probability that each pixel of certain LULC class will be transformed to another or remains in the class (Eastman, 2009). This method has an added advantage in modeling land use change especially on a large scale (Weng, 2002). Although different from logistic regression, Markov chain analysis cannot assume statistical independence data (Overmars et al., 2003) but is suited for spatial dependent land use data but has the ability to forecast all multidirectional land use changes among all classes land use available (Pontius and Malanson, 2005). One problem that can arise when using Markov chain models is that this method is more suitable for short term projections (Sinha and Kimar, 2013) and not spatially explicit especially not providing the spatial distribution of the changes (Sklar and Costanza, 1991). However, this problem can be overcome by integrating with other different dynamic empirical models e.g. cellular automata models (Guan et al., 2011; Weng, 2002). The CA- Markov is regarded as a spatial transition model as it contains the stochastic aspatial Markov techniques with the stochastic spatial cellular automata method (Eastman, 2009) which is capable of predicting the two-way transitions among the available LULC classes (Pontius and Malanson, 2005). Therefore, the main purpose of this study is to demonstrate the ability of CA-Markov models to predict the LULC changes for year 2042 with special attention on the ecologically impaired forest land in Penang Island, Malaysia.

Materials and methods

Study area

Penang Island is located in the northern part of Malaysia which lies within a latitude of 5°12’N to 5°30’N and longitude of 100°09’E to 100°26’E (*Fig. 1*). The total area of Penang Island is approximately 295 km^2, and is also the most populated island in the country with an estimated population of 720 000 (Tan et al., 2011, 2010). George Town is the main capital city which is located in the east region of Penang Island. Generally, Penang Island enjoys an equatorial climate with hot and humid conditions throughout the entire year. In other words, the average mean of daily temperature is about 27 °C, with a maximum and minimum average mean of daily temperature at 31.4 °C and 23.5 °C respectively. Specifically, the average annual temperature varies between 27 to 30 °C (Tan et al., 2011, 2010). Meanwhile, the average humidity is between 70 to 90%, and having the daily mean humidity between 60.9 and 96.8% (Tan et al., 2011, 2010). The average annual rainfall is 267 cm, and the annual total can reach up to a maximum of 624 cm (Ahmad et al., 2006). When the monsoon winds arrive, the population of Penang Island experienced sunshine during the day and rainfall in the evenings.

Figure 1. *Study area of Penang Island*

Since George Town constitutes a unique architectural and cultural townscape in the country, the island received recognition from UNESCO World Heritage Site as one of the tourism centres in Malaysia. This recognition will help to increase the number of visitor arrivals to Penang Island. Nevertheless, an increase in population will increase in the built up area and decline in forest land. Generally, the total area of forest land is approximately 154 km^2 with a population density of 132 persons per km^2. Forest land (41%) was the predominant land use in Penang Island, followed by urban area (18%), agriculture area (8%) and water bodies (33%) in 1990. Urbanisation and agricultural practices indirectly had a negative impact on the fate of ecology and biodiversity of the forestry land. The main reasons for choosing Penang Island for LULC change prediction are the rapid population growth, availability of data sets with zero cost, and

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ecological of forest land impaired (Tan et al., 2011, 2010). According to Tan et al. (2011, 2010), the growing population rate between the year 2000-2010 was higher than the years from 1990-2000 and will continue to increase in the coming future as well as the infrastructure of development. Therefore, identifying the potential areas that are likely to be converted into other land use classes would benefit the decision makers and landscape planners as references and guidelines for the policies to be designed in a better way for sustaining the ecology integrity of forest land.

Data sources

Three LULC vector data sets for Penang Island for 1990, 2006 and 2016 (*Table 1*) were taken from USGS Earth Explorer. But the land use was grouped into four classes, namely built-up area, agriculture area, forest land, and water bodies while the road vector data was used to generate the land change suitability maps. Generally, images for classification were chosen between the months of February to April because of clear sky or cloud free during this period. All the dataset was rectified to Universal Transverse Mercator (UTM) coordinate system, Malaysian Cassini State Plane zone 03, and WGS 1984 Datum and clipped to the island boundaries. For this particular study, different software packages were applied as each one has its strength in certain operations needed for analysis. ENVI v4.7 was used for the classification of images and accuracy assessment; IDRISI Selva v.17 was used for CA-Markov modeling (Eastman, 2009); and ArcGIS v10.1 was used to produce suitable maps and final map. The steps of the research study are shown in *Figure 2*.

Table 1. *Specific of remotely sensed data used for the study*

Sensors	Month/day	Year	Spatial resolution (m)	Path/row	Band combination
Landsat MSS	03/04	1990	60	128/56	1,2,3
Landsat TM	02/21	2006	30	128/56	1,2,3
Landsat OLI	03/20	2016	15	128/56	2,3,4

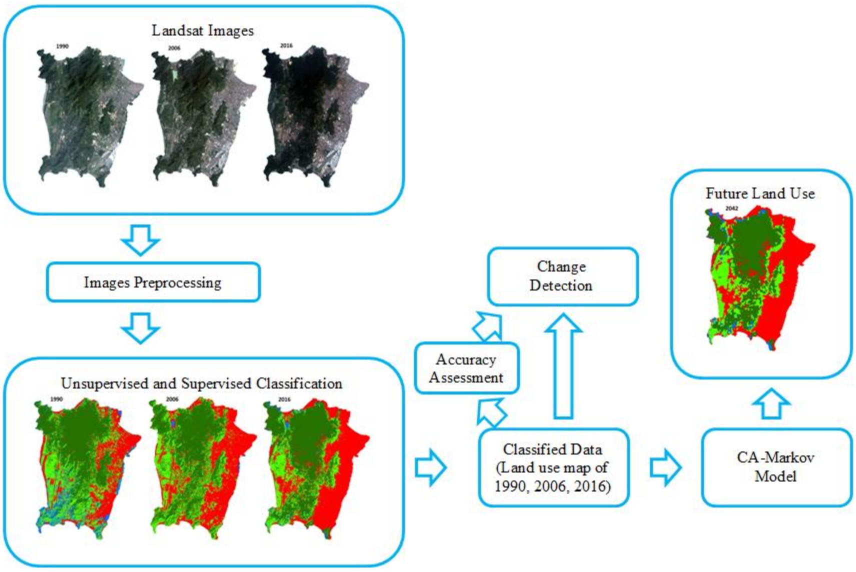

Figure 2. *Demonstration of research methodology as a flowchart*

Data preprocessing, LULC classification and change detection

To set up a direct link between data and the biophysical phenomena it represents, it is essential to preprocess the satellite images (Parsa et al., 2016). Pre-processing can be achieved by using ArcGIS version 10.1 for geo-referencing, mosaicking and sub setting of the image for the Area of Interest (AOI). The Landsat OLI has experienced spatial sharpening using the panchromatic bands which caused a 15 m resolution. The Landsat MSS and TM images for 1990 and 2006 were originally in 30 m resolution. However, further image processing analysis was carried out using ENVI 4.7. The image appeared in a composite of natural colours using a combination of 3,2,1 for Landsat MSS and TM, and 4,3,2 for Landsat 8. The maximum likelihood supervised and unsupervised classification was performed using several selected regions, and Regions of Interest (ROI) were based on delineated classes of agriculture area, forest land, built up area and water bodies (*Table 2*).

Table 2. *Description of the LULC classes mapped in the study area*

Class name	Description
Vegetation area	Includes all agricultural lands
Forest land	Includes all forest fields
Built up area	Includes all residential, industrial area, commercial, administration, cemetery and transportation, as well as sewage treatment plant (include individual septic tank)
Water bodies	Includes all water bodies (river, lakes, gravels, stream, canals, and reservoirs)

To carry out the LULC change detection, it is proposed to apply the post classification detection method in the ENVI 4.0, for purpose of comparison, by using two classified images to produce change information on a pixel basis. In simple words, the interpretation between the two images will provide changes “from- to” information. All the data were geo-rectified and resampled to ground resolution of 15*15 m for Landsat OLI and 30*30 m for Landsat MSS and TM which was projected toWGS84 UTM with a RMSE of less than 0.5 pixels. Subsequently, the classified images from two different data sets are compared using a cross-tabulation in determining the qualitative and quantitative aspects of changes for the periods from 1990 to 2016. The extent of change and percentage of change can be expressed in a simple formula (*Eqs. 1* and *2*) as follows:

$$K = F - I \qquad \text{(Eq.1)}$$

$$A = \frac{(F-I)}{I}\ x\ 100 \qquad \text{(Eq.2)}$$

where K is the magnitude of changes, A is percentage of changes, F is first data, and I is reference data (Mahmud and Achide, 2012). This research study uses LULC techniques to decide on the differences and to explain the percentage of land use changes with the period of time. Furthermore, the prediction of LULC changes for 2042 will involve IDRISI Selva which will be further explained in CA-Markov model analysis.

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Accuracy assessment

To find out the quality of information provided from the classification process, an accuracy assessment for 1990, 2006 and 2016 images was carried out to establish the quality of information taken from the classification process. It is important to conduct an accuracy assessment for individual classification before the change detection analysis (Behera et al., 2012). Kappa tests are used to measure the accuracy of classification as the test is able to account for all elements in confusion matrix including diagonal elements (Halmy et al., 2015). Kappa test measures predefined producer rating and user assigned rating and are expressed in *Equation 3:*

$$K = \frac{P(A) - P(E)}{1 - P(E)} \tag{Eq.3}$$

where *P(A)* is the number of time the *k* raters agree, and *P(E)* is the number of time the *k* raters are expected to agree only by chance (El-Kawy et al., 2011; Pontius and Millones, 2011). Meanwhile, user accuracy is defined as the probability of a pixel on the image actually representing a class on the ground. The producer's accuracy will show the probability a pixel being correctly classified and is mainly used to determine how well an area can be classified (Pontius and Millones, 2011). As mentioned earlier, 4 categories of classes were delineated. Each category have a minimum of 50 points to increase the percentage of accuracy assessment (El-Kawy et al., 2011). Therefore, the accuracies of classification for 1990, 2006 and 2016 are 87.31%, 88.49% and 91.62 with a kappa statistic of 0.86, 0.85, and 0.90 respectively. According to Weng (2010) the lowest level for accuracy assessment in identification of LULC categories in remote sensing should be at least 85%. Then, the data will be imported into IDRISI Selva v.14.0 as an ASCHII text file for further analysis.

Markov model

The Markov model is capable of calculating past conditions and predict on how a particular variable changes over time. This model has been extensively used in ecological modeling (Adhikari and Southworth, 2012; Behera et al., 2012). The uses of the Markov model in LULC change modeling is promising due to its ability to quantify the states of conversion between land use types as well as the rate of conversion among the land use type (Pontius and Malanson, 2005). A homogenous of the Markov model for predicting land use change can be represented mathematically as *Equations 4* and *5* (Sinha and Kumar, 2013);

$$L_{(t+1)} = P_{ij} * L_{(t)} \tag{Eq.4}$$

and

$$P_{ij} = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1m} \\ P_{21} & P_{22} & \cdots & P_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ P_{m1} & P_{m2} & \cdots & P_{mm} \end{bmatrix} \tag{Eq.5}$$

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where, $L_{(t+1)}$ and $L_{(t)}$ are the land use status at time t + 1 and t respectively. $0 \leq P_{ij} < 1$ and $\sum_{j=1}^{m} P_{ij} = 1\ (i, j = 1,2,3 \ldots . m)$ is the transition probability matric in a state.

Cellular automata (CA) model

The cellular automata (CA) model, is an area spatially dynamic model, which is frequently used for LULC change studies. In this model, the transition of a cell from one land-cover to another depends on the state of the neighbourhood cells (Verburg et al., 2004). Generally, a cell has a high probability to change to land-cover class ‘A’ than to a land-cover class ‘B’ if the cell is closer proximity to land-cover class ‘A’. Similar to the Markov Model, the CA applies previous state information of a land-cover as well as the state of neighbourhood cells for its transition rules. Since CA models have been extensively used in LULC changes analysis especially in forest cover change analysis (Verburg et al., 2004; Messina and Walsh, 2001), it has the ability to integrate with the Markov model and make it a dynamic spatial model.

CA-Markov model

The CA-Markov model is a combination between cellular automata, Markov chain, multi-criteria, and multi-objective land allocation to predict land cover change over time (Parsa et al., 2016; Behera et al., 2012). The Markov model is not only spatial contiguity but is also the probable spatial transitions occur in a particular area over a time. Markov and CA-Markov modules in IDRISI Selva were used to create transition probability and transition area matrix (Eastman, 2009). Transition probability matrix is formed by cross tabulation of two images of different time and determines the probability of a pixel in a land use class to change into another class during that time (Parsa et al., 2016; Eastman, 2009). Transition area matrix contains the number of pixels that are expected to change to a land use class from another class during a time period (Parsa et al., 2016; Behera et al., 2012; Eastman, 2009). Land use map dated 1990 and 2006 were used to create transition probability matrix in order to project land use map for the year 2016. In creation transition probability matrix, Markov module in IDRISI Selva was used and the proportional error was set to be 15% (Eastman, 2009).

IDRISI Selva uses CA-Markov model that repeatedly produce the land use allocation until areas that are predicted by the Markov model are identified. The number of times it is repeated depends on the number of years a projection is made. Here in this study, the number of repeated process performed was 9 because the land use map of 2006 was taken as a base map for projecting the land use in 2016. A contiguity filter of a kernel size of 5*5 pixels that accounts the neighbourhood pixels was used to create spatially explicit continuous weighting factors so that the pixels that are far from the existing land use class have a lower suitability than the pixels that are near. In this study, the filter used was for analysis:

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

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After a predictive data has been built, the model is then validated to test the accuracy of the model. The process of gauging the accuracy of the model will be illustrated in the validation prediction model section. Then, the techniques of CA-Markov for producing the transition probability matrix and transition area matrix is repeated by using land use map dated 2006 and 2016 to cross tabulate to produce the land use map of the year 2042 (*Table 8*). In other words, the actual land use map of 2016 are used as based map to produce simulated 2042 map of LULC at the study area.

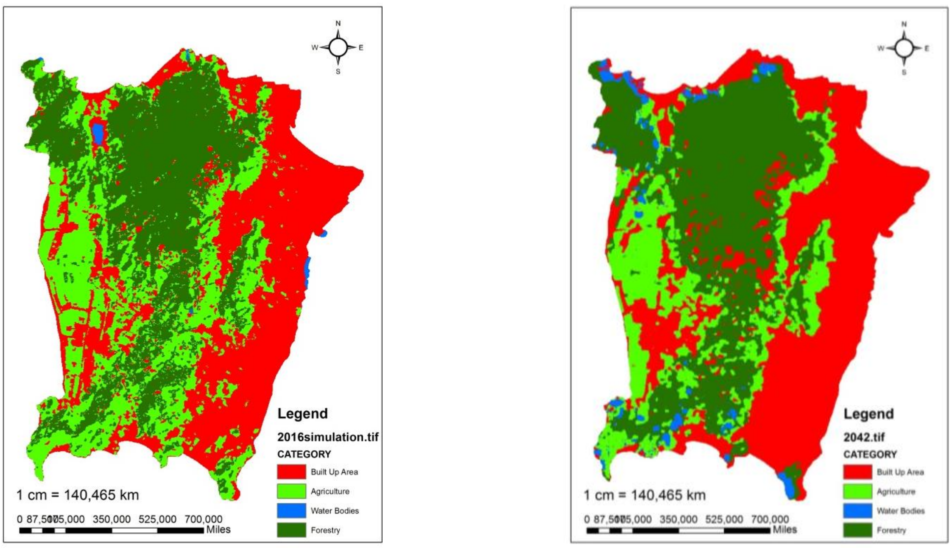
Validation LULC prediction model

For purpose of evaluating and to avoid any miscalculation of the model, it is necessary to investigate between the actual map and simulated map and to compare the output from the model with the actual land use map. The evaluation model is based on the Kappa Index of Agreement (KIA) approach, which is widely used in validation of LULC change predictions (Parsa et al., 2016; Halmy et al., 2015; Behera et al., 2012). Whereas the accuracy assessment process was done using the VALIDATE module in IDRISI Selva. For this study, a simulated land use map of 2016 will be used to compare with the actual land use map of 2016. The results of the comparison between the simulated and actual map for year 2016 can be shown in *Table 3* as well as *Figure 3a* and *b*.

Table 3. *Comparison of actual and projected LULC types in 2016*

Category	2016A (ha)	2016S (ha)
Forest land	110 854	109 350
Built-up area	88 183	83 742
Agriculture area	53 992	62 617
Water bodies	41 971	39 291
Total	295 000	295 000

2016A = 2016 actual map, 2016S = 2016 simulated map



a b

Figure 3. *LULC simulated map of 2016 (**a**) and 2042 (**b**)*

A Kappa value of 0 illustrates the agreement between actual and reference map (equals chance agreement), the upper and lower limit of kappa is +100 (it occurs when in total agreement) and -1.00 (it happens when agreement is less chance) (Sinha and Kumar, 2013). In this study, the validation indicates K values (Kno = 0.823, Klocation = 0.851; KlocationStrate = 0.851; Kstandard = 0.831) above 0.8 showing satisfactory level of accuracy. According to Pontius and Millones (2011), if the results are greater than 0.8 for each kappa index agreement, then the K statistics are considered accurate. Hence, CA-Markov modeling is suitable for accurate prediction of future LULC's.

Results and discussion

Land use land cover (LULC) changes

According to *Table 4*, the results indicate the forest land, built-up area, agriculture area, and water bodies for 1990, 2006, 2016 and 2042 (*Figs. 3a, b* and *4a, b, c*). In other words, the LULC changes between 1990 to 2006 showed the built-up area and agriculture area have increased by 19 633 ha and 44 302 ha, while the forest land and water bodies have decreased by -7 218 ha and -56 717 ha, respectively (*Table 4; Fig. 4a* and *b*. This situation has occurred because the forest land and water bodies were converted into built-up area and agriculture area. Specifically, forest land and water bodies are likely to transform into agriculture area, before these activities are transformed again into built-up area (*Table 5*).

Table 4. *Area (ha) of LULC type in Penang Island for 1990, 2006, 2016 and 2042*

Category	1990 ha (%)	2006 ha (%)	2016 ha (%)	2042 ha (%)
Forest land	126 330 (43)	119 112 (40)	110 854 (38)	89 568 (30)
Built-up area	53 810 (18)	73 443 (25)	88 183 (30)	97 350 (33)
Agriculture area	25 650 (9)	69 952 (24)	53 992 (18)	61 412 (21)
Water bodies	89 210 (30)	32 493 (11)	41 971 (14)	47 200 (16)
Total	295 000 (100)	295 000 (100)	295 000 (100)	295 000 (100)

ha = hectare; % = percentage

Table 5. *Transition probability of area and matric calculated using land use maps of 1990-2006*

Category		1990–2006			
		Forest land	Built-up area	Agriculture area	Water bodies
Forest land	F	64 894.87	17 500.01	40 326.12	0
	P	52.88	14.26	32.86	0.00
Built-up area	F	4 492.03	50 341.29	8 793.18	0
	P	7.06	79.12	13.82	0.00
Agriculture area	F	7 064.99	14 942.59	25 726.50	66.92
	P	14.78	31.26	53.82	0.14
Water bodies	F	11 732.17	13 594.22	23 074.89	12 450.22
	P	19.28	22.34	37.92	20.46

F = frequency in hectare, P = Percentage

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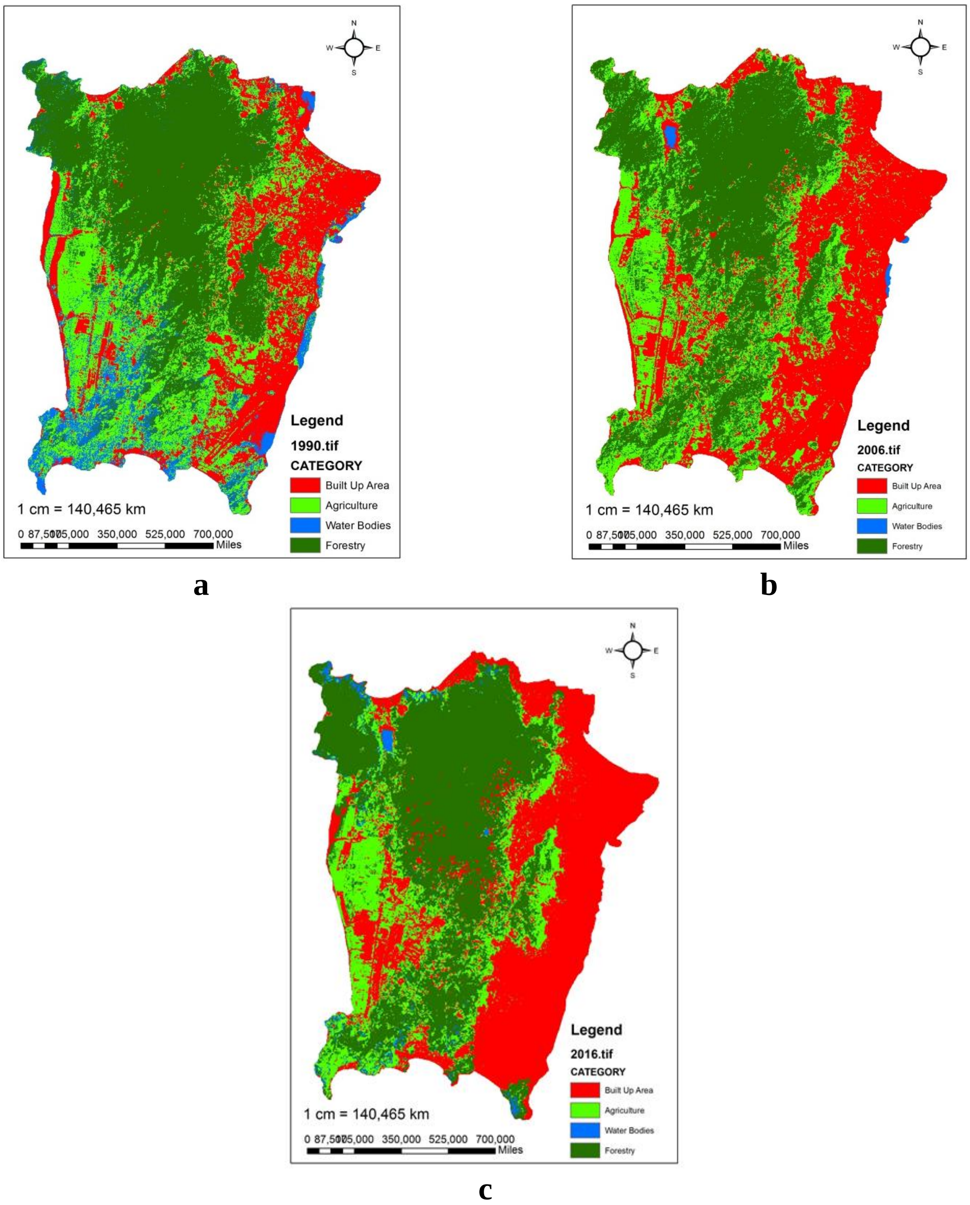

Figure 4. *LULC actual map of 1990 (**a**), 2006 (**b**), 2016 (**c**)*

Sufficient water supply with fertile soil leads to the agriculture activities to be carried out, while abandoned forest land would be in demand for built-up and agriculture activities. In addition, with the country's vision of 2020 to be a developed country, the rapid development becomes prioritised and these encouraged the attraction of local and non-local residents to concentrate on Penang Island. Due to the population growth and rapid urbanisation, the demand for shelter and job opportunities could also increase. Indirectly, this situation will raise the pressure on forest land and water bodies to negatively affect in the quality and quantity, which could bring harm to living species and cause extinction.

Nevertheless, the LULC change for the next 10 years indicated that forest land continued to donate to the coverage area for agriculture activities for 31.22% before its transformation into a built-up area for 29.72% (*Table 6*). Meanwhile, only the built-up

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area will continue to increase especially in the north, south and centre of the island; while others in east, northeast, and southeast show a high cluster of built-up area in Penang (*Fig. 4c*). Besides that, water bodies also showed positive development, where the minority coverage area of forest land and agricultural activities are being converted into water bodies for 6.70% and 10.66%, respectively (*Table 6*). Generally, the recognition of Penang Island as a tourist centre from World Heritage Site in 2008 had raised the economic value of the country, and indirectly increased the tourists' arrival in the island. As a result, the built-up area is detected to have enlarged the area to fulfil the demand for commercial activities such as hotels, restaurants, shopping malls, hypermarkets, etc. As a proof, several residential activities are suspected to concentrate on the surroundings of Penang Hill (which was highlighted as one of the historical heritage attraction as well as for its flora and fauna). Indirectly, this area is exposed to the danger of landslide and rock falls. Simultaneously, although the water especially from the river is not supplied as drinkable sources, but the awareness of the need for quality and quantity of water supply for agriculture activities and aquatic species had been extended and were detected scattered in the north and the south of Penang Island. Hence, these situations will continue to decline from the forest land into built-up area, agriculture activities, and water bodies. Therefore, the natural biodiversity especially living animals on the island will become extinct due to the rampant deforestation for the human activities.

Table 6. *Transition probability of area and matric calculated using land use maps of 2006-2016*

Category		2006–2016			
		Forest land	**Built-up area**	**Agriculture area**	**Water bodies**
Forest land	F	48 683.80	22 697.64	35 897.70	7 703.86
	P	42.34	19.74	31.22	6.70
Built-up area	F	8 016.65	61 143.12	11 346.14	307.09
	P	9.92	75.66	14.04	0.38
Agriculture area	F	17 959.49	18 418.07	18 988.22	6 606.22
	P	28.98	29.72	30.64	10.66
Water bodies	F	320.19	2 092.44	439.34	34 380.03
	P	0.86	5.62	1.18	92.34

F = frequency in hectare, P = percentage

Overall, LULC changes for 26 years from 1990 showing only the built-up area and agriculture area are having an increment steadily for more than 20%; while forest land are having a positive effect for approximately 15% and water bodies are less than 5% (*Table 7*). Increase in built-up area proved that population growth and rapid urbanisation have succeeded in archiving the country's vision of 2020 as a developed country. Indirectly, these results will enhance the demand towards agricultural activities as well as decline in the forest land and water bodies. When the water quantity decreases through the coverage area and evaporation process during droughts season, plus with drastic climate change and water pollution through anthropogenic activities, this resulted to pressuring the supply of water as a whole. So, this situation shows that the water bodies should paid attention to avoid excessive negative impact that may affect the aquatic species and reduce the food supply through agricultural activities.

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Simultaneously, forest land provides various benefits in terms of climate regulation, human health, recreation, refuge, fresh water supply, etc. In other words, declining forest land will reduce the possibility of accessible freshwater supply resources. Hence, forest land should be protected from deforestation on a large scale. This is because forest land not only links to the water bodies, but also consists of various species of flora and fauna which exist indigenously or naturally. Therefore, destruction towards forest land and water bodies will bring negative impact and will decline the human quality life.

Table 7. *Transition probability of area and matric calculated using land use maps of 1990-2016*

Category		1990–2016			
		Forest land	**Built-up area**	**Agriculture area**	**Water bodies**
Forest land	F	37 024.42	34 201.93	36 478.90	10 886.75
	P	31.22	28.84	30.76	9.18
Built-up area	F	4 046.80	57 024.39	9 925.31	0
	P	5.70	80.32	13.98	0.00
Agriculture area	F	4 428.09	16 000.08	16 517.75	2 875.08
	P	11.12	40.18	41.48	7.22
Water bodies	F	18 155.45	12 396.60	12 718.51	20 319.94
	P	27.68	18.90	22.44	30.98

F = frequency in hectare, P = percentage

Prediction of future LULC changes

Simulated future LULC change is extended for the next 26 year from 2016, which has been interpreted in *Table 8*.

Table 8. *Transition probability of area and matric calculated using land use maps of 2016-2042*

Category		**2016–2042**			
		Forest land	**Built-up area**	**Agriculture area**	**Water bodies**
Forest land	F	35 795.37	32 849.16	21 204.65	10 361.82
	P	35.72	32.78	21.16	10.34
Built-up area	F	2 170.74	83 063.12	7 532.64	0
	P	2.34	89.54	8.12	0.00
Agriculture area	F	10 317.12	13 986.96	27 662.34	5 735.58
	P	17.88	24.24	47.94	9.94
Water bodies	F	1 979.60	8 694.17	3 174.49	30 737.24
	P	4.44	19.50	7.12	68.94

F = frequency in hectare, P = percentage

The result indicates that the built-up area, agriculture area, water bodies, and forest land are detected to continue to ‘grow’ in the coverage area of about 18 510 ha (26%), 10 637 ha (12%), 5 365.8 ha (7%), and 4 822 ha (8%), respectively. In other words, the future LULC map only shows the built-up area and water bodies are having an increment in the coverage area, while agricultural activities and forest land are

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suspected to decline. Generally, water provides food and water sources, recreation activities, sustaining the ecosystem, maintaining the humidity of land surface from overheating and the climate changes, etc. The benefits and importance of water resources had increased the awareness of local residents to sustain the quality and quantity from 'disappearance' and be concerned with environmental issues. Nevertheless, LULC map in 2042 resulted to an increase in built-up area showing a sign of warning that the population growth has increased and urbanisation could be achieved in making Penang Island as one of the developed states. Indirectly, the built-up area will increase the demand for water and food sources, shelter, employment, recreations, etc.; as well as creating various numbers of environmental problems such as pollution, the cause of extinction towards living and non-living being. This situation also signalled that 'confiscation' of other class area in fulfillment of the quantity of the population will happen.

As a proof that confiscation could happen, the CA-Markov analysis has shown that forest land and agricultural activities is declining in the coverage area to contribute to the built-up area. To be more specific, future LULC map in 2042 indicated that several areas of forest land in the centre of Penang Island especially surrounding the high hills. This was transformed into built-up area, as well as the north and the west of agriculture area had been converted into water bodies. As explained previously, the forest land plays an important role in providing the sustainability of water resources, food resources, land resources, and air source (which was also referred to as the climatic matter) to provide the comfort continuance of living overall. However, pressured in fulfilling the demand of humans on the 'greedy' attitude had caused the forest land to become a 'victim' of deforestation, which can be shown in *Figure 3b*. There are only several areas that remained as forested land especially the high hills like Batu Feringghi, Bukit Bendera, Bukit Ayer Hitam, and Bukit Relau; including several forested areas at ground land like Teluk Bahang, Pantai Acheh, and Balik Pulau (*Fig. 3b*). Therefore, these areas should be preserved and conserved so that nature can be maintained for its originality and avoid from being damaged or destructed. As a summary, LULC change for 1990 to 2016 shows that the built-up area and agriculture area experienced a gain more than a loss by 29% and 21% (*Fig. 5a*); while forest land and water bodies have a loss more than a gain by -33% and -17% (*Fig. 5a*). Furthermore, the next 26 years of LULC change will indicate that the built-up area, agriculture area, and water bodies are having a gain more than a loss (*Fig. 5b*) by 46%, 2% and 2% (*Fig. 6b*), respectively; while only the forest land are having a loss more than a gain (*Fig. 5b*) by -50% (*Fig. 6b*). Therefore, forest land should be given attention and priority from deforestation on a large scale through various methods of laws, policies, moral and ethical value, religion, and awareness, which are important to prevent it from being constantly taken advantage of by other classes.

Conclusion

This study utilised satellite images (1990, 2006, and 2016) to analyse the land use land cover of Penang Island, Malaysia. Two classified images (1990 and 2006) were used as an input to the CA-Markov model to predict the 2016 land use land cover. The model output is validated with an actual image of 2016. Based on the results, the model is used to predict land use land cover for 2042. The overall results showed a predominant increase in built-up areas from 18% of total land use in 1990 to 77% by

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2042. The increase is found mainly at the expense of forest land, where these areas are reduced from 41% in 1990 to 25% in 2042. Based on the environmental framework of Penang Island in 2042 as planned by City Council of Penang Island, it is noted that Penang Island is planned to expand more to the east towards north and south. Nevertheless, the result of CA-Markov model in this study complied with the 2042 Master Plan, where the built-up areas are expected to encounter an expansion not only from the east to the north and south, but also towards the centre of the island and moving upwards to the north. In this model, it could suggest to limit urban development in the centre of the island to protect forest landscapes. To understand how the changes in the landscapes may influence the distribution of the important species will help guide conservation planning in the area. This study can serve as guidelines for other studies which attempt to project land use land cover change in forest landscape experiencing similar land use changes.

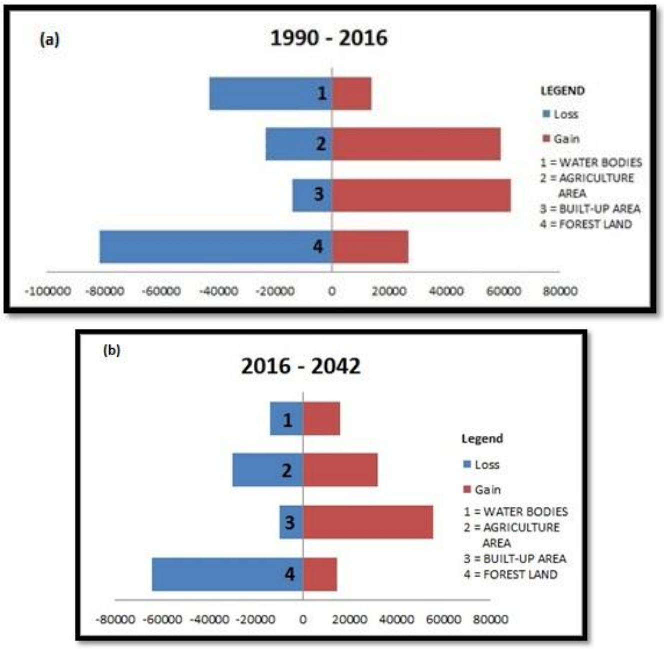

Figure 5. *Loss and gain for 1990-2016 (**a**) and 2016-2042 (**b**)*

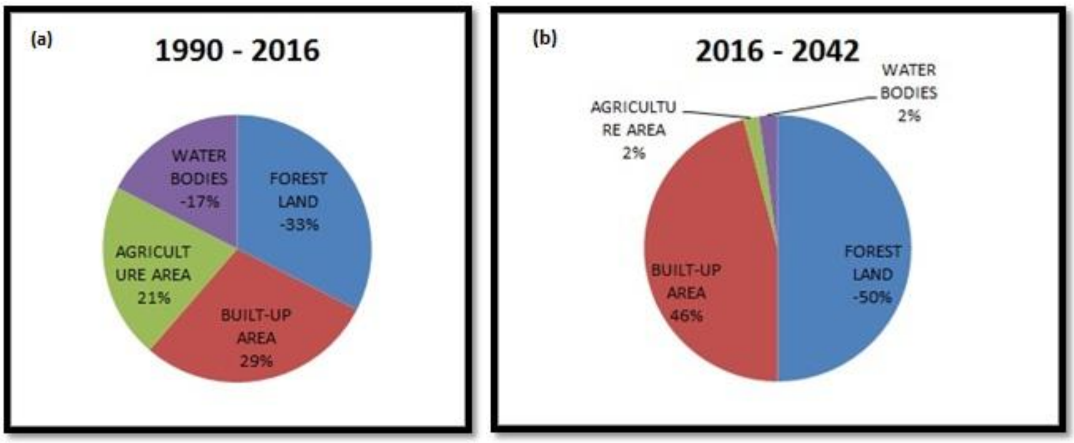

Figure 6. *Net changes for 1990-2016 (**a**) and 2016-2042 (**b**)*

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