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CASE STUDY

Integrating cellular automata Markov model to simulate future land use change of a tropical basin

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ABSTRACT

Predicting land use change is an indispensable aspect in identifying the best development and management of land resources and their potential. This study used certified land-use maps of 1997, 2006, and 2015 combined with ancillary data such as road networks, water bodies and slopes, obtained from the Department of Agriculture and the Department of Surveying and Mapping in Malaysia, respectively. The prediction of future land use changes in the Selangor River basin in Malaysia was performed using the Cellular Automata Markov model. The transition probability matrices were computed using the land use conditions of the periods 1997-2006, 2006-2015, 1997-2015. The performance of the model was very good in its overall ability to simulate the actual land use map of 2015, with the index values of 0.92% and 0.97%, respectively for Kappa for no information and Kappa for grid-cell level location which indicated the reliability of the model to successfully simulate land use changes in 2024 and 2033. Based on the expected results, the future urban area will grow faster (33%) over the next two decades, leading to a decline in forest area that is expected to lose 8% of its total space during these periods. Agricultural land will increase to 4%, while water bodies will change slightly increasing to 1%, and other areas of land use will likely become reservoirs of water, topsoil or new green spaces shrinking at 30%. Given the importance of knowledge of future land use in addressing the problems of uncontrolled development on environmental quality, this study could be valuable for land use planners of the river basin largely covered by natural forest. The study however, suggests future research to integrate geospatial techniques with biophysical and socio-economic factors in simulating land use trends.

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INTRODUCTION

Land-use change models are tools for analysing the root causes and the magnitude of changes in land-use in order to further discover the operational aspect of the land-use system in supporting planning and development of land use scenario (Verburg *et al.*, 2004). Models are essential to understand the complexity of the biophysical and socio-economic drivers that have an impact on the extent and spatial distribution of land use changes as well as to estimate the impact of these changes. Under different conditions, the pattern of land use change can also be explored using spatial modelling tools. In summary, spatial models are useful and replicable tools that complement human abilities to understand the driving forces of land use change in order to make better adequate decisions (Costanza and Ruth, 1998). Integrating ancillary data such as road network, water bodies and elevation aspects into the analysis of land use changes produces more realistic maps that can help yield more accurate results for simulating and predict future land use patterns. In addition to providing a range of different methods applicable to different scales and contexts, significant progress has been made to link different disciplinary perspectives (Verburg *et al.*, 2012; Aburas *et al.,* 2016). Therefore, methods of analysing land-use changes are critically determined by the analyst's intentions. The descriptions and choices of land use classification schemes, the theoretical systems employed and the models being used all are determined by the main problems and the needs of the users that the model aims to resolve; that is to say on its purpose (Verburg *et al.*, 2012). However, impact assessment is another important goal of land use change analysis. The current concern is not a major change in land use, as it has many environmental, social and economic impacts at all spatial levels. In addition, since policies aim to address different environmental, social and economic problems to which land use change contributes relatively, political impact assessment has become an important scientific focus (Helen, 2000). The science of land-use change has been hindered by a range of data, procedural and analytical issues related to the complexity of the integration of different phenomena, spatio-temporal models, socio-biophysical processes, and different disciplinary approaches to deal with them (Ronald *et al.,* 2004). These challenges are magnified by the necessity to respond not only to the question of why and how land use is changing, but also when and where it is changing. The specificity of location and time poses particular problems for the analysis of land changes, particularly with regard to the dynamic anthropogenic aspects of land use analysed at the micro-scale (e.g. household, individual, community) (Ronald *et al.,* 2004). These complex, dynamic and nonlinear characteristics of land use change modelling require the development of advanced models and methods. Today, a wide range of models and modelling methods are available to researchers and each type has certain advantages and disadvantages depending on the purpose of the research. Individual models, however, occupy a much more limited spatio-temporal role, therefore, the growing hybrid models in addressing multiple spatial analysis problems provided more advantages with regard to pairs of similar parameters of spatial, temporal and decisional scales: 1) spatial resolution and scope, 2) time step and duration, and 3) agent and domain of decision-making (Chetan *et al.*, 2002). As such, a dynamic simulation model using empirical relationships between changes in land use and the driving forces of multi-scale cross-sectional analysis can be used to analyse changes of multiple land use types. The Cellular Automata-Markov model has been the most widely used hybrid model to simulate urban growth (Aburas *et al.,* 2016). The model incorporates the benefits of cellular automata (CA) and Markov chain analysis to simulate future land-use change. It combines the ability of the CA model to simulate spatial variations in complex systems and the long-term predictions of the Markov model (Liping *et al.,* 2018; Aburas *et al.,* 2017). The Markov chain model component controls time dynamics between land-use categories via transition probabilities, while spatial dynamics are automatically guided by local rules defined by CA spatial filters or potential transition maps, the matrix of transition probability generated by the Markov chain model is one of the entries in CA Model (Singh *et al.,* 2017). Therefore, the CA Markov model successfully integrates the benefits of the Markov and CA models. The accuracy of spatial prediction can be modelled efficiently at the same time, and the prediction steps with the CA-Markov model involve 1) the construction of the MCE-based suitability atlas; 2) the generation of the transfer matrix and the state of transition probability matrix by means of the Markov model; 3) the prediction

of future land use using the CA model (Liping *et al.,* 2018). The main purpose of the present study is to simulate and predict future land use changes in the Selangor River basin from the advantage of integrating cellular automata and Markov chain analysis with ancillary factors. Results may be invaluable for land use planners of the basin largely covered by natural forest. This study has been conducted in the Selangor River basin, Malaysia, in 2020.

MATERIALS AND METHODS

Study area

This study was conducted in the Selangor River basin, located in the State of Selangor in Malaysia. The basin is the largest water source in the States of Kuala Lumpur and Selangor, about 60% of the water consumed in these States comes from the Selangor River (Sakai *et al.,* 2017). Located within 3.3500° N and 101.2333° E, the basin is roughly 70 km long by 30 km wide and covers almost 28% of the State of Selangor, where about 406,000 people lived in 2006 (Fulazzaky *et al.,* 2010). The basin weather is equatorial with average annual precipitation of 2750 mm, higher precipitation periods occur during monsoon periods, with peak precipitation between October and December, while lower precipitation periods generally occur during the monsoon between March and July in each year (Ong, 1991). The basin has a high average air temperature with a maximum and a minimum of 33.4 and 22.8 ° C, respectively. The average annual relative humidity varies between 78 and 87%, with small seasonal variations while the average annual evaporation varies from 1200 to 1650 mm (Ong, 1991). Approximately 57 % of the river basin is still covered by natural forests, while agricultural activities use 22%, 17% is used for development areas and 4% occupied by water (Kusin *et al.,* 2016) . The geographic location of the study area is shown in Fig. 1**.**

Data sources

This study used certified land-use maps of 1997, 2006, and 2015 (Fig. 2), combined with ancillary data such as road networks, water bodies and slopes (Fig. 4), obtained from the Department of agriculture (DOA) and the department of surveying and mapping in Malaysia, respectively. The interview with the technicians of the DOA indicated that, the land use maps were extracted from high resolution satellite imageries, namely Spots 2, 4 and 5 with a spatial resolution of 10 m and 2.5 m, respectively. All pre-processing and processing analyses of the satellite imageries, including radiometric and geometric corrections, were performed at DOA in Malaysia. These imageries were spatially registered, corrected and classified into several land use classes using the field ground control points and the supervised classification method. Field data were collected

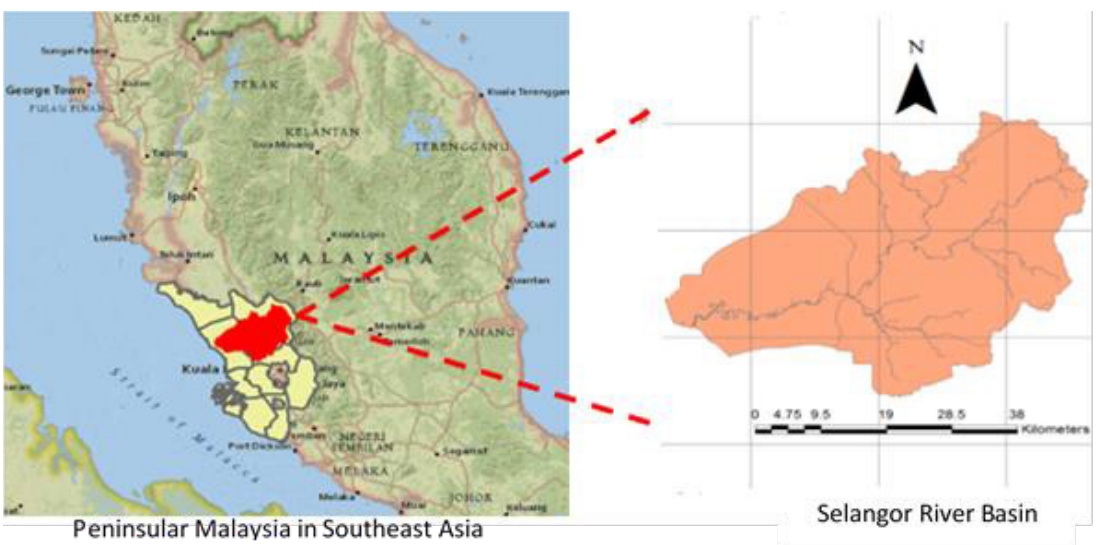

Fig. 1: Geographic location of the study area in the State of Selangor in Malaysia, Southeast Asia

using GPS to evaluate the classification accuracy by comparing the classified images with the GPS points from the field for each land use type. In this study, the land use attributes were broader categorized into five classes. Forest land includes swamp forest, wetland forest, secondary forest and mangrove areas; Agriculture land is composed of various agricultural areas such as oil palm, rubber, cocoa, aquaculture, short term fruit, etc.; Urban land includes urban and residential areas, recreational areas and facilities; Water bodies are areas occupied by water; And other lands comprise abandoned mining areas, eroded land, cleared land, marshland, etc.

CA–Markov model

This study applied the CA - Markov model for simulating and predicting land use change in Selangor River basin. The CA model is expressed by Eq.1 (Liping *et al.,* 2018):

$$S_{t+1} = f\left(S_t, N\right) \tag{1}$$

In which, S is the set of states of finite cells; While $t+1$ are different moments; the neighbourhood of cells is N; and the transformation rule of local space is f.

Markov model is a discrete random process both

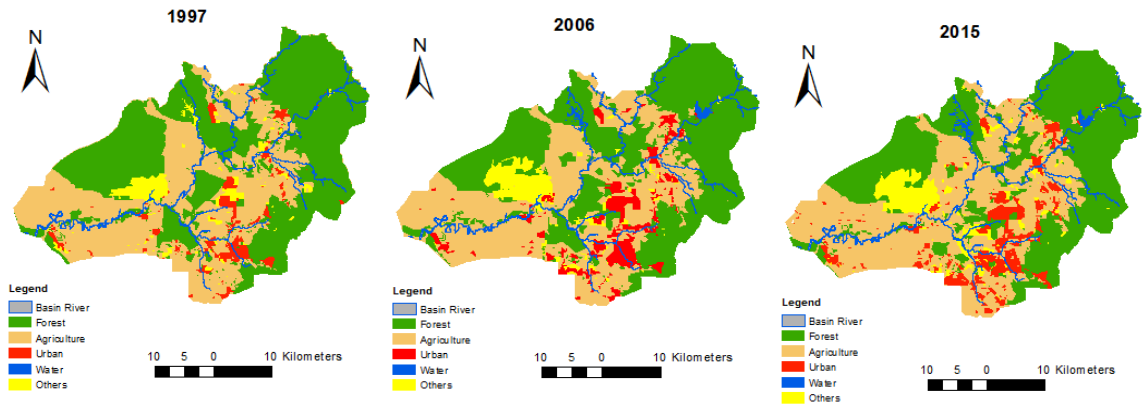

Fig. 2: Land-use maps: 1997, 2006, and 2015 (DOA, 2019)

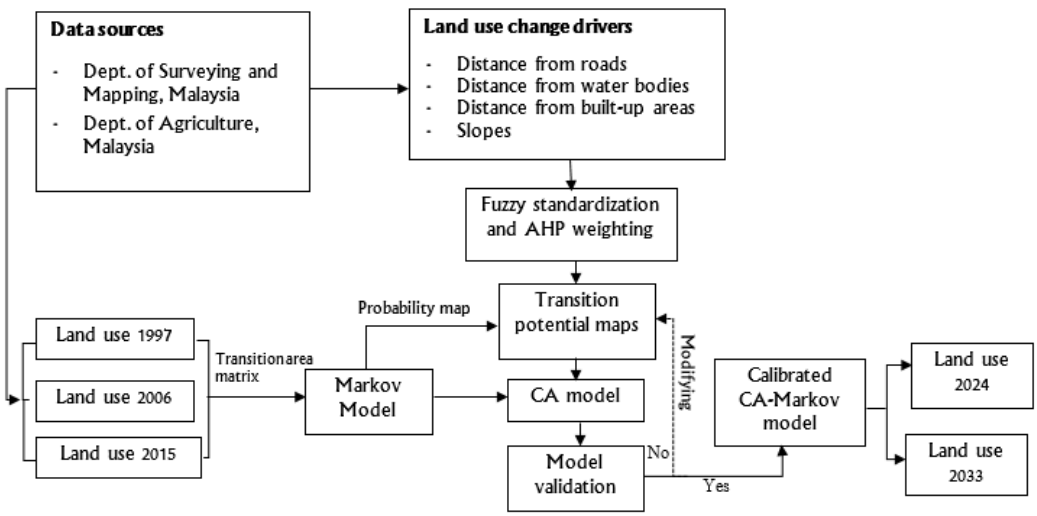

Fig. 3: The method flowchart for predicting land use changes in 2024 and 2033

in time and in state (Al-sharif and Pradhan, 2014). The simulation process of the model mainly generates a land use area transfer matrix and a probability transfer matrix to predict the trends of land use change; so, the Markov chain model could be defined as a set of states, S = {S0, S1, S2 ,. . ., Sn}, assuming that the present state is St, then move to the state Sj in the next step with a probability noted by the transition probabilities pij; Thus, the St + 1 state in the system could be determined by the former St stage in the Markov chain by applying Eq. 2 and 3 (Liping *et al.,* 2018; Ma *et al.,* 2012):

$$P_{ij} = \begin{bmatrix} P_{11} & \cdots & P_{1n} \\ \vdots & \vdots & \vdots \\ P_{n1} & \cdots & P_{nn} \end{bmatrix} \quad (2)$$

$$(0 \le P_{ij} < 1 \ and \sum_{j=1}^{n} P_{ij} = 1, i, j = 1, 2, \ldots, n)$$

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

In which the state of transition probability matrix is P_{ij} and the type number of land use is n; and S is the status of land use, while $t+1$ is the time point.

The CA Markov model successfully integrates the benefits of the Markov and CA models as shown in Fig. 2. Implemented into the IDRISI software model, the prediction steps with the CA-Markov model involve 1) the construction of the MCE-based suitability atlas (Fig. 4); 2) the generation of the transfer matrix and the state of transition probability matrix using the Markov model; 3) the prediction of future land use using the CA model. In this study, the transition potential matrix was derived from land use conditions in 1997-2006, 2006-2015, and 1997-2015. Four general drivers of land use changes such as distance from main roads, distance from urban areas, distance from water bodies, and slope were used (Fig. 4). These drivers of land use changes were selected based similar previous studies (Keshtkar and Voigt, 2016; Rimal *et al.,* 2017; Alilou *et al.,* 2018). Using fuzzy membership functions, the driver maps were rescaled from 0 to 1, with 0 indicating unsuitable locations and 1 indicating perfect locations. With pair-wise evaluations, the weight of the driving factors were determined using AHP model. Table 1 shows the weight and control point of each driving factor. The CA–Markov model was evaluated by comparing the actual and simulated maps of 2015 based the kappa index values. Finally, the land-use map of 2015 was used as the reference map for simulating land-use maps for the years 2024 and 2033 by computing the matrix of transition areas of 2006–2015 and 1997–2015, correspondingly. All the mappings and analyses were conducted using ArcGIS 10.2 and IDRISI 17.0 software.

RESULTS AND DISCUSSION

Transition probability matrices

The transition probability matrices were computed using the land use conditions of the periods 1997-2006, 2006-2015, 1997-2015 to show the projection of each land use category (Table 2). The probability maps generated by Markov model convey initial information on the likelihood of land use change occurrence prior to the final CA–Markov model. Table 2, for example, shows that the probability of future changes of agricultural land to urban area

Table 1: Extracted weights based on AHP and fuzzy standardization for urban areas

Change drivers	Function	Control points	Weights
Slope	Sigmoid	0 % maximum suitability 0–15 % declining suitability >15 % no suitability	0.19
Distance from roads	J-shaped	0–50 m maximum suitability 50–1500 m declining suitability >1500 m no suitability	0.28
Distance from built-up areas	Linear	0–100 m maximum suitability 100–5000 m declining suitability >5000 m no suitability	0.38
Distance from water bodies	Linear	0–100 m no suitability 100–7500 m increasing suitability >7500 m maximum suitability	0.15

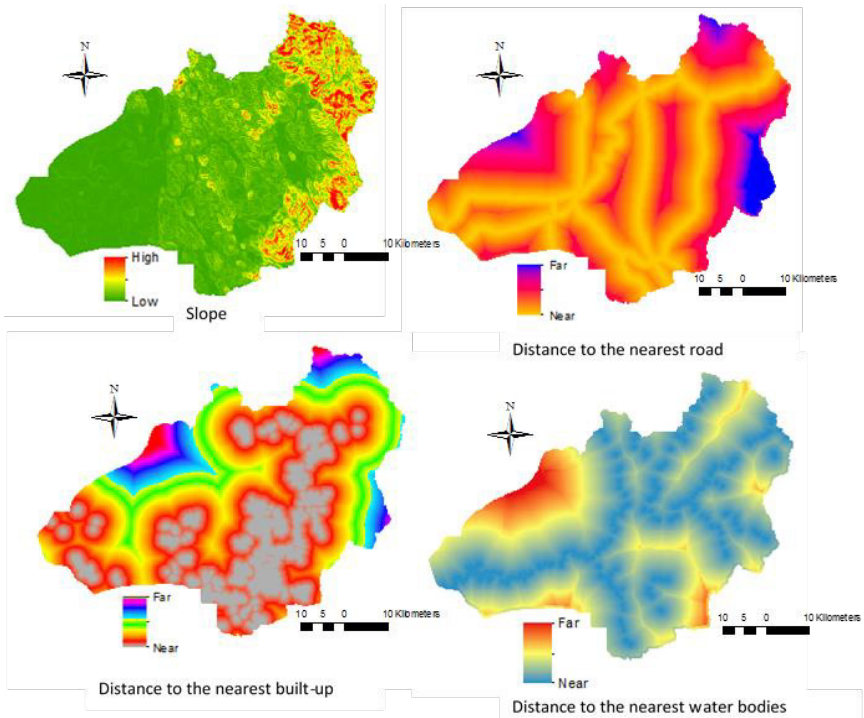

Fig. 4: The drivers of land use change used for AHP and fuzzy standardization

from 1997 to 2006 is 12%. This probability of change increased reasonably to 14% in 2015. However, for both periods, agricultural land was more likely to transform into urban areas. In addition, urban, forest and agricultural lands were more probable to remain steady in the second period (2006-2015) compared to the first period (1997-2006), while water and other lands were more likely to change during the second period. After 18 years, the likelihood of water to remain in the same class is the highest of all, while other land exhibited the lowest probability of remaining in the same category. In general, one trend is that, for all periods the chance of remaining in the same land use class is higher. This is the trend commonly observed in many similar studies (Rimal *et al.,* 2017; Keshtkar and Voigt, 2016; Subedi *et al.,* 2013; Panandiker *et al.,* 2019).

Land use change modelling and validation

In addition to visual comparison between the actual and simulated maps of 2015 (Fig. 4), the performance of the CA–Markov model was also assessed based on three more statistics: 1) Kappa index of agreement (denoted Kstandard); 2) Kappa for no information (denoted Kno), and 3) Kappa for grid-cell level location (denoted Klocation). A model is typically considered to be very predictive if it has an accuracy greater than 80% (Araya and Cabral, 2010). In this study, the Kstandard value was 0.90%, which validates the accuracy of this model. In addition, a higher value of Kno is a better option than Kstandard for evaluating the overall accuracy of the model (Pontius, 2000). Therefore, the performance of the CA–Markov model in this study was very good in its overall capability to simulate the 2015 land use map, with the Kno value of 0.92% and Klocation value of 0.97% indicating the reliability of the model to provide a reasonable representation of location. Both visual comparison and Kappa values of the real and simulated maps of 2015 showed an obvious similarity between the maps (Fig. 5). Therefore, the model was reliable and successfully simulated the future land use changes in 2024 and 2033 that are shown in Fig. 6.

Analysis of prediction results

Fig. 7 shows the results of gains and losses in different types of land use from the different periods of simulated land use changes. Table 3 presents

Table 2: Transition probability matrices of time periods of 1997-2006, 2006-2015, 1997-2015

Periods	Land use	Urban	Forest	Agriculture	Others	Water
1997-2006	Urban	0.5877	0.0453	0.3271	0.0243	0.0155
	Forest	0.0123	0.6794	0.1897	0.0805	0.0381
	Agriculture	0.1203	0.1338	0.6804	0.0437	0.0219
	Others	0.0125	0.1186	0.0189	0.8500	0.0000
	Water	0.0282	0.0751	0.0467	0.0000	0.8500
2006-2015	Urban	0.6998	0.0300	0.1737	0.0943	0.0021
	Forest	0.0161	0.6847	0.1994	0.0871	0.0126
	Agriculture	0.1427	0.0756	0.7115	0.0695	0.0008
	Others	0.2952	0.0550	0.1585	0.4377	0.0535
	Water	0.0000	0.2031	0.0000	0.0000	0.7969
1997-2015	Urban	0.7630	0.0189	0.1298	0.0884	0.0000
	Forest	0.0000	0.7588	0.1522	0.0817	0.0074
	Agriculture	0.1063	0.0593	0.7717	0.0627	0.0000
	Others	0.2360	0.0387	0.1116	0.5729	0.0407
	Water	0.0019	0.1752	0.0000	0.0000	0.8229

the proportion of these changes (Gain versus Loss) in all the five classes of land use over the predicted time periods. Based on these results, the difference in gains and losses (Gain - Loss) indicates that agricultural land is expected to win more space in 2015-2024 (4%) and 2015-2033 (8%), and lose 8% in 2024-2033. This indicates an overall increase estimated at 4% (4% + 8% - 8%) for agricultural land for the next 18 years to come. However, a loss of 19% and 10% in forest area is expected in 2015-2024 and 2015-2033, respectively, while this area will gain 21% of space in 2024-2033. The overall difference in gains and losses shows that forest land will lose 8% of its space by the next 18 years. Moreover, urban land will reasonably win 33% in 2015-2024 and 10% in 2015-2033, and it is expected to lose 10% between 2024 and 2033. Considering the overall trend, urban area is expected to increase to 33% during next two decades. However, water area will remain stable in 2015-2024 and 2024-2033, while it is expected to increase to 1% in the future (2015-2033). On the other hand, other lands will gradually lose more area (-30%) during these forecasted periods.

Given the significant expected increase in urban area (33%) over the next two decades, the results of this study reasonably indicate that development

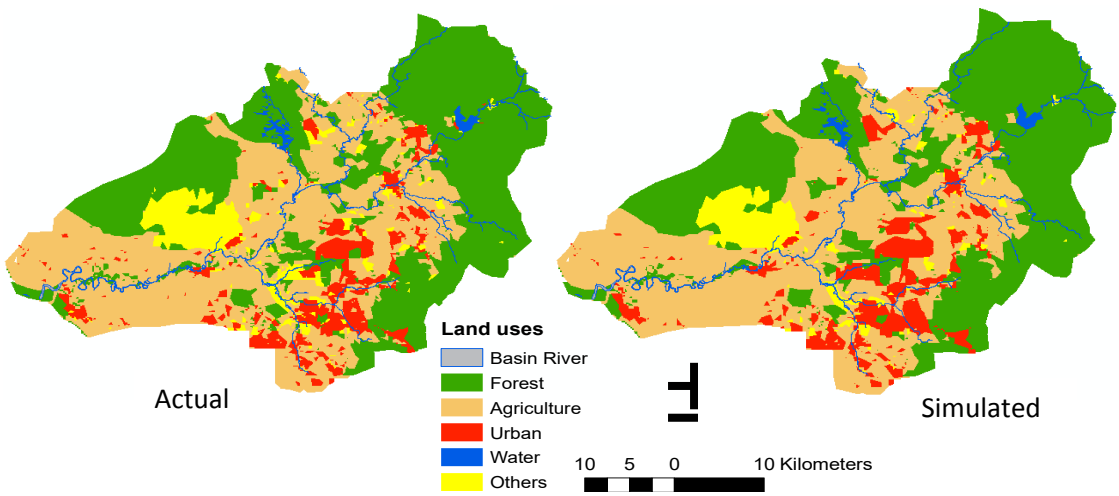

Fig. 5: The actual and simulated land use change in 2015

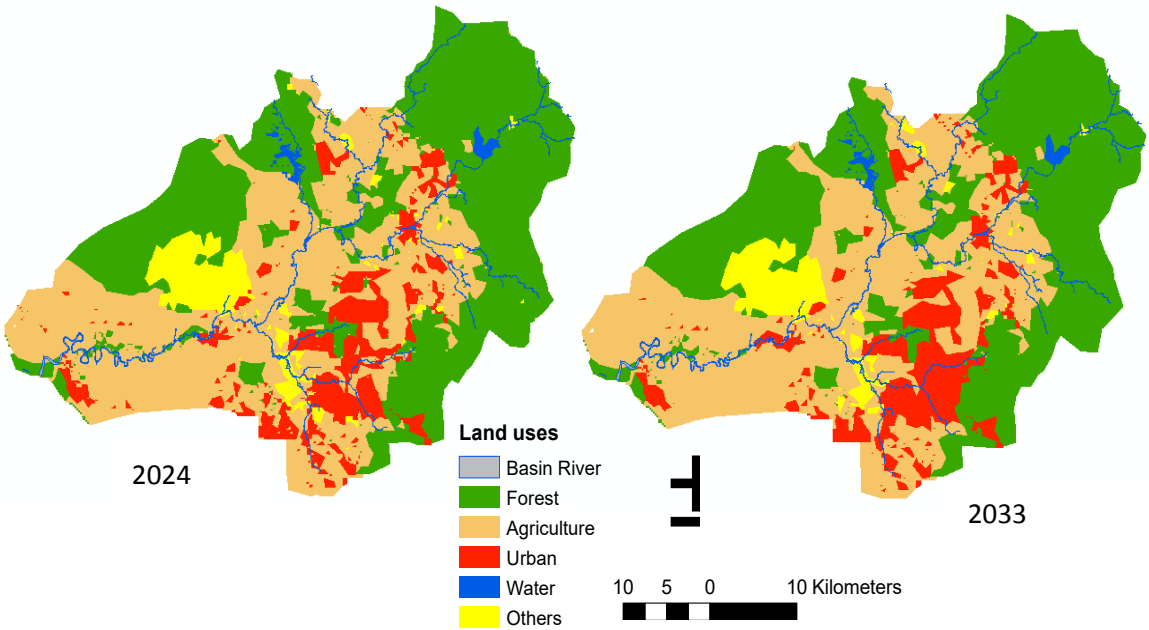

Fig. 6: The future simulated changes in land use of the Selangor River basin in 2024 and 2033

Table 3: Total predicted change (%) of each type of land use in the different periods

	2015-2024			2024-2033			2015-2033			Total
	Loss	Gain	Change	Loss	Gain	Change	Loss	Gain	Change	change
Agriculture	22	27	4	47	39	-8	31	39	8	4
Forest	34	14	-19	19	40	21	31	21	-10	-8
Urban	11	44	33	19	9	-10	12	21	10	33
Water	1	1	0	2	2	0	2	2	1	1
Others	32	14	-18	12	9	-3	25	16	-9	-30

activities accompanied by urban expansion resulting from population growth are not without negative consequences on the basin landscape. Subedi *et al.* (2013) also affirmed that population growth and migration to urban areas will result in a relatively higher conversion of land use to urban and residential areas. While other factors such as family size and income can have expected influence on the dynamics of land-use change (Kautz *et al.,* 2007). Since the CA-Markov model allows for the inclusion of the effects of the driving factors on land-use change, previous studies have successfully used predicted land use changes using hybrid models as in this study (Weng 2002; Sang *et al.,* 2011; Subedi *et al.,* 2013). Nevertheless, as foreseen in this study, the natural forest which occupies until today the highest percentage of land cover in the basin, would be constraint to continuously cede space to the urban development areas. In addition to a slight increase in agricultural area due to the expansion of various crops (e.g. oil palm, rubber, cocoa, aquaculture, short term fruit) alongside the river profile, the squatter communities located on the riverbank also encourage townships development in these areas. These squatter areas are not usually provided with proper sewage and rubbish disposal facilities, thus, contributing to the river pollution (Nurhidayu *et al.,* 2016; Camara *et al.,* 2019a) and green areas deterioration. Moreover, watersheds are also lowland areas that are very attractive for urban development, therefore, human activities will continue to have negative impacts to the natural environments of watersheds around the world. These impacts cannot be totally eliminated, but they can be minimize by appropriate

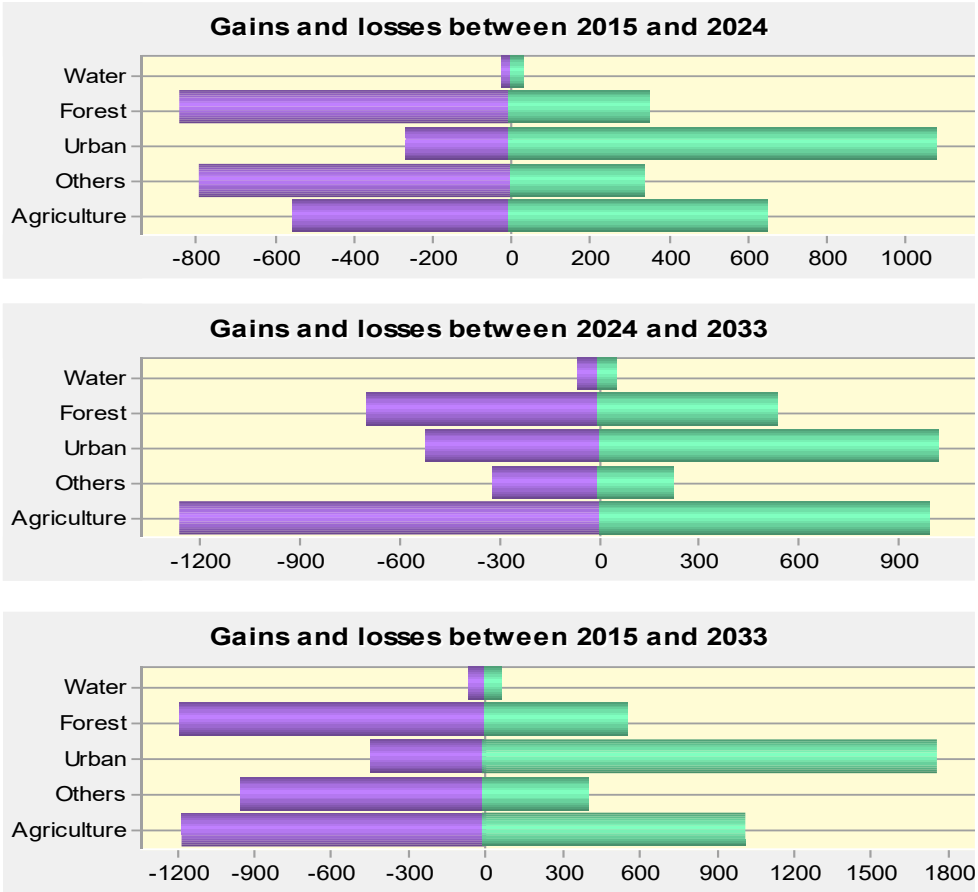

Fig. 7: Gains and losses in each type of land-use in 2015-2024, 2015-2033, and 2024-2033

planning and management of coastal areas. However, historical data also demonstrated that agricultural development, such oil palm and rubber plantations, is associated with forest disintegration in the State of Selangor (Abdullah and Nakagoshi, 2007), while clearing activities are more associated with the degradation of biodiversity (Camara *et al.,* 2019b). In addition, other land use areas, including abandoned mining areas, eroded zone and cleared land, are likely to be gradually transformed into water reservoirs, topsoil or vegetated lands, usually after government intervention. However, emerging countries like Malaysia face the highest dynamism of land use transformation, which is mainly due to the fact that these countries welcome new development projects and lay the foundations of an industrialized nation. As such, the Selangor River basin (1,820 km2) is located in the most developed state of Malaysia, Selangor, in the western part of Peninsular Malaysia, implying its rapid land development and changes in land use since the 1970s (Nurhidayu *et al.,* 2016). These development processes are supported by a growing population and rapid urbanization. For this reason, achieving coherence between river basin management and sustainable urban development is more difficult in suburban areas like Selangor due to the presence of different forms of land use that require a policy of constant control. Multiple types of land use deserve much more attention than what they currently receive in the academic and political fields (Brandeler *et al.,* 2018). The sustainable management of urban development in the Selangor River basin and its associated environmental risks should be a new path to follow to ensure the continuous supply of the basin's resources. This should be primordial because urbanization augment

the impervious surface, produces pollution and transforms the structure, configuration and context of land cover and therefore has direct or indirect effects on aquatic systems (Yu *et al.,* 2013; Rodrigues *et al.,* 2018).

CONCLUSION

Predicting land-use change is an indispensable aspect in identifying the best development and management of land resources and their potential. In this study, the projection of future land use trends in the Selangor River basin was performed using the CA-Markov model. Classified land use maps for 1997, 2006 and 2015 were associated with four factors of land use change, such as distance to main roads, distance to urban areas, distance to water bodies and the slope to simulate future changes in land use within the river basin. The performance of the model was evaluated by visual comparison of the real and simulated maps of 2015 and also by observing the kappa index values for the predictions accuracy. The results showed an obvious similarity between the two maps of 2015 and the kappa index values were 0.90%, 0.92%, and 0.97% for Kstandard, Kno and Klocation, respectively. These results indicated the reliability of the model to provide a reasonable representation of location and predict future changes in land use. Therefore, the model was used to successfully simulate land use changes in 2024 and 2033. Based on the expected results, the future urban area will grow faster (33%) over the next two decades, leading to a decline in forest area that is expected to lose 8% of its total space during these periods. Agricultural land will increase to 4%, while water bodies will change slightly increasing to 1%, and other areas of land use will likely become reservoirs of water, topsoil or new green spaces shrinking at 30%. Since knowledge of future trends in land use is particularly important in combating the effects of uncontrolled land development on environmental quality, this study suggests future research to integrate geospatial techniques with biophysical and socio-economic components in simulating land use trends that could provide more realistic results.

AUTHOR CONTRIBUTIONS

N.R. Jamil performed the data collection, supervised the study and approved the results. M. Camara performed the literature review, analysed and interpreted the data and prepared the manuscript text. A.F. Bin Abdullah supervised the study and edited the manuscript text. R.B. Hashim verified the reference sources and approved the analysis procedures and the results.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancy have been completely observed by the authors.

ABBREVIATIONS

-	Minus
%	Percent
()	Bracket
+	Plus
° C	Degree celsius
° N	Degrees north
° E	Degrees east
AHP	Analytic hierarchy process
CA	Cellular automata
CA-Markov	Cellular automata markov
Dept.	Department
DOA	Department of agriculture
e.g.	Example
Eq.	Equation
etc.	Et cetera
Fig.	Figure
GPS	Global positioning system
Km	kilometre
km^2	Square kilometre

Klocation	Kappa for grid-cell level location
Kno	Kappa for no information
Kstandard	Kappa index of agreement
m	Meter
mm	Millimetre
MCE	Multi criteria evaluation

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