SIMULATING THE DISTRIBUTION OF FUTURE LAND USE CHANGE IN NAKHON RATCHASIMA, THAILAND

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Abstract

We studied the future land changes for sustainable land use planning within 20 years in Nakhon Ratchasima province, Thailand. CA-Markov integrated model with GIS was applied to forecast land use changed. The land use map from the Land development department, Thailand years 2007, 2011, and 2015 classified to 9 classes were used. Classes selected from major pollution sources and area sizes were urban and built-up land, paddy field, corn, sugarcane, cassava, other agriculture, forest, water body, and miscellaneous land. land use map year 2019, 2023, 2027, 2031, and 2035 are the destination of the land use prediction. Percent accuracy was 91.46% with 0.016% of total area error between predicted and actual land use map of 2015. The results of this simulation showed that the area and characteristics of each LU type of each predicted year. However, the area of urban and built-up land, cassava cultivation, and water body were increased by 4.22%, 8.29%, and 0.8% respectively. Meanwhile, corn cultivation, other agriculture, and sugarcane were decreased by 24.15%, 11.76%, and 6.89% respectively. The area for paddy field, forests, water body appear low changed or no changed. The distribution of community forms has expanded from the center of Nakhon Ratchasima, which is a large urban community and spread out along the major roads. The most other agricultural distribution that does not include paddy field spread out on the west, east, and southeast of the province. The most increasing area is cassava that substitutes the area of corn, sugarcane, and other agriculture.

Keywords: **Land use, CA-Markov, distribution, spatial, GIS**

Introduction

Land use change (LUC) is one of the global problems concerned due to its effect on the environment through various pathways that alteration soil erosion, soil surface temperature, pollutant loading, carbon emission, etc. The intensity of land use has responded to world population growth (Wu *et al*., 2006). This problem has become an important research topic on global environmental changes that need to be prevented and resolved (Fikir *et al*., 2009). Land use type (LUT) is an important factor for pollution sources, which are point source and non-point source (Zhen *et al*., 2010). Non-point source pollution which is often caused by agriculture is complex and unpredictable.

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Changes in land use also have a direct impact on the hydrology process within the watershed because of sediment and pollutants that are an important factor affecting runoff and flow into the basin, causing problems in the water source (Baker and Miller, 2013).

The rapid expansion of the agricultural industry in Thailand has put pressure on many regions of Thailand, resulting in plant cultivation and agriculture area. Studying future land use changes can help assess the impact and seeking suitable land use patterns that help planners finding ways to prevent and resolve the environmental impacts leading to sustainable development (Li and Yeh, 2002). The problem of land use management in Thailand mostly is the land use is not suitable to the conditions of the area which are limited by geographical, climatic characteristics, soil types and other, causing soil erosion and flood in many areas. The land use management problems are reported in Krabi, Nan, Chiang Mai, and some areas of Nakhon Ratchasima province (Sarang, 2006; Phakularbdang, 2006; Aingorn, 2008; Wittaya, 2009). A numbers of studies have been conducted on agricultural land use patterns, predictions of land use changes in forest, mangrove, and wetland (Pornsi, 2001; Noppon, 2005; Srithairak *et al*., 2006; Oradee, 2015). Nakhon Ratchasima, which is Thailand's largest province, is also facing land use management problems. There are some related researches in the area focused on some parts of Nakhon Ratchasima, such as the Lamtakong basin, the Lam Phra Phloeng basin, and urban communities. However, the information is not sufficient to proceed in land use management (Tharapong, 2010; Limgomonvilas, 2014). Thus, there is a need to clarify the pattern of land use changes to assess the impacts that might occur in the area.

Various tools have been used to predict land use change. Commonly used models for estimating land cover changes are analytical equation-based models, statistical models, evolutionary models, cellular models, Markov models, hybrid models, expert system models, and multiagent models. Among these, the CA-Markov model is one of the most accurate and frequently used (Dong *et al*., 2011). The application includes the prediction of land use change, population growth, public utility system, facilities, and soil types change (Veldkamp and Lambin, 2001). The CA-Markov model is a combination of Cellular automata (CA) model and Markov chain model that used to determine the probability of land use change. The Markov chain process controls the quantitative change based on the transition probabilities matrix while the CA model controls spatial pattern changes through local rules, taking into account the neighborhood determination and map the potential for changing (Thomas and Laurence, 2006).

Geographic information system (GIS) is an essential tool in tracking down spatial data with time for land use and land cover, as well as analyzing the changes in a study area. The application of GIS and the CA-Markov model offers planners and policy makers to creatively devise a unique solution to specific areas. Therefore, the data can be easily understood and adapted to solving land use management problems.

Although the CA-Markov model is wildly adapted for land use change prediction, the land use pattern change analysis over time is still unusual. Although the CA-Markov model is wildly adapted for land use changes prediction, short-term and middle-term study of land use changes, the increase or decrease of each type of land use are still uncommon. The study of the distribution of land use patterns will depend on changes in the past two years analyzed with the model to find the probability of future volume and area changes. The distribution of land use that is unique to each area. Therefore, the use of information for future land use planning will be different in each area. The study of land use patterns and the distribution of land use in a wide area gives an overview of the area and is easy to determine preventive and corrective policies in the future. Due to the insufficient studies in Nakhon Ratchasima on the land use change over time and the changing pattern. Therefore, the objectives for this study were to (1) analyze the Spatio-temporal changes of LU in last 20 years from 2015 to 2035 and to (2) predict land use maps for the area using spatial modeling (The CA-Markov) for 9 land types and (3) land use change patterns in Nakhon Ratchasima province

Materials and Methods

Study Area

The study area is Nakhon Ratchasima Province, Thailand (UTM zone 48N 188076, 1657602 or 14° 58′ 30″ N latitude and 102° 6′ 0″ E longitude). Nakhon Ratchasima Province is Thailand's largest province by area and ranked second by population. The province covers an area of 20,726.87 km^2 with a total population of 2,645,927 people, representing 3.98 percent of the total population of Thailand (The National Statistical Office of Thailand, 2019).

Nakhon Ratchasima locates in the northeastern region which is on Khorat plateau at an altitude of 90-1,338 MSL (Figure 1). The province is on a plateau shaped by valleys along with the Dong Paya Yen mountain ranges on the southeast.

The elevation gradually decreases from the south (1,338 MSL) to the north (90 MSL). The study area covers many water streams, majorly the Lam Takhong River basin. All the streams are rise from the Dong Paya Yen mountain ranges and are the origin of the Mekong River. The high mountain ranges area is on the south cover by the forest. The forest is strictly reserve and is in UNESCO World Heritage List for its biodiversity. In the study area, the average 30-year annual rainfall is 1,034.7 mm with 108.2 rain-day, in which the highest rainfall in September (226.6 mm) and the lowest in December (3.0 mm).

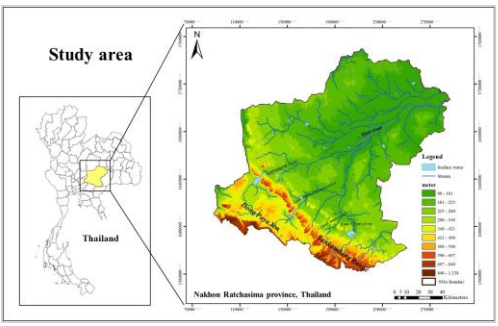

Figure 1. Study area

Method

The secondary data source is digital base maps form the Land Development Department (LDD), Thailand. The digital base map comprises administrative boundaries, road, waterbody, and land use. The land use data in the years 2007, 2011, and 2015 (Figure 2) were used in this study. Before data processing, land use was reclassified into 9 categories; urban and built-up land (U), paddy field (R), corn (M), sugarcane (S), cassava (C), other agriculture (A), forest land (F), water body (W), and miscellaneous land (O).

The processing procedure (Figure 3) is as follows: (1) the vector land use data of the three periods with 4 years interval were separately converted into raster data (grid units of 30×30 m) using the spatial analysis function by ArcGIS10.5. (2) IDRISI Selva, modules, Markov and CA-Markov were used for modeling and simulating land use in the year 2019 by using 2007 and 2011 land use data as the base maps. Data in the year 2015 was used for validation with over 90% accuracy. (3) The prediction of LU in 2019, will be used to project land use patterns in 2023. (4) The further 4 years interval projection for 20 years period (2023, 2027, 2031, and 2035) was repeatedly simulated. (5) Land use change trend and spatial distribution were analyzed and explained with CA-Markov.

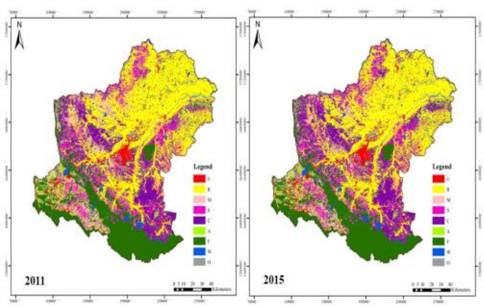

Figure 2. The land use data in year 2011 and 2015

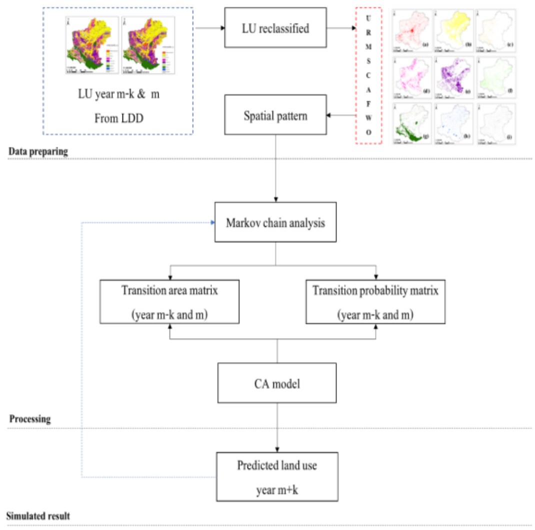

Figure 3. Flowchart of the processes of land use simulation

Modeling LULC Change

Markov Model

The Markov model developed by Andrei A. Markov is a mathematical model used for predicting future changes based on historical data. The Markov model can be used to explain the quantification of conversion states between the land use types and the transfer rate among different land use types. This model is commonly used in the prediction of geographical characteristics with no aftereffect event which is now becoming an important predicting method in geographic research. The relation between land use in State 0 at the beginning of the interval and the probability of the transition during an interval can be explained with the following equation;

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

where S (t), S (t + 1) are the system state at the time of t or t + 1; Pij is the transition matrix for the change in the state which is calculated as follow

$$P_{ij} = \begin{bmatrix} P_{11} & P_{12} & \dots & P_{1n} \\ P_{21} & P_{22} & \dots & P_{2n} \\ \dots & \dots & \dots & \dots \\ P_{n1} & P_{n2} & \dots & P_{nn} \end{bmatrix}$$

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

CA Model

Cellular Automata (CA) is a discrete model. It consists of a regular grid of cells with the ability to transform itself into a new cell (Tommaso and Norman, 1987). A spaces are separated into normal cells and the status of each cell is determined by the state of the cell itself, as well as the surrounding cells at an earlier time through a set of predefined change rules. In this research, CA model is extensively used in the simulation of urban systems as sprawl. In this study, the cellular network represents each land use base cell and each cell has 8 nearby cells. Its status means the land use type of a cell for 4 years. The changing rules of the CA use 3×3 neighborhoods to predict future land use types.

Combination System of CA-Markov Model

The hybrid CA-Markov model is commonly used for land use change simulation, and prediction (Wang *et al*., 2012). This Markov-CA model that combines geographic information system information (GIS) was proven as a suitable method to determine time and spatial change patterns (Guan *et al*., 2011). In the CA-Markov model, the Markov chain process controls the change over time between land use types according to the change model (Lopez *et al*., 2001). The CA model controls changes in spatial patterns through local regulations when considering neighborhoods (Clarke *et al*., 1994).

Principles of Land Use Change Model Analysis in Nakhon Ratchasima

Changes in land use will depend on land use patterns over the past 2 years, which will be determined by the Markov model that will determine short-term future probability changes. And will be stable in the long run. The Markov model in studying land use dynamics determines the amount of land use in each type with the spatial change model determined by the Cellular automata (CA) model, which predicts the opportunities for a transition rule with information about the surrounding environment (Pontius, 2000) CA is a sub cell that shows the area as a square called the grid or cell. Each cell is one data unit that can change format into a new cell, (Tommaso and Norman, 1987) which the Markov and CA models that are combined with the GIS data processing program, the pattern of change in each cell is determined by the chance of change. The transition areas in which the final results of the model are described following the “The game of life” theory (Pontius, 2000).

Analysis of land use change patterns in this research will study the amount of increase and decrease and the change of land use in all 9 categories in the next 20 years. The area analyzed will be a large area (The proportion of the area more than 5% of the total area of Nakhon Ratchasima) and is important for the economy of the province.

Results and Discussion

Transition Probabilities Matrix

In this study, spatial data from the LDD during 2011-2015 were used to predict future LUC in the next 20 years using the Markov chain model. The results from the model can be displayed as the transition probabilities matrix. During the first step, the probability matrix of the LUC pattern in 2019 was calculated based on the 2011-2015 data. Then, the LU 2019 was used as the base data to predict LUC in 2023. The step was repeated for 4 years interval until 2035.

From the transition probabilities matrix of LU 2011-2015, the most probability changed was from sugar(S) to cassava(C) cultivation, which is 0-23. The second and the third probability changed were changing from corn to cassava 0.19 and changing from general agriculture to cassava (0.16).

Sugarcane to cassava cultivation. The probabilities change of the 2011-2015 period was 0.23 in decreasing to 0.16, 0.10 in 2015-2019 and 2019-2023, respectively. There was no change since the year 2027 onwards. The second most possible land use change was from corn to cassava cultivation which is 0.19 during 2011-2015 and increased to 0.24 during 2015-2019, then decreased in 2019-2023 until no change from 2027 onwards. Third, the possibility of land use change as a general agricultural to cassava cultivation which is 0.16 during 2011-2015 and decreased until there was no change from 2023 onwards. In summary, the highest possibility of land use changing because the crops, sugarcane, corn, and general agriculture, were changed to cassava. The change was high at the beginning then decrease until there is no change from 2023 onwards. The graph showing the change with time for the top three probability change is shown in Figure 4.

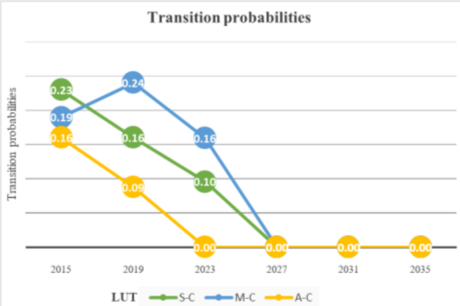

Figure 4. Transition probabilities of land use change with the highest probability values between 2015-2035

Transition Area

The transition areas represent quantitative land use change during the predicted period. In this research, each cell is equal to 30×30 m raster image. Transition area of land use types during 2001-2015 is the greatest change is 265,198 (238.68 km^2) of S cells converted to C cells. The second greatest opportunity is 198,360 (178.52 km^2) M cells transform into C cells. The third change is 131,051 (117.95 km^2). A cells change to C cells. Corresponding to the Transition probabilities matrix, from 2015-2019 onwards, the chances of changing grid cells will decrease until there are no changes in many land types.

Validation of Land Use Change

For model validation, 2015 land use areas obtained from Markov chain simulated from 2007 and 2011 data were compared with the real land use area in 2015. Land use type used for comparison was urban and built-up land, paddy field, corn, sugarcane, cassava, other agriculture, forest land, water body, and miscellaneous land (9 land use types). The area simulated from Markov chain model was 20,729 km^2 where the area obtained from the year 2015 map was 20,726 km^2. Percent accuracy obtained from the model was 91.46% with 0.016% of total area error (Table 1). Comparing to other study, the accepted accuracy was ranged more than 80% (Halmy *et al*., 2015; Siddiqui *et al*., 2017; Sun *et al*., 2018). Thus, the developed model was considered effective in predicting future land use changes.

Analysis of Simulation Results

For the land use change, there are many factors that are important for the types of land use change. The population increasing, transportation system development, and tourism that affects to the expansion of both rural and urban communities. Industrial investment affects the change in plantations for different types of crops in the area. Furthermore, uncontrollable factors such as rain, water bodies, soil types, and slopes of the area that also affect land use changes.

In the simulation resulted of land use change, the prefix image and the transition area matrix obtained from Markov model together with the 2015 land use map were used to simulate land use patterns. From the analysis of spatial overlays in GIS, land use types have shown changed in the last 4 years. As shown in Table 1, it was found that the area of cassava cultivation increases 346 km^2 or 8.75%.

Comparing between land use type, the corn cultivation area has shown the observable change, -18.98%, followed by cassava and other agriculture with 8.75% and -7.45% change, respectively. Corn cultivation and other agriculture decrease while cassava cultivation area increases.

Comparing land use between 2 periods, 2011-2015 (observed) and 2015-2019 (simulate data), as shown in Table 1. The most area change between 2011-2015 was cassava plantation that increases by 463 km^2. The most decrease was corn planting that the area was reduced by 216 km^2. As for the LU changes between 2015-2019, which are the simulation results, it was found that the area of cassava planting is the most increase. However, the increasing area, 346 km^2, is less than during the years of 2011-2015. The cassava plantation increasing rate is 74.84% of the increasing rate in 2011-2015. While the area of

Table 1. Simulated results as area and percentage of changes from land use change model in NMA

	U	R	M	S	C	A	F	W	O
2011 (km^2)	1349	6841	952	1634	3495	1452	3682	465	859
2015R (km^2)	1373	6824	736	1519	3958	1335	3669	470	843
2015P (km^2)	1411	6682	832	2026	3485	1410	3625	468	791
2019 (km^2)	1389	6814	596	1421	4304	1236	3669	474	826
*Change area 2011-2015 (km^2)	24	-17	-216	-115	463	-116	-12	6	-16
**Change area 2015-2019 (km^2)	16	-10	-140	-98	346	-99	0	4	-17
Change ratio (%) 2015-2019	1.15	-0.14	-18.98	-6.44	8.75	-7.45	0	0.77	-1.97
Change ratio (* and **) (%)	64.92	54.83	64.79	85.03	74.84	85.55	0.32	65.58	103.75
% Error (2015R & 2015P)	97.20	97.92	86.92	66.60	88.06	94.38	98.79	99.47	93.82

R is observed map, P is predicted map

corn planting has decreased 139.69 km^2, representing 64.79% of the decreasing rate in 2011-2015. Considering the change ratio between the two periods, the change of miscellaneous areas between 2015-2019 decreased by 16 km^2, which is higher than the decreasing of 2011-2015, which decreased by 17 km^2. The ratio between the two period is 103.73%. The changes in other agricultural land and sugarcane planting areas also show a high rate of change. The rate of change was 85.55% and 85.03% compared to the previous period.

Land use change prediction every 4 years interval is shown in Figure 5. The figure illustrated land use maps of the year 2019, 2023, 2027, 2031, and 2035 base on 2011 and 2015 data. Based on the simulation, LU changed can be remarkably seen in years, 2019, 2023, and 2027, then stable or unchanged afterward.

Analyzed Results of Land Use Change Pattern in Nakhon Ratchasima Province Land Use Area Changes

From the simulation, the land use change pattern can be categorized in 3 forms (Figure 6). The patterns are likely to increase, tends to decrease and no changes or very a few changes. Firstly, urban and built-up land and cassava are increase with the area of 61 and 357 km^2, respectively. Secondly, the area of corn, sugarcane, and other agriculture has decreased by 143, 100, and 141 km^2, respectively. Finally, paddy field, forest, water body, and miscellaneous land has very little changed areas, with areas of 13, 2, 15, and 19 km^2, respectively.

Comparing the change with time (Table 2), areas change from 2023 onwards shown very little change or no change. This might due to the limitation of the method used, CA-Markov model (Samat, 2009). The change of area predicted depends on the transition probabilities that analyzed from the area difference of 2 periods making it inaccurate in long term prediction. Similar results also reported by Predicting Land Use/Land Cover Changes Using

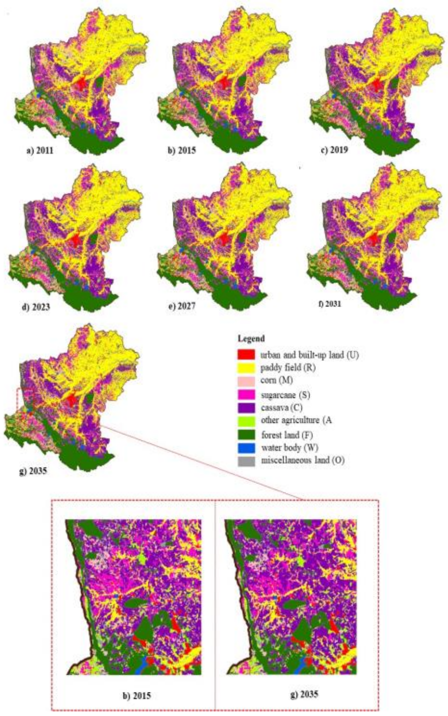

Figure 5. The simulated results of land use change pattern from 2015 to 2035

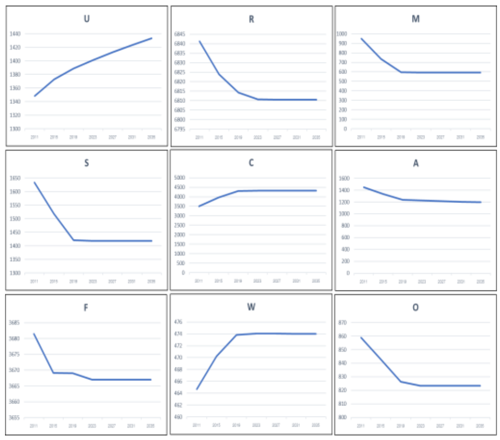

Figure 6. Simulated results as area from year 2011-2035 where Axis X is year, Axis Y is area (km^2)

Table 2. Land use change with time

Year	land use/land use change (km^2)								
	U	R	M	S	C	A	F	W	O
2011	1,349	6,841	952	1,634	3,495	1,452	3,682	465	859
2015	1,373	6,824	736	1,519	3,958	1,335	3,669	470	843
2019	1,389	6,814	596	1,421	4,304	1,236	3,669	474	826
2023	1,402	6,811	594	1,419	4,315	1,225	3,667	474	823
2027	1,413	6,811	593	1,419	4,315	1,215	3,667	474	823
2031	1,423	6,811	593	1,419	4,315	1,205	3,667	474	823
2035	1,433	6,810	593	1,419	4,314	1,195	3,667	474	823
Change area (2015-2035)	61	-13	-143	-100	357	-141	-2	4	-19
Change ratio (%)	4.41	-0.20	-19.45	-6.58	9.02	-10.52	-0.06	0.81	-2.31

a CA-Markov Model under Two Different Scenarios (Lopez *et al*., 2001).

Spatial Change Patterns

Spatial distribution of the land use from 2015 to 2035 is shown from Figure 4. The observations are as follow:

1) Urban and built-up land type expands from the center of Nakhon Ratchasima to the rural area along the National Highway No. 2 and other rural road (Figure 7). The city is the 2nd largest most populated in Thailand. The National Highway is the major road runs between Bangkok to Laos. It passes many major cities in the northeastern region of Thailand.

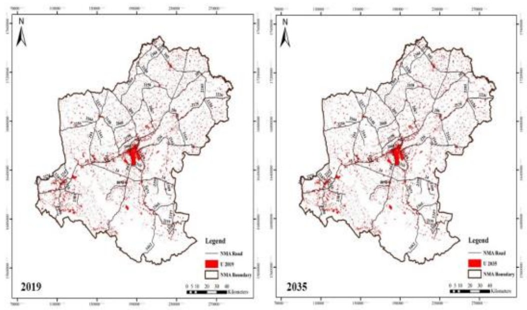

Figure 7. The distribution of land use as U type in the year 2019 and 2035 that compare with the Road No. 2 and rural road in NMA area

2) The land use in the northeastern part of the province shows little to no change. This are is a lowland with many rivers suitable for rice cultivation. It is now using for paddy field which is the economic crop of Thailand. The land use is already optimal, thus no future change will occurred. The same phenomena is also found in the rice field cultivation area on the west, east and northwest area of the province.

3) The major land use change are corn, cassava and general agriculture plantation changing to cassava plantation.

Conclusions

This study demonstrates that CA-Markov combined with GIS technology can be applied to simulate land use change in Nakhon Ratchasima. The land use models were based on land use maps of 2007, 2011, and 2015 from the Land Development Department, Thailand. Data of 2007 and 2011 were used for model development and data of 2015 were used for model validation.

The analysis results provide 91.46% accuracy with 0.016% error which considered highly accurate and reliable. The CA-Markov model simulated future land use changes up to 2035 with a 4-year interval. it appears corn, sugarcane, and other agriculture areas were decreased while urban and built-up land and cassava areas were significantly increased. When considering some areas of Pak Chong district, it was found that the urban area has steadily increased every year due to the economic expansion and land use modifications that affect the decline in agricultural land use (Limgomonvilas, 2014). It is suspected that the cassava cultivation area will increase by 346 km^2 or 8.75%. This might due to the demand for cassava which is the raw material for ethanol production. During the year 2010-2015 ethanol production in Thailand was increased by 3.80% per year, resulting in the change of cultivation into cassava. The area of land use in forest type and water body has a very little changed or no changed according to the actual principles. From the characteristic changing of land spatial patterns from 2015 to 2035, built-up land will expand to suburban, which have been changed from agricultural land and some built-up land will expand to the rural area along the National Highway No. 2. However, at present, the construction of motorways (Bang Pa-in - Nakhon Ratchasima) and policy for the construction of a high-speed train (Bangkok-Nakhon Ratchasima) affects to traveling, economic expansion, and the expansion of the community. So, it causes to change in the use of various types of land use distortion from the normal simulation.

Most of the agricultural land located in the high area in the west, east, and southeastern of the study area, which is a lot of slopes affecting high soil erosion. Therefore, if the sustainable development policy, which has been cooperated by farmers in the study area, was not created to change the current land use trends. Future land use may have seriously harmful to the environment.

In summary, our study offers significant support to create spatial land use models using the CA-Markov combined with GIS. The simulated future land use map can be used as an early warning system to understand the future trend of land use change. The results received are useful to other sites that have similar changing patterns. The simulation results can be used for land use planning for the complex changes and can help local officials to understand land use systems and able to improve land use management. The application of the model results in policy planning provides a holistic solution balancing between changes in land use in economic and environmental development.

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