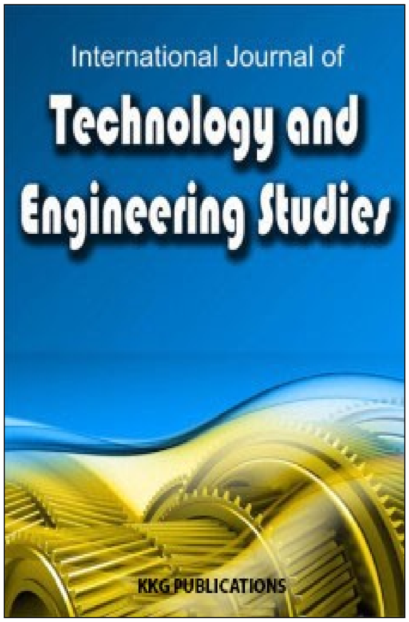

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PREDICTION FOR NONTHABURI URBAN PARKS BY INTEGRATED GEO-INFORMATICS TECHNIQUES

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Abstract. This research aims to find a suitable area for urban parks in Nonthaburi province, Thailand, and predict future land use (2019 and 2024) to support urban parks. Data analysis was under integrated Remote Sensing (RS) to classify existing land use, Geographic Information System (GIS) with Multi-Criteria Analysis (MCA) to find the suitable area, and CA-Markov model to predict the future land use. Finally, we integrated MCA with CA-Markov to improve future land use for urban parks. Then we compared the alternative of letting urban expansion without direction with an alternative of prepared suitable land use for urban parks in the future. The study concludes that integrating Geo-Informatics modeling can increase suitable urban park areas from urban expansion up to 7.58 and 12.56 sq. km. in 2019 and 2024, respectively. The increase of the urban park areas in 2019 can increase about 6.41 sq.m. per person, which is higher than the Thailand standard (4 sq.m. per person) and is close to the world standard. These findings will help in solving the urban parking problem in Thailand such that the results can be used to support decisions of all sectors related to the urban park including government agencies.

INTRODUCTION

Environmental problems in big cities result from the rapid growth of the residential and business areas in the city as a result of the economic development. The rapid rising of population causes environmental problems, negative social impact and low quality of life. Any big city in the world has the same problem, including Nonthaburi, Thailand. The population increased from 740,565 in 1994 to 1,052,592 in 2009 or over 70 percent [1].

Nonthaburi lacks a plan for green space. While green space in Nonthaburi is enormous but there are only a few urban parks. Nonthaburi has 11 parks, representing an area of 0.47 sq.m. per person, which is not enough for a minimum requirement of the world's standard park area for the people (8 sq.m.).

Remote Sensing technology (RS) is a powerful tool to identify a large spatial data with multi-temporal that can monitor the spatial change, particularly in land use classification.

In addition, the output from RS can combine with Geographic Information System (GIS) as the input data or criterion to evaluate and solve the geographic problems. Another geographic model that can integrate with RS and GIS is CA-Markov model.

CA-Markov model is a tool for predicting future land use, particularly green space for urban parks. This model sets up two conditions: first, it determines the proportion of land use and second, it estimates the probability of a change. Moreover, it can combine with other factors that relate to suitable parks such as accessibility, distance from main roads or population density by changing the probability of land use to meet the requirement.

So, it can be used for prediction of green space that is suitable for urban parks in Nonthaburi. RS and CA-Markov models are the optimized tools for planning green areas in the future pursuit as urban growth is likely to happen continuously: Increasing urban parks will enhance the quality of life, preserve the nature and keep the environment sustainable.

METHODOLOGY AND MATERIALS

Methodology and data for prediction of Urban Park are including Study area, RS, MCA and CA-Markov Model.

Study Area

Nonthaburi is located in the central part of Thailand and it is one of five vicinity provinces around Bangkok that support the metropolitan expansion. The length of border of Nonthaburi and Bangkok is about eight kilometers. Chao Phraya River cuts the central Nonthaburi and results in the flood plain in this

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area. Nonthaburi located between latitude $13^0$47’- $14^0$04’N and longitude $100^0$15’-100^0 34’ E. Nonthaburi is 1.8 meters above mean sea level and has an area of 622.303 km^2. It is the third smallest province of Thailand [2] (Figure 1).

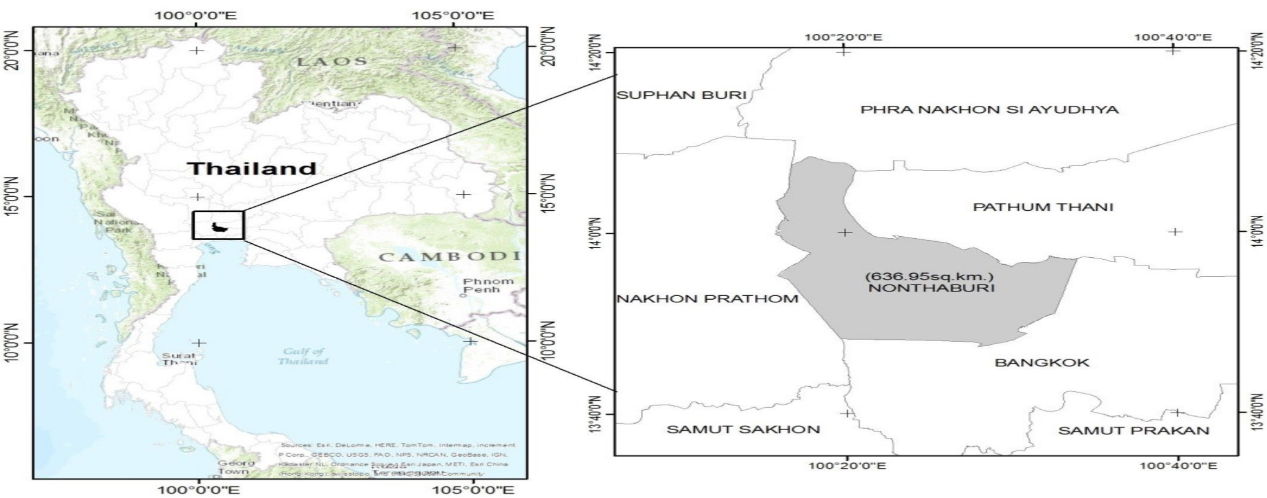

Fig. 1. Study area

RS from Landsat Data

Satellite data are suitable for monitoring land use change and land use and land cover (LULC). Classification of satellite data can be done by using several methods such as the multi-temporal Supervised or Unsupervised Classification [3] and classified information for management land use [4][5]. Satellite data used in this study, include Landsat 5 (2009) and Landsat8 (2014) that have image enhancement and false color composite satellite data. The used bands are 432 (RGB) and 543 (RGB). Supervised Classification Technique was used to classify land use types into four types 1) Urban area 2) Green Space 3) Water and 4) other and we evaluate its accuracy by ground check. Land use types from two years are used to predict future land use in the next five and ten years by CA-Markov model.

CA-Markov Model

CA-Markov is a model that combines CA and Markov. First the Markov model must be calculated (transition areas and transition probability) then, we apply CA to allocate spatial data. Markov model is widely used [6][7]. Markov model compares two states from past to present and predicts factors that have changed through time. Markov model has been applied to the study of land use by using mathematical equations as follows:

$L_{(t+1)} = p_{ij} \times L_{(t)}$

and

$$p_{ij} = \begin{bmatrix} P_{11} & P_{12} & \dots P_{1m} \\ P_{21} & P_{22} & \dots P_{2m} \\ \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots \\ P_{m1} & P_{m2} & \dots P_{mm} \end{bmatrix}$$

Where

L_{t+1} and $L_{(t)}$ is land use at t+1 and t Consequent

$(0 \leq P_{ij} < 1) and \sum_{m}^{j=1} P_{ij} = 1, P_{ij}$ is transition matrix

$(i, j = 1, 2, ..., m)$ is probability matrix of change

Cellular Automata (CA) are the independent cells that can change by the rules “The game of life” of John Conway. The grid cell analysis can be either 3x3 or 5x5 grid cells to determine the dynamics of each cell in the middle regardless of the surrounding Shells for consideration of the loop on the set [8].

Suitable Green Space for Urban Park by MCA

There are many ways to gain GIS, for example potential surface analysis: PSA, multi-criteria analysis: MCA and fuzzy logic analysis. The present study uses MCA because it can analyse complex spatial data by configuring the factor scores and weight of each factor by ordering the importance of different factors. Factors involved in a green space in the city are correlated with the density of population, distance from the original park, land use and land cover etc. [9]. An analysis of green space that is suitable for urban parks requires appropriate factors: 1) the distance from the original park 2) Population density (persons per rai) 3) Vegetation greenness (NDVI) and

4) the distance from the main road. The scores for each factor use fuzzy membership (the highest value is 1 and the lowest is 0). Weighted value of each factor uses AHP to prioritize and determine the weighting factor. Each factor is expanded below:

1) The distance from the original park is defined as the service area based on the size or type of park like a small park (Pocket Park) with an area not exceeding 3.125 rai (0.5 hectares) with a service area of 200 meters or City park area more than 166 rai service area about 1,300 meters [10].

2) The population density is important for locating urban park because they should be located in urban areas or near a city for easy accessibility. Areas with high population density are given priority [11][12]. The highest density of Nonthaburi municipality is up to 14 persons per rai, which represents score of 1.0. In contrast, Klongkwang sub-district in Sai Noi district has the lowest population density: 0.5 person per rai, so the score is 0.

3) The Greeness index or NDVI value is the value that indicates the plant status. NDVI can distinguish between no plants and density of plants. In park areas, NDVI is used to determine the selection of suitable areas for parks in the city with regard to areas with dense vegetation, primarily with the NDVI (high score = 1) or no plant lower NDVI values (Low score = 0) [13].

4) The distance from the main road. A car is the main choice to get access to the park [14]. Park areas should be located near the main road to accommodate those who want to access [15]. The province of Nonthaburi has 78 routes of main road and sets the buffer every 200 meters. Buffer zone near the road is most likely to have the highest rating of 1 and a buffer to the distant road. The most valuable point of buffer is 0.

Probability map within the high suitability for urban park must comply with two criteria as follows: 1) it must control the existing green space in high suitability classed to no change by setting the probability of change from green area to another land use equal to 0.00 and 2) it must keep the existing suitable green area for urban parks to the same or set probability of change from green area to future green area equal to 1.00. Finally, the new transition probability from improved probability maps by MCA and original transition area are used for allocation by CA model again to predict land use that supports urban parks in 2019 and 2024. The first prediction of land use is compared with improved prediction of land use by Cross -Tabulation to define change of each land use type, especially green area.

Integration of MCA and CA-Markov

The core idea of this paper is trying to differentiate the transition probabilities for urban parks from MCA. Essentially, green spaces within different spatial regions often have different potentials for urban parks that make different transition probabilities of each land use. The integration model can be divided into four parts as 1) determine transition area and transition matrix from Markov model 2) determine suitable urban parks probability by MCA 3) improve probability of change from original transition probability to new probability from MCA and 4) perform LUC simulation using CA model to simulate future land use for urban parks.

Case Study

Satellite data from LANDSAT 5 TM (24 DEC 2009) and LANDSAT 8 OLI (30 NOV 2014) are acquired during the same season and used to classify land use of Nonthaburi. Interpreted land use is used as input of traditional CA-Markov model to analyse transition matrix and transition probability to predict land use in 2019 and 2024. The next process is finding the suitable green space for urban park by MCA with the above processes applied with following criteria: 1) population density 2) accessibility from existing park 3) accessibility from main road and 4) Normalized Different Vegetation Index (NDVI). These criteria used Analytical Hierarchy Process (AHP) to rank the weighting score and were overlaid together to calculate final scores then reclassify final map into four classes: 1) High suitable for urban parks 2) Medium suitable for urban parks 3) Low suitable for urban parks and 4) Non-suitable for urban parks. The next step is improving the transition probability from Markov model. The changed probability technique is to adjust the probability map within the high suitability for urban park under two criteria: 1) control the existing green space in high suitability classed to no change by setting the probability of change from green area to another land use equal to 0.00 and 2) keep the existing suitable green area for urban park to the same situation or set probability of change from green area to future green area equal to 1.00. Finally, the new transition probability from improved probability maps by MCA and original transition area are used for allocation by CA model again for predicting land use that supports urban park in 2019 and 2024. The first prediction land use is compared with improved prediction land use by Cross-Tabulation to define change of each land use type especially, green area.

RESULTS AND DISCUSSION

Land use classification in 2009 and 2014 from satellite data are shown in Table 1. Land use in year 2009 shows 1) 204.35 sq.km. of urban area 2) 423.33 sq.km. of green area 3) 7.60 sq.km. of water area and 4) 1.70 sq.km. of miscellaneous. In year 2014, land use is defined as 1) 254.69 sq.km. of urban area 2) 366.94 sq.km. of green area 3) 9.74 sq.km. of water area and 4) 5.61 sq.km. of miscellaneous. We did an accuracy check by ground check. We found that the urban area, water area and miscellaneous are increasing. Particularly, urban area is increasing rapidly. In contrast, green area is decreasing in the same rate as that of urban area.

TABLE 1
LAND USE CLASSIFICATION FROM SATELLITE DATA IN 2009 AND 2014

	Land use	2009 (sq.km)	percent	2014 (sq.km)	percent	Change*
1	Urban	204.35	32.08	254.69	39.98	+ (7.90%)
2	Green Space	423.33	66.46	366.94	57.61	- (8.85%)
3	Water	7.60	1.19	9.74	1.53	+ (0.34%)
4	Miscellaneous	1.70	0.27	5.61	0.88	+ (0.61%)
	Total	636.98	100.00	636.98	100.00	

The results of CA-Markov model from traditional prediction area in 2019 and 2024 show that 1) The urban area will increase for 286.71 sq.km. (in 2019) and for 306.64 sq.km. (in 2024) 2) Green area is decreasing as 331.18 and 308.56 sq.km. 3) Water area will slightly increase for 11.79 and 13.70 sq.km. and 4) Miscellaneous will slightly increase for 7.30 and 8.08 sq.km. The statistics are presented in Table 2 and the class maps are presented in Figure 2.

TABLE 2
PROPORTION OF PREDICTION LAND USE BY CA-MARKOV MODEL IN 2019 AND 2024 COMPARED WITH 2014

	Land use	2014 (sq.km.)	%	2019 (sq.km.)	%	C*	2024 (sq.km.)	%	C*
1	U	254.69	39.98	286.71	45.01	+5.03	306.64	48.14	+3.13
2	G	366.94	57.61	331.18	51.99	-5.61	308.56	48.44	-3.55
3	W	9.74	1.53	11.79	1.85	+0.32	13.70	2.15	+0.30
4	M	5.61	0.88	7.30	1.15	+0.27	8.08	1.27	+0.12
	Total	636.98	100.00	636.98	100.00		636.98	100.00	

Remark U = Urban, G = Green Space, W= Water, M= Miscellaneous, C* = change: + (increasing), -(decreasing) percent from 2014

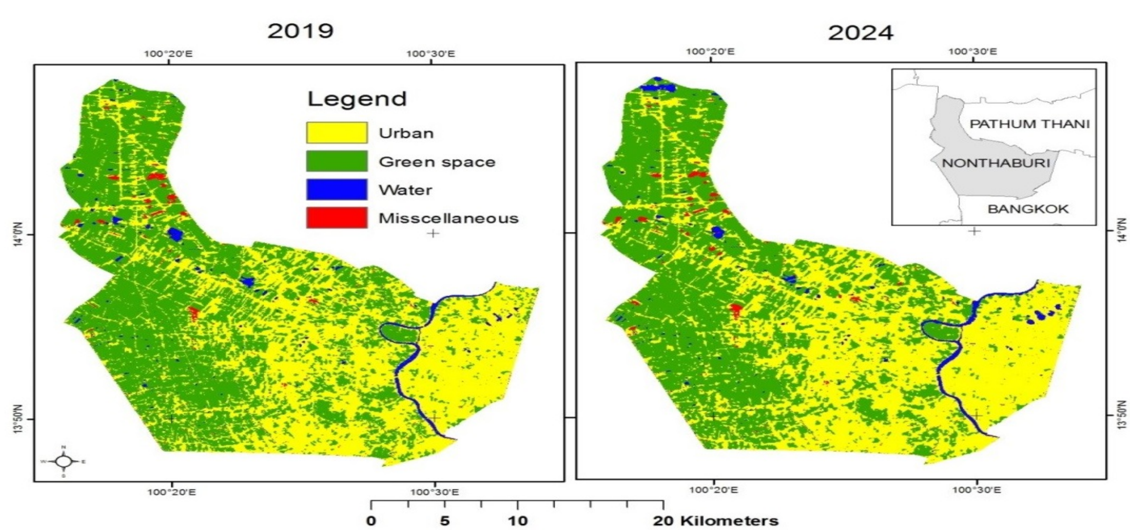

Fig. 2. Prediction of land use in 2019 and 2024 by CA-Markov model

Suitable Green space for urban park used MCA to determine those areas with 4 factors:
1) Distance from existing park
2) Population density
3) Vegetation Index (NDVI) and
4) Distance from main road.

The score and the weight of each factor are shown in Table 3 and Figure 3. These scores and the weighting of the 4 factors are calculated by overlay technique and reclassify total score to 4 classes as follows:
1) High suitability
2) Medium suitability
3) Low suitability and
4) No suitability (Figure 4).

TABLE 3
WEIGHTING SCORE AND SCORE OF 4 FACTORS FOR SUITABLE GREEN SPACE FOR URBAN PARK

Factor	Criterion	Score	Weighting
1. Distance from existing park	1.2 to 3.8 km	1.00	0.141
	0.6 to1.2 km. and 3.8 to 4.2 km.	0.75	
	0.2 to 0.6 km. and 4.2 to 4.8 km.	0.50	
	0.0 to 0.2 km. and 4.8 to 5.0 km	0.25	
	More than 5.0 km.	0.00	
2. Population density	High density (14.03 person: rai) to	1.00	0.455
	Low density (0.48 person: rai)	0.00	
3. NDVI	High NDVI to	1.00	0.263
	Low NDVI	0.00	
4. Distance from the main road	0 to 200 meters (nearest) to	1.00	0.141
	2,200 -2,400 meters (farthest)	0.00	

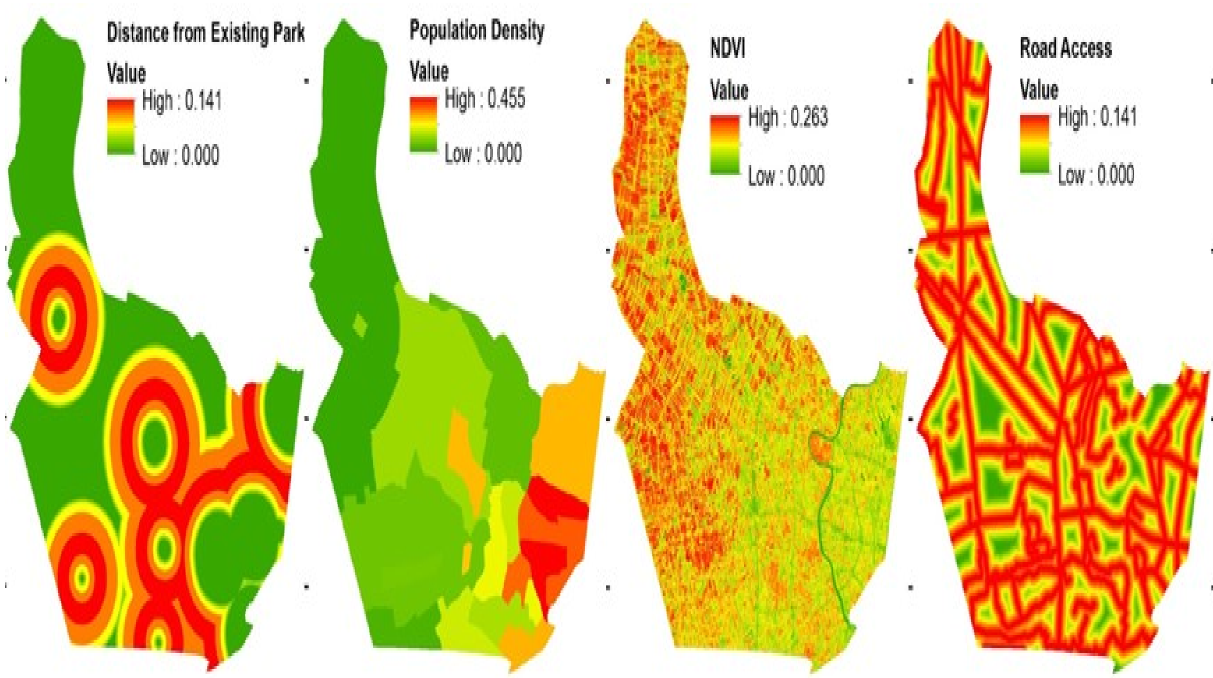

Fig. 3. Four factors of suitable green space for urban park

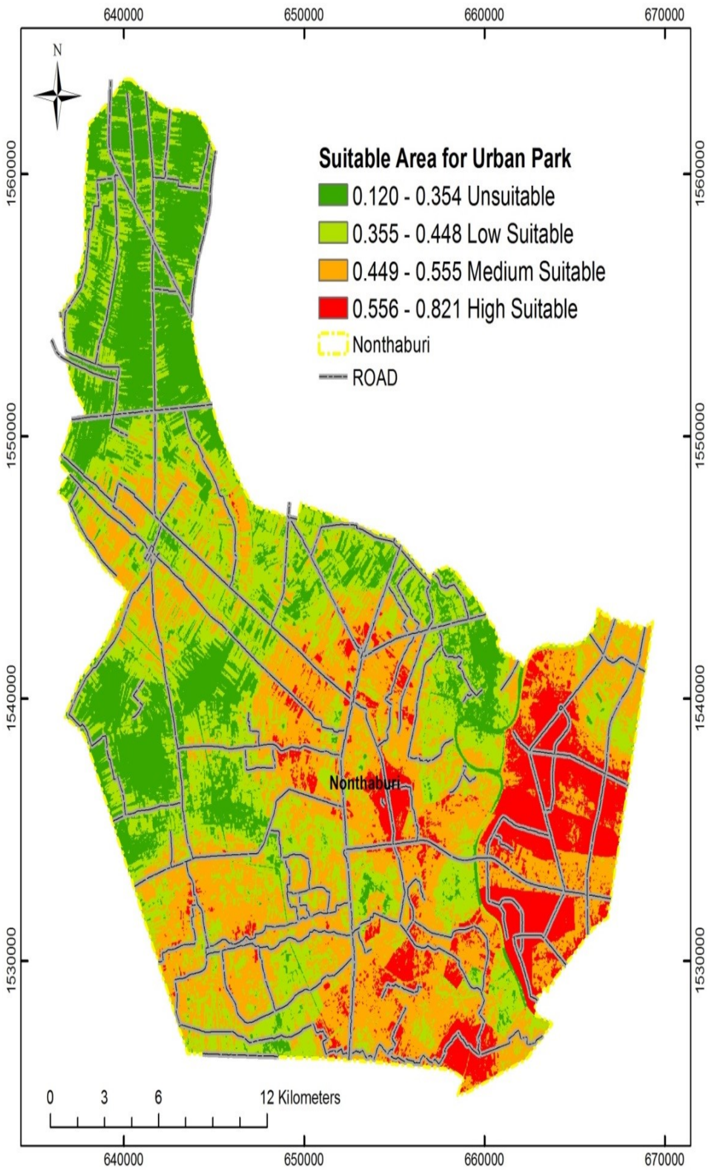

Fig. 4. Reclassify 4 classes of suitable green space for urban park by MCA

The analysis of MCA found that 1) High suitability for urban park (red color) has scores ranging from 0.556 to 0.821, with an area of 75.97 sq.km. (11.93%) 2) Medium suitability for urban park (Orange color) has scores ranging from 0.449 to 0.555, with an area of 212.53 sq.km (33.37%). This class covers most area in the study area. 3) Low suitable for urban park (Light green) with an area of 201.56 sq.km. (31.64 %) and 4) No suitable for urban park (Dark green), an area of 146.92 sq.km. (23.07 %). Areas of high suitability are located to the east of the province. The high population density is a major factor such as Nonthaburi Municipality, Pak Kret municipality and Bang Bua Thong municipality, etc. Integrated MCA with CA-Markov model by improved transition probability and prediction of the new land use for urban park in 2019 and 2024 from two objectives: Frist, to prevent the expansion of the urban (U) is not to expand to the existing green space that is suitable for urban park. The probability of new transition probability from U to G is zero. Finally, green space that is highly suitable for urban park should be reserved for next future urban park by setting the probability of G for change to another land use type equal to one.

We ran CA-Markov again with the new transition probability and the original transition area to predict land use in 2019 and 2024, then compared two future maps from original CA-Markov and improved in the same year to find the change. The results are shown in Table 4.

TABLE 4
COMPARE THE CHANGE OF LAND USE FOR URBAN PARK BETWEEN ORIGINAL CA-MARKOV AND IMPROVED CA-MARKOV IN 2019 AND 2024

Year	U	G	W	M	total
2019 (Original)	8.56	23.15	0.02	1.30	33.02
2019 (Improved)	0.98	30.75	0.00	1.29	33.02
Compare 2019	-7.58	7.61	-0.02	-0.01	00.00
2024 (Original)	13.63	18.06	0.03	1.30	33.02
2024 (Improved)	1.07	30.69	0.01	1.26	33.02
Compare 2024	-12.56	12.62	-0.02	-0.04	00.00

The improved model for transition probability will prevent city expansion into the green area (Highly suitable for urban park). In 2019 urban area in green space will decrease to 7.58 sq. km. and to 12.56 sq. km. in 2024. While the green space for urban park will recover by 7.61 sq. km. and 12.62 sq. km. respectively. Water and Miscellaneous will change slightly (See Figure 5).

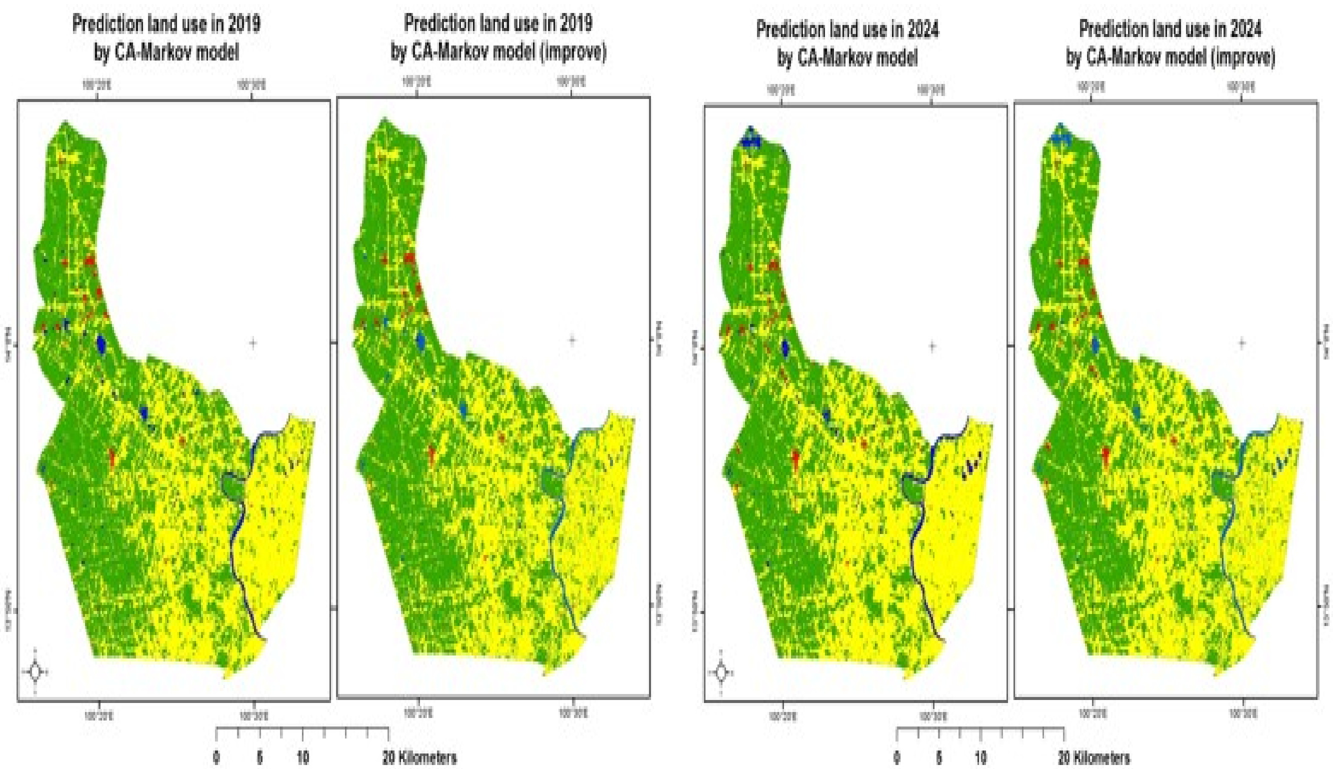

Fig. 5. Compared map between the original and the improved CA-Markov model for suitable urban park in 2019 and 2024

CONCLUSION AND RECOMMENDATIONS

Nonthaburi urban park prediction by integrated Geo-Informatics techniques including RS for identification of land use, CA-Markov model for prediction of future land use and GIS by MCA for finding suitable areas for park. This study reveals that land use is changing rapidly in Nonthaburi province. The urban area in 2014 has increased by 25 percent from 2009 or 7.90 percent of Nonthaburi. While green area sharply decreases about 8.85 percent of Nonthaburi. Almost green areas such as paddy, vegetables and orchard have changed to urban area. The accuracy of classification data from ground check is 90 percent. The urban area is expanding so rapidly because of Nonthaburi is next to Bangkok which has huge economic development. People need to live near Bangkok to get good jobs, good education or good health care service. In the next 20 years the urban area will expand 80 percent for Nonthaburi. So, the green area is decreasing too. The CA-Markov model reveals that the urban area will increase about 5 and 3 percent respectively (2019 and 2024) which correspond to the reduction of green space. Most residential growth around existing urban areas, especially areas near Bangkok, will be the first to expand. The suburban area of Nonthaburi such as Pak Kret Municipality and Nonthaburi Municipality will rapidly expand but the outer area such as Sai Noi district will have minimal expansion.

CA-Markov is a model for forecasting future land use when informed of changes in land use at two periods; However, CA-Markov model can't control or determine criteria. Other important criteria such as roads factor, land prices or other policy makers can't contribute in the forecasting process or decision support in the future. The purpose of improved prediction model is to create alternative approaches to support land-use planning decisions, particular preparation of the park in the future to improve the quality of life. The results showed that Green space in 2019 can be treated and protected for the urban park to increase up to 7.58 sq.km.. If these areas are changed to urban park, they will increase park area per capita up to 6.41 sq.m. This is close to the international standard (8 sq.m.) and greater than preset urban park area in Nonthaburi (0.41 sq.m.).

The results can be used to support decisions of all sectors related to the urban park including government agencies. The public and private sectors should cooperate to push the plan to get concrete result on the basis of participation. Urban parks are the most visible benefit for the public to improve the quality of life. It will prevent diseases and reduce the cost of healthcare. It also creates a happy society for us and the future of our children.

Declaration of Conflicting Interests

The author declares that there are no competing interests in this work.

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