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Article

Urban Growth Prediction of Special Economic Development Zone in Mae Sot District, Thailand

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Abstract. Since the ASEAN Economic Community (AEC) was activated in 2015, eight subdistricts of Mae Sot district in Tak province, Thailand have been regarded as special economic development zones (SEZ) due to their situation on the border of Thailand near the pathway of the East-West Economic Corridor project (EWEC). Thus, the Thai Government is developing many infrastructure projects there, and the urban areas are likely to expand, as the population is increasing dramatically. The study of land use could aid in more efficient decision-making in urban planning, and could mitigate the effects of uncontrolled urban development.

Based on this background, land use change monitoring was performed based on Remote Sensing and Geographic Information System (GIS) using high-resolution satellite images. The images were captured by QuickBird in 2006, and by Thaichote in 2011 and 2016. The object-based classification considers not only the reflectance of the pixels but also the size, shape, color, smoothness, and compactness of the objects. This technique will bring higher accuracy to land use classification. The eCognition Developer was employed in this study for object-based classification. The mean and standard deviation of the original band was used for principle component analysis (PCA), and the normalized difference vegetation index (NDVI) was also applied to land use classification. The types of land use were divided into five categories that followed the definitions given by the Land Development Department of Thailand (LDD): agricultural area, forest, urban area, water body, and miscellaneous land. The results of land use classification showed that urban areas increased drastically year by year. The GIS dataset for land use compiled by the LDD was employed to evaluate the accuracy of our results. The overall accuracies based on the images captured in 2006 and 2011 were 86.00% and 79.88%, respectively. To evaluate urban growth in 2015, the states of land use in 2006 and 2011 were applied to a Markov Chain and Cellular Automata model (CA-Markov), which is a model for the prediction of land use change from one period to another. The Markov model evaluates the transition probability matrix to project future change, while CA-Markov performs the spatial variations in cell time transition and neighborhood based on its element cell space, cell states, time steps, transition rules, and neighbors. The accuracy of the land use prediction obtained from CA-Markov in 2016 was evaluated by comparing it with land use classification from the object-based classification of the image captured by Thaichote in 2016. The overall accuracy was 68.45%. The pattern of land use change detected from both the projection map and the classification map showed that the urban area would spread following the development of transportation infrastructure, and would encroach on the agricultural areas, while forest areas would become agricultural areas.

Keywords: Land use change detection, urban growth, object-based classification, Markov chain, CA-Markov.

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1. Introduction

According to ASEAN Economic Community (AEC), the Thailand Government set up guidelines for economic policy to focus on promoting border trade through the establishment of Special Economic Development Zones (SEZ), which was activated in 2015 [1]. Ten stages of the Thailand border were approved of by the committees as potential areas suitable for the establishment of a SEZ. Tak province was regarded as one of the SEZs because it is situated on the path of the East-West Economic Corridor (EWEC) along the border of Thailand and Myanmar [2]. From the report of the National Housing Authority in Thailand, the characteristics of urban expansion in Tak underwent growth as sprawl from 1997 to 2013, especially in the Mae Sot district [3]. For high development potential areas such as SEZs, the study of urban growth is useful in management and decision-making for efficient urban planning, and in mitigating the negative effects of unregulated urban development.

Remote Sensing with Geographic Information System (GIS) using high-resolution satellite images is a powerful technique for analyzing urban planning [4, 5]. A spatial database of thematic maps and multi-temporal images were employed to study the spatial variations. In the study of urban planning, the pixel resolution of satellite imagery is very significant. To be able to study the details of small objects and the surrounding environment, such as buildings, construction, and transport infrastructure, images of high to medium resolution are required (e.g., aerial photos, images taken by QuickBird or Thaichote) [6]. However, the decision to select a method of classification for land use-land cover type that befits the characteristics of the image is essential. Object-based classification was used for land use classification. The strength of this method is the high accuracy of classification results with an image segmentation process and weighted conditions. According to Casey Cleve (2007) [7], the study compares pixels with object-based classification, and the results show that object-based classification provides better results than pixel-based classification. To predict future land use, Markov Chain and Cellular Automata models (CA_Markov) were used to evaluate land use in the study area [8]. A. Akin (2014) [9] studied the ecological threats of urban sprawl by using Cellular Automata (CA). Mohsen (2009) [10] combined Cellular Automata with a Markov chain model to forecast future land use change for evaluating human impact. However, urban planning must take into account the future expansion of the city, and the surrounding land uses. The past situation, and current land use and trends are the most efficient baseline data that can be used to support proper land management planning.

This study focuses on identifying land use change in the Tak SEZ in Mae Sot district, where phase 1 of the SEZ project was documented with the high-resolution image in 2006, 2011 and 2016. This study will show the pattern and trend of urban growth. The trend of urban land cover in 2016 is then simulated with Markov and CA-Markov models based on land use in 2006 and 2011. The accuracy check indicates the reliability of the model. Finally, the implementation of the growth trends in urban areas will be useful for urban management in this field of study.

2. Material and Methodology

2.1. Study Area

The study area covered eight subdistricts in Mae Sot District of Tak province Thailand which was designated as an SEZ, including Mae Sot, Mae Tao, Ta Sai Luat, Phra That Pha Daeng, Mae Kasa, Mae Pa, Mae Ku, and Mahawan subdistricts. Tak's SEZ, covering 788.54 km^2, is located between 16° 59'30" to 16°31'30" N, and 98°49'30" to 98°24'00" E in the northwest of Thailand. The border connects with Myawaddy province in Myanmar (see Fig. 1). The population in 2015 was 107,135, which has increased by 16.13% in comparison with 2014.

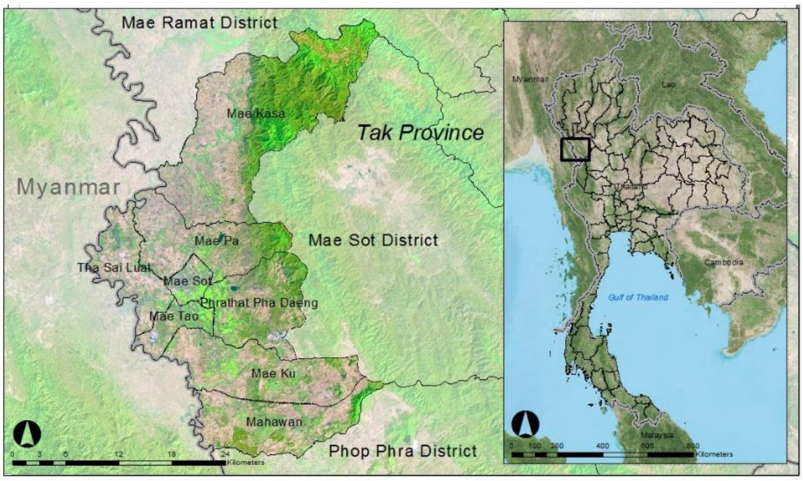

Fig. 1. The study area of Tak's SEZ in Mae Sot district, Thailand.

2.2. Material

The study of land use change was investigated over three periods between 2006 to 2016 (2006, 2011, and 2016) with high-resolution images. Spot 5 images with resolutions of 2.5 meters with 4 wave Lange: green (0.50-0.59 μm), red (0.61-0.68 μm), NIR (0.78-0.89 μm) and SWIR (1.58-1.75 μm), which belong to Astrium Cooperation of France, taken on 28 January 2006, and Thaichote images in resolution 2 meters with 4 wave Lange: blue (0.45-0.52 μm), green (0.53-0.60 μm), red (0.62-0.69 μm) and NIR (0.77-0.90 μm) that belong to Thailand Government [11] acquired on 26 December 2011, 16 January 2012 to represent the year 2011 and image acquired on 11 January 2016 to represent for year 2016. Therefore, the images were all taken during the dry season. The images are subjected to digital image preprocessing, including rectification and mosaicking, and preparation of the PCA and NDVI layers for classification analysis.

2.3. Method

In the study of predictive urban growth of SEZs in Mae Sot, the first step was to classify land use by type in 2006, 2011, and 2016 by using the Spot5 and Thaichote images. The transition probability matrix and the transition probability area of land use change between 2006 and 2011 was then estimated using a Markov model. For the geospatial simulation, CA was used to predict land use in 2016. Accuracy verification of the results is needed in this step. Finally, socioeconomic and land characteristic factors were used for the study of drivers in the urban sprawl of Tak's SEZ, Mae Sot district. The overview is given in Fig. 2.

2.3.1. Land use classification

This study divides land use classification into five types, which are agriculture area, forest area comprised of evergreen forest and deciduous forest, urban area, miscellaneous land, and water area. These types follow the Land Development Department of Thailand. Land use classification, which operates by object-based classification using eCognition Developer software. This software allows the user to segment the image object. The segmentation algorithm divides the raster image into meaningful objects. The algorithm is based on spectral information in each pixel, and also takes into account of the shape of the object by setting weight values of shape/color and smooth/compactness [12].

Threshold or rule set conditions determine whether an image object matches a condition or not. The conditions are set up by the user as a rule set to control the classification analysis [13]. The threshold depends on the type of land-use, which determines the characteristic satellite wavelength. The nearest neighbor classification was applied to classify land use in the period 2016. This classification was performed by using a sample area within the image with the classes that are used for classifying another image object [14]. In this study the sample was determined from land use data in 2012, which was used as a reference database by selecting the unvaried area.

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For classification, principal component analysis (PCA) was used. There is the element in image classify. To transform the original data, which may be large and very complex, by reduce data redundancy and correlation between bands. In the process, the optimal linear combination of original bands accounting for the variation in the pixel values in an image is identified [7]. In addition the statistical values of an image value such as mean, standard division (SD), and the normalized difference vegetation index (NDVI) was also applied to land use classification.

2.3.2. Urban growth prediction

1) Markov chain analysis describes land use change from one period to another. This analysis is used as the basis to project future changes. This analysis develops a transition probability matrix of land use change from one period to the next, which is used as the basis for projecting to a later period. Markov chains were used to analyze the probability of each land use pattern, which were calculated by digital analysis of the mapping for each land use type [10, 15, 16, 17].

2) Cellular automata Markov (CA-Markov) is the integration of Markov chains and the cellular automata (CA) approach, which is a dynamic model for simulating the spatial process to describe urban growth and land use or land cover over the space and time [18,19].

2.3.3. Classification accuracy

The accuracy assessment of land use classification uses systematic sampling, which places observations at equal intervals in a grid cell of size 100x100 meters. The comparison of the classification map is done with reference data from the GIS Database of Land Use in 2006 and 2012. The overall accuracy and Kappa coefficient were determined from the error matrix, which showed the accuracy of both the producer and user

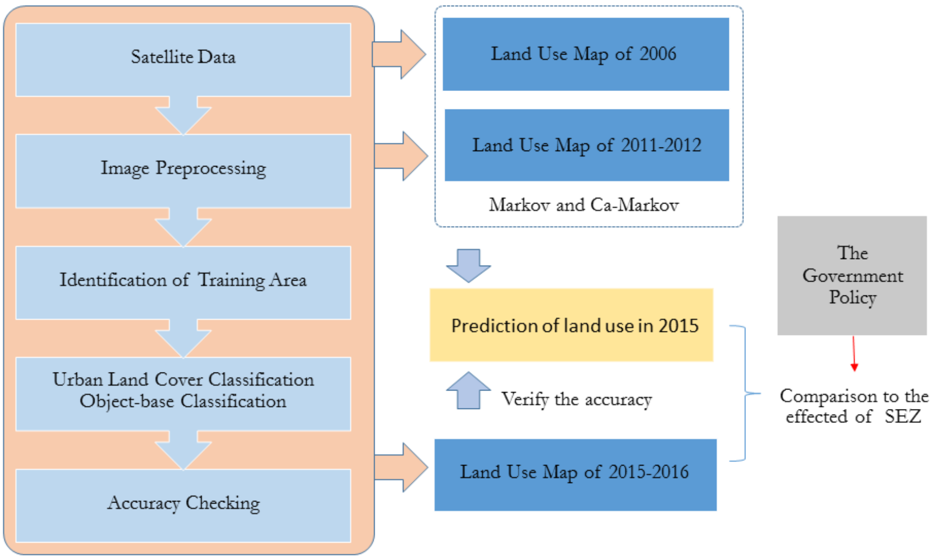

Fig. 2. Flow chart of study on urban land cover from temporal satellite data.

3. Results and Analysis

3.1. Land Use Classification in the SEZ of Mae Sot District in Tak Province.

The land use classification by object-based classification of Spot 5 and Thaichote images, consists of the land use maps in 2006, 2011, and 2016. The type of land use was reclassified according to remote sensing image characteristics within the five land use classes, which consisted of agriculture area, forest area, miscellaneous land, urban area, and water area, as shown in Table 1 and Fig. 3.

The number of land use changes was calculated by comparison with land use change in the five years between 2006 and 2011. Land types that showed increasing use included agriculture and urban, with a dramatic 91.5 km² (26.45%) and 12.47 km² (28.82%) increase, respectively. Forest, miscellaneous land, and water areas decreased by 100.21 km² (25.67%), 3.68 km² (55.02%), and 0.54 km² (14.31%) in the following period, respectively.

From 2011 to 2016, agriculture, miscellaneous land, urban, and water areas increased by 77.55 km² (17.19%), 14.03 km² (466.71%), 30.47 km² (54.66%) and 1.15 km² (35.79%), respectively. The only decreasing type was forest, by 121.2 km² (41.77%).

Table 1. The total area of each land use type between 2006, 2011, and 2016 (km²).

Land use type	Year 2006	Year 2011	Year 2016	Year 2006-2011		Year 2011-2016	
				Changing area	%	Changing area	%
Agriculture	347.63	439.58	515.13	91.95	26.45	75.55	17.19
Forest	390.39	290.19	168.99	-100.21	-25.67	-121.20	-41.77
Miscellaneous land	6.68	3.01	17.03	-3.68	-55.02	14.03	466.71
Urban	43.28	55.75	86.23	12.47	28.82	30.47	54.66
Water	3.77	3.23	4.38	-0.54	-14.31	1.15	35.79
Grand Total	**791.75**	**791.75**	**791.75**	**791.75**		**791.75**	

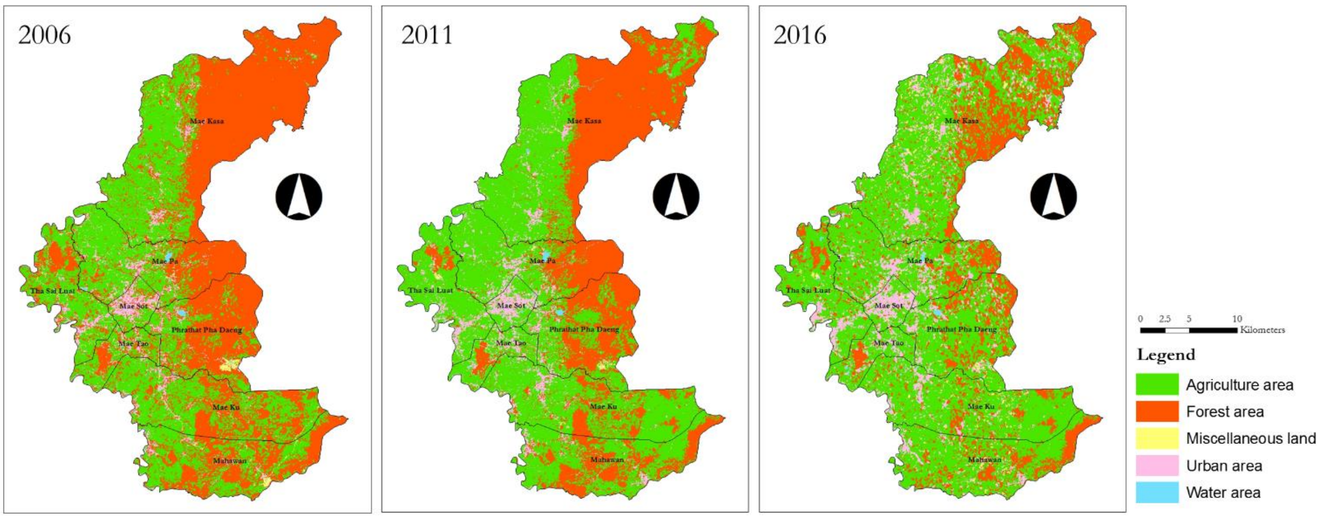

Fig. 3. Result of land-use classification in the SEZ in Mae Sot District of Tak Province, Thailand.

3.2. Urban Growth Prediction

To forecast the trend and pattern of land use in the SEZ in Mae Sot District over the next period, the CA_Markov model was used to analyze the prediction of land use in 2016. To implement the Markov model, the transition probability matrix of change in land use patterns during 2006-2011 was calculated using Markov chain analysis and shown as Table 2. To simulate the geospatial land use prediction for 2016, the CA-Markov model base on SEZ of Mae Sot District in 2011 was used to forecast land use characteristics in the next period.

The transition area of each land use classification from 2006 to 2016 by the CA-Markov Model is shown in Fig. 4 and Table 3. According to the results, urban area decreased slightly, from 55.75 km² in 2011 to 41.48 km² in 2016, while the results of land use classification in 2016 by object-based analysis showed that the urban area increased to 86.23 km². However, the results of both methods is the same regarding the change characteristics of land use. That is, urban area was transgressing on agriculture and forest areas.

Table 2. The probability of transition matrix for land use type in the SEZ of Mae Sot District during 2006 – 2011.

Land use type	Agriculture	Forest	Miscellaneous land	Urban	Water
Agriculture	0.885	0.057	0.004	0.054	0.001
Forest	0.288	0.677	0.001	0.033	0.001
Miscellaneous land	0.580	0.073	0.077	0.266	0.003
Urban	0.343	0.122	0.013	0.513	0.009
Water	0.291	0.058	0.007	0.070	0.574

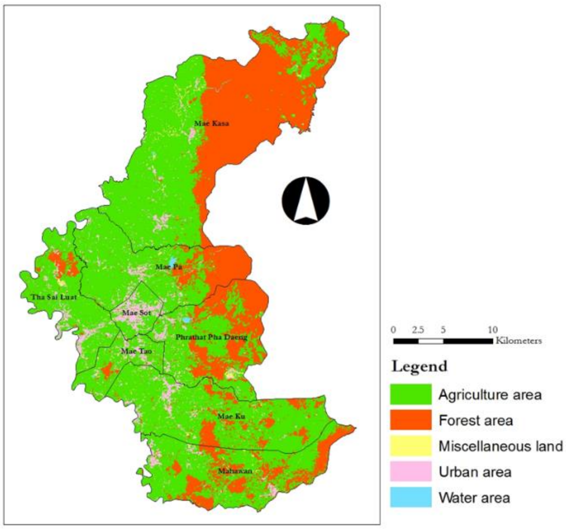

Fig. 4. Map of the land use type in the SEZ in Mae Sot District of Tak Province in 2016, from the CA-Markov model.

Table 3. The transition area of each land use classification from 2011 to 2016 by the CA-Markov model and object-based classification.

Land use type	Year 2011					
	Agriculture	Forest	Miscellaneous land	Urban	water	Total
<u>**Year 2016 from the CA-Markov model**</u>						
Agriculture	429.81	52.14	0.62	14.7	0.44	**497.71**
Forest	4.24	235.48	0	0.06	0	**239.79**
Miscellaneous land	1.68	0.16	2.16	5.95	0	**9.95**
Urban	3.85	2.39	0.23	35.02	0	**41.48**
water	0.01	0.02	0	0.02	2.78	**2.82**
Total	**439.58**	**290.19**	**3.01**	**55.75**	**3.23**	**791.75**
<u>**Year 2016 from object-based classification**</u>						
Agriculture	12.358	88.134	21.1	21.20	7.0	**13.515**
Forest	81.37	87.127	27.0	98.2	06.0	**99.168**
Miscellaneous land	91.10	41.3	59.0	02.2	1.0	**03.17**
Urban	07.31	63.23	91.0	28.30	33.0	**23.86**
water	67.1	39.0	02.0	26.0	04.2	**38.4**
Total	**58.439**	**19.290**	**01.3**	**75.55**	**23.3**	**75.791**

3.3. Accuracy Checking

The accuracy assessment of land use classification was calculated by the confusion matrix accuracy method using systematic sampling, in which observations are taken at equal intervals in a cell grid of size 100 x 100 meters as 80,268 reference point.

To determine the land use classification accuracy for the two periods of 2006 and 2011, the land use GIS database for 2006 and 2012 of LDD were compared as reference data. The overall accuracy was 86.00%, 86.98%, and the Kappa coefficient 0.733, 0.698, respectively. The accuracy assessment of this process was done by comparing the prediction map and the land use classification of Thaichote images in 2016. The overall accuracy and Kappa coefficient of land use classification is 68.45% and 0.393 (see Table 4).

Table 4. The accuracy checking of land use classification in 2006 and 2011.

Land use type	Year 2006 User Accuracy (%)	Year 2011 User Accuracy (%)	Year 2016 User Accuracy (%)
Agriculture	92.2	91.59	76.722
Forest	82.9	91.88	69.720
Miscellaneous land	36.4	16.05	8.386
Urban	53.9	59.36	29.804
Water	38.7	12.13	42.297
Overall accuracy	**86.00**	**86.98**	**68.45**
Kapa	**0.733**	**0.698**	**0.393**

3.4. Urban growth in the SEZ of Mae Sot District, Tak Province

The trend of growing urban areas in the SEZ in Mae Sot District, especially in dense residential areas, is expanding to the agriculture areas around the old city. This is related to the policy of transportation development according to the planned expedition policy of the Tak Special Economic Development Zone Office for the preparation of transport infrastructure, which began in 2014). The trend of urban growth in 2016 compared with the land use of the principle city plan of Mueang Mae Sot in 2012 shows that the greatest urban expansion has occurred mostly in the rural and agricultural zones located around the residential area (3.703 km^2).Tthe second highest growth is in the forest conservation zone (2.035 km^2). The third growth is in the residential areas in less dense zones (1.936 km^2) (see Figs. 5 and 6). However, it is possible to transform this forest conservation zone to rural and agricultural zones in the next principle city plan to support future urban expansion.

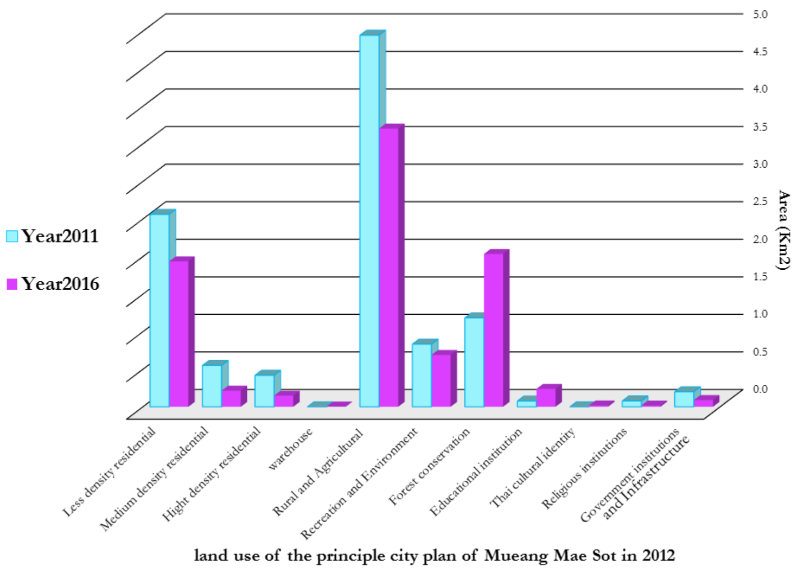

Fig. 5. The urban expansion in 2011 and 2016 in the area of the principle city of Mueang Mae Sot 2012.

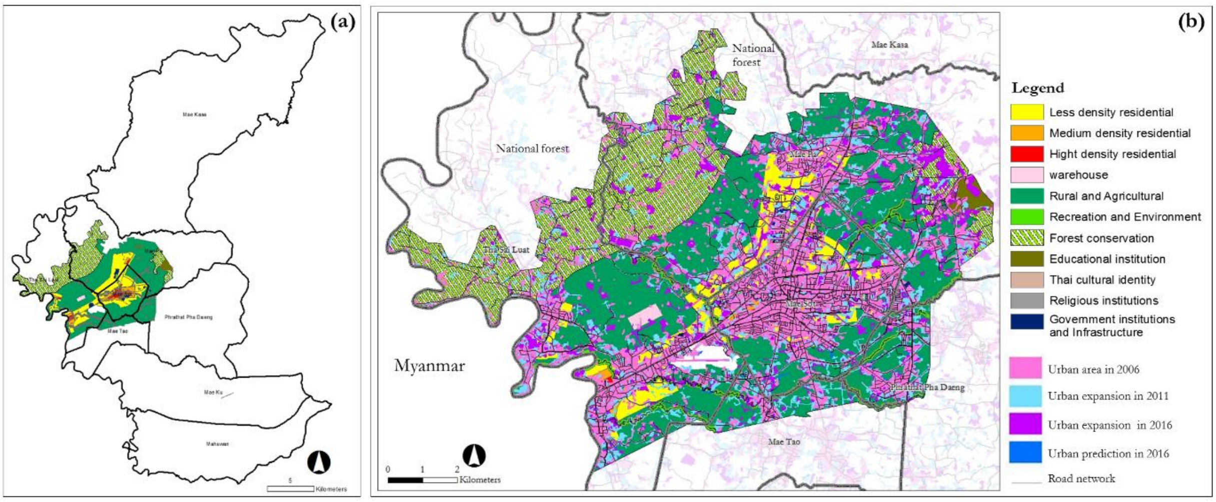

Fig. 6. (a) The land use of the principle city plan of Mueang Mae Sot in 2012 and (b) the overlay of urban growth areas in 2006, 2011, 2016, and urban expansion from predictions in 2016.

4. Recommendation/Concluding

The study of land use change simulated with the CA-Markov approach, on remote sensing data was used to evaluate changing land use in developing areas. Even though the accuracy of the overall area is not good, the results for a small area, such as a dense residential area, are satisfactory. However, this study represents other factors, such as the government policy needed as an essential element in the analysis of an urban area. The pattern of urban expansion by transportation, along with the government development policy in 2016, has been the most effective. In the future, there will be more policies to develop other areas, such as an economic one-stop service center [20], so that the pattern of urban development will be different, especially economically.

Besides changes in the urban area, the government should be aware of other changes in land use, such as in forest areas that were taken over by agriculture activity. On status and trend, the prediction of land use change in highly developed areas is necessary for sustainable development.

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