RESEARCH PAPER

ASSESSING LONG-TERM DEFORESTATION IN NAM SAN WATERSHED, LOEI PROVINCE, THAILAND USING A DYNA-CLUE MODEL

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ABSTRACT. This research analyzed land-use changes (LUC) in the Nam San Watershed (NSW) by applying geoinformatics methods and land-use modeling approach to explore LUC in the past. Landsat satellite images from years 2002, 2007 and 2013 were classified using a maximum likelihood algorithm to create land-use maps. For assessing future LUC over a period of twenty years (2014–2033), land-use simulations were conducted using a dynamic LUC model (Dyna-CLUE model) in two land management scenarios: Scenario 1 is a simple projection of the LUC trend without reservation area, while Scenario 2 projects the LUC trend with reservation area in future periods. NSW land-use maps for 2002–2013 were analyzed using geoinformatics technology. The results revealed that the amount of forested area within the NSW has reduced drastically, from 380.40 km^2 to 267.23 km^2, changing to fields and perennial crops, which the logistic regression identified as being influenced by a slope factor. These data was used as a reference for LUC detection with the model simulation in two scenarios. Model results have shown that by 2033, Scenario 1 predicts a significant decrease in the overall forest area, from 72.21 km^2 to 41.55 km^2 in Phu Ruea district, and from 107.31 km^2 to 45.62 km^2 in Phu Luang district. Whereas Scenario 2 predicts slightly decreasing forest area within the reservation area, but rapid decrease, from 177.86 km^2 to 28.54 km^2 outside the reservation area, where the distance to village factor is the main influencer. These findings highlight the importance and the potential of model predictions for planning activities to protect forested areas.

KEY WORDS: Land-Use Change, Dyna-Clue Model, Deforestation, Nam San Watershed, Loei Province

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INTRODUCTION

Over the last several decades, South East Asian ecosystems have been altered substantially as a result of the socio-economic change (Mallinis et al. 2011; Moreira et al. 2001), while future changes are also expected to occur (Islam et al. 2018; Lambin 1997). Thailand is only one of the countries in Southeast Asia facing this problem. As mentioned previously, from 1961 to 1993 Thailand's forest area decreased by an average rate of 4,368 km^2 per year, with a high tendency to continue declining, especially in Loei province in the NSW area. Even though there was a royal act to dismiss the concession forest or control the boundary of Phu Ruea National Park and Phu Luang Wildlife Sanctuary, decreasing forested areas are still found periodically (Royal Forest Department 2016). This leads to problems such as soil erosion, and cause repetitious natural disasters, i.e. landslides and floods in the monsoon season from June to October every year (Yumuang 2001), and water deficiency for agriculture in the dry season (Santiphop et al. 2012), which results in loss of agricultural production and affects public utility systems in communities in mountainous areas (Gilani et al. 2015; Lambin 1997). Generally, research related to LUC dynamics in mountainous regions of Southeast Asia has found that the push factors affecting LUC are usually of a socio-economic context in each watershed area (Geist and Lambin 2002; Luo et al. 2010; Turner II et al. 2007). For instance, in the study area of the NSW is characterized by complex mountainous geography with abundant forest resources, wild animals and seedlings, which is a unique terrain in Thailand (Department of Mineral Resources 2009). Nowadays, this watershed area has been affected by human activities (Klongvessa et al. 2018; Satika B. and Chotpantarat 2014; Satika B and Chotpantarat 2018;

Waiyasusri and Chotpantarat 2020), not only by the growing population but also by conversion of forested areas for agricultural use. The area is characterized by the presence of low plains between valleys, which bring about the ease of access to the area (Benítez-López et al. 2017; Clements et al. 2014; Consiglio et al. 2006), causing a rapid expansion of agricultural areas (Santiphop et al. 2012; Trisurat et al. 2019) and construction, leading to an increase in the economic status of the local communities and population (Hooke et al. 2012; Lagrosa IV et al. 2018; Sadler et al. 2011). This has directly affected the land-use, as agricultural areas became replaced by recreational areas, hotels, accommodations and other structures, the number of which has increased in the NSW. Geoinformatics methods can be applied to analyze the patterns of land-use change dynamics using both quantitative and qualitative approach.

The Dyna-CLUE Model (Peng et al. 2016; Verburg and Overmars 2009; Verburg and Veldkamp 2004; Verburg et al. 1999; Zhang et al. 2018) brings land-use pattern of the past to work relating to spatial data with the grid of the proper land allocations by defining top-down policy conditions, for instance, specifying reserved areas (Guang et al. 2017; Verburg et al. 2002). Specifying conditions was done for various land-uses, according to spatial demand from the people in the area (bottom-up) from the characteristics of each appropriate location for various types of land-use (Verburg and Overmars 2009). The physical and socio-economic factors are ones of the most significant factors, used to process spatial data as the grid of the proper land allocation to acquire land-use pattern for the future (Jia Z. et al. 2018). This information is complicated data that is variable all the time during the period and in study area (Verburg and Veldkamp 2004). The mentioned model utilized a logistic regression model (Gobin et al. 2002; Zhang et al. 2018), integrated with the Dyna-CLUE model analyze and effectively forecast future LUC for empirical data to make decisions in land-use planning in the NSW area, a mountainous area, in order to develop the area and allocate limited natural resources for the highest sustainable benefit and improve people's life quality in the watershed.

In this research, the pattern of LUC dynamics was analysed over the period 2002–2013 and then the Dyna-CLUE Model was applied to simulate land-use patterns in the future period covering 2014–2033 in order to detect the direction of change in the forest area and plan sustainable land-use in the NSW area, Loei Province, Thailand. Moreover, analysis of the spatio-temporal dynamics of land-use type development was conducted under the conditions of two dynamic scenarios, namely, a scenario without a reservation area, and a scenario with a reservation area, such as Phu Luang Wildlife Sanctuary and Phu Ruea National Park, to assess the direction of land-use dynamics under the 2 mentioned scenarios. The results of this paper provide important information for local land-use management by assessing the impact of LUC.

MATERIALS AND METHODS

Study Area

The NSW area located in Loei Province, Northeast Thailand (Fig. 1), is a part of the watershed area of the Khong River. The total study area is approximately 852 km^2 under coverage path 129, row 48 of LANDSAT-8 satellite (OLI/TIRS). The elevation ranges from 300 to 1600 m above mean sea level (amsl). The topography surrounding the NSW mostly consists of complex mountain ranges. Phu Luang is the highest mountain at a height of 1,571 meters located in the southeast region of the NSW. The mountain ranges are aligned from north to south and are characterized by huge sedimentary rock and mesa morphology in the southeast of the NSW. In the south of the NSW Tableland and Double Cuesta ridge morphology appears (Department of Mineral Resources 2009). At the bottom of the cliffs, there are lowlands in between narrow valleys formed by rill and gully

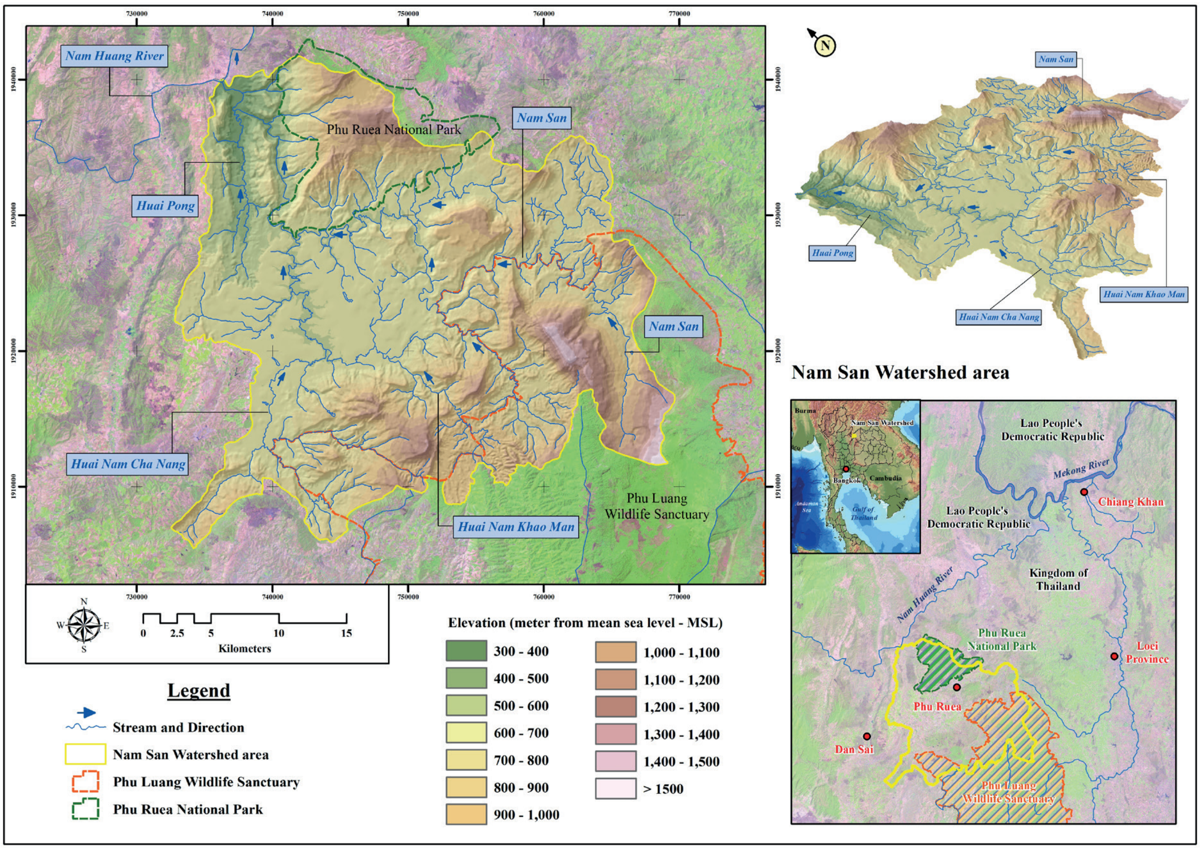

Fig. 1. Geographic map and topography in three-dimensional digital terrain of the study area NSW, Loei Province

erosion (Department of Mineral Resources 2007). The NSW includes four major watercourses: Huai Nam San stream, Huai Nam Khaw Man stream, Huai Nam Cha Nang stream and Huai Pong. Following the orientation of the mountain range, the flow of the watercourses is directed from south to north and discharges into down to the Huang river and Khong river. Moreover, the catchment includes several conservation areas such as Phu Luang Wildlife Sanctuary and Phu Ruea National Park located in the southeast and north regions of the NSW, respectively.

Data

Satellite images recorded by Landsat 5 TM, Landsat 7 ETM+ and Landsat 8 OLI/TIRS. for the years 2002, 2007 and 2013 were used in this research. The satellite images were downloaded from the U.S. Geological Survey to analyze land-use changes using Erdas Imagine 8.7 software. Table 1 contains a summary of the satellite data used for Geospatial information analysis. In addition, land-use data from the Land Development Department (LDD) was used as a land-use reference for examining the spatial land-use changes and accuracy for each year before processing the data in the next step. Table 2 shows land characteristics and socio-economic factors in the NSW, Loei Province, which are statistically processed and displayed in the form of maps. The LUC driving factors in the NSW, such as elevation, slope, soil suitability, distance to stream, distance to road, distance to a village, population density and poverty level are displayed in Fig. 2, along with information on Phu Luang Wildlife Sanctuary and Phu Ruea National Park boundaries.

Method

The research process consists of the following steps, as shown in Fig. 3 (1): Geoinformatic approach, (2) Dyna-CLUE model approach and (3) Dynamic Annual Change of LUC analysis. The details of each step are briefly explained below.

Table 1. Satellite Image Data over the NSW for LUC Analysis

Image type	Path/row	Band (R:G:B)[a]	Acquisition date	Original		
				Format	Resolution	Source[b]
Landsat 5 TM	129/048	5:4:3	2002-03-29	TIFF	25 m	USGS
Landsat 7 ETM+	129/048	5:4:3	2007-01-14	TIFF	25 m	USGS
Landsat 8 OLI/TIRS	129/048	6:5:4	2013-04-20	TIFF	25 m	USGS

[a] R:G:B red:green:blue
[b] USGS United States Geological Survey

Table 2. Description of Geo-spatial Data (Physical Factors and Socio-economic Factors) Selected for Logistic Regression Analysis

Driving Factor	Variable (Theme)	Year	Data preparation methodology	Source
Land characteristics factor	Elevation	2007	Topo to raster on spatial analyst	Royal Thai Survey Department (RTSD) topographic map sheet series L7018
	Slope	2007	Slope on spatial analyst	Derived from the DEM
	Soil Suitability	2013	Feature to raster on spatial analyst	Land Development Department (LDD), Thailand
	Distance to stream	2013	Interpolated grid theme contains a Euclidean distance from the drainage system on spatial analyst	Department of Water Resource, Thailand
Socio-economic factors	Distance to road	2013	Interpolated grid theme contains a Euclidean distance from the highway and road on spatial analyst	Department of Public Works and Town & Country Planning
	Distance to village	2013	Interpolated grid theme contains a Euclidean distance from the village in NSW on spatial analyst	Royal Thai Survey Department (RTSD)
	Population density	2002–2013	Feature to raster on spatial analyst	National Statistical Office of Thailand
	Percentage of poverty	2002–2013	Feature to raster on spatial analyst	National Statistical Office of Thailand
etc.	National park and wildlife sanctuaries area	2000	Feature to raster on spatial analyst	the Department of National Parks, Wildlife and Plant Conservation, Thailand

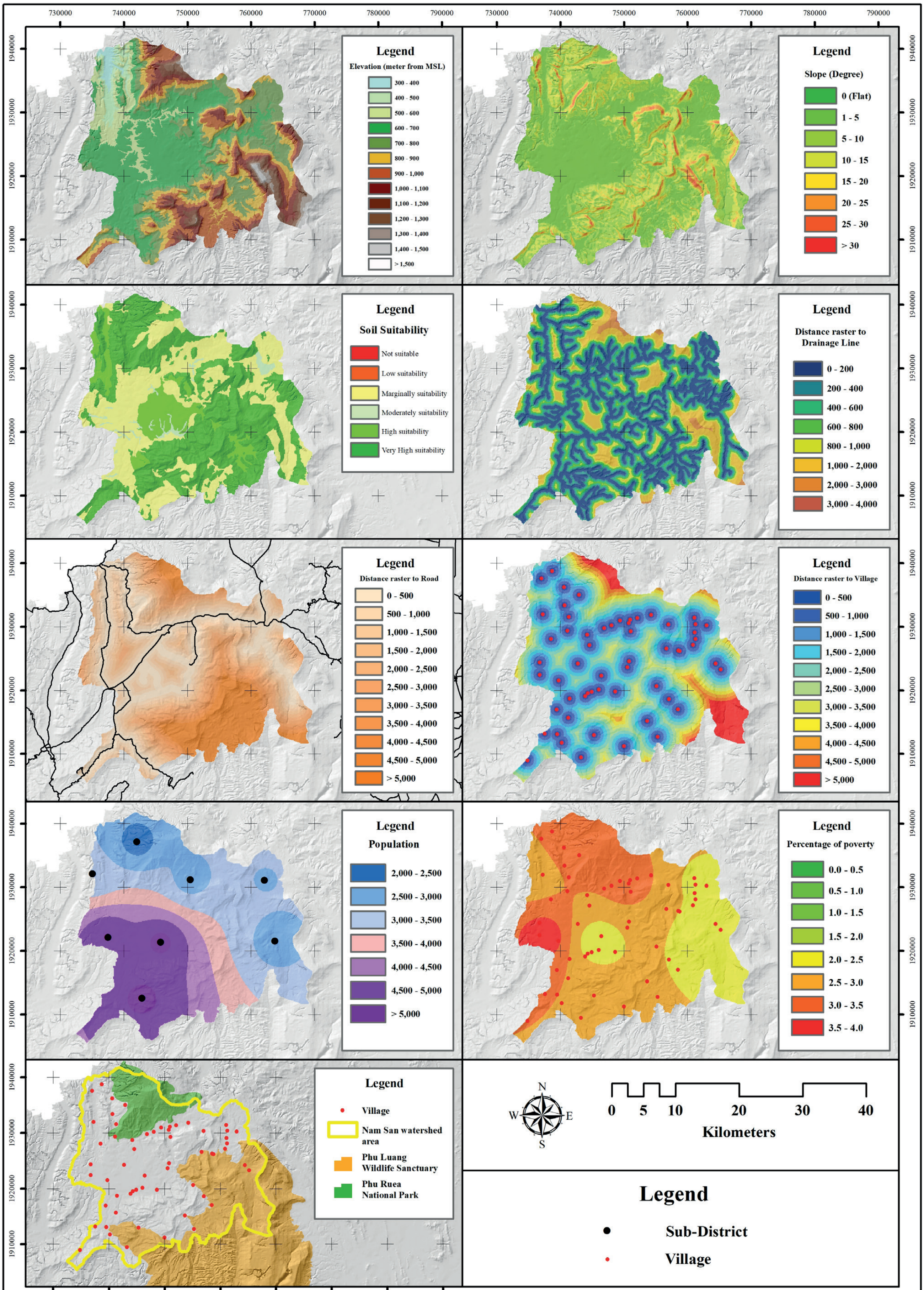

Fig. 2. Driving factors of LUC in the NSW area. a) elevation, b) slope, c) soil suitability, d) distance to stream, e) distance to road, f) distance to village, g) population density, h) income data and severity of population poverty, and i) National Park and Wildlife Sanctuary boundaries in the NSW area

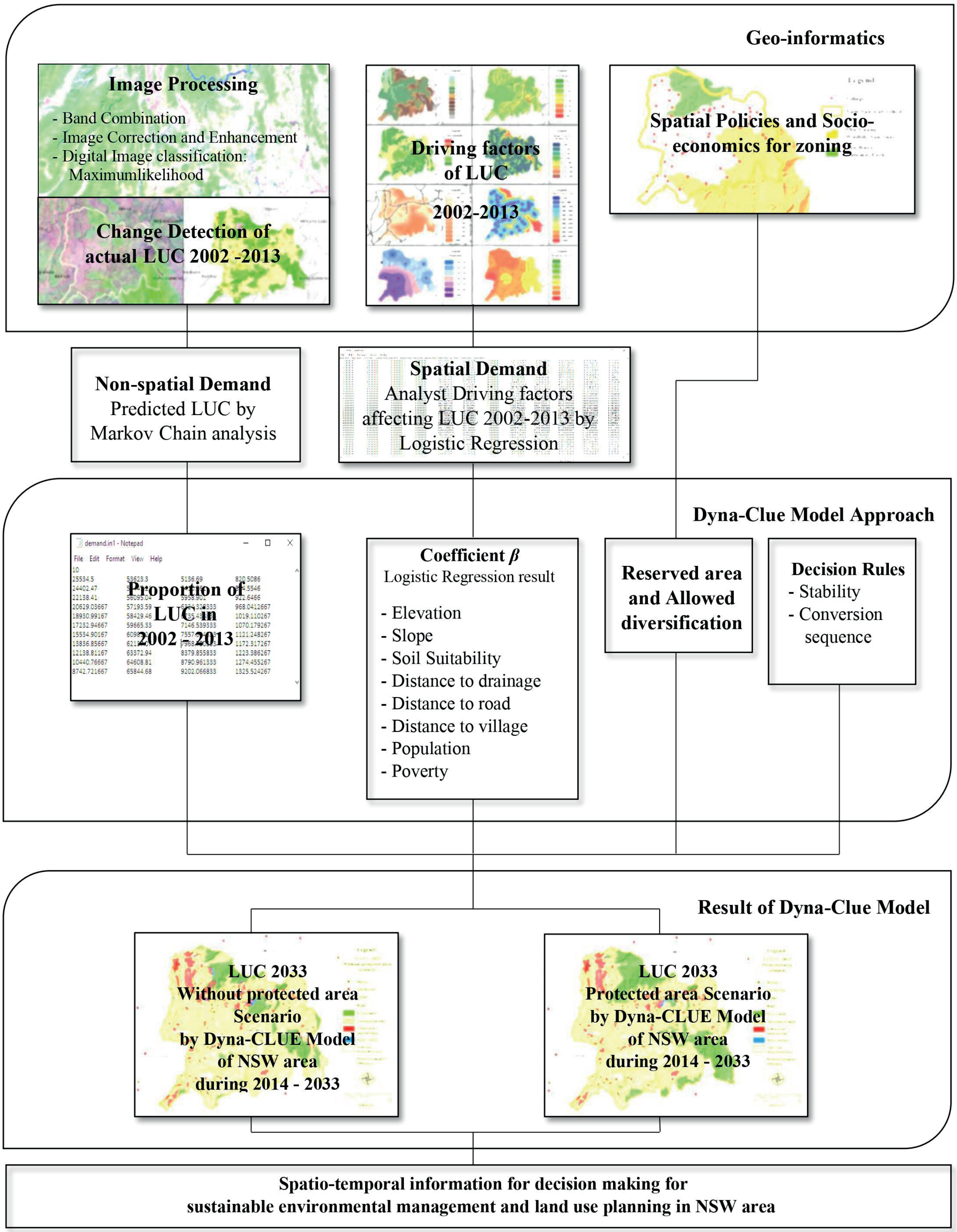

Fig. 3. Flowchart of the main methodology used in this research

Geoinformatics approach

Data in different bands from each of the Landsat satellite images were combined in three-channels red, green and blue (R:G:B). Band combination 543 corresponds to the R:G:B for Landsat 5 TM and Landsat 7 ETM+, where red is band 5 (short-wavelength infrared), green is band 4 (near-infrared), and blue is band 3. Similarly, band combination 654 including band 6 (short-wavelength infrared), band 5 (near-infrared), and band 4 was used for Landsat 8 OLI/TIRS as the R:G:B. Both band combinations 543 and 654 clearly demonstrate the extent of forest area, agricultural area and urban/built-up area (Barsi et al. 2014; U.S. Geological Survey 2014). Landsat images received enhanced contrast using a histogram equalization approach for further interpretation of the land-use. Then, the land-use map in the study area as well as field-survey data were used to verify the accuracy of LUC, the researcher collected data in several sampling points to use in the next steps for an accuracy assessment of the land-use classifications.

For image classification, a maximum likelihood algorithm (MLA) (Bakr et al. 2010; Foody and Mathur 2004; Richards and Jia 2006; Shalaby and Tateishi 2007; Waiyasusri et al. 2016) was applied to categorize the study area into four classes,

Table 3. Overall Accuracy Value and Kappa Coefficient (KHAT) for Accuracy of the Land-use Classification

KHAT Coefficient	Level of Accuracy
< 0	Unacceptable
0.01 – 0.40	Fair
0.41 – 0.60	Moderate
0.61 – 0.80	Good
0.81 – 1.00	Substantial

including agricultural (A), forest (F), water bodies (W) and urban/built up areas (U). This method used the training points from both the Landsat images and field surveys during the GPS-assisted field campaigns. First, 250 sampling ground control points were selected from all the classes (80 points from each of the A, F and U classes, and 10 points from W class) by choosing the regions of interest (ROIs) using ArcMap version 10.2 software, which contained the true samples that represent these classes. Then the study area was classified into four classes using the MLA to produce a land-use map for each Landsat image in the NSW area. In this study, Overall Accuracy values and Kappa coefficients (KHAT) were used to assess the accuracy of classification for each class, as shown in Table 3 (Jensen and Kiefer 2007; Poursanidis et al. 2015).

Dyna-CLUE model approach

The Dynamic land-use change model (Dyna-CLUE model) (Verburg and Overmars 2009; Verburg et al. 2002) is effective in eventual land-use modeling to determine LUC and affecting factors in the future which can apply to the mountainous areas (Cheng et al. 2019). In this research, the Dyna-CLUE Model has been simulated with two scenarios for the next 20 years: without (Scenario 1) and with (Scenario 2) a reservation area for land-use monitoring, in order to project the effect of urbanization and the direction of land-use dynamics into the future. The reference case scenario was based on the socio-economic trends from the past period (2002-2013). The forecasting case was based on the two simulation scenarios for the future period (2014-2033). There are two important modules in the Dyna-CLUE model: a non-spatial demand module and a spatially explicit allocation module (Fig. 4). For non-spatial demand, we used Markov chain analysis, which is a random process explaining certain types of conditions that change in sequential steps through the land-use geospatial dataset. The Markov chain can bring up a dynamic ratio of the past to the present year of the study, and then calculate it into a table matrix to determine the demand of LUC in the future. The results represent the proportion of land-use types in the future according to the study period (Guan et al. 2011). The likelihood of change from class i to class j in t time moment is shown as Equations 1 and 2.

$$P_{i,j} \times i_t = i_{t+1} \quad (1)$$

$$\begin{pmatrix} P_{UU}P_{UA}P_{UW} \\ P_{AU}P_{AA}P_{AW} \\ P_{WU}P_{WA}P_{WW} \\ P_{FU}P_{FA}P_{FW} \end{pmatrix} \begin{bmatrix} U_t \\ A_t \\ W_t \\ F_t \end{bmatrix} = \begin{bmatrix} U_{t+1} \\ A_{t+1} \\ W_{t+1} \\ F_{t+1} \end{bmatrix} \quad (2)$$

where

t : Time (Year)

$P_{i,j}$: Transition Probability Matrix (TPM) of the land-use class i change to class j

$_i$ and $_j$: the land-use class in the first year and the second year, respectively

The results of the demand module were used as input for the spatial allocation module of the Dyna-CLUE model (Verburg and Overmars 2009). Then, the Markov chain analysis was used to determine the demand for the probability of each land-use pattern, where the probability of transition (Pi, j) is given for every ordered set of conditions. In a Markov chain with a limited number of conditions, such as j, a new transition probability matrix is bounded, as in Equation 3 (Waiyasusri et al. 2016).

$$V_j \times P_{ij} = [V_1, V_2, V_3, \ldots V_n,] \begin{bmatrix} P_{1,1}P_{1,2}P_{1,3}\ldots P_{1,n} \\ P_{2,1}P_{2,2}P_{2,3}\ldots P_{2,n} \\ P_{3,1}P_{3,2}P_{3,3}\ldots P_{3,n} \\ \ldots\ \ldots\ \ldots\ \ \ldots \\ P_{n,1}P_{n,2}P_{n,3}\ldots P_{n,n} \end{bmatrix} \quad (3)$$

Where

$V_j \times P_{jk}$: Proportion of land-use in the second year

$P_{j,k}$: Land-use activity (f) derived from the TPM

V_j : Proportion of land-use in the first year

The Markov chain model is a tool that can quickly and

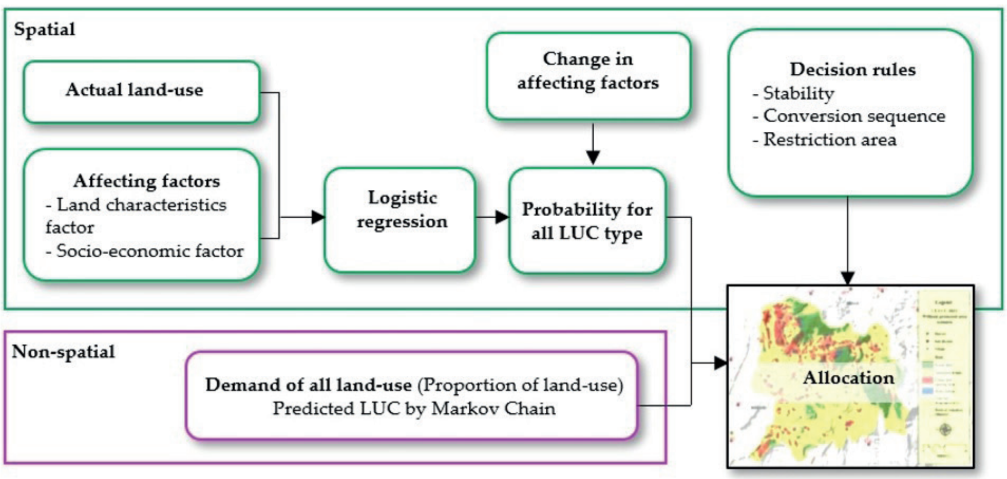

Fig. 4. The Dyna-CLUE model structure. (Adapted from (Verburg et al. 2002))

efficiently analyze land-use ratios in the future. The highlight of this model is that it uses land-use ratios for the reference year to predict the potential distribution of the land use types in the study area which may occur in the future.

Even though the Markov chain model itself can forecast the dynamic of LUC in the future, it has some restrictions, particularly in its ability to provide accurate spatial analysis or identify factors affecting land-use (Guang et al. 2017). Thus, it requires another empirical model like the Dyna-CLUE model to calculate future land-use demand. The Dyna-CLUE model was developed to include different factors affecting land-use change into the analysis. Generally, the main factors affecting LUC are physical factors (Elevation, Slope, Soil Suitability, Distance to stream) and socio-economic factors (Distance to road, Distance to village, population density, income data and population poverty) (Geist and Lambin 2002; Lambin and Meyfroidt 2010). The selection of factors was made based on Lambin and Meyfroidt (2010) study which concluded that these 8 factors that directly affect changes in land use in tropical rainforests, where also the NSW is located. The Dyna-CLUE model runs based on statistical analysis and logistic regression analysis of the factors affecting LUC on a pixel per pixel level for both future reservation area scenarios (Liu et al. 2014; Trisurat et al. 2010). The location preferences of the different land-use types were quantified by the Dyna-CLUE model based on logistic regression models. The relation between the occurrence of a land-use type and the physical and socio-economic factors of a specific location indicate the preference for a specific type of land-use by logit models. The distribution of land-use types is expressed using a binary numeral system with labels 0 (no transition) and 1 (with transition). Equation 4 is a stepwise logistic regression which was used to evaluate the relationship between the land-use and its affecting factors.

$$Log\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 x_{1,i} + \beta_2 x_{2,1} + \ldots + \beta_n x_{n,i} \tag{4}$$

where
P_i : The land-use change probability
x_i : Independent factors
ß : Coefficient value of each independent factor

The relation between the factors affecting each type of LUC was also obtained, moreover, its accuracy was assessed using Relative Operating Characteristic (ROC) (Pontius and Schneider 2001). The ROC value was used to obtain the reliability of the logistic regression results. ROC values vary between 0 and 1: ROC values between 0.5 and 0.7 indicate that the forecasting results are of low accuracy; ROC values between 0.7 and 0.9, indicate that the forecasting results are excellent; with ROC value > 0.9, the model has high precision. In the Dyna-CLUE model, after the land-use change probability, coefficient and relative elasticity are assigned, LUC is assessed through the determination of ROC for all grid cells. The total probability (TPROPi,u) is calculated for each grid cell i and each of the land-use types u, as shown in the equation below (Verburg et al. 1999).

$$TPROPi,u = Pi,u + ELASu = ITERu \tag{5}$$

Where
ITERu : Iteration variable of a specific land-use
ELASu : Relative elasticity for change specified in the decision rules and is only given a value if grid cell i is already under land-use type u in the year considered.

Dynamic Annual Change of LUC

Dynamic LUC in the NSW area in 2002, 2007 and 2013 was analyzed using the Supervised Classification technique and by reclassifying the land-use data in a raster format to obtain the results. Using a spatial analysis method of classified and tabulated data in the NSW area, the results are obtained for the period from 2002 to 2013 using a cross-classification application. Estimation of LUC was used for specifying the transition among land-use classes and for quantifying the different rates and magnitudes of these changes. Equation 6 is used for evaluating the annual change in land-use (Jia K. et al. 2014).

$$\Delta = \frac{\left(\frac{A_2 - A_1}{A_1} \times 100\right)}{(T_2 - T_1)} \tag{6}$$

where
D : Average annual rate of change (%)
A_1 : Amount of a land-use type at time 1 (T1)
A_2 : Amount of a land-use type at time 2 (T2).

RESULTS

Dynamics of LUC in the NSW area

The image classification analysis for 2002, 2007 and 2013 were reclassified into four classes (100x100 raster grid resolution), as displayed in Fig. 5. Table 4 shows the quantitative data for each land-use class for each year. The overall accuracy assessment was at 84.3, 76.5 and 75.9% for 2013, 2007 and 2002, respectively, with a kappa coefficient (KHAT) of 0.81, 0.73 and 0.71, respectively. The total area with observed land-use change in the NSW from 2002 to 2013 was equal to 258.52 km² (30.37% of the total area). Table 5 illustrates a matrix of the various LUC classes in the NSW from years 2002 to 2013. The results reveal that forests have suffered the highest loss, at 113.17 km^2. Even though there is a new-growth forest of 23.04 km^2 under a public awareness campaign, the forest decline has continued throughout the past ten years (Royal Forest Department Resources 2016). Fig. 6 shows LUC from 2002 to 2013, which confirms deforestation in the NSW, while the area of urban/build-up, agricultural land and water bodies has increased by 92.36, 16.04 and 4.77 km^2, respectively.

Factors that caused LUC in the NSW area

All 8 factors (physical and socio-economic) affecting the land-use patterns were analyzed one cell at a time to find the most important parameter for the LUC using a statistical regression equation. The results were classified into four land-use classes and displayed with a value of β coefficient in logistic regression analysis (Table 6). A positive value of the β coefficient indicates a positive correlation, whereas a negative value of the β coefficient indicates a negative correlation. We used the ROC to indicate the reliability of the affecting factors resulting from the Dyna-CLUE model. To demonstrate a probability level of %ROC, a comparison between the results and the observed values was performed. ROC above 0.5 was better than random (Pontius and Schneider 2001). As shown in Table 6, we obtained ROC values of 0.827 (forest), 0.791 (agricultural), 0.873 (urban/built-up lands) and 0.773 (water bodies). In all classes, the ROC value was more than 0.7, which indicates that the spatial distribution of all classes of land-use was explained well by the selected affecting factors.

All variables are significant at p < 0.01 entry and p > 0.02 removal levels, except for those marked * (not statistically significant). ROC is a relative operating characteristic.

The β coefficient value in Table 6 shows that the forest area is mainly affected by soil suitability and slope. When

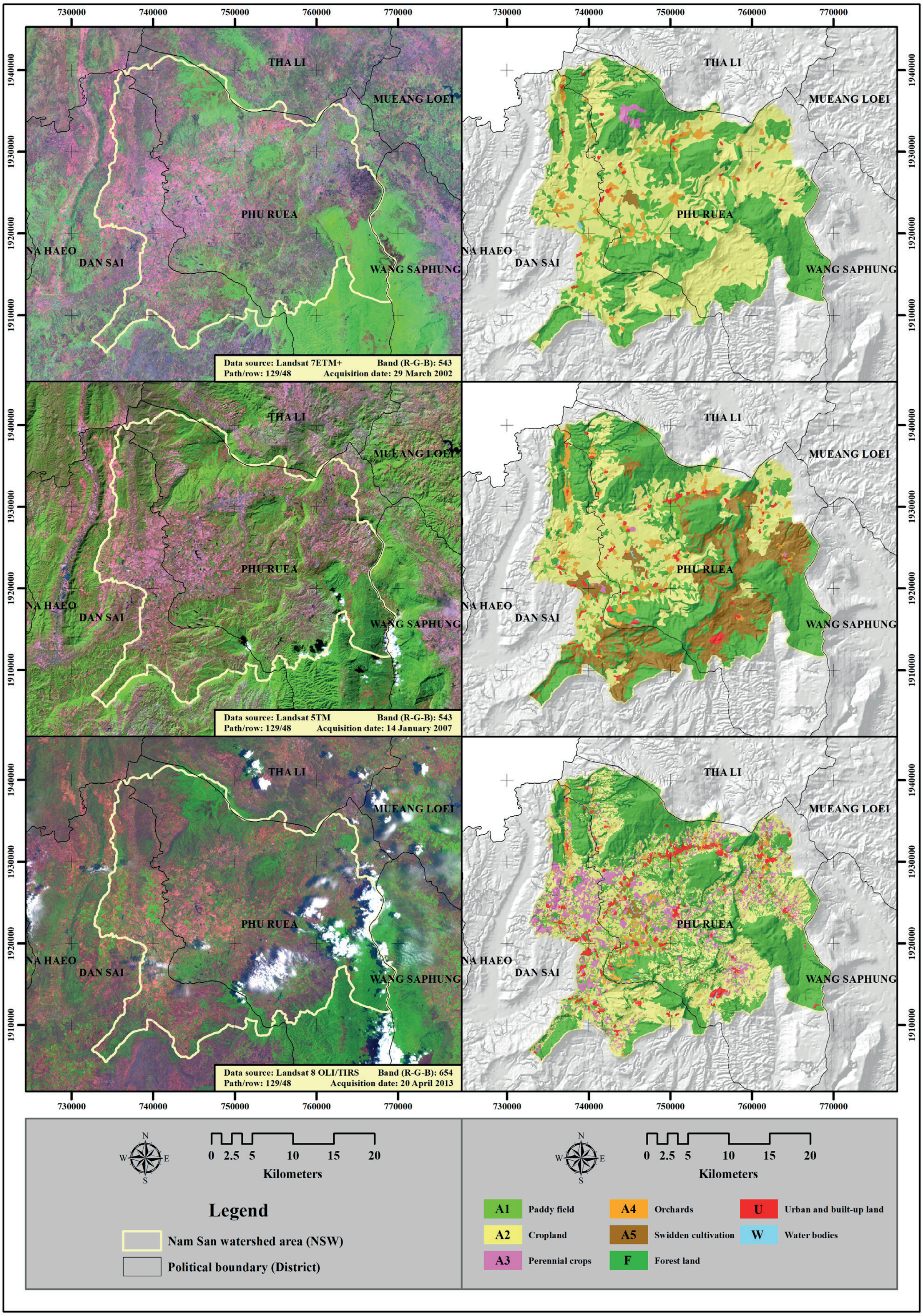

Fig. 5. Land-use pattern and Landsat 5TM (band combination 543), Landsat 7ETM+ (band combination 543), and Landsat 8OLI/TIRS (band combination 654) satellite image of the NSW area for (a, b) 2002, (c, d) 2007 and (e, f) 2013; (a, c, e) shows land-use patterns and (b, d, f) shows satellite images. Land-use codes as shown in Table 4

Table 4. Comparison of land-use in the NSW area, as derived from the Landsat 5TM, Landsat 7ETM+ and Landsat 8 OLI/TIRS satellite images in 2002, 2007 and 2013

Land-use (code)		2002		2007		2013	
Level I	Level II	km^2	%	km^2	%	km^2	%
Agricultural (A)	Paddy field (A1)	26.40	3.10	27.61	3.24	31.92	3.75
	Field crops (A2)	406.54	47.76	339.93	39.94	303.02	35.60
	Perennial crops (A3)	4.87	0.57	63.96	7.51	86.14	10.12
	Orchards (A4)	25.49	2.99	33.91	3.98	33.15	3.89
	Horticultural (A5)	2.74	0.32	9.49	1.11	7.85	0.92
	Total	466.04	54.74	474.90	55.78	462.08	54.28
Forest (F)		380.40	44.69	353.33	41.51	357.23	41.97
Water bodies (W)		0.37	0.04	4.81	0.57	5.14	0.06
Urban/built up (U)		4.34	0.51	18.11	2.13	26.70	3.14
Total		851.15	100.00	851.15	100.00	851.15	100.00

Table 5. Matrix of land-use changes in the NSW area, 2002–2013 (km^2)

		2013					Changing areas
	Land-use	Forest land	Agricultural land	Urban/built-up land	Water bodies	Total	
2002	Forest land	244.19	130.77	3.92	1.52	380.40	-113.17
	Agricultural land	22.24	348.00	92.27	3.53	446.04	+16.04
	Urban/built-up land	0.75	3.06	0.44	0.09	4.34	+92.36
	Water bodies	0.05	0.25	0.07	0.00	0.37	+4.77
	Total	267.23	482.08	96.70	5.14	851.15	

Table 6. Logistic regression analysis of the land-use patterns and affecting factors

Variable	Land-use pattern			
	β Forest	β Agricultural	β Urban/ built-up	β Water bodies
Elevation	0.0025	-0.0036	*	-0.0002
Slope	-0.1172	0.0881	-0.1591	0.2727
Soil Suitability	0.1364	0.2891	*	*
Distance to drainage	0.0018	-0.0017	*	0.0004
Distance to road	-0.1009	0.0008	0.8113	*
Distance village	-0.0008	0.1005	0.0028	*
Population	-0.0004	0.0009	0.0061	*
Poverty	-0.0007	-0.0965	0.7035	*
Constant	-4.8052	4.443	-2.758	-3.768
ROC value	0.827	0.791	0.873	0.773

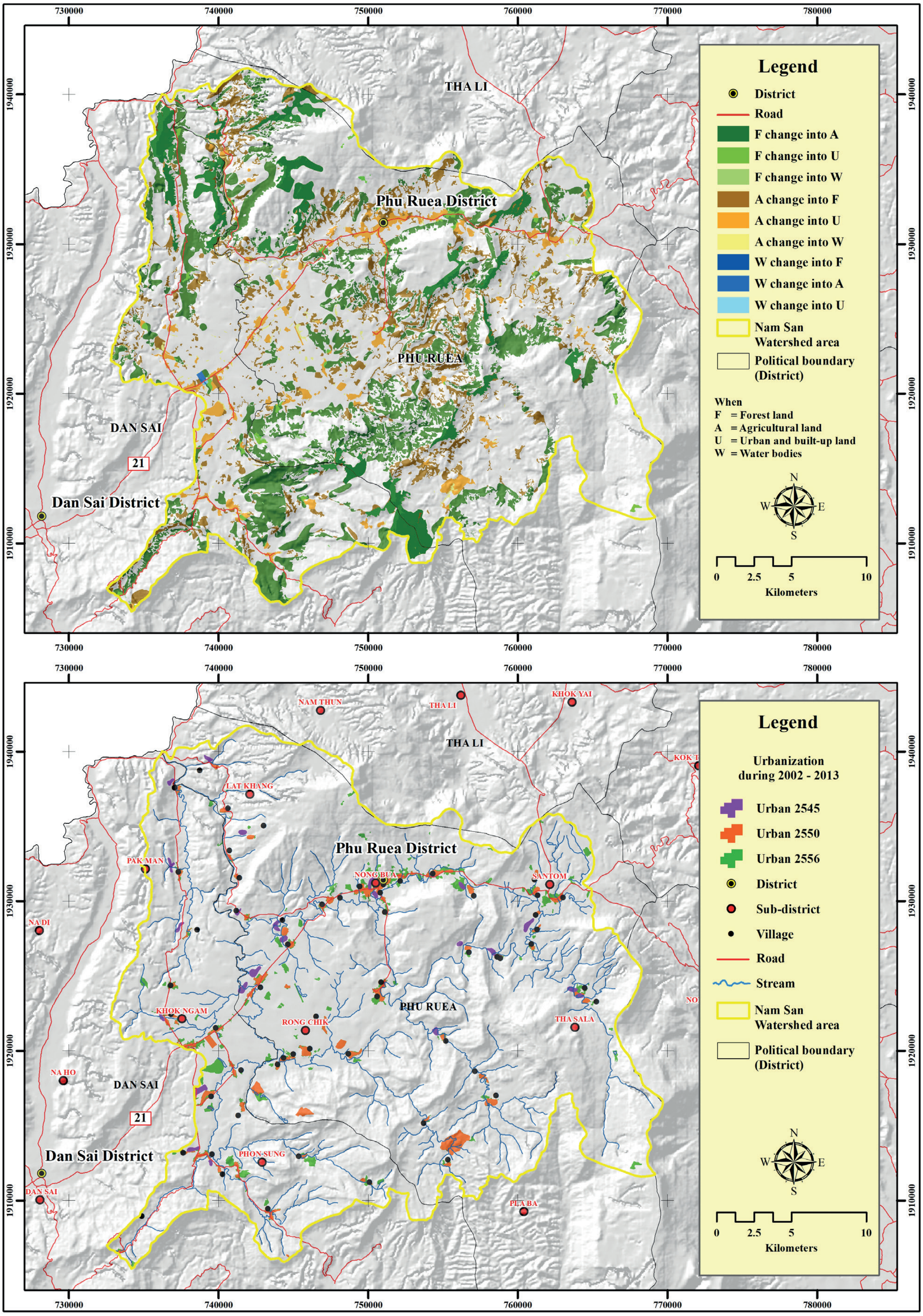

Fig. 6. Map of the land-use change dynamics from 2002 to 2013 in the NSW area, Loei Province (6a). Urbanization expansion map during 2002–2013 in the NSW area, Loei Province (6b)

soil suitability adds a one-unit change, the probability of forest area change increases by 13.64%. Soil suitability is secondary data from the analysis of soil taxonomy method (Boonsompopphan et al. 2008) obtained from the Department of Land Development, it has been analyzed and accepted at the national level. Therefore, it can be considered as an effective parameter for the model and one of the most important factors that affect the expansion of forest areas with a probability of up to 13.64%. Whereas, if slope adds a one-unit change, the probability of a forest area change decreases by 11.72%. This indicates that forest areas are characterized by abundant soil and high steepness topography. For agricultural areas, the factor of soil suitability was also found to affect its expansion by 28.91%, and the effect of distance to village factor was at 10.05%. Moreover, this indicates that factors affecting agricultural areas and forested areas tend to go in the opposite direction, which correlates with Table 6 presenting how most of the NSW area has changed into an agricultural area. For urban/built up areas, the most important factors were distance to a road and poverty factors; distance to a road influences an increase of urban/built up land with a probability of 81.13%, the second factor was poverty, affecting 70.35%. These indicate that urban development and facilities have expanded along transportation routes, and poverty has had a tendency to decrease through all previous 20 years, resulting in a higher income of inhabitants of the watershed. This has led to changes in the way of life for some families, who switched from agricultural occupations to tourism and service businesses such as opening their own shops.

Table 7. Demand area of future land-use (km^2)

Year	Land-use			
	Forest land	Agricultural land	Urban/ built up land	Water bodies
2014	265.91	483.32	96.44	5.48
2015	264.59	483.56	97.18	5.82
2016	263.27	484.46	97.26	6.16
2017	261.95	485.20	97.50	6.50
2018	260.63	485.94	97.74	6.84
2019	259.31	486.68	97.98	7.18
2020	257.99	487.42	98.22	7.52
2021	256.67	488.16	98.46	7.86
2022	255.35	488.90	98.70	8.21
2023	254.02	489.64	98.94	8.55
2024	252.70	490.38	99.18	8.89
2025	251.38	491.12	99.42	9.23
2026	250.06	491.86	99.66	9.57
2027	248.74	492.60	99.90	9.91
2028	247.42	493.33	100.14	10.25
2029	246.10	494.07	100.39	10.59
2030	244.78	494.81	100.63	10.93
2031	243.46	495.55	100.87	11.27
2032	242.14	496.29	101.11	11.61
2033	240.82	497.03	101.35	11.95

Table 8. Forecasting future deforestation using the Dyna-CLUE model, inside and outside reservation areas

Location	Forest area in 2013	Deforestation			
		Without a reservation area scenario 2033		Reservation area scenario 2033	
		km²	Decrease	km²	Decrease
Phu Ruea National Park	72.21	41.55	-30.66 (-42.46 %)	72.12	-0.09 (-0.13 %)
Phu Luang Wildlife Sanctuary	107.31	45.62	-61.69 (-57.49 %)	106.37	-0.94 (-0.88 %)
Outside reservation area	177.86	46.29	-131.57 (-73.98 %)	28.54	-149.32 (-83.96 %)

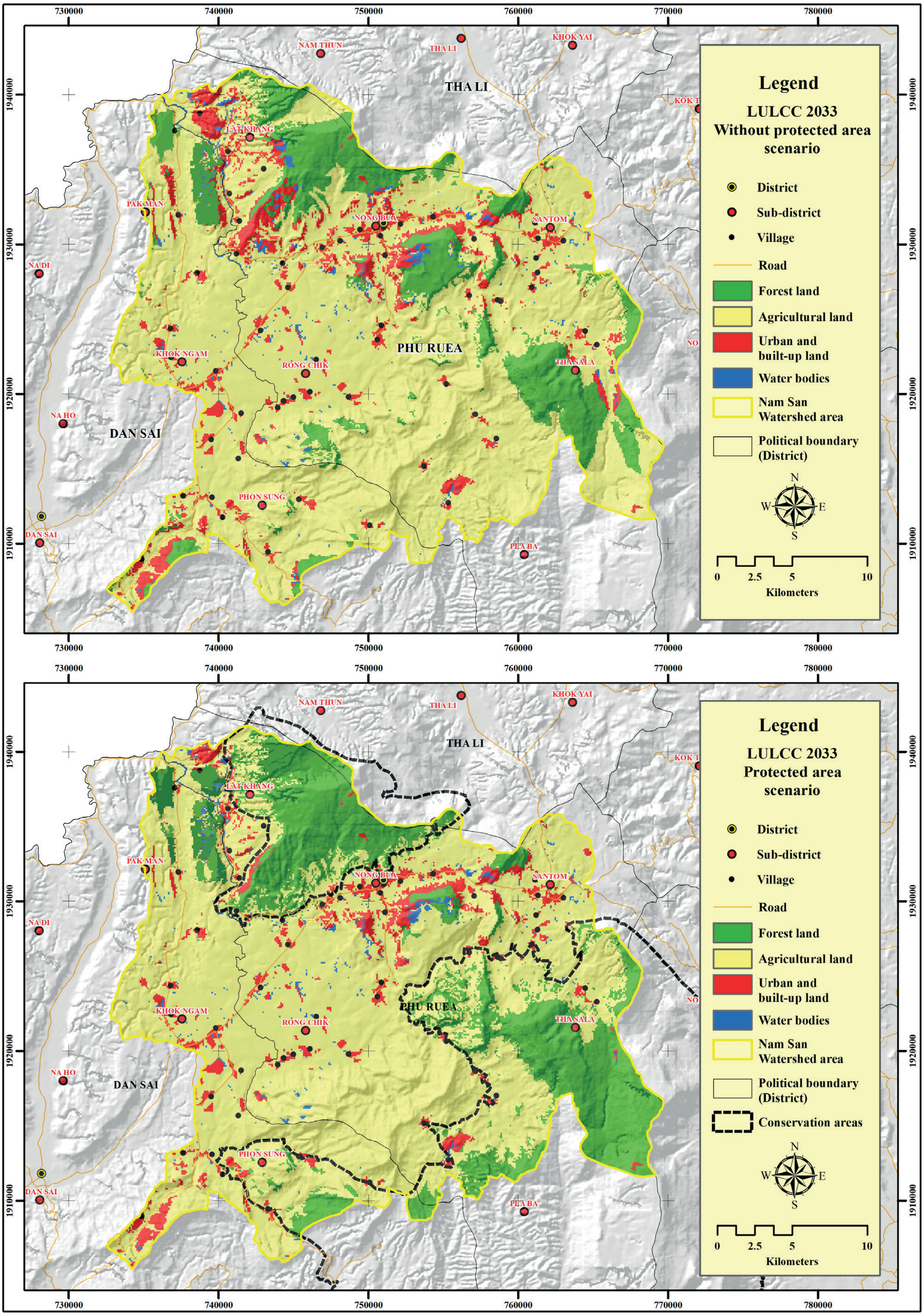

Fig. 7. Simulation results from the Dyna-CLUE model for the year 2020: without reservation area scenario (upper) and with reservation area scenario (lower)

Anyhow, the logistic regression analysis demonstrated the affecting factors of LUC indicating by the β coefficient value which are used as spatial information in the next topic.

Forecasting future land-use conditions to estimate possible land-use patterns in the NSW area

The Dyna-CLUE model has been used to simulate land-use in the future under 2 simulation scenarios: with, and without, a reservation area in the NSW from the year 2014 to 2033, as shown in Fig. 7. In addition, Markov chain analysis found the proportion of land-use change (Demand of all land-use) for 2014–2033; when inputting models with the results in Table 7. We found the tendency of the forest area ratio to decrease by 0.546% on average, while the ratio of water bodies, urban and agricultural areas tended to increase by 0.045%, 0.025% and 0.001%, respectively.

Scenario 1: without reservation area

Results of the land-use simulation in Scenario 1: without a reservation area in 2033, was compared with the land-use in 2013. The comparison showed that the north region of the NSW area is sensitive to the change in the proportion of the land-use types, as the forest area reduces from 31.47% to 28.30% due to agricultural expansion, which covers 58.40% of all the watershed area. This is especially true for the forests in Phu Luang Wildlife Sanctuary and Phu Ruea National Park, which have rapidly decreased from 107.31 km^2 to 45.62 km2, and from 72.21 km2 to 41.55 km^2, respectively (Table 8). Moreover, urbanization also occurs as the area of urban/built-up land expands from 11.36% in 2013 to 11.91% in 2033. Concerning the affecting factors (Table 6), induced agricultural and urbanization expansion occurs in Nong Bua Sub-district, Khok Ngam Sub-district, and Lat Khang Sub-district, but especially in Nong Bua Sub-district with the highest rate of urban expansion being observed in Phu Ruea district. This results from the role it has as a trading, services and tourism center due to its location near recreation areas such as Phu Luang Wildlife Sanctuary and Phu Ruea National Park and their businesses of tourism, hotels and resorts.

Scenario 2: with reservation area

In Scenario 2: with reservation area, the obvious restriction of the national park and wildlife sanctuary border in the watershed was set into the Dyna-CLUE model. The results of the model indicate that forested areas in the national park and wildlife sanctuary are well-protected (Table 8). On the other hand, for the land outside the reservation area the model shows a decrease of forest area by 83.96% in the middle of the watershed, from 177.86 km^2 in 2013 to 28.54 km^2 in 2033. The results indicate that distance to the village and steepness of the mountain range are major and minor affecting factors of forest decline. The areas with high steep mountains, mainly around cuesta mountain, and tableland are the dominant types of topography in the southeast section of the NSW.

Finally, evaluation of the model results was done by comparing the simulated map from the Dyna-CLUE model with the actual map derived from the LDD that was surveyed in 2016 to obtain the overall accuracy and the kappa coefficient value. We found that results from the spatio-temporal model in Scenario 1 had overall accuracy of 0.8421, and a kappa coefficient value at level 0.8178. Whereas, the result of the spatio-temporal model in Scenario 2 had an overall accuracy of 0.8368 and a kappa coefficient value of 0.8073. This indicates that simulations of both scenarios are in substantial agreement. In addition, simulation of LUC using this model allows to make a long-term projection, such as for the next 20 years (2014-2033), as shown in Fig. 8. The simulation results could be essential information for making decisions on land-use planning and monitoring deforestation in the NSW.

DISSCUSSION

Deforestation in the NSW area during 2002–2013

There were LUC in the NSW from 2002 to 2013, the results show a decrease of the southern forest area in a corridor pattern near the Dan Sai district, Loei Province, in an area characterized by piedmont topography and flatland valleys. Urban and agricultural land also expanded into the eastern forest and some of the reservation areas in a patchy pattern near Phu Luang Wildlife Sanctuary, around San Tom Sub-district, Tha Sala Sub-district, and Rong Chik Sub-district, as well as near Phu Ruea National Park, around Nong Bua Sub-district and Lat Khang Sub-district. Because that area is characterized by cuesta mountains, there is a higher population density, which has contributed to a loss of forest area at a higher rate. In winter, there are commercial crops such as corn, rubber and others, which are found in the eastern part of the NSW area. Moreover, urban expansion is found in particular in the regions of the road network growth, especially along the highway no. 21, which connects Dan Sai district and Phu Ruea district. Regarding the support of tourism businesses, land development includes new community areas, built-up hotels and resorts. In the NSW, the rapid expansion of urban areas and agriculture has taken place over the last 10 years. This result is in contrast to a study of LUC in Bhutan during 1990–2010 (Gilani et al. 2015), which found that overall forest area increased with an average annual rate of 59 km^2/year (0.22%) within the reservation areas and biological corridors as well as outside of those territories. Moreover, their results showed that the forest changed to another type of land-use when urban area expanded around a reservation area. This can be found all over Thailand and Southeast Asia where there is a valley landform (Geist and Lambin 2002; Trisurat et al. 2019; Verburg and Veldkamp 2004). It is possible that all 3 types of land-use can be transformed into forest areas. Due to the NSW watershed campaign to create teak plantations, the agricultural area has been transformed into a protected forest area (Komaki et al. 2012) and forest areas near the national park and wildlife sanctuaries are being restored due to the forest fires, replacing the water resources, communities, and agricultural areas. There is a forest fire prevention, reforestation and development project for community forest conservation (Konpian et al. 2020), which however only slightly affects the NSW area, only 22.24 km^2.

Driving factors of deforestation and LUC in the NSW

Deforestation within the NSW area was caused by the expansion of agricultural land and urban expansion. The results indicate that slope and distance to a road are important factors driving agricultural and urban expansion. The study of β coefficient value shows that forest area is mainly affected by the slope factor that diminishes (Royal Forest Department, 2007) The most sensitive area for change often corresponds to the watershed classification class 1, 2 and 3 respectively, especially watershed classes 2 and 3 with only 35-50% and 25-35% slopes (Chunkao 2008), which are sensitive to changes in forest areas in the NSW watershed, where land-use patterns are changed to rubber, corn and

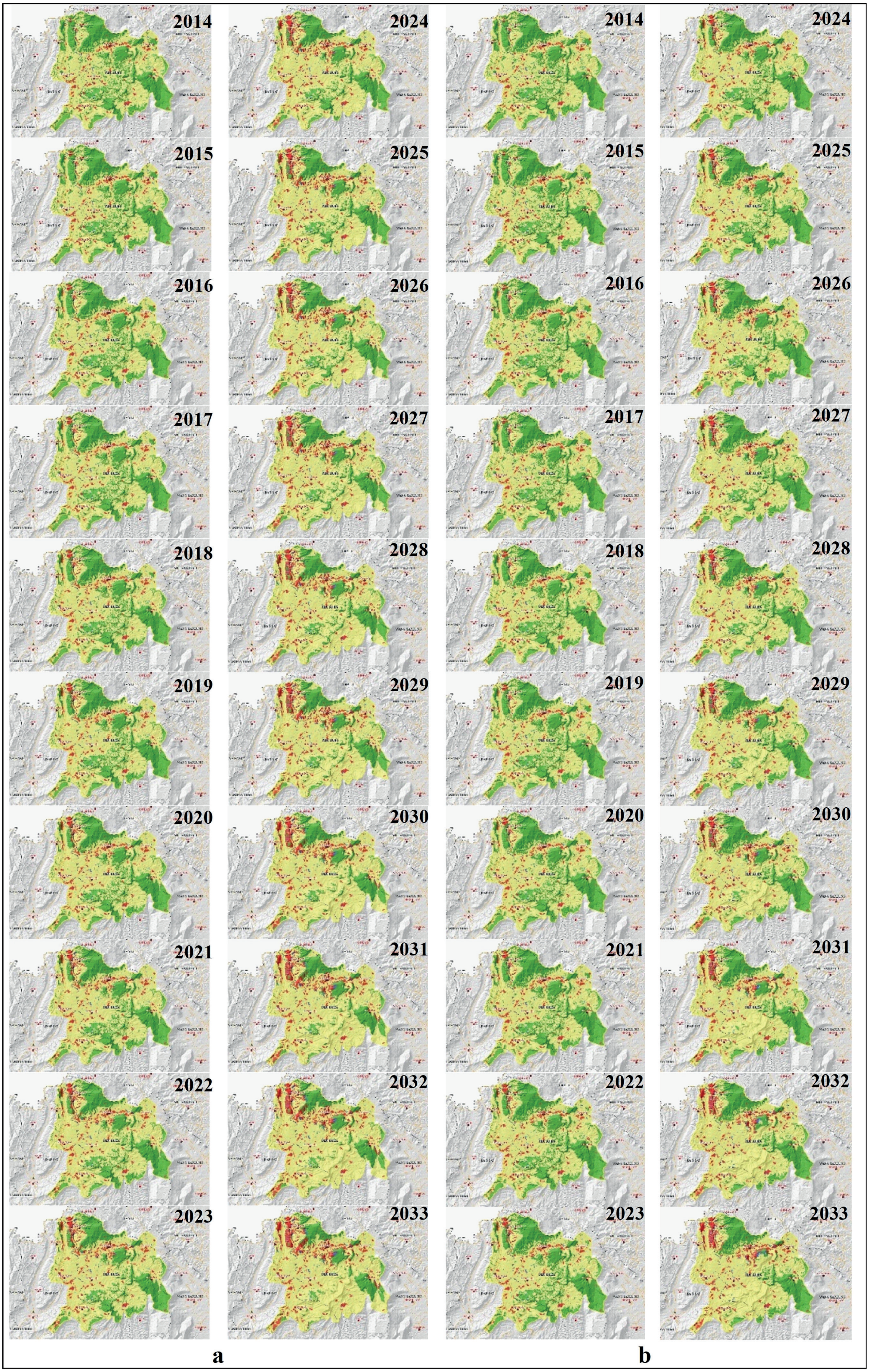

Fig. 8. Spatial allocation maps from 2013–2032 with a reservation area scenario (a) and without a reservation area scenario (b) by Dyna-CLUE model for decision-making on land-use planning and sustainable development in the NSW area

orchards. Meanwhile, Waiyasusri et al. (2016) found LUC in Huai Thap Salao Watershed area, Uthaithani Province, Thailand trend towards an increase in the forest area driven by the slope factor, which can be explained by the geology and topography of the area as it includes a granite mountain with high slopes. The NSW, however, contains sandstone mountains with cuesta mountain formations and lower slopes, which makes it easier for agricultural and urban areas to expand. This deforestation characteristic can be found in the east and northern regions of Thailand, particularly Chiang Mai and Chiang Rai (Tabor et al. 2018). A secondary driving factor is a distance from a village, which has a direct effect on agricultural land change because most communities in NSW are farmers. The area close to the community is, therefore, an agricultural ground, with most of the land being planted with rice and corn. Today, however, the expansion of agricultural land is observed closer to the park area, which is mostly occupied by rubber because it is an commercial plant. This results in an increasing deforestation rate. Similarly, results by Trisurat et al. (2010) found that in north Thailand LUC is driven by slope, distance to a road and distance to a village, especially along the highway no. 21, where mixed forest and deciduous dipterocarp forest has rapidly been decimated, which was shown in a report by Royal Forest Department (2016). Additionally, rock and topography types are minor driving factors, particularly in the NSW where sedimentary rock is mostly found in lowlands and alluvial landforms. Since suitability of the soil in the NSW is only at a moderate level due to winter crop farming. The forested areas' decreasing trend is growing every year due to the replacement of forests by agricultural fields with cultures like corn, cassava and sugar cane. In contrast to a study by Santiphop et al. (2012), it was found that most cash crops are grown in the upland areas rather than in the lowland areas as there do not get submerged.

Sensitivity of reservation area to deforestation in the future

Continuous deforestation over the past few decades has caused rapid LUC in the NSW. Most of the reservation areas in Thailand has changed to agricultural fields, which are used to grow rubber trees and winter crops (Trisurat et al. 2019). Regarding the study area, deforestation has dominated in the central and southern parts of the NSW where the upstream forest is located. Therefore, the Dyna-CLUE model employed two land-use scenarios in this study to test the sensitivity of reservation areas to deforestation patterns in the NSW over the next twenty years. Different deforestation patterns under two scenarios were shown, the results of Scenario 1 indicated large forest area loss spreading throughout the NSW due to the extension of city areas, which was observed mostly along the edge of forested areas (hotels and resorts in Thailand are often built there because of the good location and low land prices) (Clements et al. 2014). On the other hand, Scenario 2 showed a forest area loss of 83.96 % outside the reservation area, but inside the reservation area, the forest was preserved. Regarding the results, the edge of forest areas should be the first point of concern (Gilani et al. 2015). It is important for policy makers to know how future deforestation will happen, and what actions need to be taken to restrict future LUC in the NSW by enforcing local laws and regulations, following the Thai government's strategy to encourage an increase in forest area by 15% overall in Thailand, especially in reservation areas (Royal Forest Department Resources 2007; Royal Forest Department Resources 2016). However, the spatial and socio-economic factors that affect forest area changes in NSW also affect temperature changes in that region, it is estimated that the mean temperature in Thailand would rise by 2.0. – 5.5 ° C under the HadCM3 A2 scenario (IPCC 2007). Under the current climate change situation, National Mitigation/Adaptation Plans and Policies should be implemented in watershed planning by the local authorities throughout the assessment, policy making, and implementation steps (Dastgerdi et al. 2020) to deal with disasters that may occur in the NSW.

This research shows the sensitivity of the reservation area to future deforestation in the NSW and reveals the importance of providing the biological reservation area to ensure environmental resilience. In addition, Dastgerdi et al. (2020) laid out constructive strategic guidelines for sustainable environmental management in the Umbria Region in Italy which solve the environmental problems by cooperation between local community networks such as local residents, concerned government agencies, and stakeholders. The relevant departments will develop skills and find support markets to add value to agricultural products. This will enable farmers living near the reservation area to have a better life in harmony with nature by cooperating to protect the forest area and sustainably reducing forest encroachment. They also highlight that sustainable management requires the integration of an inclusive effort in the social, economic, and environmental policies with regional plans.

CONCLUSIONS

The NSW is located in northeastern Thailand near the Thai-Laos border crossing point which is abundant with natural and environmental resources. The public authority has defined 2 conservation areas, Phu Ruea National Park and Phu Luang Wildlife Sanctuary. Over the years, forest area has decreased by 70.25% and was mostly replaced by agricultural area such as cropland (corn or sugar cane) and perennial plants such as rubber trees. Moreover, the local government authorities have improved transportation routes to allow more efficient access in order to support agricultural industries and transportation of agricultural products. This has continuously decreased the value of the slope and distance to a road factor.

Results from the 2 model scenarios - with, and without, reservation area, describe the context of what could happen in the future in the NSW area. Various factors affecting the area are taken into account, which allows to effectively indicate sensitive areas of dynamic land-use. This allows to describe the agricultural expansion and urbanization in the areas of Lat Khang sub-district, Khok Ngam sub-district and Nong Bua sub-district all along the road, especially in Lat Khang sub-district where expansion is happening continuously. The expansion of local villages is appeared in the downstream area, with a piedmont topography characterized by lowland between valleys. Besides this subdistrict, there is a compromising point at the border where the people of 2 countries can enter and do trade. This can also easily affect the expansion of building areas in the future. For deforestation and agricultural expansion occurring by 2033, or throughout the next 20 years, we found that in the south of Lat Khang sub-district and the south of Nong Bua sub-district, in the scenario without a reservation area, forests occupied a wider area than in the scenario of reservation area. In other words, in the scenario without a reservation area, the expansion of urbanization and agriculture into Phu Ruea National Park is observed over a wider area up to the slope of sandstone mountains because of the low steepness of the area and its good accessibility via connected roads. The results of two model scenarios occurring in Nam San Watershed show that what is happening there should be a cause of great concern.

The results of the Dyna-CLUE model shown for the spatio-temporal dynamics land type were analyzed for the overall accuracy and kappa coefficient by comparing them with the data on actual land-use from 2016. The results show that for the scenario without a reservation area the criteria values of 0.8421 and 0.8178, and 0.8368 and 0.8073 for the reservation area scenario. This validation results confirm the good accuracy of the model. Besides, Dyna-CLUE model can show the future of land use patterns every year that are forecasted, which is a strong point of the model: simulation images through the study period spanning the next 20 years (2014–2033), as shown in Fig. 8. However, this research only shows validation of the model for the year 2016 because of a limitation of available validation data at the Land Development Department, which in the present is only collected once every 2 years. However, studying land-use requires continuous monitoring of the LUC information in this study area, as well as greater frequency of study and more validation to ensure the accuracy of the model to examine the trends of land-use change. Availability of the observations in the actual area and understanding the context of each watershed, especially regarding factors that determine physical characteristics of the watershed and socio-economic factors, before bringing the model in is also very significant. Regarding this study, the analysis of the LUC is necessary to understand the context of the physical change of the watershed. These results revealed the guidelines and conclusions on the future land use predictions that can be applied to other sub-watershed studies at both local and regional levels. Future approaches should study additional sub-watersheds in order to monitor areas sensitive to changes in deforestation that may occur in other watersheds. Because watershed areas are extremely important and affecting watershed systems might lead to the more frequent disaster events, it is necessary to define reservation areas to be concrete and create an empirical database for the conservation of watershed areas in the future.

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