

INTEGRATION OF GEOSPATIAL MODELS FOR THE ALLOCATION OF DEFORESTATION HOTSPOTS AND FOREST PROTECTION UNITS

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Abstract

Geospatial models play an important role in predicting land use and land cover (LULC) data and are applied in various aspects such as land use planning and management, and deforestation vulnerability analysis for forest conservation and protection. Therefore, integration of geospatial models for a LULC prediction and deforestation vulnerability analysis (DVA) are here examined for the allocation of deforestation hotspots and forest protection units to prevent deforestation in the protected forest areas (PFAs) of Phuket Island. The main objectives of the study were: (1) to identify the optimum geospatial model for the LULC prediction, (2) to examine the optimum geospatial model for the DVA and zonation, and (3) to allocate deforestation hotspots and forest protection units for the PFAs. The 4 main components of the research methodology that were implemented comprised: (1) data collection and preparation; (2) optimum geospatial modelling for the LULC prediction; (3) optimum geospatial modelling for the DVA; and (4) the allocation of deforestation hotspots and forest protection units.

From the results of the LULC interpretation of remote sensing data between 1995 and 2014, all 15 PFAs on Phuket Island were deforested with an annual rate ranging between 0.0001-0.2082 sq.km. The causes of deforestation were the conversion of forest land to urban and built-up areas and the expansion of agricultural land. In this study, the CLUE-S and CA-Markov models were chosen as the optimum geospatial models for the LULC prediction of 9 and 6 PFAs, respectively, while the frequency ratio model was identified as the optimum geospatial model for the DVA and zonation of the 15 PFAs. According to the LULC prediction for 2026, the highest annual deforestation rate of the PFAs during the period from 2014 to 2026 will occur in Khao Kamala national reserved forest (NRF) with a value of 0.1400 sq. km, while the lowest annual deforestation rate will occur in Khong Tarau NRF with a value of 0.0001 sq. km. Meanwhile, the number of PFAs with low and high risks of deforestation in the future based on the percentages of deforestation vulnerability zonation was 11 and 4, respectively. In the case of the allocation of deforestation hotspots and forest protection units, 408 deforestation hotspots were

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distributed over 12 FPAs, with the exception of Khao Sam Liam, Khao Tosae, and Khlong Tarau NRFs, while 5 PFAs - Khao Kamala, Khao Nak Keod, Khlong U-Tapao, Khlong Para, and Khlong Tajin NRFs - required the establishment of 15, 20, 1, 2, and 6 forest protection units, respectively

In conclusion, it appears that the integration of geospatial models for the LULC prediction and DVA with zonation can be used as an efficient tool for the allocation of deforestation hotspots and forest protection units to fulfill the forest conservation and protection program of the Thai Government.

Keywords: Land use and land cover prediction, deforestation vulnerability analysis, allocation of deforestation hotspots and forest protection units, Phuket Island

Introduction

Changes in land use and land cover (LULC) are directly linked to the issues of the sustainability of the social-economic system because they influence essential parts of humans' natural capital, i.e., climate, soils, vegetation, water and biodiversity. They are also considered as central to the sustainable development debate (Mather and Sdasyuk, 1991). In recent decades, Thailand has developed rapidly, resulting in the expansion of services, tourism, transport, industry, commerce, and agriculture. LULC change has been continuously transforming the essential functions of the Earth's terrestrial systems (Lambin *et al.*, 2000) and affecting the structuring and functioning of ecosystems (Vitousek *et al.*, 1997).

The depletion of forests in developing countries, particularly tropical forests, has been an increasing concern to policy makers. Forest resources are being exploited for economic returns rather than for balancing the ecosystem. When deforestation which is the conversion of forest to non-forest land takes place, it may lead to several environmental consequences that include changes in the ecological, hydrological, and climatic processes on both the local and global scales. Deforestation is occurring at an alarming rate in many parts of the world, especially in developing countries (Khoi, 2011). It may cause a variety of effects that include climate change (Gupta *et al.*, 2005), the loss of water and soil resources and flooding (Yin and Li, 2001; Bruijnzeel, 2004), decreased biodiversity, habitat loss, and conflicts (Mangave, 2004), economic losses (Hansen, 1997), and social

consequences (Colchester and Lohmann, 1993).

According to statistics of the Royal Forest Department (2010), the forest cover of Thailand between 1973 and 2008 continuously decreased from 221707 sq. km or 43.21% in 1973 to 171586 sq. km or 33.44% in 2008.

Meanwhile, the growth in tourism in Thailand has often been supported by national or local government to improve services to facilitate the expansion. Tourism development is one of the important economic activities used to promote economic growth in local communities (Kaosa-ard, 2007). The development or promotion of local tourism also creates employment, income, and tax revenue, as well as being an opportunity to develop community infrastructure (Untong, 2006). These benefits are often quoted as successful outcomes of local tourism development (Lawton, 2005). In developing countries, the economic benefits of tourism development are often regarded as being of primary importance, while the social, cultural and environmental costs and impacts are considered as being of secondary importance (Ko and Stewart, 2002).

Phuket Island is one of Thailand's most popular tourist destinations and home to a very large community of foreigners from all over the globe. Phuket has emerged as Thailand's strongest hotel market (Jones Lang LaSalle, 2013) while it has dramatically increased its population in the last decade (Department of Provincial Administration, 2013). The island is a net importer of migrants, with a significant portion of the population coming over from the mainland. As the largest source of income on

Phuket Island, tourism has a great impact on the livelihood of the local community. The growth of tourism has positive impacts on both the local and national economy; the rapid expansion clearly comes with risks or side effects (Sae-Tan, 2013).

Therefore, the integration of geospatial models for the LULC prediction and deforestation vulnerability analysis (DVA) for the allocation of deforestation hotspots and forest protection units in protected forest areas (PFAs) of Phuket Island is very important to prevent deforestation in the future. The objectives of the study are (1) to identify the optimal geospatial model for the LULC prediction, (2) to examine the optimal geospatial model for the DVA and zonation, and (3) to allocate deforestation hotspots and forest protection units for the PFAs.

Materials and Methods

Study Area

Phuket Island is Thailand's largest island with an area of 522 sq. km, and has 15 PFAs

comprising Sirinath Marine National Park (MNP), Khao Phra Thaeo Wildlife Conservation Development and Extension Center (WCDEC), Khao Mai Kaew National Reserved Forest (NRF), Khao Bang Khanun NRF, Khao Sam Liam NRF, Khao Kamala NRF, Khao Nak Keod NRF, Khao Tosae NRF, Khlong U-Tapao NRF, Khlong Tha Maphrao NRF, Khlong Para NRF, Khlong Bangrong NRF, Khlong Tarau NRF, Khlong Tajin NRF, and Khlong Khopee NRF (Figure 1). In this study, a proximity operation with 2.5 km buffering outward from a PFA's boundary was applied to represent the effect of human interaction with the PFAs (Horning *et al.*, 2010).

Research Methodology

The research methodology and its workflow consisted of 4 components: (1) data collection and preparation, (2) the optimum geospatial model for the LULC prediction, (3) the optimum geospatial model for the DVA, and (4) the allocation of deforestation hotspots and forest protection units, and is displayed in Figure 2. Details of each component and

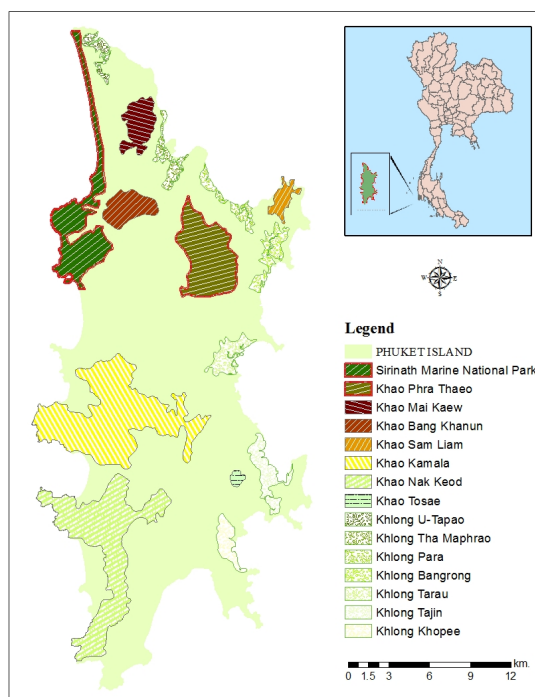


Figure 1. Distribution of 15 protected forest areas on Phuket Island

sub-component are separately summarized in the following sections.

Component 1: Data Collection and Preparation

The required input data included remote sensing and GIS data that were collected and

prepared in advance (Table 1). Firstly, the black and white orthophotos from 1995, color orthophotos from 2002, and pan-sharpened THEOS images from 2014 were used to interpret visually the LULC classes of the whole of Phuket Island with the elements of image interpretation (location, size, shape,

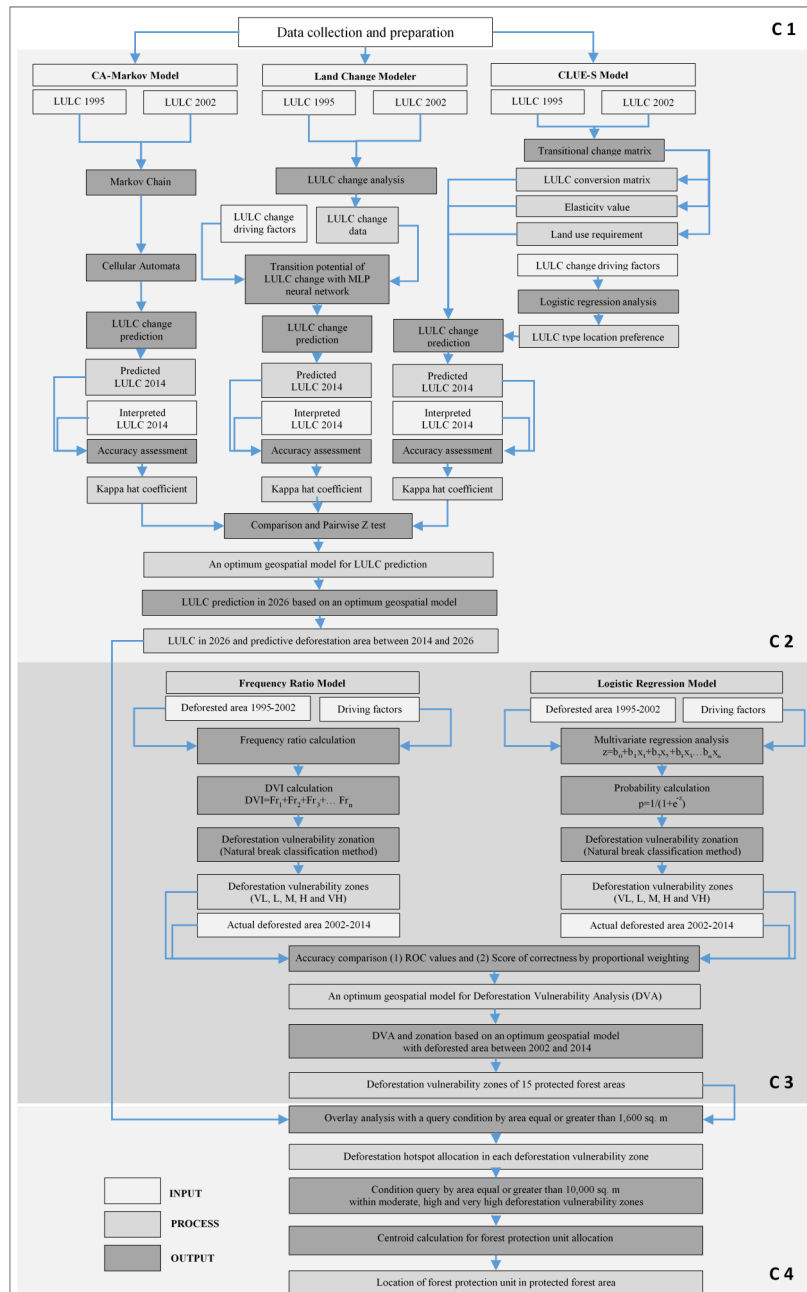


Figure 1. Distribution of 15 protected forest areas on Phuket Island

shadow, tone and color, texture, pattern, height and depth, and site/situation and association) in order to assess the LULC data of the 15 PFAs. In this study, the LULC classes consisted of (1) urban and built-up areas (city and commercial, institutional land, industrial land, poultry farms, houses, airport, and seaport), (2) paddy fields, (3) field crops and horticulture, (4) orchards and perennial trees, (5) aquaculture areas, (6) idle land, (7) evergreen forests, (8) mangrove forests, (9) scrub, (10) water bodies (natural and artificial), and (11) miscellaneous land (beaches, soil pits, laterite pits, and landfill). Then, the interpreted LULC in 2014 was assessed for accuracy using 743 randomly stratified sampling points based on the multinomial distribution theory (Congalton and Green, 2009) with the desired levels of 95% confidence and 5% precision in a field survey in 2015.

Component 2: Optimum Geospatial Model for the LULC Prediction

Sub-component 1: Optimum Geospatial Model Identification for the LULC Prediction

The 3 geospatial models for the LULC prediction, the CA-Markov model, Land Change Modeler (LCM), and CLUE-S model, were firstly applied to predict the LULC in 2014 and their results were then used to compare with the interpreted LULC in 2014 for the identification of the optimum geospatial model for the LULC in 2026 prediction based on the Kappa hat coefficient (KHAT). In addition, a pairwise Z test was also applied to examine significant differences of the KHAT accuracy of the 3 geospatial models as suggested by Congalton and Green (2009), as below:

$$Z = \frac{|\hat{K}_1 - \hat{K}_2|}{\sqrt{\widehat{var}(\hat{K}_1) + \widehat{var}(\hat{K}_2)}}, \quad (1)$$

where Z is the normalized and standard normal distribution,

$\hat{K}_1$ is the KHAT of the first geospatial model,

$\hat{K}_2$ is the KHAT of the second geospatial model,

$\widehat{var}(\hat{K}_1)$ is the variance of the KHAT of the first geospatial model, and

$\widehat{var}(\hat{K}_2)$ is the variance of the KHAT of the second geospatial model.

Table 1. List of data collection and preparation for data analysis and modeling in the study

Data	Data collection	Data Preparation	Source
Remote Sensing	B & W orthophotos in 1995	LULC interpretation	MNRE
	Color orthophotos in 2002	LULC interpretation	LDD
GIS	THEOS data in 2014	LULC interpretation	GISTDA
	Administrative boundaries	Study area extraction	DEQP
	National parks	Proximity operation	DNP
	National reserved forests	Proximity operation	RFD
	LULC in 2002	Ancillary data for visual interpretation	OAE
	Contour lines	DEM creation	DPT
	Elevation	Created from DEM	
	Slope	Created from DEM	
	Distance from roads	Euclidean distance operation	PSO of MOT
	Distance from settlements	Euclidean distance operation	LULC data
	Distance from water bodies	Euclidean distance operation	LULC data
	Soil series	Soil fertility extraction	LDD
	Population density (people/sq.km)	Calculation from number of population	DOPA
	Average income (baht/person/sub-district)	Calculation from personal income	CDD

Meanwhile, the variance of the KHAT is calculated from the error matrix of each model using the following equation:

$$\widehat{var}(\widehat{K}) = \frac{1}{n} \left\{ \frac{\theta_1(1-\theta_1)}{(1-\theta_2)^2} + \frac{2(1-\theta_1)(2\theta_1\theta_2-\theta_3)}{(1-\theta_2)^3} + \frac{(1-\theta_1)^2(\theta_4-4\theta_2^2)}{(1-\theta_2)^4} \right\}, \quad (2)$$

where $\theta_1 = \frac{1}{n} \sum_{i=1}^k n_{ii}$,

$$\theta_2 = \frac{1}{n^2} \sum_{i=1}^k n_{i+} n_{+i},$$

$$\theta_3 = \frac{1}{n^2} \sum_{i=1}^k n_{ii} (n_{i+} + n_{+i}), \text{ and}$$

$$\theta_4 = \frac{1}{n^3} \sum_{i=1}^k \sum_{j=1}^k n_{ij} (n_{j+} + n_{+i})^2.$$

In practice, given the null hypothesis $H_0: (\widehat{K}_1 - \widehat{K}_2) = 0$ and the alternative $H_1: (\widehat{K}_1 - \widehat{K}_2) \neq 0$, H_0 is rejected if $Z \geq Z_{\alpha/2}$, where $\alpha/2$ is the confidence level of the two-tailed Z test, and the degrees of freedom are assumed to be ∞ (infinity).

For the CA-Markov model, 2 main sets of input data, the LULC in 1995 and 2002, were used to predict the LULC in 2014 with the Markov chain and cellular automata. An application of this model was described in more detail by Paegelow and Camacho Olmedo (2005) and its application can be found in Kamusoko *et al.* (2009), Ongsomwang

Table 2. Classification system of driving factors for LULC prediction and deforestation vulnerability analysis

Biophysical factors		References
Elevation	0-100 m	Panayotou and Sungswan, 1989; Tongpan <i>et al.</i> , 1990; RFD, 1993; Siangwan, 2008; Arekhi, 2011; and Khoi, 2011
	100-200 m	
	200-300 m	
	300-400 m	
	> 400 m	
Slope	0-8%	Panayotou and Sungswan, 1989; Tongpan <i>et al.</i> , 1990; RFD, 1993; Siangwan, 2008; Arekhi, 2011; and Khoi, 2011
	8-16%	
	16-35%	
	35-60%	
	> 60 %	
Soil fertility	Attributed from soil types	Siangwan, 2008
Distance from roads	0-500 m	Panayotou and Sungswan, 1989; Tongpan <i>et al.</i> , 1990; RFD, 1993; Siangwan, 2008; Arekhi, 2011; and Khoi, 2011
	500-1,000 m	
	1,000-1,500 m	
	1500-2,000 m	
	> 2,000 m	
Distance from settlements	0-500 m	Panayotou and Sungswan, 1989; Tongpan <i>et al.</i> , 1990; RFD, 1993; Siangwan, 2008; Arekhi, 2011; and Khoi, 2011
	500-1,000 m	
	1,000-1,500 m	
	1,500-2,000 m	
	>2,000 m	
Distance from water bodies	0-500 m	Khoi, 2011
	500-1,000 m	
	1,000-1,500 m	
	1,500-2,000 m	
	>2,000 m	
Socio-economic factors		References
Population density at sub-districts' level	Person/sq. km	Panayotou and Sungswan, 1989
		Arekhi, 2011
		Khoi, 2011
Average income of population at sub-districts' level	Baht/head/sq. km	RFD, 1993

and Saravisutra (2011), Sang *et al.* (2011), and Adhikari and Southworth (2012).

Meanwhile, the LCM required the LULC in 1995 and 2002 as basic input with driving factors on the LULC change (Table 2) which were applied to predict the LULC in 2014 based on the LULC change analysis and transition potential of the LULC change with a multilayer perceptron neural network. Basically, the LCM can be applied to identify trends in the LULC change (Ongsomwang and Pimjai, 2014), tropical deforestation (Khoi and Murayama, 2010), and habitat modeling (Gontier *et al.*, 2009).

Likewise, the CLUE-S model required the LULC in 1995 and 2002 with the LULC change driving factors to predict the LULC in 2014. The LULC in 1995 and 2014 were used to analyze the transitional LULC change for extracting the LULC conversion matrix, elasticity values, and land use requirement. Additionally, the LULC change driving factors were used to identify the LULC type location preference by logistic regression analysis to allocate the LULC type in 2014. The basic concept of this model and its development were explained in more detail by Verburg *et al.* (2002) and Verburg and Overmars (2009). The CLUE-S model has been applied in various aspects including tropical deforestation (Verburg and Veldkamp, 2004), the effects of LULC change on carbon sequestration (Schulp *et al.*, 2008), biodiversity conservation (Trisurat *et al.*, 2010; Trisurat *et al.*, 2014), watershed management (El-Khoury *et al.*, 2014), and optimum land use allocation (Ongsomwang and Iamchuen, 2015).

Sub-component 2: The LULC in 2026 Prediction

The identified optimum geospatial model for the LULC prediction in the previous sub-component was here applied to predict the LULC in 2026 for each PFA for the analysis of deforestation in the future.

Component 3: Optimum Geospatial MSodel for the DVA

Sub-component 1: Optimum Geospatial Model Identification for the DVA

The 2 geospatial models for the DVA were the frequency ratio (FR) and logistic

regression (LR) models which were firstly applied to analyze the DVA and zonation based on the deforested areas between 1995 and 2002.

Under the FR model, the spatial relationships between the locations of these deforested areas and each driving factor and the class of deforestation occurrence were firstly calculated for the frequency ratio (Fr) and each factor's frequency ratio values were summed to calculate the deforestation vulnerability index (DVI) as:

$$DVI = Fr_1 + Fr_2 + Fr_3 + \dots Fr_n. \quad (3)$$

In principal, if the frequency ratio (Fr_i) value for a specific class of each factor is above 1, it indicates a very high probability of a deforestation occurrence. In contrast, if the frequency ratio (Fr_i) value for other classes of factors is below 1, it indicates a low probability of a deforestation occurrence. Good examples of the FR model's applications can be found in Pradhan and Lee (2010) and Karim *et al.* (2011).

Meanwhile, the LR model is a model to discover the empirical relationships between a binary dependent and several independent categorical and continuous variables (Arsanjani *et al.*, 2013). The LR model was used here to associate the deforested areas between 1995 and 2002 with the driving factors on deforestation for generating the DVI. In practice, a multivariate regression analysis was firstly used to identify the linear relationship (Z) between the deforested areas and their driving factors ($x_1, x_2, x_3, \dots, x_n$) as:

$$Z = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + \dots + b_nx_n. \quad (4)$$

After that, the probability values of the driving factors were transformed into a nonlinear relationship by a logistic curve to create the *DVI* as a probability value as:

$$DVI = \frac{1}{1+e^{-z}}. \quad (5)$$

Examples of the LR model's application on deforestation and degradation can be found in Arekhi (2011) and Mon *et al.* (2012).

Subsequently, the derived DVI from each model (FR and LR) was further classified into 5 zones (very low, low, moderate, high, and very high) with a natural break classification method for accuracy assessment using the relative operating characteristic (ROC) and total score of correctness by the proportional weighting method based on the deforested areas between 2002 and 2014. In this study, the total score of correctness by proportional weighting was calculated by summation of the multiplication between the proportional deforested areas between 2002 and 2014 and the weight of the deforestation vulnerability zone with 1, 2, 3, 4, and 5 for very low, low, moderate, high, and very high zones, respectively. The geospatial model that provided higher accuracy was chosen as the optimum geospatial model for the DVA and zonation.

Sub-component 2: Deforestation Vulnerability Analysis and Zonation

The derived optimum geospatial model for the DVA was here applied to create a deforestation vulnerability index for each of the PFAs based on the deforested areas between 2002 and 2014 with their driving factors on deforestation. The derived DVI was further reclassified into 5 deforestation vulnerability zones using the natural break classification method again.

Component 4: Allocation of Deforestation Hotspots and Forest Protection Units

Sub-component 1: Allocation of Deforestation Hotspots

The predicted deforestation areas between 2014 and 2026, which were extracted from the actual LULC data in 2014 and the predicted LULC data for 2026, and the deforestation vulnerability zones of each PFA were combined by an overlay analysis for allocation of the deforestation hotspots. The predicted deforestation areas, which have areas equal to or greater than 1600 sq. m (1 *rai*) in each deforestation vulnerability zone, were identified as deforestation hotspots.

Sub-component 2: Allocation of Forest Protection Units

The predicted deforestation hotspot areas between 2014 and 2026, which have areas

equal to or greater than 10000 sq. m (6.25 *rai*) and are located in moderate, high, and very high deforestation vulnerability zones in each PFA were extracted to allocate the forest protection units using the centroid of their polygons.

Results and Discussion

LULC Assessment of Phuket Island in 1995, 2002, and 2014

The areas and percentages of the LULC classes on Phuket Island in 1995, 2002, and 2014 are comparatively summarized in Table 3 and displayed in Figure 3. They show a dramatic increase of the urban and built-up areas from 12.80% in 1995 to 24.15% in 2014. Conversely, areas of agricultural land and forest land continuously decreased during the same period. These basic LULC data were further used to extract the deforestation on Phuket Island and the 15 PFAs.

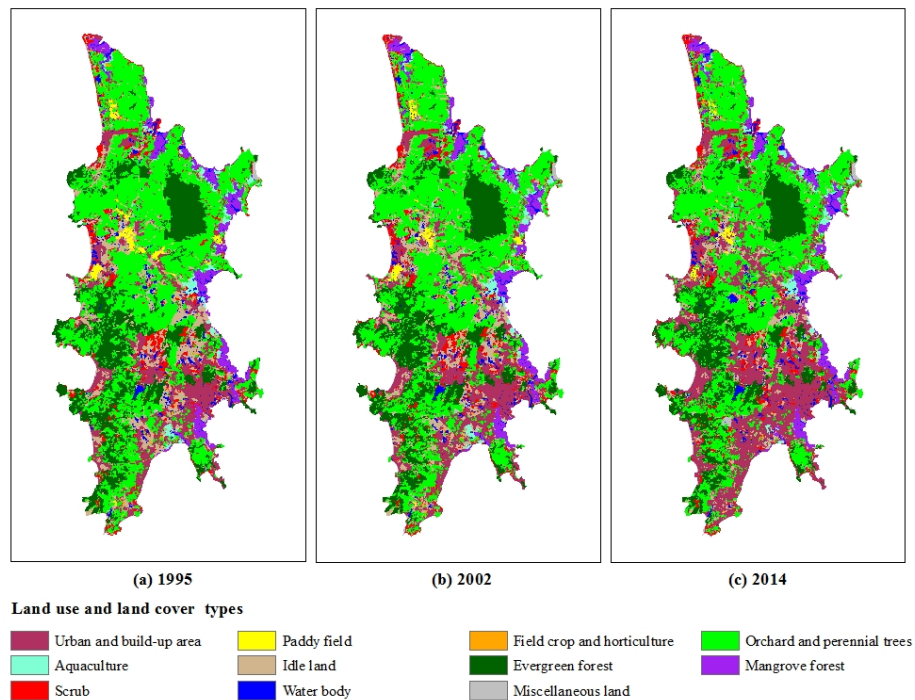
In addition, an accuracy assessment of the interpreted LULC map in 2014 by a ground survey in 2015 was 98.38% for overall accuracy and 97.89% for the KHAT. The producer's accuracy (omission error) of each LULC class varied between 81.40% (9.60%) and 100% (0%) while the user's accuracy (commission error) of each LULC class ranged from 87.50% (12.50%) to 100% (0%). Based on Fitzpatrick-Lins (1981), a KHAT more than 80% represents a strong agreement or accuracy between the interpretation map and the ground reference information.

Deforestation in Phuket Island Between 1995 and 2014

Based on the transitional LULC change data in 3 periods (1995-2002, 2002-2014, and 1995-2014), deforestation and its annual rate in evergreen and mangrove forests on Phuket Island is summarized in Table 4. It is evident that from 1995 to 2002 deforestation on Phuket Island was about 5.444 sq. km with an annual rate of 0.778 sq. km. Deforestation on Phuket Island from 2002 to 2014 was about 9.437 sq. km with an annual rate of 0.786 sq. km. In addition, the deforestation on Phuket Island for the longer period of time from 1995 to 2014 was about 14.881 sq. km with an annual rate of

Table 3. Area and percentage of LULC classes on Phuket Island in 1995, 2002, and 2014

LULC class	1995		2002		2014	
	sq. km	%	sq. km	%	sq. km	%
Urban and built-up areas	66.909	12.80	78.817	15.07	126.276	24.15
Paddy fields	6.351	1.21	4.438	0.85	2.710	0.52
Field crops and horticulture	1.518	0.29	1.953	0.37	1.447	0.28
Orchards and perennial trees	217.265	41.56	210.960	40.35	196.239	37.53
Aquaculture areas	8.759	1.68	9.614	1.84	8.724	1.67
Idle land	53.964	10.32	53.114	10.16	33.631	6.43
Evergreen forests	94.780	18.13	90.356	17.28	81.489	15.59
Mangrove forests	26.744	5.12	25.724	4.92	25.154	4.81
Scrub	28.160	5.39	28.849	5.52	26.329	5.04
Water bodies	13.951	2.67	14.231	2.72	14.536	2.78
Miscellaneous land	4.436	0.85	4.779	0.91	6.302	1.21
Total	522.836	100.00	522.836	100.00	522.836	100.00

**Figure 3. Distribution of LULC pattern of Phuket Island in 1995, 2002, and 2014**

0.783 sq. km. The major causes of deforestation on Phuket Island are the conversion of forest land to urban and built-up areas and the expansion of agricultural land. In addition, the annual deforestation rate of evergreen forests is higher than that of mangrove forests in the 3

periods. This finding indicates that the accessibility to both forest types is different. It means that evergreen forests are more easily accessed when compared with mangrove forests.

Table 4. Forest areas and deforestation of Phuket Island between 1995 and 2014

Forest area and deforestation	Forest areas in sq. km		
	Evergreen forest	Mangrove forest	Total
Forest areas in 1995	94.780	26.744	121.524
Forest areas in 2002	90.356	25.724	116.080
Deforestation areas: 1995-2002	4.424	1.020	5.444
Annual deforestation rate (sq. km)	0.632	0.146	0.778
Forest areas in 2002	90.356	25.724	116.080
Forest areas in 2014	81.489	25.154	106.643
Deforestation areas: 2002-2014	8.867	0.570	9.437
Annual deforestation rate (sq. km)	0.739	0.047	0.786
Forest areas in 1995	94.780	26.744	121.524
Forest areas in 2014	81.489	25.154	106.643
Deforestation areas: 1995-2014	13.291	1.590	14.881
Annual deforestation rate (sq. km)	0.699	0.084	0.783

Table 5. Deforestation areas and rates of 15 protected forest areas

Protected forest areas	Deforestation				
	1995-2002		2002-2014		1995-
	Area (sq. km)	Rate	Area (sq. km)	Rate	Area (sq. km)
Sirinath MNP	0.1050	0.0150	0.2213	0.0184	0.3263
Khao Phra Thaeo WCDEC	0.0156	0.0022	0.0600	0.0086	0.0756
Khao Mai Kaew NRF	0.0000	0.0000	0.0225	0.0019	0.0225
Khao Bang Khanun NRF	1.1525	0.1646	0.5488	0.0457	1.7013
Khao Sam Liam NRF	0.0075	0.0011	0.0000	0.0000	0.0075
Khao Kamala NRF	0.3275	0.0468	2.1006	0.1751	2.4281
Khao Nak Keod NRF	1.5550	0.2221	2.4013	0.2001	3.9563
Khao Tosae NRF	0.0000	0.0000	0.0019	0.0002	0.0019
Khleng U-Tapao NRF	0.0000	0.0000	0.0069	0.0006	0.0069
Khleng Tha Maphrao NRF	0.0131	0.0019	0.0844	0.0070	0.0975
Khleng Para NRF	0.2644	0.0378	0.0069	0.0006	0.2713
Khleng Bangrong NRF	0.1281	0.0183	0.0038	0.0003	0.1319
Khleng Tarau NRF	0.0010	0.0001	0.0230	0.0019	0.0240
Khleng Tajin NRF	0.0913	0.0130	0.2450	0.0204	0.3363
Khleng Khopee NRF	0.2844	0.0406	0.0206	0.0017	0.3050
Total	3.9454	0.5636	5.7470	0.4789	9.6924

Deforestation in Forest Protected Area During 1995 to 2014

Based on the LULC change data in 3 periods, deforestation of the 15 PFAs is summarized in Table 5. It is revealed that from 1995 to 2002 there was no deforestation in 3 PFAs, namely Khao Mai Kaew, Khao Tosae, and Khleng U-Tapao NRFs. The smallest

annual deforestation rate occurred in Khleng Tarau NRF with a rate of 0.0001 sq. km while the greatest annual deforestation rate occurred in Khao Nak Keod NRF with a rate of 0.2221 sq. km. From 2002 to 2014 there was only 1 PFA, Khao Sam Liam NRF, that had no deforestation. The smallest annual deforestation rate in this period occurred in Khao Tosae NRF

Table 6. Accuracy assessment of 3 models of each protected forest area by Kappa hat analysis

Protected forest area	Kappa hat coefficient of model		
	CA-Markov	LCM	CLUE-S
Sirinath MNP	76.99	75.18	79.18
Khao Phra Thaeo WCDEC	83.35	81.82	83.89
Khao Mai Kaew NRF	78.87	76.46	83.27
Khao Bang Khanun NRF	75.96	73.36	79.66
Khao Sam Liam NRF	83.32	81.64	87.46
Khao Kamala NRF	74.33	71.85	73.36
Khao Nak Keod NRF	69.94	64.09	70.52
Khao Tosae NRF	73.76	69.06	73.57
Khloneg U-Tapao NRF	86.03	84.74	84.40
Khloneg Tha Maphrao NRF	78.48	75.88	83.29
Khloneg Para NRF	82.43	79.94	86.26
Khloneg Bangrong NRF	81.57	79.69	85.40
Khloneg Tarau NRF	76.50	73.22	74.80
Khloneg Tajin NRF	78.77	74.92	76.56
Khloneg Khopee NRF	74.88	71.77	74.74

with a rate of 0.0002 sq. km while the greatest annual deforestation rate occurred in Khao Nak Keod NRF with a rate of 0.2001 sq. km.

However, during the longer period from 1995 to 2014, all 15 PFAs were deforested with a variety of deforestation rates. The smallest annual deforestation rate in this period occurred in Khao Tosae NRF with a rate of 0.0001 sq. km while the greatest annual deforestation rate occurred in Khao Nak Keod NRF with a rate of 0.2082 sq. km. The derived annual deforestation rate of the PFAs reflects the probability of the risk of deforestation in the future.

In addition, the deforestation of all 15 PFAs between 1995 and 2002 with an annual rate of 0.5635 sq.km was higher than the deforestation of all 15 PFAs between 2002 and 2014 with an annual rate of 0.4789 sq.km. This finding shows that forest protection activity between 2002 and 2014 was more intensive than between 1995 and 2002.

Optimum Geospatial Model for LULC Prediction

The accuracy of the 3 geospatial models for the LULC prediction, the CA-Markov, LCM, and CLUE-S, is summarized in Table 6. As a result of the KHAT values, the optimum geospatial model for the LULC prediction in 9 PFAs, Sirinath MNP, Khao Phra Thaeo WCDEC, and Khao Mai Kaew, Khao Bang

Khanun, Khao Sam Liam, Khao Nak Keod, Khlong Tha Maphrao, Khlong Para, and Khlong Bangrong NRFS, was the CLUE-S model. The CA-Markov model was the optimum geospatial prediction model for the LULC prediction in 6 PFAs, Khao Kamala, Khao Tosae, Khlong U-Tapao, Khlong Tarau, Khlong Tajin, and Khlong Khopee NRFS.

These findings suggest the effect of the driving factors on the LULC type allocation for the CLUE-S model. However, the CA-Markov model, which generally operates without driving factors for the LULC prediction, can provide a KHAT higher than the CLUE-S model in 6 PFAs. The results further suggest that the most appropriate geospatial model for the LULC prediction in practice is the CA-Markov model while the least appropriate geospatial model is the LCM. This finding is similar to the previous study of Ongsomwang and Pimjai (2014) who found that the CA-Markov model provided a higher accuracy for the LULC prediction than the LCM.

Furthermore, the results of the pairwise Z-test between the optimum geospatial model and the other models for the LULC prediction for each PFA is summarized in Table 7. As a result, the accuracy of the optimum geospatial model for the LULC prediction of the 15 PFAs was statistically significantly different from

Table 7. Pairwise Z test between the optimum geospatial models with other models for LULC prediction

Protected forest area	Optimum geospatial model	Pair-wise Z test between	Z statistic	Z $\alpha/2$ value confidential level at		
				90%	95%	100%
Sirinath MNP	CLUE-S	CA-Markov and CLUE-S	10.88	1.65	1.96	2.58
Khao Phra Thaeo WCDEC	CLUE-S	LCM and CLUE-S	19.58	1.65	1.96	2.58
		CA-Markov and CLUE-S	3.19	1.65	1.96	2.58
Khao Mai Kaew NRF	CLUE-S	LCM and CLUE-S	12.16	1.65	1.96	2.58
		CA-Markov and CLUE-S	16.28	1.65	1.96	2.58
Khao Bang Khanun NRF	CLUE-S	LCM, CLUE-S	24.70	1.65	1.96	2.58
		CA-Markov and CLUE-S	27.50	1.65	1.96	2.58
Khao Sam Liam NRF	CLUE-S	LCM and CLUE-S	24.70	1.65	1.96	2.58
		CA-Markov and CLUE-S	12.09	1.65	1.96	2.58
Khao Kamala NRF	CA- Markov	LCM and CLUE-S	16.62	1.65	1.96	2.58
		CA- Markov and LCM	16.07	1.65	1.96	2.58
Khao Nak Keod NRF	CLUE-S	CA-Markov and CLUE-S	6.32	1.65	1.96	2.58
		CA-Markov and CLUE-S	3.26	1.65	1.96	2.58
Khao Tosae NRF	CA- Markov	LCM and CLUE-S	34.89	1.65	1.96	2.58
		CA- Markov and LCM	12.16	1.65	1.96	2.58
Khlung U-Tapao NRF	CA- Markov	CA- Markov and CLUE-S	0.47	1.65	1.96	2.58
		CA- Markov and LCM	30.65	1.65	1.96	2.58
Khlung Tha Maphrao NRF	CLUE-S	CA-Markov and CLUE-S	29.59	1.65	1.96	2.58
		CA-Markov and CLUE-S	18.29	1.65	1.96	2.58

other models except for Khao Tosae and Khlung Khopee NRFs. The accuracy of the CLUE-S model for the LULC prediction in both NRFs was not significantly different at the 90%, 95%, or 100% confidential levels from the CA-Markov model as the optimum geospatial model.

LULC Prediction in 2026

The derived optimum geospatial model of each PFA was used to predict the LULC in 2026. The result of the LULC for the 2026 prediction of each PFA is displayed in Figure 4. The results provide the possibility of a LULC change, especially deforestation, within the boundaries of the PFAs and their buffer zones between 2014 and 2026.

Deforestation Prediction Between 2014 and 2026

The predictive deforested areas and their percentages and annual rates of deforestation for the 15 PFAs during the period from 2014 to 2026 is summarized in Table 8. From the results, the annual highest deforestation rate will occur in Khao Kamala NRF with a value of 0.1400 sq. km while the lowest annual lowest deforestation rate will occur in Khong Tarau NRF with a value of 0.0001 sq. km. However, the highest percentage of deforestation of the existing forest area in 2014 was found in Sirinath MNP with a value of 18.7632% and the lowest percentage of deforestation from the existing forest area in 2014 occurred in Khao Phra Thaeo WCDEC with a value of 0.0267%.

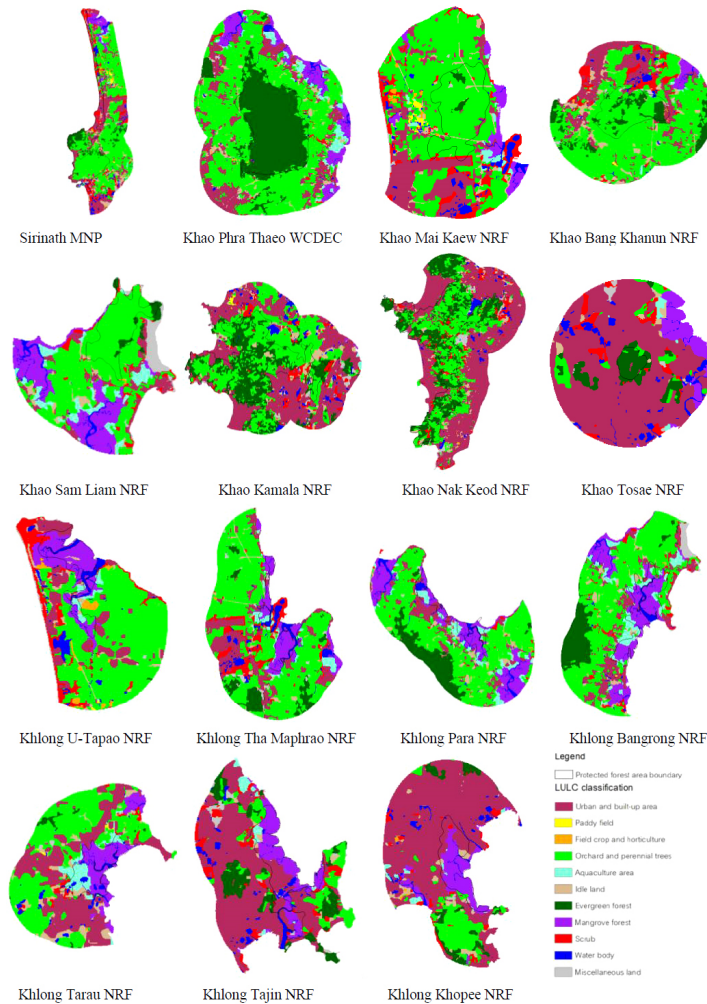


Figure 4. Distribution of predicted LULC in 2026 of 15 protected forest areas

These results imply the vulnerability to and severity of deforestation in each PFA in the future.

Furthermore, it was found that the annual predictive deforestation rate between 2014 and 2026 of 5 PFAs, namely Sirinath MNP, Khao Mai Kaew, Khao Kamala, Khao Tosae, and Khlong U-Tapao NRFs is higher than the actual annual deforestation rate from 1995 to 2014. Conversely, the actual annual deforestation rate between 1995 and 2014 of the other 10 PFAs will tend to decrease between 2014 and 2026 (Table 9). The results also suggest the risk of deforestation based on the change of the deforestation rate between

the 2 periods in terms of gain and loss. Hence, 5 PFAs, namely Sirinath MNP, Khao Mai Kaew, Khao Kamala, Khao Tosae, and Khlong U-Tapao NRFs, should be more patrolled by forest rangers than the other PFAs.

Optimum Geospatial Model for Deforestation Vulnerability Analysis

The frequency ratio (Fr_i) of a deforestation occurrence for each class of the biophysical and socio-economic driving factors for the DVA of the 15 PFAs under the FR model is summarized with the frequency (the number of PFAs with a high probability of a deforestation occurrence ($Fr_i > 1.0$) in each factor class) in

Table 8. Predictive deforestation areas between 2014 and 2026 of each protected forest area and its derivation

Protected forest area	Total area	Forest area in 2014	Deforested area	% of total area	% of forest area in 2014	Unit: sq. km
						Annual rate
Sirinath MNP	21.161	3.218	0.6038	2.8534	18.7632	0.0503
Khao Phra Thaeo WCDEC	20.368	18.708	0.005	0.0245	0.0267	0.0004
Khao Mai Kaew	7.308	0.324	0.0213	0.2915	6.5741	0.0018
Khao Bang Khanun	7.291	2.098	0.18	2.4688	8.5796	0.0150
Khao Sam Liam	3.046	0.265	0.0019	0.0624	0.7170	0.0002
Khao Kamala	47.448	21.393	1.68	3.5407	7.8530	0.1400
Khao Nak Keod	37.55	15.17	1.1525	3.0692	7.5972	0.0960
Khao Tosae	0.938	0.88	0.0025	0.2665	0.2841	0.0002
Khleng U-Tapao	2.495	1.871	0.0131	0.5251	0.7002	0.0011
Khleng Tha Maphrao	3.573	2.508	0.0275	0.7697	1.0965	0.0023
Khleng Para	3.365	1.964	0.0394	1.1709	2.0061	0.0033
Khleng Bangrong	4.662	3.15	0.0094	0.2016	0.2984	0.0008
Khleng Tarau	4.829	2.839	0.0013	0.0269	0.0458	0.0001
Khleng Tajin	6.109	3.569	0.1813	2.9678	5.0799	0.0151
Khleng Khopee	3.954	2.572	0.0631	1.5959	2.4533	0.0053

Table 9. Comparison of actual and predictive deforestation rate of each protected forest area

No	Protected forest area	Annual deforestation rate (sq. km)			Remark
		1995-2014	2014-2026	Change	
1	Sirinath MNP	0.0172	0.0503	0.0331	Loss
2	Khao Phra Thaeo WCDEC	0.0108	0.0004	-0.0104	Gain
3	Khao Mai Kaew NRF	0.0012	0.0018	0.0006	Loss
4	Khao Bang Khanun NRF	0.0895	0.015	-0.0745	Gain
5	Khao Sam Liam NRF	0.0004	0.0002	-0.0002	Gain
6	Khao Kamala NRF	0.1278	0.14	0.0122	Loss
7	Khao Nak Keod NRF	0.2082	0.096	-0.1122	Gain
8	Khao Tosae NRF	0.0001	0.0002	0.0001	Loss
9	Khleng U-Tapao NRF	0.0004	0.0011	0.0007	Loss
10	Khleng Tha Maphrao NRF	0.0051	0.0023	-0.0028	Gain
11	Khleng Para NRF	0.0143	0.0033	-0.011	Gain
12	Khleng Bangrong NRF	0.0069	0.0008	-0.0061	Gain
13	Khleng Tarau NRF	0.0013	0.0001	-0.0012	Gain
14	Khleng Tajin NRF	0.0177	0.0151	-0.0026	Gain
15	Khleng Khopee NRF	0.0161	0.0053	-0.0108	Gain

Tables 10 and 11, respectively. In principle, the frequency ratio value for the specific classes of each factor above 1 indicates a very high probability of a deforestation occurrence. From the results of the biophysical factors (Table 10), it was found that deforestation in the PFAs frequently occurs at an elevation of 0-100 m, a slope of 16-35% or 35-60%, a moderate soil fertility, and a distance from roads, settlements, or water bodies between 0 and 500 m. Meanwhile, the socio-economic

factors (the number of the population and average income at the sub-district level) on deforestation with a high probability are directly related to the location of the PFA (Table 11).

Meanwhile, the derived multiple linear equation of the LR model for the DVA of each PFA is summarized in Table 12. From the results, the top 3 driving factors on deforestation in this study according to the frequency of the top 3 dominant factors based on the coefficient

Table 10. Frequency ratio of deforestation occurrence by each class of biophysical driving factor for DVA under the FR model

Deforestation factor and classes	Frequency ratio of deforestation occurrence in each protected forest area														Frequency (Fr > 1.0)	
	SN	PT	MK	BK	SL	KL	NK	TS	UT	TM	PR	BR	TR	TJ		KP
Elevation																
0-100 m	0.59	1.31	1.04	0.63	1.09	1.09	0.6	1.02	1	1.06	1.13	1.14	1.07	1.03	1.03	12 of 15
100-200 m	4.45	0	0	3.9	0	0.94	1.51	0.49	0	0.1	0	0	0	0	0.2	3 of 15
200-300 m	0	0	0	0	0	1.3	2.09	0	0	0	0	0	0	0	0	2 of 15
300-400 m	0	0	0	0	0	0.23	2.06	0	0	0	0	0	0	0	0	1 of 15
Slope																
0-8%	0.23	1.86	1.69	0.32	0.23	0.49	0.28	0.72	0.6	1.69	1.78	1.67	1.18	0.93	0.81	6 of 15
8-16%	1.27	0.6	0	1.27	0.85	1.08	1.05	0.85	3.77	0.35	0.49	0.88	1.48	1.06	0.92	7 of 15
16-35%	1.93	0.23	0	1.63	1.77	1.54	1.61	2.11	0	0.21	0.1	0.18	0.34	1.23	1.74	8 of 15
35-60%	2.54	0.11	0	2.14	2.23	1.3	1.49	2.76	0	0.08	0	0.09	0	1.07	2.03	8 of 15
> 60%	2.14	0.22	0	1.47	2.79	1.05	1.41	1.1	0	0.34	0	0	0	0	1.52	6 of 15
Soil fertility																
Low	0.34	1.52	1.08	0.46	0.16	0.67	0.25	0.7	1.01	1.12	1.29	1.26	1.16	0.71	0.9	7 of 15
Moderate	3.63	0.21	0	3.13	3.87	1.34	1.71	2.58	0	0.19	0.07	0.13	0.29	2.13	1.35	8 of 15
Distance from roads																
0-500 m	1.05	1.11	1.02	1.06	1.05	1.17	0.99	1.1	1.03	0.88	1.03	1.1	1.21	1.1	1.06	13 of 15
500-1000 m	0.69	0.86	0	0.53	0.66	0.12	1.23	0.27	0	2.73	0.89	0.48	0	0.37	0.23	2 of 15
Distance from settlements																
0-500 m	0.17	1.54	0.55	0.07	1.52	1.15	0.54	1.04	0	1.32	1.82	1.28	1.4	1.07	1.03	10 of 15
500-1000 m	0.89	0.79	2.53	0.89	0.34	1.11	1.56	0	2.49	0.31	0.35	1.07	0.65	0.23	0.61	4 of 15
1000-1500 m	3.22	0.21	0	3.16	0	0.68	1.91	0	0	0.78	0	0.08	0	0	0	3 of 15
1500-2000 m	13.78	0	0	10.89	4.25	0.24	3.84	0	0	4	0	0	0	0	0	5 of 15
> 2000 m	27.02	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1 of 15
Distance from water bodies																
0-500 m	0.17	1.83	1.61	0.21	1.78	0.69	0.67	1.12	1.44	1.81	1.63	1.4	1.29	1.2	1	11 of 15
500-1000 m	1.77	0.37	0	1.12	0	1.19	1.13	0.63	0	0.15	0.05	0.74	0.46	0.33	0.98	4 of 15
1000-1500 m	4.8	0	0	3.37	0	1.34	1.29	0	0	0.06	0	0	0	1.52	1.49	6 of 15
1500-2000 m	2.41	0	0	0.84	0.46	0.15	2.32	0	0	0	0	0.24	0	0	0	6 of 15
> 2000 m	0	0	0	0	0.53	4.54	0.61	0	0	0	0	0	0	0	0	1 of 15

Note: SN: Srinath MNP, PT: Khao Phra Thaeo WDEC, MK: Khao Mai Kaew NRF, BK: Khao Bang Khanun NRF, SL: Khao Sam Liam NRF, KL: Khao Kamala NRF, NK: Khao Nak Keod NRF, TS: Khao Tosae NRF, UT: Khlong U-Tapao NRF, TM: Khlong Tha Maphrao NRF, PR: Khlong Para NRF, BR: Khlong Bangrong NRF, TR: Khlong Tarau NRF, TJ: Khlong Tajin NRF, KP: Khlong Khopee NRF

Table 12. Multiple linear equation of each protected forest area for DVA under the LR model

Protected forest area	Constant	Coefficient of							
		X ₁	X ₂	X ₃	X ₄	X ₅	X ₆	X ₇	X ₈
Sirinath MNP	-8.03	-0.1	0.07	1.58*	-2.49*	1.36*	0.59	-0.22	0.15
Khao Phra Thaeo WCDEC	-6.09	0.17	-0.47*	-0.31	1.07*	-0.25	-1.07*	0.16	0.44
Khao Mai Kaew NRF	-20.6	18.69*	-15.3	-17.72*	-15.37	1.11	-18.76*	0.84	4.77
Khao Bang Khanun NRF	-7.58	0.15	0.01	0.62*	-2.17*	1.68*	0.4	-0.27	0.22
Khao Sam Liam NRF	-20.14	-14.75*	-0.43	-0.48	-0.89	-0.17	-0.37	7.2*	2.06*
Khao Kamala NRF	-7.93	-0.82*	0.14	1.15*	-0.98*	-0.01	0.54	0.11	0.12
Khao Nak Keod NRF	-8.07	-0.15	0.02	2.03*	-0.44*	0.46*	-0.03	-0.02	0.06
Khao Tosae NRF	-8.34	-0.9*	0.25	1.24*	-0.85	-0.53	-1.32*	0.41	0.03
Khleng U-Tapao NRF	-20.72	-1.67	0.55	-4.39	-16.95*	1.72	-17.08*	7*	0
Khleng Tha Maphrao NRF	-7.59	2.6*	-0.69	1.95*	0.95	-0.7	-2*	1.24	-0.82
Khleng Para NRF	-376812	-12.65*	-1.01	-0.59	0.09	-1.59	-2.95	113047.7*	-37682.1*
Khleng Bangrong NRF	-20.31	-14.87*	-0.75	-1.26*	-0.79	-0.08	-0.45	8.44*	0.31
Khleng Tarau NRF	-8.13	1.6*	-0.25	1.14*	1.19*	-0.94	-0.22	-0.23	-0.06
Khleng Tajin NRF	-9.44	-0.06	-0.22	1.79*	-1.08*	0.34	-1.36*	0.39	-0.21
Khleng Khopee NRF	-7.37	-0.29	0.35*	0.43*	-0.45*	0.18	-0.34	0.29	-0.07
Frequency of top 3 factors (*)		8 of 15	2 of 15	11 of 15	9 of 15	3 of 15	6 of 15	4 of 15	2 of 15

Note: X₁: Elevation; X₂: Slope; X₃: Soil fertility; X₄: Distance from roads; X₅: Distance from settlements; X₆: Distance from water bodies; X₇: Population density; and X₈: Average income.

values of the 15 PFAs were soil fertility (X₃), distance from roads (X₄), and elevation (X₁). This finding implies that deforestation in a PFA is related to soil fertility, distance from roads, and elevation.

The results of the deforestation vulnerability index from the FR and LR models based on the deforestation areas between 1995 and 2002 of the 15 PFAs show similar and dissimilar patterns of deforestation vulnerability. The accuracy assessment of the DVA with the ROC and total score of correctness by the proportional weighting method of the FR and LR models is presented in Table 13.

According to the accuracy assessment using the ROC method, the FR model is the optimum geospatial model for the DVA in 10 PFAs, Sirinath MNP, Khao Phra Thaeo WCDEC, and Khao Mai Kaew, Khao Bang Khanun, Khao Sam Liam, Khao Kamala, Khao Nak Keod, Khleng Tha Maphrao, Khleng Para, and Khleng Bangrong NRFs. Meanwhile the LR model is the optimum geospatial model for the DVA in 5 PFAs, Khao Tosae, Khleng U-Tapao, Khleng Tarau, Khleng Tajin, and Khleng Khopee NRFs. These results imply that the accuracy of the FR and LR models depends on the location of the study site and the driving factors on deforestation. This

Table 13. Accuracy assessment of deforestation vulnerability analysis of 15 protected forest areas under the FR and LR models

Protected forest area	ROC value		Total score	
	FR	LR	FR	LR
Sirinath MNP	0.928	0.874	4590	3258
Khao Phra Thaeo WCDEC	0.610	0.591	2282	1848
Khao Mai Kaew NRF	0.692	0.488	970	324
Khao Bang Khanun NRF	0.776	0.695	4191	3614
Khao Sam Liam NRF	0.849	0.754	210	195
Khao Kamala NRF	0.802	0.786	19764	10857
Khao Nak Keod NRF	0.875	0.864	26712	20,494
Khao Tosae NRF	0.734	0.745	2123	2165
Khlung U-Tapao NRF	0.769	0.796	83	25
Khlung Tha Maphrao NRF	0.825	0.790	3340	2200
Khlung Para NRF	0.845	0.780	1065	714
Khlung Bangrong NRF	0.741	0.691	879	626
Khlung Tarau NRF	0.761	0.820	2397	1657
Khlung Tajin NRF	0.892	0.900	2397	1376
Khlung Khopee NRF	0.804	0.842	2721	2100

Table 14. Areas and percentages of deforestation vulnerability zonation of 15 protected forest areas with their buffer zones

Protected forest area	Deforestation vulnerability zones											
	Very low		Low		Very low		High		Very low		Total	
	km ²	%	km ²	%	km ²	%	km ²	%	km ²	%	km ²	%
Sirinath MNP	39.48	49.3	14.48	18.1	11.24	14	8.5	10.6	6.41	8	80.09	100
Khao Phra Thaeo WCDEC	1.86	2.07	54.17	60.6	16.41	18.4	9.82	11	7.14	7.99	89.4	100
Khao Mai Kaew NRF	13.85	32.1	21.92	50.8	3.1	7.18	1.42	3.3	2.86	6.63	43.16	100
Khao Bang Khanun NRF	20.08	38	15.97	30.2	8.37	15.8	6.05	11.4	2.43	4.59	52.89	100
Khao Sam Liam NRF	1.29	6.97	4.8	25.9	4.47	24.1	6.76	36.4	1.24	6.68	18.56	100
Khao Kamala NRF	24.61	17.9	37.81	27.5	29.16	21.2	25.14	18.3	20.75	15.1	137.46	100
Khao Nak Keod NRF	43.05	38.1	19.3	17.1	23.79	21	19.05	16.8	7.95	7.03	113.13	100
Khao Tosae NRF	9.77	34.2	12.52	43.8	3.14	11	1.78	6.24	1.37	4.8	28.59	100
Khlung U-Tapao NRF	0.19	0.89	0.9	4.12	2.86	13.2	7.92	36.5	9.86	45.4	21.72	100
Khlung Tha Maphrao NRF	16.42	38.6	10.12	23.8	12.49	29.4	3.06	7.19	0.44	1.03	42.53	100
Khlung Para NRF	1.46	3.64	4.56	11.3	10.63	26.4	13.36	33.2	10.22	25.4	40.23	100
Khlung Bangrong NRF	4.17	11	9.34	24.7	18.76	49.6	3.59	9.48	1.97	5.2	37.83	100
Khlung Tarau NRF	12.59	33	12.95	34	8.22	21.6	3.03	7.95	1.33	3.49	38.12	100
Khlung Tajin NRF	1.38	4.02	6.13	17.9	3.86	11.3	5.53	16.1	17.43	50.8	34.34	100
Khlung Khopee NRF	11.81	34.7	13.26	38.9	4.63	13.6	4.35	12.8	0.04	0.12	34.08	100

finding was similar to the previous study of Lee and Pradhan (2006) who applied the FR and LR models for landslide hazard mapping at Selangor, Malaysia. They found that the FR

model with an accuracy of 93.04% could predict a landslide hazard better than the LR model with an accuracy of 90.34%. However, Pradhan and Lee (2010) also applied both

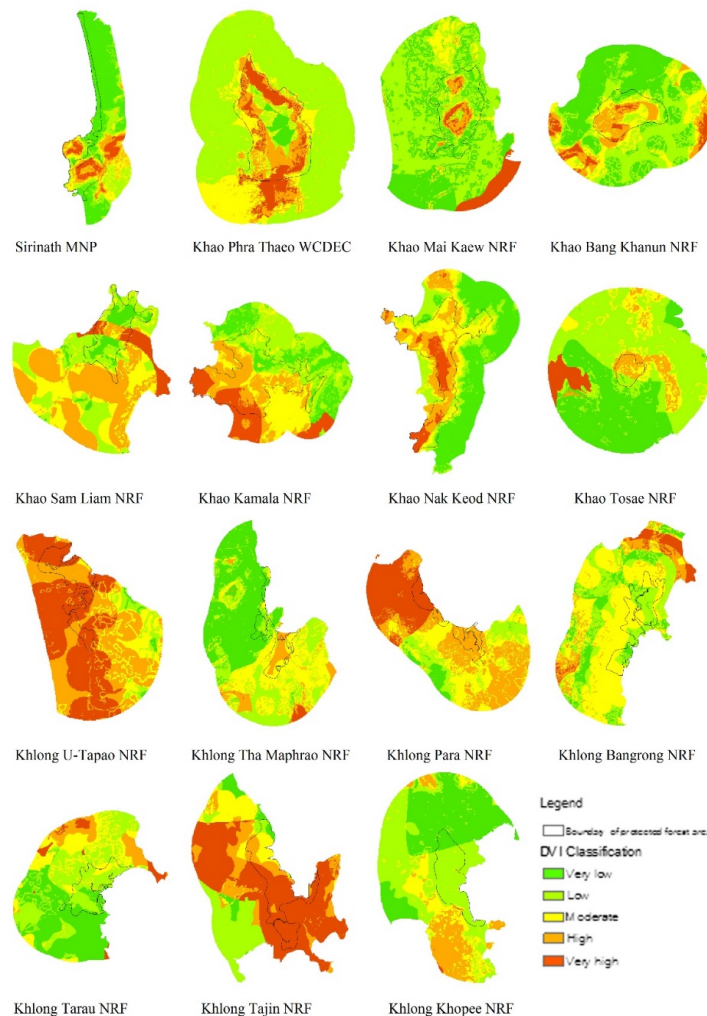


Figure 5. Deforestation vulnerability zonation of 15 protected forest area

models for landslide hazard analysis on Penang Island, Malaysia and they found that the LR model with an accuracy of 89.59% could predict a landslide hazard better than the FR model with an accuracy of 86.41%.

Meanwhile, the accuracy assessment using the total score of correctness by proportional weighting shows that the FR model provided a total score higher than the LR model in all PFAs. Therefore, the FR model was selected as the optimum geospatial model for the DVA and it was further applied for the DVA and zonation based on the deforested areas between 2002 and 2014.

Deforestation Vulnerability Analysis and Aonation

The DVA of the 15 PFAs was conducted again using the FR model based on updated driving factors on deforestation and deforestation areas between 2002 and 2014. Figure 5 displays the deforestation vulnerability zonation (very low, low, moderate, high, and very high) of the 15 PFAs while the areas and the proportional percentages of the deforestation vulnerability zones of the 15 PFAs with their buffer zones is summarized in Table 14.

Table 15. Areas and percentages of forest areas in 2014 in each deforestation vulnerability zone of 15 protected forest areas with their boundaries

Protected forest area	Forest areas in 2014 in deforestation vulnerability zones											
	Very low		Low		Moderate		High		Very high		Total	
	Km ²	%	Km ²	%	Km ²	%	Km ²	%	Km ²	%	Km ²	%
Sirinath MNP	0.224	6.97	1.276	39.7	1.616	50.2	0.102	3.17	0	0	3.218	100
Khao Phra Thaeo WCDEC	1.458	7.79	2.18	11.7	5.178	27.7	8.335	44.6	1.556	8.32	18.708	100
Khao Mai Kaew NRF	0.014	4.44	0.049	15.3	0.108	33.4	0.108	33.4	0.044	13.5	0.324	100
Khao Bang Khanun NRF	0.325	15.5	0.785	37.4	0.797	38	0.086	4.08	0.105	5.01	2.098	100
Khao Sam Liam NRF	0.044	16.8	0.158	59.7	0.053	20.1	0.008	2.83	0.002	0.71	0.265	100
Khao Kamala NRF	1.504	7.03	4.608	21.5	8.921	41.7	3.945	18.4	2.415	11.3	21.393	100
Khao Nak Keod NRF	0.029	0.19	2.054	13.5	7.418	48.9	5.382	35.5	0.287	1.89	15.17	100
Khao Tosae NRF	0.175	19.9	0.653	74.2	0.053	5.97	0	0	0	0	0.88	100
Khlong U-Tapao NRF	0	0	0	0	0.064	3.41	0.794	42.4	1.013	54.2	1.871	100
Khlong Tha Maphrao NRF	0.648	25.8	1.009	40.2	0.852	34	0	0	0	0	2.508	100
Khlong Para NRF	0	0	0	0	0.016	0.8	1.514	77.1	0.435	22.1	1.964	100
Khlong Bangrong NRF	0.068	2.16	1.891	60	1.191	37.8	0	0	0	0	3.15	100
Khlong Tarau NRF	2.839	100	0	0	0	0	0	0	0	0	2.839	100
Khlong Tajin NRF	0.005	0.14	0.338	9.46	0.901	25.2	2.267	63.5	0.059	1.65	3.569	100
Khlong Khopee NRF	2.541	98.8	0.031	1.22	0	0	0	0	0	0	2.572	100

Based on the percentages of the deforestation vulnerability zones of the 15 PFAs with their buffer zones (Table 14), the terms of the deforestation risk for each PFA with the specific conditions can be elaborated as below.

Low deforestation risk. The additive percentage of the very low and low deforestation vulnerability zones is equal to or more than 50%, or the additive value of the very low and low deforestation vulnerability zones is higher than the additive percentage of the high and very high deforestation vulnerability zones.

High deforestation risk. The additive percentage of the high and very high deforestation vulnerability zones is equal to or more than 50%, or the additive value of the high and very high deforestation vulnerability zones is higher than the additive percentage of the very low and low high deforestation vulnerability zones.

The results show that there were 11 PFAs with a low risk of deforestation and that they were Sirinath MNP, Khao Phra Thaeo WCDEC, and Khao Mai Kaew, Khao Bang Khanun, Khao Kamala, Khao Nak Keod, Khao Tosae, Khleng Tha Maphrao, Khleng Bangrong, Khleng Tarau, and Khleng Khopee NRFS. On

the other hand, there were 4 PFAs with a high risk of deforestation and they were Khao Sam Liam, Khleng U-Tapao, Khleng Para, and Khleng Tajin NRFS. These findings can be used as basic information for a deforestation protection and prevention plan in each PFA, particularly those PFAs with a high risk of deforestation.

Forest Area in 2014 and Deforestation Vulnerability Zonation

The relationship of the existing forest area in 2014 and the deforestation vulnerability zonation of the 15 PFAs within their boundaries by overlay analysis is presented in Table 15. It reveals that there were 7 PFAs, Khao Bang Khanun, Khao Sam Liam, Khao Tosae, Khleng Tha Maphrao, Khleng Bangrong, Khleng Tarau, and Khleng Khopee NRFS, which had an existing forest area in 2014 of which more than 50% was located in very low and low deforestation vulnerability zones. In contrast, there were 5 PFAs, Khao Phra Thaeo WCDEC, and Khao Mai Kaew, Khleng U-Tapao, Khleng Para, and Khleng Tajin NRFS, which had an existing forest area in 2014 of which more than 50% was situated in high and very high deforestation vulnerability zones. Meanwhile, there were 3 PFAs, Sirinath MNP, and Khao Kamala and Khao Nak Keod NRFS, which had

Table 16. Number of the predicted deforestation hotspots with deforestation vulnerability zones of 15 protected forest areas

Protected forest area	Annual predictive deforestation rate	Number of deforestation hotspots in deforestation vulnerability zones					Total
		Very low	Low	Moderate	High	Very High	
Sirinath MNP	0.0503	16	25	1	-	-	42
Khao Phra Thaeo WCDEC	0.0004	-	1	-	-	-	1
Khao Mai Kaew NRF	0.0018	1	3	-	-	-	4
Khao Bang Khanun NRF	0.0150	4	3	-	-	-	7
Khao Sam Liam NRF	0.0002	-	-	-	-	-	0
Khao Kamala NRF	0.1400	14	61	84	37	33	229
Khao Nak Keod NRF	0.0960	2	25	56	9	-	92
Khao Tosae NRF	0.0002	-	-	-	-	-	0
Khloneg U-Tapao NRF	0.0011	-	-	-	-	1	1
Khloneg Tha Maphrao NRF	0.0023	1	1	-	-	-	2
Khloneg Para NRF	0.0033	-	-	-	3	-	3
Khloneg Bangrong NRF	0.0008	-	-	2	-	-	2
Khloneg Tarau NRF	0.0001	-	-	-	-	-	0
Khloneg Tajin NRF	0.0151	-	-	3	14	-	17
Khloneg Khopee NRF	0.0053	8	-	-	-	-	8
Total	46	119	146	63	34	408	

an existing forest area in 2014 approximately 50% of which was situated in moderate deforestation vulnerability zones.

These findings show the vulnerability to deforestation in the future and can be used as basic information for a forest patrolling program for the PFAs. In particular, 8 PFAs, namely Sirinath MNP, Khao Phra Thaeo WCDEC, and Khao Kamala, Khao Nak Keod, Khao Mai Kaew, Khloneg U-Tapao, Khloneg Para, and Khloneg Tajin NRFs, which had an existing forest area in 2014 more than 50% of which was located in moderate, high, and very high deforestation vulnerability zones, should be frequently patrolled by forest rangers for deforestation prevention.

Allocation of Deforestation Hotspots

The number of the predictive deforestation hotspots in the deforestation vulnerability zones of the 15 PFAs and their annual predictive deforestation rate are presented in Table 16. The results show that no deforestation hotspots were found in Khao Sam Liam, Khao Tosae, and Khloneg Tarau NRFs. This result implies that the probability of a deforestation occurrence

in these areas is rather low. However, there were 12 PFAs which had varying numbers of the predictive deforestation hotspots located over different deforestation vulnerability zones. Khao Kamala NRF had the highest number of deforestation hotspots with 229 points while Khao Phra Thaeo WCDEC and Khloneg U-Tapao NRF had the lowest number of deforestation hotspots with 1 point each. The top three PFAs which had high numbers of deforestation hotspots were Khao Kamala NRF, Khao Nak Keod NRF, and Sirinath MNP, and an intensive patrolling plan to protect them from deforestation in the future should be prepared.

In fact, the number of deforestation hotspots is directly related to the annual predictive deforestation rate between 2014 and 2026. The relationship can be confirmed by simple linear regression analysis, which shows a positive correlation between the annual predictive deforestation rate (x) of the 15 PFAs and the number of deforestation hotspots (y) with R^2 at 92.88%, as shown in the following equation:

Table 17. Number of the forest protection units with deforestation vulnerability zones of protected forest areas

Protected forest area	Number of forest protection units			Total
	Moderate	High	Very high	
Sirinath MNP	-	-	-	0
Khao Phra Thaeo WCDEC	-	-	-	0
Khao Mai Kaew NRF	-	-	-	0
Khao Bang Khanun NRF	-	-	-	0
Khao Sam Liam NRF	-	-	-	0
Khao Kamala NRF	6	1	8	15
Khao Nak Keod NRF	19	1	-	20
Khao Tosae NRF	-	-	-	0
Khleng U-Tapao NRF	-	-	1	1
Khleng Tha Maphrao NRF	-	-	-	0
Khleng Para NRF	-	2	-	2
Khleng Bangrong NRF	-	-	-	0
Khleng Tarau NRF	-	-	-	0
Khleng Tajin NRF	1	5	-	6
Khleng Khopee NRF	-	-	-	0

$$y = 1404x - 3.8667 \quad (6)$$

Allocation of Forest Protection Units

The number of the forest protection units with deforestation vulnerability zones in the PFAs is presented in Table 17. There were 5 PFAs, Khao Kamala, Khao Nak Keod, Khleng U-Tapao, Khleng Para, and Khleng Tajin NRFs, which required the establishment of forest protection units over hotspot areas; the numbers were 15, 20, 1, 2, and 6 units, respectively. Figure 6 displays an example of the distribution of forest protection units and their locations at Khao Nak Keod NRF.

Conclusions

The optimum geospatial models for the LULC prediction and DVA were successfully examined and identified based on an accuracy assessment. In this study, the CA-Markov and CLUE-S models were recognized as the optimum geospatial models for specific PFAs and they were further applied to predict the LULC in 2026; meanwhile the FR model was identified as the optimum geospatial model for the DVA and it was applied to analyze and classify the deforestation vulnerability zones based on the deforested areas between 2002 and 2014. The derived predictive LULC in 2026 was then used to identify the deforested areas between 2014 and 2026 and they were

overlaid with deforestation vulnerability zones to allocate the deforestation hotspots and forest protection units. There were 408 deforestation hotspots distributed over 12 PFAs, excluding Khao Sam Liam, Khao Tosae, and Khleng Tarau NRFs, while 5 PFAs, Khao Kamala, Khao Nak Keod, Khleng U-Tapao, Khleng Para, and Khleng Tajin NRFs, required the establishment of 15, 20, 1, 2, and 6 forest protection units, respectively, for protection from deforestation in the future. In conclusion, it appears that the integration of geospatial models for LULC prediction and deforestation vulnerability analysis can be used as an efficient tool for the allocation of deforestation hotspots and forest protection units to fulfill the forest conservation and protection program of the Thai Government. In addition, the research methodology framework of the study can be used as a guideline for a deforestation protection and prevention plan for PFAs in Thailand.

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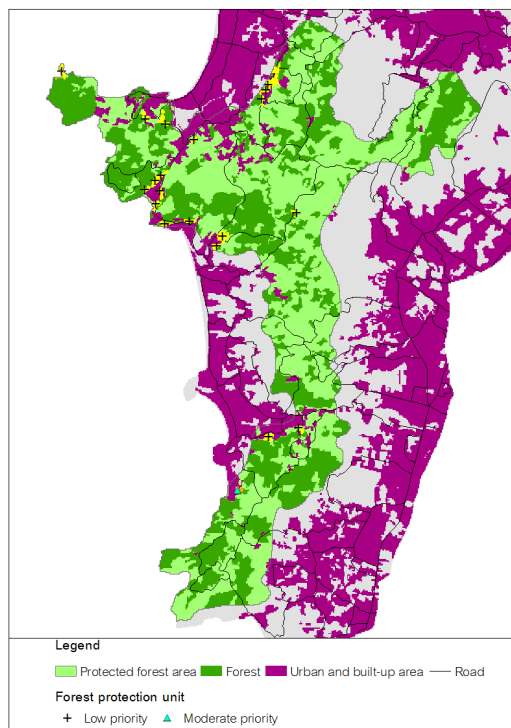


Figure 6. Distribution of forest protection unit of Khao Nak Keod NRF

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