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SPATIAL MODEL FOR DETERMINING RISK AREA OF DEFORESTATION

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Abstract

Tropical deforestation is now widely recognized as one of the most critical environmental problems facing the world, with serious long-term economic and social consequences. In most cases, deforestation is a process that involves competition amongst different land users for scarce resources. To understand the causes of the deforestation, a spatial relation between deforestation areas and landscape attributes was characterized. The study focused on integrating a Geographic Information System (GIS) and a spatial model based on a Composite Mapping Analysis (CMA) technique to express the vulnerability value of risk factors for determining deforestation risk areas in the future. Forest areas have mainly been changed into agricultural land. Nine variables relating to biophysical environment and human activity were used to develop the spatial model for predicting the areas at risk of deforestation. Forest type and distance from agricultural land were the most important variables for deforestation. The human activity factor had much more influence the risk of deforestation than the biophysical environment. Deforestation risk was classified into five classes; very high, high, moderate, low, and very low. The existing forest area in year 2002 was mostly classified as being in the high risk class. The accuracy of the deforestation risk model has been evaluated using the area which coincided with the deforestation risk class and the actual deforested area in the period 2000/2002. This study expands the basic function of GIS technology to map the deforestation risk zone at different severity levels, which could give effective information for developing deforestation prevention in study area.

Keywords: Deforestation, spatial model, geographic information system, Tung Salaengluang, Thailand

Introduction

World population is rapidly increasing while natural resources are still limited. The conflicts between limited resources and increasing human requirement causes forest deterioration and changes the dense forest into urbanized areas. Tropical forests of the world are being degraded at an alarming rate because of human-induced activities (Islam *et al*., 2001). At the present time, 14 to 16 million hectares of tropical forests are being converted each year to other land uses, mostly agricultural land. The principal agents of deforestation - those individuals who are cutting down the forests - include slash-and-burn farmers, commercial farmers, ranchers, loggers, firewood collectors, infrastructure developers and others (Roper and Roberts, 2003). In the past

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two decades, large-scale removal of forest has been typical in Thailand, due to commercial logging and expansion of agricultural lands to feed the growing population (Dyhr-Nielsen, 1986). The deforestation process is very complex because a variety of interacting and interrelating factors are responsible for this process. Thus, many researchers have sharply increased their efforts to model the factors influencing forest clearing in recent years (Kaimowitz and Andersen, 1997). Human impact is the main reason for deforestation and the cause of deforestation lies in the social and economic problems of the rural people living in the vicinity of the forest. Specifically, Barrow (1991) had listed the primary reasons for tropical forest degradation as population increase, improved access ways, large hydroelectric dams, expansion of shifting subsistence agriculture, large-scale agriculture, failure to assist the poor, increasing demand for forest products, administrative errors, and land settlement schemes (Grünberg, 2000).

Tung Salaengluang National Park, an important protected area for forest resource conservation and tourism, is located in the lower part of northern Thailand. Tung Salaengluang National Park with a buffer zone 2 km wide in Phitsanulok and Phetchabun provinces, Thailand, is located approximately 16°25' to 16°57' N and 100°37' to 101°00' E. It covers approximately 1,670 km^2. The topography varies from about 60 m above mean sea level in a flat area in the western parts to 1,100 m of a hilly and mountainous area on the southeastern edge (Figure 1). The climatic data was recorded during the period 1972 to 2004. The climate is associated with low temperature from November to January, rising to high from January to April. Its mean annual rainfall amounts to 1,300 mm and mean temperature is 27°C. The Oxic Paleustults and Typic Paplustox (soil family) dominate the soil types in the study area. The study area was mostly covered by forest, approximately 125,647.56 hectares or 75.27% of the study area (in year 2002). The natural forest of the study area is a mixture of dry evergreen, mixed deciduous, and dry dipterocarp forest. Shifting cultivation is the most common method of agriculture in this area. The cash crops consisted mainly of maize, cassava, and ginger. Other agricultural practices are fruits such as longan, mango, tamarind, and custard apple, including eucalyptus and Para rubber. The settlers around the area are generally poor and depend on agriculture for their living. Some of the setters destroy the primary forest and change it into agricultural land for shifting cultivation and fruit tree orchards. However, there are still insufficient information regarding the specific environmental and human factors (such as change of land use type and forest cover, current transportation network, and community location) which are contributing to deforestation in Tung Salaengluang National Park.

The increasing sophisticated tools for spatial modeling and analysis provide by today's GIS are leading to a new revolution in environmental modeling, one which encourages scientists to incorporate spatial processes and relationships in their models (Kemp, 1996). The GIS model can be widely used for spatial analysis of environmental management. Regarding deforestation, there have been studies by several researchers with various methods (Singh, 1993; Joseph and Stephen, 2000; Rahman *et al.*, 2000). Most of the studies had employed the GIS to relate the deforested areas with certain spatial characteristics (Bryan, 2000; Geoghegan *et al.*, 2000; Grünberg, 2000; Aondee, 2003). Deforestation is ultimately a spatial and temporal phenomenon. Furthermore, the question of quantifying and locating deforestation leads often to the question of identifying deforestation causes (Grünberg, 2000). The spatial models of deforestation is certainly appropriate if one had spatial data. It is useful in explaining the spatial pattern of deforestation - how likely deforestation is to occur as a result of distance from roads or variability of soil quality (Cropper *et al.*, 1996). Hepner (1999) has reported that the main technique used in a GIS-based community vulnerability model is Composite Mapping Analysis (CMA). This methodology involves combining separate spatial data layers in a meaningful manner to generate useful information regarding the spatial relationship among those data (Boonyanuphap *et al.*, 2001). This study aims at developing a GIS-based CMA modeling approach for assessing the deforestation risk using the relationship between the environmental conditions and the actual-deforested area during year 2000-2002.

Materials and Methods

Materials and Procedures

Datasets used to create the deforestation risk model in this study were gathered from field surveys and various sources (Table 1). The GIS datasets were organized and manipulated in form of shape file of ArcView 3.2a. The method applied in this study was based mainly on cell-based overlay analytical techniques at a 30 by 30 m resolution of a LANDSAT Thematic Mapper (TM) image. The digital elevation model (DEM) was converted from a triangulated irregular network (TIN). The slope dataset was derived from the DEM using 3D analyst extension. To detect, the forest cover change during the period 2000-2002 was done by GIS overlay techniques. This study investigated the change study of land use during the period 2000-2002 using the land use dataset from the Land Development Department of Thailand (LDD). Land use and land cover can be classified into 7 major land use categories namely, forest area, agricultural land, community area, grassland and savanna, water bodies, old clearing and shifting cultivation, and other categories (such as industrial area and government office). In addition, field survey for ground truth was conducted in this study during May to July 2003. Nine variables of deforestation risk model namely, slope, forest land use type, agricultural soil suitability, distance to drainage network, distance to water body, distance to transport network, distance to village location, distance to community area, and distance to agricultural area. Finally, the Spatial Analyst 2 extension allows an acceptable determination of the vulnerability score in order to predict a deforestation risk area in the further. The flow diagram of the study is shown in Figure 2.

Determining the Deforestation Risk Factors

Due to the spatial nature of deforestation, deforestation studies have employed a GIS to correlate the deforested area with spatial

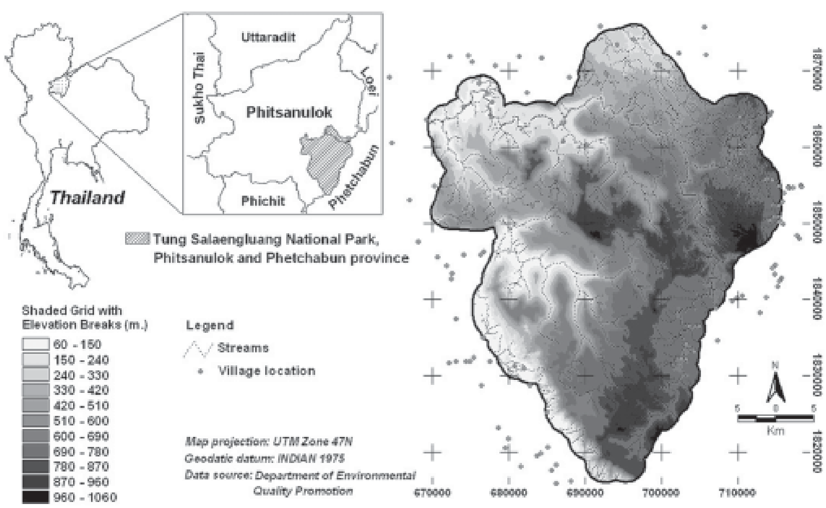

Figure 1. Location of the Tung Salaengluang National Park with 2 km buffer zone

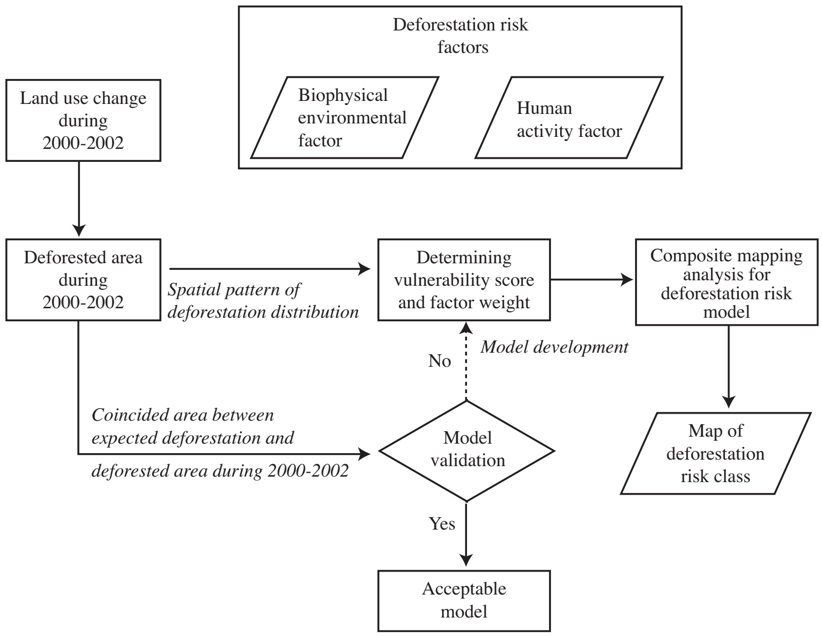

Figure 2. The general flow of the study activities

environmental and agricultural factors such as roads, settlements, soil quality, slope, and agricultural area (DeCola, 1989; Grünberg, 2000). In this study, the input factor influencing the deforestation risk model consists of nine variables, as shown in Table 2. Those variables were grouped into two deforestation risk factors, namely a biophysical environmental factor and a human activity factor. The categories of each variable were ranged on the basis of the rank of data value. However, the category classification of the variables can be modified to adjust the vulnerability score after model evaluation.

Deforestation Risk Model using CMA

The actual deforested area during year 2000-2001 was correlated to all variables in order to calculate the composite vulnerability value (V) in deforestation risk using Eqn. (1). The vulnerability value can assess the susceptibility to deforestation in the study area and forecast the probability level of deforestation in the future.

$$V = \left(E \sum w_i x_i + H \sum y_i z_i\right) \qquad (1)$$

Where $E + H = 1$; and

V = the composite vulnerability value
E = weight of the biophysical environmental factor related to the human activity factor
H = weight of the human activity factor related to the biophysical environmental factor
w_i = weight of variable within the biophysical environmental factor
y_i = weight of variable within human activity factor
x_i = vulnerability score of category in the biophysical environmental variable
z_i = vulnerability score of category in human activity variable

Table 1. Input datasets of the deforestation risk model using GIS

Theme	Data layer	Type of datasets	Source
Basic data	Boundary of national park, Administrative boundaries	Polygon	National Park, Wildlife and Plat Conservation Department (DNP); Department of Environmental Quality Promotion (DEQP)
Land use	Land use cover map in year 2000 and 2004, Forest land use cover map in year 2000	Polygon	Land Development Department (LDD); Royal Forest Department (RFD)
Soil	Soil group map, Soil characteristics	Polygon, Attribute table	Land Development Department (LDD)
Topography	Contour line, Spot height, Triangulated Irregular Network,	Line, Point, TIN,	Department of Environmental Quality Promotion (DEQP); Create TIN from contour line, spot height, drainage
	Digital Elevation Model (DEM),	GRID,	system, surface water body, and
	Slope gradient	GRID	transport network; Convert from TIN; Deriving slope from DEM
Hydrology	Drainage system, Surface water body	Line, Polygon	Department of Environmental Quality Promotion; Topographic map at 1:50000 scale (RTSD)
Human activity	Transportation network, Village location, Community area, Agricultural land	Line, Point, Polygon, Polygon	Field survey; Topographic map at 1:50000 scale; Department of Environmental Quality Promotion; Select from Land use cover map in year 2000

Table 2. Category in each variable of the deforestation risk model

Risk factor	Variable	Category
biophysical environmental factor	Agricultural soil suitability	Highly, Moderately, Marginally suitabl
	Slope	0-8%, 8-16%, 16-35%, 35-60%, 60-85%, more than 85%
	Forest land use type	Dry evergreen forest, Mixed deciduous forest, Dry dipterocarp forest, Grass land and Savanna, Secondary growth forest, Forest plantation, Other categories
	Distance to drainage network	0-1 km, 1-2 km, more than 2 km
	Distance to water body	0-2 km, 2-3 km, 3-4 km, 4-5 km, more than 5 km
human activity factor	Distance to transport network	0-2 km, 2-3 km, 3-4 km, more than 4 km
	Distance to village location	0-1 km, 1-2 km, 2-3 km, 3-4 km, 4-5 km, more than 5 km
	Distance to community area	0-1 km, 1-2 km, 2-3 km, 3-4 km, 4-5 km, more than 5 km
	Distance to agricultural area	0-1 km, 1-2 km, 2-3 km, 3-4 km, 4-5 km, more than 5 km

Determining the Deforestation Vulnerability Value and Weighting Factor

The composite mapping analysis (CMA) requires assigning weights to each spatial data layer that reflects the variable's contribution to deforestation vulnerability. To determine the vulnerability value and weighting factor, the relationships among categories with each variable were analysed base on the percentage of actual deforested area and the expected deforested area during year 2000-2002. The vulnerability score was calculated from 0 to 100 by using Eqns. (2) and (3).

$$x_i \text{ and } z_i = [(o_i/e_i) * 100] / \Sigma (o_i/e_i) \quad (2)$$

$$e_i = (T * Fa) / 100 \quad (3)$$

Where

x_i = vulnerability score of category within biophysical environmental variable
z_i = vulnerability score of category within human activity variable
o_i = observed area of deforestation during 2000-2002 in each category
e_i = expected area of deforestation during 2000-2002 in each category
T = total area of deforestation during 2000-2002
Fa = area percentage of each category within variable

The weighting score of each variable was calculated using Eqns. (4) and (5).

$$w_i = (M_i / \Sigma M) \quad (4)$$

$$y_i = (N_i / \Sigma N) \quad (5)$$

Where

w_i = weight of variable within biophysical environmental factor
y_i = weight of variable within human activity factor
M_i = average percentage of deforested area of each category within variable
ΣM = sum of average percentage of deforested area from all biophysical environmental variables
N_i = the percentage of deforested area within the buffer zone of 2 km in each human activity variable
ΣN_i = sum of deforested area percentage within the buffer zone of 2 km from all human activity variables

The weight of the biophysical environmental (E) and human activity (H) factors were determined by the assumption of human impact on deforestation using Eqn. (6) and Eqn. (7). This study assumed that the deforested area located within the buffer zone of 2 km surrounding area of human activities was more influenced by the human activity factor based on the consideration of the resistance to the movement of foot and vehicular traffic in relation to the type and condition of the roads, slope gradient along the roads, and in essence the energy and time distance needed to negotiate the deforested areas, whereas the deforested area outside the buffer zone of 3 km from human activities was more influenced by the biophysical environmental factor. The deforested area which is between 2 km and 3 km from human activities was equally impacted by both factors. This concept was used to calculate the weight of deforestation risk factors

$$E = (o_{>3km} / e_{>3km}) / [(o_{>3km} / e_{>3km}) + (o_{2km} / e_{2km})] \quad (6)$$

$$H = (o_{2km} / e_{2km}) / [(o_{>3km} / e_{>3km}) + (o_{2km} / e_{2km})] \quad (7)$$

Where

E = weight of biophysical environmental factor related to human activity factor
H = weight of human activity factor related to biophysical environmental factor
$o_{>3km}$ = observed deforested area outside the buffer zone of 3 km from human activities
$e_{>3km}$ = expected deforested area outside the

buffer zone of 3 km from human activities

o_{2km} = observed deforested area within the buffer zone of 2 km from human activities

e_{2km} = expected deforested area within the buffer zone of 2 km from human activities

Afterward, the map for deforestation risk class was created from the datasets of composite vulnerability values. The entire study area was classified into 5 severity classes of deforestation risk namely, very low (VL), low (L), moderate (M), high (H), and very high (VH), using an equal interval range as a class break because the numbers of composite vulnerability values are less in the classes (7.25 - 43.90). This interval method is useful to highlight changes in the extremes. It is also probably best applied to familiar data ranges such as percentages or temperature. A GIS-based map of the deforestation risk areas helps to delineate and identify existing forest areas in year 2002 that are vulnerable to being encroached on in the future.

Model Validation

In order to validate the model result, the spatial comparison between the deforestation risk area and actual deforested area during year 2000-2002 was used to calculate the spatial coincided value (CV) for each deforestation risk class using Eqn. (8). The coincided value implies the accuracy of the model. These will expresses how precise deforestation risk factors can be used to predict the spatial distributions of deforestation in the future: the higher CV value shows the more precise model.

$$CV = [2 \times S \times 100] / (R+F) \tag{8}$$

Where

CV = the coincided value of each deforestation risk class as compared with total deforested area

R = total deforested area during 2000-2002

F = area of deforestation risk class in forest area

S = the coincided area between a certain class of deforestation risk and actual deforested area during 2000-2002

Results and Discussion

Forest Cover Change Detection and Assessment of Deforestation

A land use change matrix, which describes its dimension, presents the forest cover change during the period 2000-2002 (Table 3). The forest area had increased around 78.56 km^2 due to the success of promotion in forest plantations and forest protection. Approximately 34.84% of agriculture land and 19.76% of grassland in year 2000 have rehabilitee into secondary forest, whereas forest areas have mainly been changed into agricultural land and shifting cultivation. In addition, around 5.97% of old clearing and shifting cultivation has also recovered into grassland and savanna. This was partly because the abandon areas of old clearing and shifting cultivation in the National Park were returned to the government by the official policy on forest conservation. The deforested areas were the areas transferred from forest land in year 2000 to non-forest area uses in year 2002. As shown in Figure 3, the deforested areas occupied approximately 8,358.84 hectares or 7.11% of the forest area in year 2000. The estimates of forest cover change based on interpretation of LANDSAT-TM images indicate that forest cover in the study area had increased from 70.57% in 2000 to 75.27% in 2004 due to the success of reforestation activities. At the same time, the remaining forest area is concentrated in the highlands or the lowlands that are hardly accessible. The increased shifting cultivation and agricultural areas expanded and occupied forested areas of approximately 6,651.71 hectares or 80.77% of the total deforested area. This result could indicate that agricultural activities were a main deforestation cause in this area. In the national park, the deforested area mostly tended to be in agricultural areas, whereas the deforested area in the buffer zone evidently occurred surrounding the villages.

Spatial Pattern of Deforestation Distribution and the Relative Vulnerability Score

The distribution of deforestation simply depicted the spatial relationship between the environmental conditions and the occurrence of deforestation in the study area. The spatial comparison between actual deforested area and expected deforested area for each category expressed a likelihood of encroachment into the forest area in the future. The relative vulnerability scores of the different categories were illustrated in Table 4. In this study, the better soil suitability for agriculture was more likely to be in the deforested area than poor soil suitability for agricultural purposes, which agreed with the study carried out by Grünberg (2000). Among the forest land use types, dry dipterocarp forest had the highest correlation in deforestation. Although soil quality of dry dipterocarp forest is rather poor for agriculture,

Table 3. The matrix of land use change detection during period 2000-2002

Land use type in 2000 (hectare)	Land use type in year 2002 (hectare)							Total (hectare)
	Forest	Agricultural land	Community area	Grassland and savanna	Water bodies	Old clearing and shifting cultivation	Other categories	
Forest	109,286.19	4,929.57	44.73	1,408.95	146.16	1,822.14	7.29	117,645.03
Agricultural land	16,007.85	14,844.51	643.68	4,569.84	168.39	9,628.47	90.00	45,952.74
Community area	57.06	422.10	553.50	6.84	8.28	103.59	7.02	1,158.39
Grassland and savanna	249.84	10.44	0.00	987.21	0.00	17.10	0.00	1,264.59
Water bodies	30.96	45.27	6.21	0.00	79.74	31.77	0.00	193.95
Old clearing and shifting cultivation	9.00	0.00	0.00	39.24	0.00	609.39	0.00	657.63
Other categories	6.66	20.07	0.00	0.00	1.98	14.85	9.36	52.92
Total	125,647.56	20,271.96	1,248.12	7,012.08	404.55	12,227.31	113.67	166,925.25

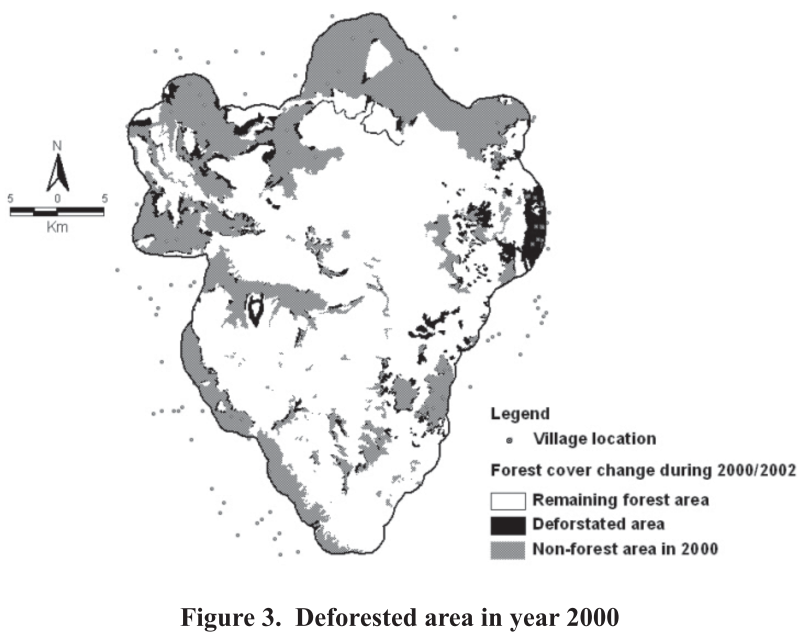

Figure 3. Deforested area in year 2000

Table 4. The percentage of deforestation area and vulnerability scores in each variable category

Variable	Category	% of deforested area	Score (x_i or z_i)
Agricultural suitability of land	highly suitable	8.24	43
	moderately suitable	7.17	38
	marginally suitable	3.67	19
Slope	0-8%	5.89	-
	8-16%	2.98	-
	16-35%	2.69	-
	35-60%	4.95	-
	60-85%	6.60	-
	more than 85%	0.00	-
Forest land use type	dry evergreen forest	1.25	2
	mixed deciduous forest	3.01	5
	dry dipterocarp forest	23.18	36
	grass land and savanna	20.40	32
	secondary growth forest	2.74	4
	forest plantation	0.52	1
	other categories	12.97	20
Distance to drainage network	0-1 km	5.28	64
	1-2 km	2.82	34
	more than 2 km	0.19	2
Distance to water bodies	0-2 km	10.39	32
	2-3 km	8.06	27
	3-4 km	5.67	17
	4-5 km	5.48	17
	more than 5 km	2.91	9
Distance to transport network	0-2 km	6.97	40
	2-3 km	4.42	26
	3-4 km	3.86	22
	more than 4 km	2.01	12
Distance to village location	0-1 km	11.94	33
	1-2 km	5.97	17
	2-3 km	5.52	15
	3-4 km	5.07	14
	4-5 km	4.84	13
	more than 5 km	2.85	8
Distance to community area	0-1 km	5.57	-
	1-2 km	4.70	-
	2-3 km	4.48	-
	3-4 km	5.89	-
	4-5 km	4.53	-
	more than 5 km	5.01	-
Distance to agricultural area	0-1 km	10.06	59
	1-2 km	3.70	22
	2-3 km	1.77	10
	3-4 km	1.58	9
	4-5 km	0.00	0
	more than 5 km	0.00	0

but it is easier than other forest types to contribute to land clearance. Because this type of forest is quite open and occurred mostly near agricultural land and villages, which is easy for land clearing. The results also indicated that the distance to drainage network and water bodies, which is a majority of water sources for agriculture, was also the significant factor for deforestation. Most of people living in or around the study area are rather poor, but the results could not indicate deforested area has changed significantly associated with the distance to the community area. This was partly because the major sources of income were from non-agricultural work. Kaimowitz and Andersen (1997) had explained that more off-farm employment and higher wages should decrease deforestation because agriculture and forestry become less profitable. Likewise, higher input costs reduce deforestation by making agriculture less profitable. The slope gradient did not play a significant role to effect on deforestation. The shifting cultivation, which is a major agricultural system in this area, can be potentially practiced without the limitation of topography, except for limestone cliffs in the southwest of the study area. The variables of slope and distance to community area had no relation to deforested areas, and had no influence on the settler in clearing and occupying the forest area. Even so, the results partly conflicted with some studies, which indicated the slope gradient as an important factor of deforestation (Mertens and Lambin, 1997; Bryan, 2000; Grünberg, 2000; Mas *et al.*, 2000; Aondee, 2003). Thus, these two variables are not added into the model. The effects of the distance from human activities relating to deforestation indicated that the deforestation was intensive when situated within the zone of 2 km from human activity (Table 5).

Relative Weight of Deforestation Risk Variables and Factors

The higher value of weight expressed the higher influence on decision making of the people in forest encroachment. Among the variables, the forest type and the distance from agricultural land acted as the most important variables of the biophysical environmental factor and the human activity factor, respectively. The weight of variables was determined from Eqns. (4) and (5). Among the variables in Table 6, the forest land use type and the distance to agricultural land acted as the most important

Table 5. The relationship between deforestation and distance from human activities

Distance from human activities	Total area (hectare)	Deforested area (hectare)	% of deforested area
0-2 km	114,399.72	8,245.62	7.21
more than 3 km	5,038.29	41.40	0.82

Table 6. Weighting score of deforestation risk variables

Biophysical environmental factor	Average percentage of deforestation	Weight (w_i)	Human activity factor	Average percentage of deforestation	Weight (y_i)
Agricultural soil suitability	6.36	0.24	Distance to transport network	6.64	0.32
Forest land use type	9.15	0.34	Distance to village location	7.08	0.34
Distance to drainage network	2.76	0.10	Distance to agricultural area	7.30	0.35
Distance to surface water body	8.43	0.32			
Sum	26.71	1.00		21.01	1.00

factors of the biophysical environmental factor and the human activity factor, respectively. According to the human activity factors, normally greater access to forest leads to more deforestation, but this study indicated that the distance to a transportation network has less importance in influencing deforestation and land clearing. This is because most of the roads in the national park are dirt roads that limit accessibility of to the area during the rainy season and the agricultural areas are more easily penetrated on foot. The relative weight of the factor as shown in Table 7, evidently indicated that the human activity factor had a much higher influence than the biophysical environmental factor on the risk of deforestation. Mertens and Lambin (1997); Grünberg (2000); Mas *et al*. (2000) and Aondee (2003) have similarly demonstrated that the human activities associated with agricultural work can play an important role in determining the deforestation.

Deforestation Risk Model

The vulnerability score and weight value of seven variables were used to create the deforestation risk model according to the following equation:

$$V = \{[0.14 (0.24 x_1 + 0.34 x_2 + 0.10 x_3 + 0.32 x_4)] + [0.86 (0.32 z_1 + 0.34 z_2 + 0.35 z_3)]\}$$

Where

V = the composite vulnerability value of deforestation

x_1 = vulnerability value of category in agricultural soil suitability variable

x_2 = vulnerability value of category in forest land use type variable

x_3 = vulnerability value of category in distance to drainage network variable

x_4 = vulnerability value of category in distance to water body variable

z_1 = vulnerability value of category in distance to transport network variable

z_2 = vulnerability value of category in distance to village location variable

z_3 = vulnerability value of category in distance to agricultural area variable

The composite vulnerability value had a range between 7.25 and 43.90, in which the higher value expressed the higher probability of deforestation. This vulnerability value can be used to forecast the deforestation risk zone at different severity levels.

Mapping the Deforestation Risk Area

The forest area in year 2002 was classified into 5 severity classes of deforestation risk. As shown in Table 8 and Figure 4, the moderate-risk class (M) and the high-risk class (H) predominantly appear in the study area at 29.43% and 24.32% of the forest area, respectively. These two risk classes mostly occurred in a wide area along the western boundary of the national park which was easily accessible by road. The forest area in year 2000 that located neighboring to the village locations and agricultural areas, was mainly classified as the very high risk class (VH) and the high-risk class (H) due to the high influence of human activities. This results evidently implie that the human impacts on rates of deforestation are the significant of converting the forest area to agricultural purposes.

Table 7. Weighting score of deforestation risk factors

Deforestation risk factor	Observed deforested area (hectare)	Expected deforested area (hectare)	*o*/*e*	Weight
biophysical environmental factor (E)	41.40	252.29	0.16	0.14
human activity factor (H)	8,317.44	8,106.55	1.03	0.86

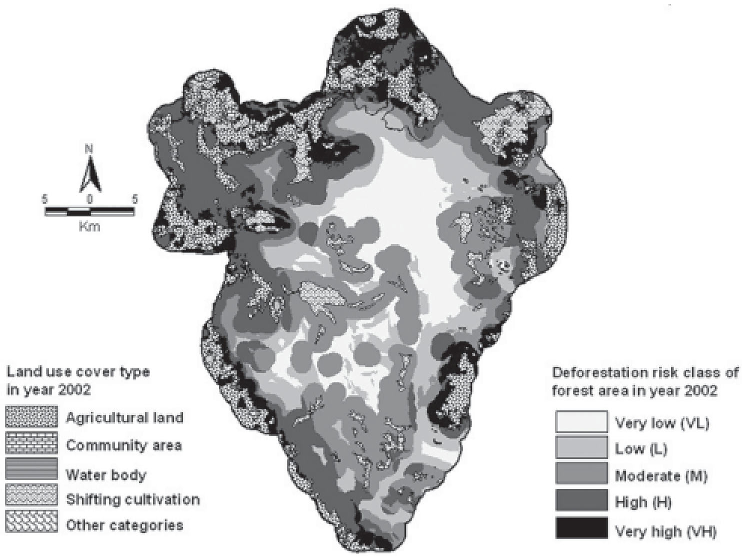

Figure 4. Deforestation risk class of the forest area in year 2002

Model Validation

According to the model validation, Eqn. (8) was used to calculate the spatial coincided value (CV) for comparing the risk area with the actual deforested area during the period 2000-2004. The coincided value can imply the accuracy of the model, which expresses how precise risk factors can be used to predict the spatial distributions of deforestation in the future. The result in Table 9 shows that the higher deforestation risk classes contributed positively to the coincided value. Even though the very high risk class (VH) had the highest accuracy at 33.46 among the classes, this result showed a very low accuracy for the model. This is partly because of the short period used for forest change detection. The area deforested within 2 years may not have a wide distribution. It would much rather see the model calibrated using year 2000-2002 and then tested using year 2003-2005 data. Moreover, this study did not include socioeconomic and demographic factors, which are important in identifying the causes of deforestation. The information involving the socioeconomic factor is necessary to provide the perspective and basic requirements of the local people in degrading the forest. For example, Kaimowitz and Andersen (1997) have reported that higher agricultural prices stimulate greater forest clearing, because agriculture is more profitable and finances the clearing of additional land. The effect is stronger when agricultural product and labor supply are elastic. However, population density and the deforestation area are only strongly correlated at the national level, while at the local and regional levels; deforestation is determined by infrastructure availability, soil quality, distance to markets, and career of the settlers. Therefore, at the local level, population density often shows no statistically significant relation to deforestation once these variables are taken into account.

Conclusion

The pattern of deforestation in each area is unique and can only be partially attributed to the variables analysed in the model. The result of this study was to demonstrate significant effects of variables such as soil suitability for agriculture, forest land use type, distance to drainage network, distance to surface water body, distance to transport network, distance to village location, and distance to agricultural area in relation to the deforestation phenomenon. The deforestation phenomenon in the study area is negatively correlated with the distance to human

Table 8. The deforestation risk class in the forest area year 2002

Deforestation risk class	Range of vulnerability value	Forest area (hectare)	% of the study area (hectare)
Very low (VL)	7.25 - 14.58	19,362.52	11.60
Low (L)	14.58 - 21.91	26,894.59	16.11
Moderate (M)	21.91 - 29.24	36,974.17	22.15
High (H)	29.24 - 36.57	30,552.57	18.30
Very high (VH)	36.57 - 43.90	11,863.71	7.11
Total		125,647.56	75.27

Table 9. The coincided value (CV) of deforestation risk class and actual deforested area

Deforestation risk class	Forest area year 2000 (hectare)	Deforested area 2002 (hectare)	Coincided area (hectare)	CV (%)
Very low (VL)	18,214.29	8,358.84	31.14	0.23
Low (L)	21,369.33	8,358.84	339.63	2.28
Moderate (M)	36,061.02	8,358.84	1,624.66	7.32
High (H)	30,271.77	8,358.84	3,002.43	15.54
Very high (VH)	11,728.62	8,358.84	3,360.98	33.46
Total	117,645.03		8,358.84	

activities, especially to agricultural works. However, the vulnerability of the model depends on the classification of category within each variable such as the intervals of slope class, and the defined distances of buffer area from deforestation sources, thus some iterate reclassification of category is required for a more effective model. The more precise model may focus explicitly on the socioeconomic variables such as population, income/economic growth, debt, product prices, land tenure, input costs, technological change, conservation policies, and opinions of people toward forest conservation. According to the limit of time and financing fund, these socioeconomic variables should be considered as the additional factors, besides the model could include a differentiation of deforestation into the permanent conversion to farmland and the temporary shifting cultivation activities to increase the predictability power of the model in the future study. However, the variables must be carefully considered to avoid the spurious results.

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