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Mapping forest types using ecological niche modeling and fuzzy accuracy assessment in Thailand

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ABSTRACT

The forest map remains essential for investigating plant ecology and biodiversity patterns. This study proposed methods for mapping forest types based on ecological niche modeling and then used fuzzy error matrix for accuracy assessment. The upper Ping basin of northern Thailand was selected as study area. The modeled data included forest inventory, topographic, climatic, soil, and geological data. Ecological niche factor analysis was used to model and produce the best habitat suitability index of each forest type, which were then combined using hierarchically generated coding. As a result, eight classes of forest types were generated: dry dipterocarp forest (7,373.94 km^2, 32.81%), evergreen ecotone or transition area (3,666.97 km^2, 16.32%), mixed deciduous forest (3,440.79 km^2, 15.31%), deciduous ecotone or transition area (3,225.58 km^2, 14.35%), deciduous and evergreen forest (2,027.12 km^2, 9.02), coniferous forest (CF; 365.28 km^2, 1.63%), moist and dry evergreen forest (290.08 km^2, 1.29%), and hill evergreen forest (270.56 km^2, 1.21%). Four variables were found to be critical in forest type distribution: elevation, mean annual temperature, annual maximum temperatures and annual minimum temperatures. To assess map accuracy, fuzzy error matrix, which allows the recognition of ambiguous classes and does not ignore variation in the interpretation of the reference data at class boundaries, was used (75.89% of overall accuracy).

Keywords: tropical forest type; ecotone forest; ecological niche model; fuzzy accuracy assessment

1. INTRODUCTIONห

Understanding and monitoring the state of the world's forests have never been as important as it is today (FAO and UNEP, 2020). Typically, plant ecology investigations include four types of studies (Gerhart et al., 2004): plant species surveys; estimates of cover percentages and age structures of dominant perennial plant species; evaluations of the composition, relative abundance, and distribution of plant associations; and vegetation mapping. Vegetation mapping is particularly critical for understanding biodiversity patterns through space and time and underpins biodiversity management and planning at local and global scales (Tierney et al., 2019). It is a key resource for the assessment of woodland resources and National Forest Inventories (NFIs) (Waser et al., 2017). Vegetation maps using remote sensing and GIS modeling techniques have been used, for example, to investigate landscape changes and analyze vegetation transitions, forest limits, and expected future forest expansion (e.g., Ihse, 2010; Miller et al., 1994). Therefore, vegetation maps consist of two essential elements: a classification of vegetation and a spatial attribution of that classification (Tierney et al., 2019).

This article focused on the spatial attribution of vegetation pattern-based on GIS modeling techniques. The use of GIS for vegetation-related research has been a key focus from the very beginning of the development of GIS in the early 1960s (Bareth and Waldhoff, 2017). Mapping of vegetation has progressed from the earliest geographical approaches through the development of systematic methods based on naturalists' understanding of observable patterns to today's highly technical modeling approaches (Tierney et al., 2019). Although forest types dominant within a region depend on climate, elevation, wind, rainfall, temperature, and soil conditions (Oregon Forest Resources Institute, 2021), these physical variables can be modeled in an ecological niche approach with GIS modeling techniques. In other words, we can view forest ecosystems, in terms of ecological niches—the particular sets of environmental conditions and resources that allow a given organism or species to survive and grow (Barve et al., 2011; Peterson et al., 2011). This allows us to address a variety of important problems, including resource use, geographical diversity, and many aspects of community composition and structure (McGill et al., 2006). However, the maps generated must still be assessed for accuracy. Accuracy information is integral to a user's ability to responsibly utilize such maps for forest management decisions (Milliken and Woodcock, 1996). In addition, accuracy assessment can contribute to improving the quality of maps' information by identifying the sources of errors and correcting them (Lunetta and Lyon, 2004). The underlying principle of accuracy assessment is that it compares mapped land classifications to higher quality reference data, collected through a sample-based approach (FAO, 2016).

With a traditional error matrix, only one possible answer (the one considered to be the best answer by an 'expert' in the field) is compared to the map label. In contrast, fuzzy set theory allows both users and producers to look at ranges of acceptable answers (Milliken et al., 1998). Therefore, the current study used a modified fuzzy accuracy assessment, based on the fuzzy error matrix approach of Congalton and Green (2009). Because it allows for grades of membership and provides considerably more flexibility than classical set theory, fuzzy set theory has many applications ranging from pattern recognition to control engineering to modeling human decision-making (Woodcock and Gopal, 2000). In the case of a vegetation map, one label may be absolutely correct, but other labels may be considered good or acceptable (Milliken et al., 1998). For example, for a given site (in this case an inventory plot within a map polygon), a map label of 'red fir' may be considered absolutely correct, but a map label of 'subalpine conifer' might still be considered acceptable (Congalton and Green, 2009).

In this study, fuzzy error matrix approach was used to accurately assess the relationship between predictive forest type map and ground checking. However, accuracy assessment may be difficult because of appropriate map label for some locations (Gopal and Roodcock, 1994), produced by a resultant multi-layer model involving representation of forest types (Zadeh, 1965; Burrough, 1989; Brown, 1998) that any given location in area with two events (Brown, 1998). Additionally, it is less certain in places where the neighboring trees are not clearly indicative of one forest type and more certain where the trees more clearly suggest one forest type. For example, possible gradations between two classes in a map of forest (Woodcock and Gopal, 2000) that considered the difference between the vegetation categories conifer forest and hardwood forest (Gopal and Roodcock, 1994) as the same problem was defined by the breaking line between mixed forest and both hardwood forest and conifer forest (Woodcock and Gopal, 2000).

Based on the above reasons, the purpose of this research was to present a method for mapping forest types based on ecological niche modeling, which was then accurately assessed by technique of fuzzy error matrix. This study focused on the upper Ping basin because it has available forest inventory data from Forest Royal Department (FRD) of Thailand. Moreover, the Ping basin is considered the most degraded natural forest area in Thailand; currently, it is intensively managed based on academic principles and fundamentals of forest ecology with the goal of conservation and rehabilitation of the forest lands.

2. MATERIALS AND METHODS

2.1 Study area

The upper Ping basin is a major watershed in northern Thailand. The study area is part of the Ping basin I, which is one of the four upper tributary basins forming the Chao Phraya river system, the most important river basin in Thailand. The study area is 22,473.66 km^2 and is situated approximately between latitudes 17° and 20° N and between longitudes 98° to 100° E, or from 1925648–2190195 N to 402478–542869 in the UTM coordinate system (WGS 1984 and 48N), as shown in Figure 1a. The topography of the study area included a series of complex mountains that range in elevation from 0 m to 2,775 m above mean sea level (MSL), as shown in Figure 1b; the area comprised steep lands of more than 35% slope, which restricted its uses to woodland, watershed protection, and wildlife conservation. Data on the climate, which is dominantly affected by the monsoon, came from 21 meteorological stations of the Thailand Meteorological Department (TMD), as shown in Figure 1c. In addition, forest area in the upper Ping basin currently covered 16,947.38 km^2, as seen in Figure 1d. Soil data of study area were mostly classified as slope complex (Figure 1e) and geological data included 32 geological formation characteristics with mostly sedimentary and metamorphic rock types in study area, as shown Figure 1f.

2.2 Datasets and sources

This study required ecological niche modeling. Therefore, datasets of ecogeographical variables (EGV) related to forest types in Thailand were selected, which included forest inventory data, climatic data, topographical data, soil data, and geological data. Characteristics and sources of the EGV datasets are summarized in Table 1.

The forest inventory dataset focused on 460 permanent plots, which included 179 plots of dry dipterocarp forest (DDF), 164 plots of mixed deciduous forest (MDF), 83 plots of hill evergreen forest (HEF), 19 plots of moist and dry evergreen forest (MDEF), and 15 plots of coniferous forest (CF). Forest inventory data of Thailand from the Department of National Parks, Wildlife and Plant Conservation (DNP) has been surveyed every five years with same positions and points to monitor changing forest communities. Forest inventory points are usually collected with a uniform spacing size of 20 x 20 km but forest inventory data of Ping basin was surveyed with spacing size 5 x 5 km grid. Each forest inventory point included 5 circular plots (1 plot which located on intersection grid of 5 x 5 km was assigned as permanent plot while other 4 plots were temporary). Each plot were superimposed by concentric circular plots. Each circular plot was designed to collect a specific forest inventory data. In this study, identified forest types in permanent plot were selected for studying forest ecological model because they are a key component of a long-term ecological research program.

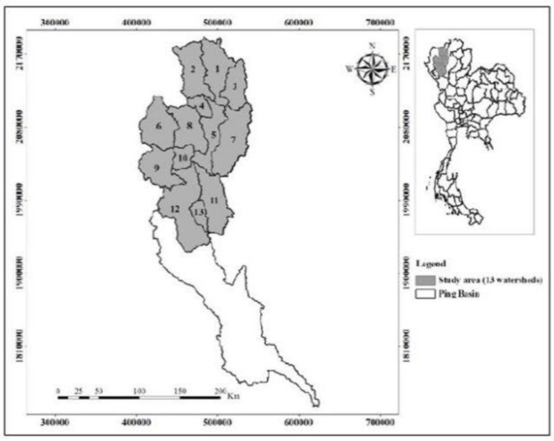
Topographical data is essential for modeling ecological niche of forest. Therefore, this study considered elevation (m), slope (degree), and aspect (direction). Elevation data were not only directly extracted from a Digital Elevation Model (DEM) 30 m but slope and aspect were also derived using standard GIS techniques from DEM 30 m.

The climatic data includes rainfall and temperature data, which have an influence on forest distribution. These climatic data were characterized by using the monthly mean data from a recently released 30-year period (1985-2014) from TMD of Thailand that was modeled by BIOCLIM. In this climatic modeling, we provided bioclimatic variables derived from the monthly temperature and rainfall values in order to generate more biologically meaningful variables (WorldClim, 2020). The BIOCLIM modeling produced 19 bioclimatic variables that were examined by using correlation analysis, which showed 10 of the 19 bioclimatic variables to be strongly correlated: mean annual temperature (BIO1), mean diurnal range (BIO2), temperature seasonality (BIO4), annual maximum temperature (BIO5), annual minimum temperature (BIO6), annual temperature range (BIO7), mean annual precipitation (BIO12), annual maximum precipitation (BIO13), annual minimum precipitation (BIO14), and precipitation seasonality (BIO15). These 10 bioclimatic variables conform to the climate factors identified by Kutintara (1999) and Santisuk (2006) as fundamental to Thai forest ecology.

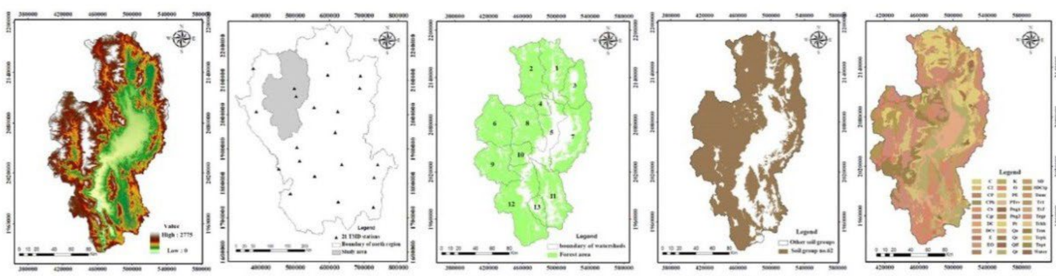
Soil data were mostly classified by slope complex (about 71.5%) and characterized based on geological formation. Thirty subtypes modified soil data were used for modeling.

2.3 Ecological niche modeling and validating

Data input for the ecological niche modeling comprised four datasets: 460 forest inventory plots, three topographic variables, 10 bioclimate variables, and 30 subtypes of soil data based on slope complex and geological formation. These datasets were transformed into GIS data with WGS 1984 UTM Zone 48N and were used for the ecological niche factor analysis (ENFA) in BIOMAPPER 4.0, developed by Hirzel et al. (2007). ENFA produced habitat suitability (HS) indices based on the extracted variables for each forest type, which were validated by using the absolute validation index (AVI) and the contrast validation index (CVI) to select the best HS index for each of the forest types.



(a) The upper Ping basin



(b) Topographic data **(c) Climatic data** **(d) Forest data** **(e) Soil data** **(f) Geological data**

Figure 1. The study area: (a) map, (b) topography, (c) climatic, (d) forest, (e) soil, and (f) geology

Table 1. Compilation of ecological niche modeling sources and datasets

EGV data	Characteristics of available data	Sources
1. Forest inventory data and topographical data based on digital elevation model (DEM)	- Forest inventory data based on permanent plots is in the form of vector-based GIS and spreadsheet data (2004-2007) - DEM is in the form of raster-based GIS with cell size of 30 x 30 m.	Department of National Parks, Wildlife and Plant Conservation (DNP) at https://www.dnp.go.th/inventory/ping/method.htm
2. Climatic data	The 30-year meteorological data of monthly mean rainfall and temperature (1985-2014) is in the form of spreadsheet data and paper reports	Thailand Meteorological Department (TMD)
3. Soil data	Vector-based GIS and paper and digital reports	Land Development Department (LDD)
4. Geology data	Vector-based GIS and paper and digital reports	Department of Mineral Resources (DMR)

2.4 Mapping forest types

The best HS indices based on ENFA for each forest type were combined using GIS techniques, based on codes for the forest types. The five forest types were placed into two groups: deciduous forest (MDF and DDF) and evergreen forest (CF, MDEF, and HEF). There were two steps for coding forest types to produce the forest map. In the first step, a hierarchical coding system was set and applied to each forest type according to HS classes (see Figure 2 for the example of deciduous forest). Next, the codes for the deciduous and evergreen forest types were combined and assigned to each forest type using a maximum operator in the GIS program. For example, MDF with moderate HS (code 2) combined with DDF with high HS (code 30) became DDF (code 32), as shown in Figure 3. If the HS class or code of forest type was equal, it was labeled an 'ecotone'. In the last step, the existing coding for the deciduous forest type was assigned a new code by multiplying by 1,000; this new code was combined with the code for the evergreen forest type using a maximum operator in the GIS program. For example, DDF with high HS (code 32000) combined with CF with moderate HS (code 112) became DDF (code 32112). Again, if the codes were equal, it was labeled an 'ecotone'. For example, DDF with moderate HS (code 22000) combined with CF with moderate HS (code 112) became deciduous and evergreen ecotone (code 22112).

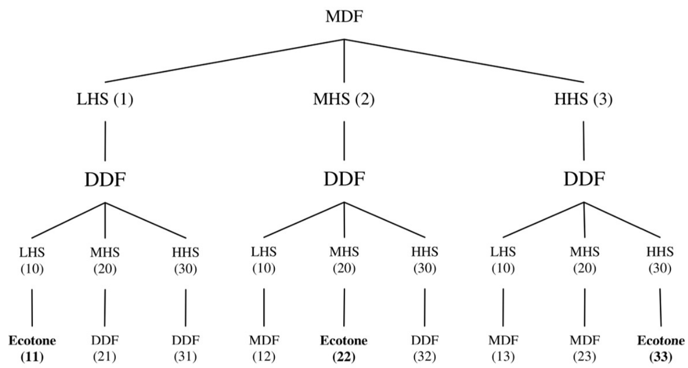


Figure 2. Example of hierarchical code system for deciduous forest
Note: MDF = mixed deciduous forest, LHS = low habitat suitability, MHS = moderate habitat suitability, HHS = high habitat suitability, and DDF = dry dipterocarp forest

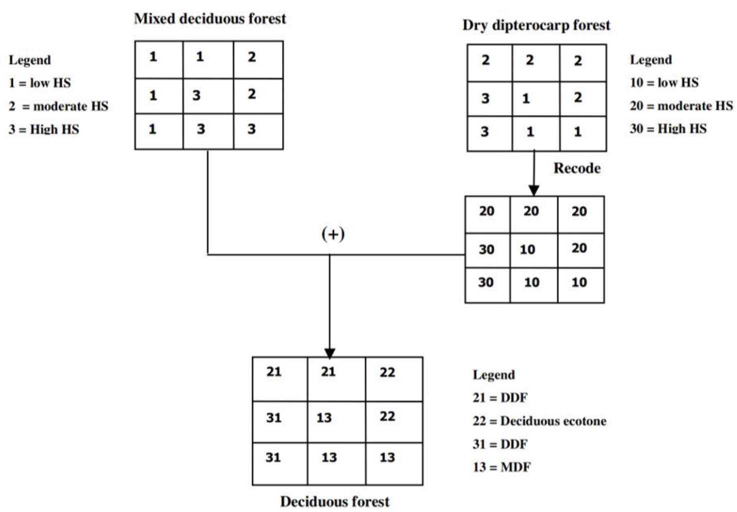


Figure 3. GIS spatial analysis for combining deciduous forest types

2.5 Fuzzy accuracy assessment

In this study, fuzzy set approach was set by accuracy level (modified from Landis and Koch (1977) for forest type) (Table 2), as follows:

- Forest type value higher than 50% represents perfect (P) accuracy between the classified map and the ground reference data.

- Forest type value close to (fuzzy) 50% represents approval (A) accuracy between the classified map and the ground reference data.

- Forest type value lower than 50% represents imperfect (I) accuracy between the classified map and the ground reference data.

For accuracy assessment, the most common way to represent the classification accuracy of remotely sensed data is in the form of an error matrix (Congalton, 1991; Foody, 2008; Rogan et al., 2008; Lawrence and Moran, 2015; Maxwell et al., 2018). Such metrics generally assume that map features have discrete and well-defined boundaries, and that the true value of all pixels can be ascertained with equal accuracy, regardless of spatial location relative to feature edges (Maxwell and Warner, 2020). Moreover, the error matrix can be implemented as a starting point for a series of descriptive and analytical statistical technique (Congalton and Green, 2009). One advantage of these techniques is that they yield a single overall map accuracy index, usually presented as a percent correct (Gopal and Roodcock, 1994). However, the classification scheme breaks represent artificial distinctions along continuum of land cover or observer variability, which is often difficult to control but can be solved by the fuzzy error matrix (Green and Congalton, 2009). For example, the possibility of three classes (such as deciduous and evergreen forest and their ecotones) were considered by accuracy evaluation of fuzzy vegetation maps (Berberoglu and Satir, 2008; Zlinszky and Kania, 2016).

Table 2. Fuzzy logic for accuracy assessment of forest type map in this study

Mapped forest type	Ground references							
	Deciduous forest (D)			Evergreen forest (E)				DEEco
	MDF	DDF	DEco	CF	MDEF	HEF	EEco	
MDF	**P**	A	A	I	I	I	I	Approval with D:E = 50:50
DDF	A	**P**	A	I	I	I	I	Approval with D:E = 50:50
DEco	A	A	**P**	I	I	I	I	Approval
CF	I	I	I	**P**	A	A	A	Approval with E:D = 50:50
MDEF	I	I	I	A	**P**	A	A	Approval with E:D = 50:50
HEF	I	I	I	A	A	**P**	A	Approval with E:D = 50:50
EE	I	I	I	A	A	A	**P**	Approval
DEEco	A	A	A	A	A	A	A	**P**

Note: P = perfect, I = imperfect, A = approval, MDF = mixed deciduous forest, DDF = dry dipterocarp forest, DEco = deciduous ecotone, CF = coniferous forest, MDEF = moist and dry evergreen forest, HEF = hill evergreen forest, EEco = evergreen ecotone and deciduous and evergreen ecotone

3. RESULTS

3.1 HS for forest type distribution

In the forest type distribution, HS indices were produced by ENFA, and then analyzed to determine relationships among the EGVs and to find combinations of specific EGVs (also called 'forest components') to produce correlated HS indices of the five forest types (MDF, DDF, HEF, MDEF, and CF). In general, ENFA, marginality, and specialization coefficients of EGV for each forest type were computed and combined to generate a global HS map using a median algorithm. The values of the HS indices varied from 0 to 100. Thus, all derived HS-index-based forest components of each forest type were validated as the best HS-based ENFA using AVI and CVI (in BIOMAPPER. The most accurate model is one that maximizes both AVI and CVI), as shown in Table 3.

3.1.1 Mixed deciduous forest (MDF)

The best HS of MDF was derived by using component 1 of MDF, or 'MDF1', comprised of four EGVs: elevation, BIO1, BIO5, and BIO6. The proportion of explainable information preferred 92% of marginality as a result of the best MDF-HS, indicating that the distribution of MDF species in the study area was greater than the species variation. Moreover, BIO1 (mean annual temperature) and BIO5 (mean monthly maximum temperature) are critical in the ecological niche model.

3.1.2 Dry dipterocarp forest (DDF)

The best HS of DDF was derived by using component 2 of DDF, or 'DDF2', and comprised of four EGVs: elevation, BIO1, BIO5, and BIO6. The proportion of explainable information preferred 91% of marginality as a result of the best DDF-HS, which indicated that the distribution of DDF species in the study area was higher than the species variation. Although BIO6 (mean monthly minimum temperature) was the highest essential EGV for the ecological niche model, the marginality value was not much different from the three other EGVs.

3.1.3 Hill evergreen forest (HEF)

The best HS of HEF was derived by using component 1 of HEF, or 'HEF2', comprising of four EGVs: elevation, BIO1, BIO5, and BIO6. The proportion of explainable information preferred 75% of marginality as a result of the best HEF-HS, which indicated that the distribution of HEF species in the study area was higher than the species variation. Moreover, elevation is critical in the ecological niche model.

3.1.4 Moist and dry evergreen forest (MDEF)

The best HS of MDEF was derived by using component 1 of MDEF, or 'MDEF1', comprising of four EGVs: elevation, BIO1, BIO5, and BIO6. The proportion of explainable information preferred 60% of specialization as a result of the best MDEF-HS, which indicated that MDEF species variation in the study area was higher than the global distribution of species. Moreover, BIO5 (mean monthly maximum temperature) is critical for the ecological niche model.

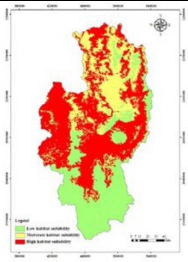
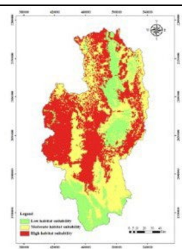
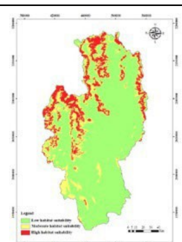
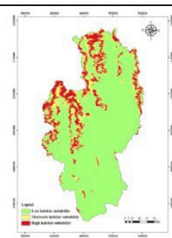
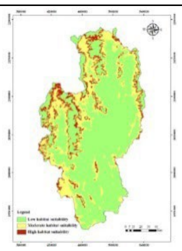
3.1.5 Coniferous forest (CF)

The best HS of CF was derived by using component 2 of CF, or 'CF2', comprising four EGVs: elevation, BIO1, BIO5, and BIO6. The proportion of explainable information preferred 80% of marginality as a result of the best CF-HS, which indicated that the distribution of CF species in the study area was higher than the species variation. Moreover, elevation is critical for the ecological niche model.

3.2 The forest type map

To obtain the forest type map, this study combined all five forest types based on hierarchical coding of HS indices in a GIS operation, as seen in Figure 5. In this GIS operation, there were three specific outputs.

Table 3. The best HS-based ENFA using maximum values of AVI and CVI for distribution of forest suitability

Forest type	EGVs	Marg.	Spec.1	Spec.2	Spec.3	
1. MDF	BIO1	**0.718**	0.244	-0.379	0.643	
	BIO5	0.620	-0.362	0.708	-0.748	
	BIO6	0.243	0.690	-0.582	0.111	
	Elevation	-0.204	0.577	0.124	0.123	
	% of Explanation	92%	6%	1%	1%	
HS(MDF1) = [1/(0.725+0.268+0.007+0.001)]*[0.725HS(marg.,c) + 0.268HS(spec.1,c) + 0.007HS(spec.2,c)+ 0.001H(spec.3,c)						
2. DDF	BIO6	**0.572**	-0.351	0.209	-	
	BIO1	0.521	-0.330	0.578	-	
	Elevation	-0.449	0.042	0.170	-	
	BIO5	0.447	0.875	-0.770	-	
	% of Explanation	91%	7%	1%	-	
HS(DDF2) = [1/(1.912+0.069+0.011)]*[1.912HS(marg.,c) +0.069HS(spec.1,c) +0.011HS(spec.2,c)						
3. HEF	Elevation	**0.805**	0.047	-0.296	-	
	BIO6	-0.510	0.495	-0.645	-	
	BIO1	-0.247	-0.287	-0.123	-	
	BIO5	-0.175	-0.819	0.694	-	
	% of Explanation	75%	24%	1%	-	
HS(HEF1) = [1/(1.747+0.243+0.006)]*[1.747HS(marg.,c) + 0.243HS(spec.1,c) +0.006HS(spec.2,c)						
4. MDEF	Elevation	0.862	0.111	-	-	
	BIO6	-0.444	0.386	-	-	
	BIO1	-0.217	0.136	-	-	
	BIO5	-0.115	**-0.906**	-	-	
	% of Explanation	40%	60%	-	-	
HS(MDEF1) = [1/(1.389+0.606)]*[1.389HS(marg.,c) +0.606HS(spec.1,c)						
5. CF	Elevation	**0.903**	-0.027	-	-	
	BIO6	-0.396	0.259	-	-	
	BIO1	-0.159	-0.911	-	-	
	BIO5	-0.058	0.319	-	-	
	% of Explanation	80%	20%	-	-	
HS(CF2) = [1/(1.805+0.187)]*[1.805HS(marg.,c) +0.187HS(spec.1,c)						

Note: MDF = mixed deciduous forest, DDF = dry dipterocarp forest, HEF = hill evergreen forest, MDEF = moist and dry evergreen forest and CF = coniferous forest, BIO1 = mean annual temperature (°C), BIO5 = mean monthly maximum temperature (°C), BIO6 = mean monthly minimum temperature (°C) and positive and negative signs of marginality and specialization coefficient indicate whether each ecological model prefers higher or lower than the mean and variation of global distribution in each particular variable of environment.

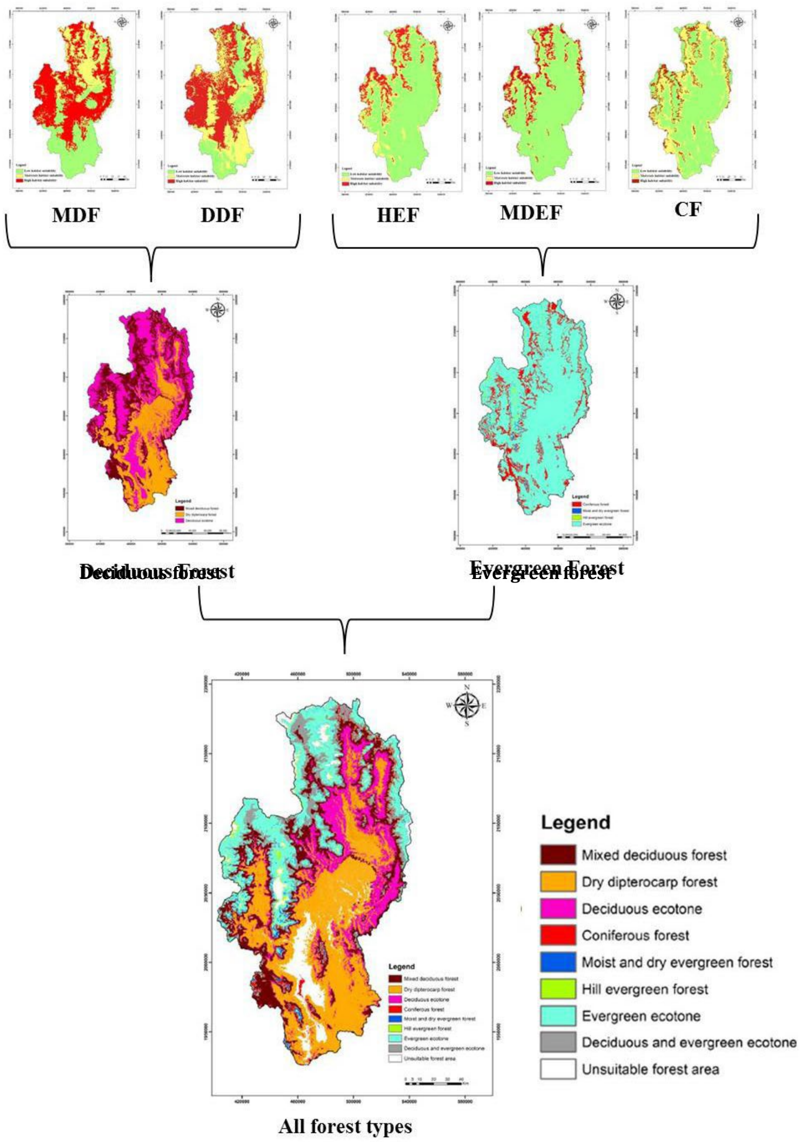


Figure 5. Combination of forest type map using hierarchical coding and GIS techniques
Note: MDF = mixed deciduous forest, DDF = dry dipterocarp forest, CF = coniferous forest, MDEF = moist and dry evergreen forest, and HEF = hill evergreen forest

3.2.1 Map of the deciduous forest type

We produced a map of the deciduous forest (DF) type by combining MDF and DDF with their assigned HS class codes, and then overlaid them in a GIS map to generate the DF type distribution. As a result, the DF types in the study area included DDF (7,400.20 km^2, 32.93%), MDF (5,912.58 km^2, 26.31%) and a deciduous ecotone (9,159.47 km^2, 40.76%).

As explained above, DF was combined by using HS classes of DDF and MDF, modeled by four EGVs (BIO1, BIO6, BIO5, and elevation). According to Kutintara (1999) and Santisuk (2006), in Thai forest ecology, BIO1 (mean annual temperature) is a major determinant of DDF, while BIO6 (mean monthly minimum temperature) is the main determinant of MDF.

3.2.2 Map of evergreen forest type

The map of the evergreen forest (EF) type combined HEF, MDEF, and CF, with their assigned HS class codes, and then overlaid them in a GIS operation to generate the EF types' distribution. As a result, the EF types in the study area included evergreen ecotone (19,052.70 km^2, 84.78%), CF (2,845.98 km^2, 12.67%), MDEF (295.04 km^2, 1.31%), and HEF (278.53 04 km^2, 1.24%). EF was produced by using HS classes of HEF, MDEF, and CF, modeled with four EGVs (BIO1, BIO6, BIO5, and elevation).

3.2.3 Map of deciduous and evergreen forest type

The maps of deciduous and evergreen forest type were integrated to generate a map of all occurring forest types in the study area using GIS-operation-based hierarchical coding. This process generated eight forest types: DDF (7,373.94 km^2, 32.81%), evergreen ecotone (3,666.97 km^2, 16.32%), MDF (3,440.79 km^2, 15.31%), deciduous ecotone (3,225.58 km^2, 14.35%), deciduous and evergreen forest (2,027.12 km^2, 9.02), CF (365.28 km^2, 1.63%), MDEF (290.08 km^2, 1.29%), and HEF (270.56 km^2, 1.21%). Moreover, the eight forest types were generated by using the HS classes of deciduous and evergreen forests, which were ecologically modeled by mainly four EGVs (BIO1, BIO6, BIO5 and elevation).

3.3 Ground checking and fuzzy accuracy assessment

The combined forest type map was created by using hierarchical coding and GIS techniques, and assessed for accuracy with fuzzy logical rule based on field surveys conducted from January to April 2021. Using multinomial distribution theory at a 90 percent confidence level and 10 percent precision, 141 sampling points were calculated. The sampling method was stratified random sampling with the proportion of sampling points of each forest type, including ecotone types, shown in Table 4 and Figure 6.

Table 4. Points of stratified random sampling for ground check

Forest type	Area (km^2)	Percent	Sampling points
1. MDF	3,440.79	15.31	23
2. DDF	7,373.94	32.81	50
3. DEco	3,225.58	14.35	22
4. CF	365.28	1.63	3
5. MDEF	290.08	1.29	2
6. HEF	270.55	1.20	2
7. EEco	3,666.97	16.32	25
8. DEEco	2,027.12	9.02	14
9. Unsuitable forest area	1,811.93	8.06	0
Total	22,472.25	100.00	141

Note: MDF = mixed deciduous forest, DDF = dry dipterocarp forest, DEco = deciduous ecotone, CF = coniferous forest, MDEF = moist and dry evergreen forest, HEF = hill evergreen forest, EEco = evergreen ecotone and deciduous and evergreen ecotone

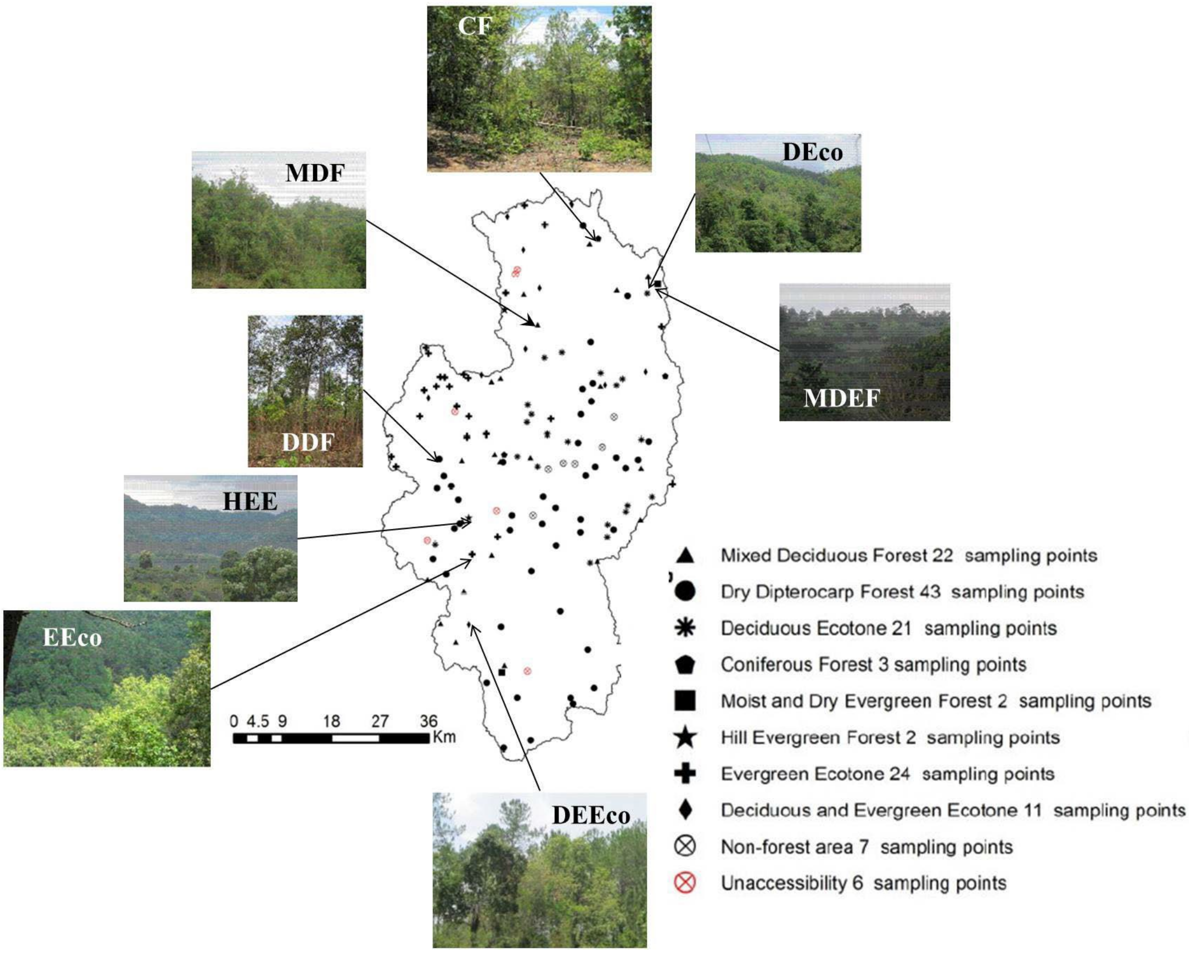


Figure 6. Sampling points for ground check and fuzzy accuracy assessment

Note: MDF = mixed deciduous forest, DDF = dry dipterocarp forest, DEco = deciduous ecotone, CF = coniferous forest, MDEF = moist and dry evergreen forest, HEF = hill evergreen forest, EEco = evergreen ecotone and deciduous and evergreen ecotone

In the fuzzy accuracy assessment, the 141 sample points based on the field data on September-December 2021 were used for the fuzzy error matrix, as in Figure 7. The overall accuracy in the fuzzy assessment of the forest-type-based ecological niche modeling was 75.89%. At the same time, producer's accuracy (PA) varied from 72.73% for DEco to 100% for CF, MDEF and HEF. User's accuracy (UA) varied from 81.82% for DEco to 100% for CF, MDEF and HEF.

Ground reference

Map classification	MDF	DDF	DEco	CF	MDEF	HEF	EEco	DEEco	Row Total
MDF	20	0	0,2	0	0	0	0	0,1	23
DDF	0	43	6,0	0	0	0	0	0,3	50
DEco	1,0	3,1	10	0	0	0	2,3	0	22
CF	0	0	0	3	0	0	0	0	3
MDEF	0	0	0	0	2	0	0	0	2
HEF	0	0	0	0	0	2	0	0	2
EEco	0	0,1	2,1	0	0	0	19	1,1	25
DEEco	2,0	2,0	1,0	0	0	0	0,1	8	14
Column Total	23	50	22	3	2	2	25	14	141 (107)

Points of stratified random sampling for field

Forest types	Area (km²)	%	Sampling points
1. MDF	3,440.79	15.31	23
2. DDF	7,373.94	32.81	50
3. DE co	3,225.58	14.35	22
4. CF	365.28	1.63	3
5. MDEF	290.08	1.29	2
6. HEF	270.55	1.20	2
7. EEco	3,666.97	16.32	25
8. DEEco	2,027.12	9.02	14
9. Unsuit	1,811.93	8.06	0
Total	22,472.25	100.00	141

Producer's accuracy
MDF = 22/22 = 100.00%
DDF = 51/53 = 96.23%
DEco = 17/20 = 72.73%
CF = 3/3 = 100.00%
MDEF = 2/2 = 100.00%
HEF = 2/2 = 100.00%
EEco = 20/25 = 80.00%
DEEco = 12/14 = 85.71%

User's accuracy
MDF = 20/23 = 86.96%
DDF = 47/50 = 94.00%
DEco = 18/22 = 81.82%
CF = 3/3 = 100.00%
MDEF = 2/2 = 100.00%
HEF = 2/2 = 100.00%
EEco = 22/25 = 88.00%
DEEco = 12/14 = 85.71%

Overall fuzzy accuracy = 107/141 = 75.89%

Figure 7. The fuzzy error matrix for accuracy assessment of forest type map

4. DISCUSSION

Map of the deciduous forest type can be explained in terms of a continuum with changing species composition along environmental gradients arising in antithesis to the community-unit theory, which states that plant communities are natural units of coevolved species populations forming homogeneous, discrete, and recognizable units. In DE, this can be explained by Gleason's view (Cox and Moore, 2005) of plant communities in which the ecological ranges of two species or more coincide precisely, and the degree of association between ground flora and canopy is often weaker than one might assume from casual observation. In other words, in Gleason's 'individualistic' model, each species is distributed independently and 'communities' are not apparent.

Map of evergreen forest type in Thai forest ecology as reported by Kutintara (1999) and Santisuk (2006) indicated that the influence of a common topographic factor (especially elevation) is the main determinant of the distribution of CF and HEF, while BIO5 (mean monthly maximum temperature) is an important factor in MDEF distribution. In addition, the distribution of EF can be explained by Gleason's continuum concept; in this view, the coincident area labeled 'evergreen ecotone' identifies the overlapping of the three evergreen forest types.

Map of deciduous and evergreen forest types can be explained by Gleason's continuum concept in which the overlapping of deciduous and evergreen ecotones has the same explanation as the distribution of deciduous and evergreen forest types above.

In accuracy assessment of forest type map-based field data, fuzzy accuracy assessment provided a high value of overall accuracy because it does not ignore any variation in the interpretation of reference data or inherent fuzziness at class boundaries. Therefore, it is not the same as simple descriptive statistics or discrete multivariate analytical statistics ('kappa analysis').

5. CONCLUSION

The best HSs of five forest types (MDF, DDF, HEF, MDEF, and CF) were derived from using four EGVs: elevation, BIO1, BIO5, and BIO6. In the best HSs, the proportion of explainable information preferred marginality coefficients, except for MDEF. These results revealed that the distribution of species in MDF, DDF, HEF, and CF was greater than the species variation in the study area. In this ecological niche modeling, elevation is of the highest importance for CF and HEF, while BIO5 is more important for MDF and MDEF.

The forest type map was produced by using ENFA based on the best HSs of the five forest types, which were combined using hierarchical-coding-based GIS techniques. This process resulted in the generation of eight classes of forest type. DDF covered the highest proportion of the study area at 32.81%, while HEF and MDEF were very rare, at 1.21% and 1.29% of the study area, respectively. The overall accuracy for the fuzzy assessment of the forest type-based on ecological niche modeling was 75.89%; this overall accuracy value was possible because this approach does not ignore any variation in the interpretation of the reference data or the inherent fuzziness at class boundaries. However, in general, the wise use of emerging technologies and thoughtful standardization of mapping approaches holds significant promise for the management of vegetation and ecosystems in the future.

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