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Article

Forecasting Areas Vulnerable to Forest Conversion in the Tam Dao National Park Region, Vietnam

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Abstract: Tam Dao National Park (TDNP) is a remaining primary forest that supports some of the highest levels of biodiversity in Vietnam. Forest conversion due to illegal logging and agricultural expansion is a major problem that is hampering biodiversity conservation efforts in the TDNP region. Yet, areas vulnerable to forest conversion are unknown. In this paper, we predicted areas vulnerable to forest changes in the TDNP region using multi-temporal remote sensing data and a multi-layer perceptron neural network (MLPNN) with a Markov chain model (MLPNN-M). The MLPNN-M model predicted increasing pressure in the remaining primary forest within the park as well as on the secondary forest in the surrounding areas. The primary forest is predicted to decrease from 18.03% in 2007 to 15.10% in 2014 and 12.66% in 2021. Our results can be used to prioritize locations for future biodiversity conservation and forest management efforts. The combined use of remote sensing and spatial modeling techniques provides an effective tool for monitoring the remaining forests in the TDNP region.

Keywords: multi-layer perceptron neural network; Markov chain; deforestation; Vietnam

1. Introduction

Three well-known global changes are increasing carbon dioxide in the atmosphere, alterations in the biochemistry of the global nitrogen cycle and continuing land-use/land-cover change [1].

Land-use/land-cover change (LULC) generates many environmental consequences globally and locally, such as the release of greenhouse gases, the loss of biodiversity and the sedimentation of lakes and streams [2]. In particular, it is recognized as the major driver of the loss of biodiversity and ecosystem services [3]. The effect of land use change on biodiversity may be greater than climate change, nitrogen deposition, biotic exchange, and elevated carbon dioxide concentration at the global scale [4]. Deforestation is known as one of the most important elements in LULC. Large-scale deforestation is occurring in the tropical forests, which contain most of the species in the world [5]. Globally, deforestation has been occurring at an alarming rate of 13 million hectares per year [6].

In Vietnam, two-thirds of the territory was primary forest until the mid-twentieth century [7]. Though forest cover in the country as a whole was 40.7% in 1943, it declined to 27.7% by 1993 [8]. Primary forest was deforested to its lowest levels in the late 1980s and early 1990s [9]. Vietnam's deforestation rate was the highest among low-income countries over the period from 1965 to 1989 [10]. This trend still continued for the period from 1990 to 2005. The primary forest area per total forest area for the entire country declined from 4.1% in 1990 to 0.7% in 2005 [6]. However, from the mid-1990s until now, there has been an increase in new forest plantations across the country [9].

Deforestation not only reduces forest area but also alters landscape configuration. Therefore, protected areas should be established to maintain the large, contiguous areas of forests for the protection of threatened species. Globally, 11.2% of the total forest area had been designated for the conservation of biological diversity in 2005 [6]. In Vietnam, protected areas were established in most of the representative ecological zones for the period from 1995 to 2005. The country's protected areas now account for 14.7% of the total forest area [6]. Many protected areas in the country are experiencing forest changes [11]. The management of the remaining forests within protected areas is very difficult to achieve because the livelihoods of local residents in the surrounding areas often heavily depend on agriculture and the extraction of forest products [12]. From a protected area management perspective, there is a need to identify the areas vulnerable to forest conversion in order to prioritize conservation efforts. One way to achieve this identification is to use remote sensing data and spatial models to map forest change patterns. Satellite remote sensing plays a key role in mapping and predicting forest changes [13,14]. Satellite imagery provides an accurate measure of forest cover and deforestation [15]. Changes in land use, derived from remotely sensed data, can be related to landscape and location attributes. A model can be established to describe the relationship between the dependent variable (forest cover change) and independent location variables [16]. Then, the model can be used for predicting the spatial patterns of forest cover changes.

Tam Dao National Park (TDNP) is a protected area in Vietnam. It contains the last remaining primary forest. It is endowed with rich biodiversity and is known to host a number of rare and endemic animal species. Yet, the park has been experiencing considerable forest changes due to population pressure in the surrounding areas. As a result, several species are in danger. For example, 45 rare animal species are known to be threatened by habitat destruction [17]. Much of the primary forest has been cleared for cropland. These forest changes are exerting an increasing pressure on biodiversity conservation efforts. Different protection measures have been introduced to control forest logging, but illegal logging is still a significant threat to the remaining forest areas [12].

Modeling forest conversion can be an important instrument for understanding forest cover dynamics in the TDNP region. Forest change models can provide a better understanding of the factors that drive forest changes, they can generate future forest cover scenarios, and they can support the design of policy responses to forest changes [18]. Forest change is associated with multiple factors. The relationships between change and its driving factors can be very complex and are often non-linear [19], requiring an appropriate modeling approach that accounts for such complex non-linear relationships.

Forest change can be predicted using empirical models and simulation models [16]. The multi-layer perceptron neural network (MLPNN) with an integrated Markov model (M) (hereby referred to MLPNN-M) is a recently developed approach for spatiotemporal dynamic modeling of forest change [20]. The MLPNN allows the integration of the driving factors of forest change, whereas the Markov model controls the temporal dynamics of forest change. A multi-regression approach often performs poorly when the relationships between variables are non-linear and some variables must be transformed. Conversely, the MLPNN models are good at dealing non-linear relationships and do not require the transformation of variables [21]. It is generally recognized that the MLPNN models can perform better in land change modeling [19,21-23]. In a recent study, the MLPNN was found to be better than logistic regression and other empirical modeling tools, such as empirical probabilities and empirical likelihoods, in land change modeling [20]

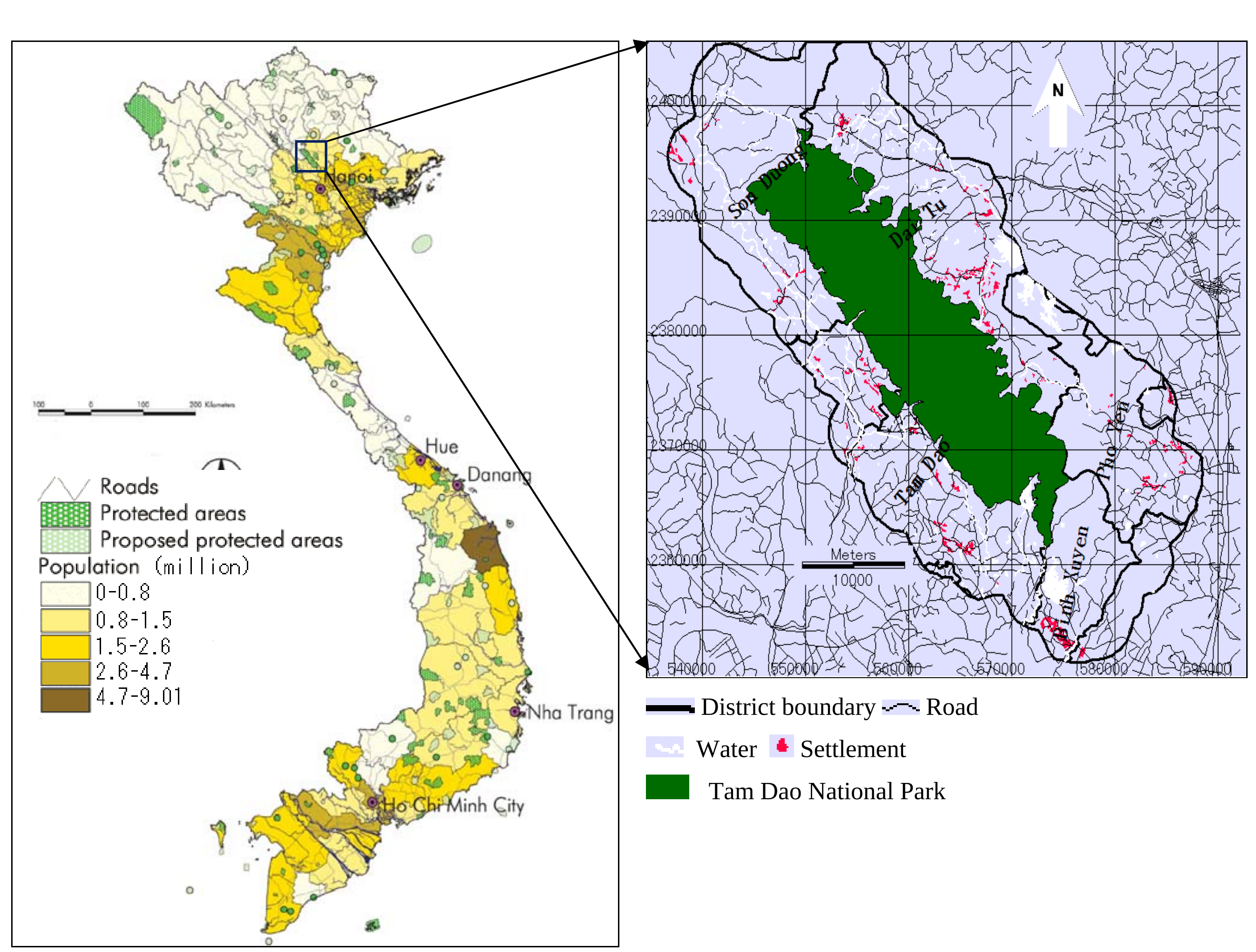
This paper aims to predict areas vulnerable to forest conversion in the TDNP region using remote sensing data and the MLPNN-M model. Multi-temporal satellite images were used to detect changes in forest cover, and then the MLPNN-M model was applied to predict changes in forest cover in the near future. Predicting forest change patterns provides important information for identifying priority areas for conservation and forest management in the TDNP region. These predictions may improve the efficiency of efforts to protect the remaining primary forest in the study area.

2. Methods

2.1. Study Area

The study area covers a region of 141,238 ha that includes the TDNP (35,000 ha) and the buffer zone. The area is located in three provinces, namely Vinh Phuc (Binh Xuyen and Tam Dao district), Tuyen Quang (Son Duong district) and Thai Nguyen (Dai Tu and Pho Yen district) in the northern part of Vietnam (Figure 1). The TDNP is considered to be one of the best and largest examples of rainforest habitat in Vietnam. It is known to host a variety of insects, butterflies, birds, medical plants and rare animal species [24]. Furthermore, the TDNP supports some of the highest levels of recorded insect diversity in Vietnam. A recent biological survey identified 1,436 plant species and 1,141 animal species in the park [17]. The region is characterized by a tropical monsoon climate with a mean annual rainfall of around 2,600 mm, and most of the rainfall occurs from April to October. The elevation of the TDNP varies from 100 to 1,580 m above the mean sea level.

Figure 1. Tam Dao National Park region.



Source: [12]

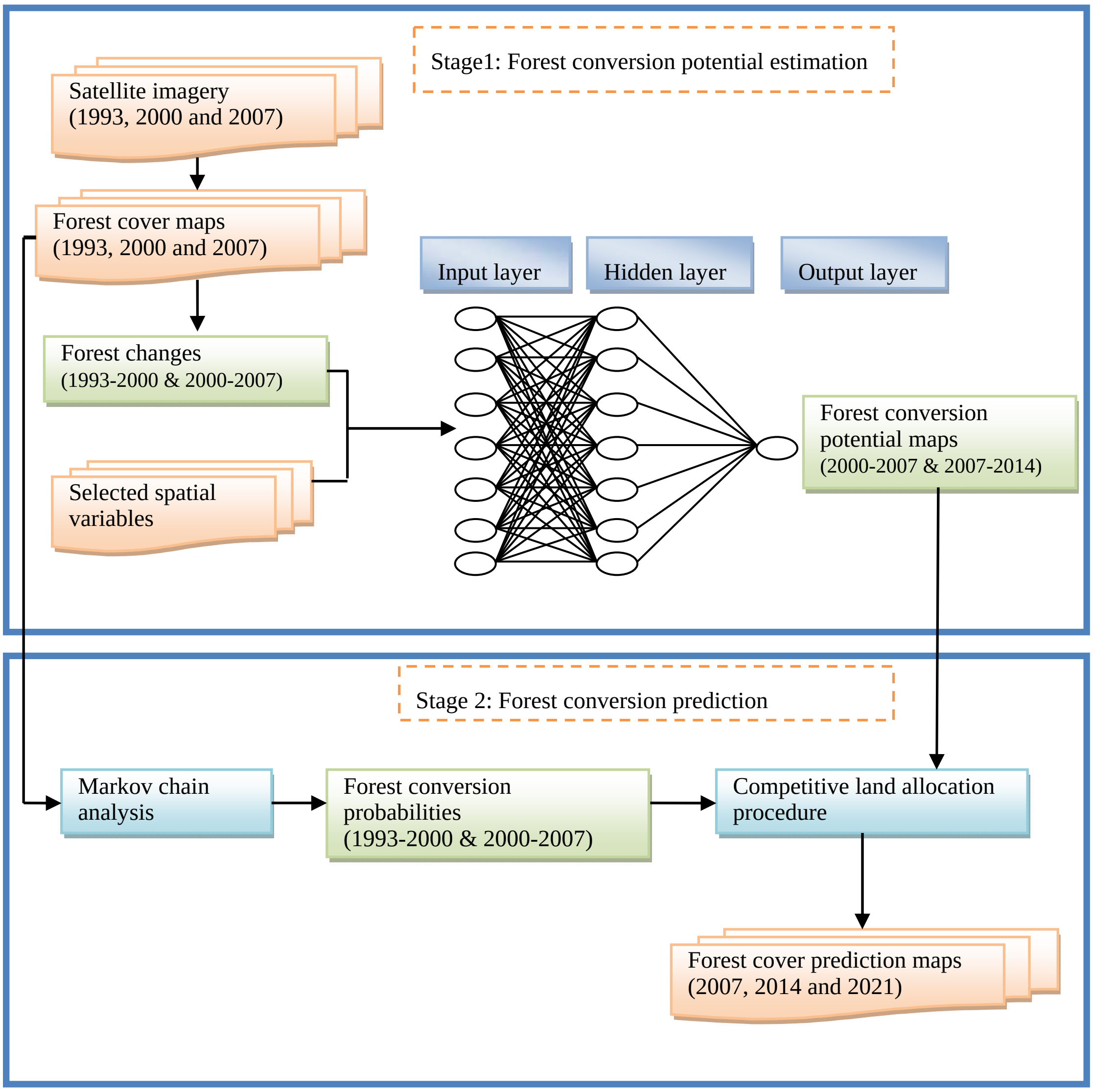
The TDNP is the last remaining primary forest close to Hanoi, the capital of Vietnam. In the early 1960s, the population density in the area was relatively low; therefore, primary forest was dominant. In the 1970s, primary forest was gradually deforested by slash and burn farming. Due to the biological values of Tam Dao, the area was recognized as a nature reserve in 1977. Before 1985, forest logging took place at low level, but in the early 1990s, the intensity of logging increased in response to an increased demand for timber [17]. In 1996, Tam Dao nature reserve was declared to be a national park. The decision to establish the park halted commercial forest logging; however, illegal forest logging still exists. Intensive population pressure and weakly enforced management have seriously degraded the park's natural resources and resulted in the destruction of most low-lying forest areas. The park is still threatened by deforestation (Figure 2) due to the high level of firewood extraction and agricultural encroachment. Most of the 200,000 inhabitants in the surrounding areas of the park generate their incomes from small-scale farming and timber extraction. The high incidence of poverty and the poor awareness of conservation are major challenges to forest management and biodiversity conservation efforts [12].

Figure 2. Forest clearing for agricultural use in the TDNP region (Photo by author, 2009).

2.2. Implementation of the Multi-Layer Perceptron Neural Network and the Markov Model

We implemented the model MLPNN-M within the Land Change Modeler (LCM) available in IDRISI Taiga GIS and Image Processing software [20] to predict primary and secondary forest conversions. In general, two forest cover maps derived from satellite imagery from two different dates were used to predict a forest cover map for a third date. The prediction process can be characterized by the estimation of forest conversion potentials followed by the forest conversion prediction stage (Figure 3). Firstly, observed forest changes were used as the dependent variables and spatial variables were used as the independent variables (Table 2) to train the MLPNN and then estimate the primary and secondary forest conversion potential maps. Secondly, forest conversions were predicted using a competitive land allocation algorithm similar to the multi-objective land allocation (MOLA) algorithm. The MOLA looks through all conversions to list the host classes that lose some amount of land and the claimant classes that acquire some amount of land from each host. The quantities of conversions were determined by the Markovian conversion probabilities. After this, a multi-objective allocation was run to allocate land for all claimants of a host class. The results of the reallocation of each host class were then overlaid to produce a final prediction map [20]. Detailed descriptions of the multi-objective land allocation algorithm can be found in [25].

Figure 3. Flowchart of the MLPNN-M model for predicting forest conversion.



2.2.1. Observed Changes in Forest Cover Using Remotely Sensed Data

Changes in forest cover are often related to the vicinity of land uses. Therefore, we interpreted land-use patterns to capture such variables for forecasting the location of changes in forest cover. Multi-temporal Landsat satellite images (path 127 and row 045) from December 27, 1993, October 04, 2000, and November 11, 2007, were obtained from the Global Land Cover Facility (http://www.landcover.org), University of Maryland. The digital maps of general land use (1993 and 2000), topography, and the road network were gathered from the TDNP office as reference data for land-use classification. In addition, field observations and interviews were conducted in March 2009 to supplement the reference data.

Each LANDSAT satellite image was rectified to a common UTM/WGS84 coordinate system based on a 1:50,000 scale topographic map. These data were re-sampled using the nearest neighbor algorithm. The root mean square error of the image was found to be less than one pixel. The resolutions of all images were adjusted from 28.5 m × 28.5 m to 30 m × 30 m. Then, contrast stretching, color composites and normalized difference vegetation indexes were generated to enhance the interpretability of features in the images. A number of land-use types were determined using unsupervised classification, reference maps and the authors' a *priori* knowledge of the study area. The categorized classes were primary forest, secondary forest, rain-fed agriculture, paddy rice, settlement and water. Clusters of pixels representing various land-use types were identified as training sites based on unsupervised classification, field observations, interviews and the knowledge of the authors on the relative location of land-use types in the study area. After all training sites were identified and digitized by the on-screen method, class signatures were generated. A maximum likelihood classifier was used to classify these images into land-use maps. These procedures were applied to map land-use patterns in the years 1993, 2000 and 2007. Finally, the accuracies of the classified land-use maps were investigated. A stratified random sampling design was used to select a total of 270 points (pixels) for each land-use map (1993, 2000 and 2007). These point data were used for calculating Kappa statistics. The accuracy of the classified land-use maps for 1993 and 2000 was assessed with general land-use maps in 1993 and 2000 and point data gathered from GPS-based interviews. The accuracy of the land-use map for 2007 was evaluated with field survey data from March 2009.

Finally, changes in forest cover for the periods 1993–2000 and 2000–2007 were detected using cross-tabulation technique. Cross-tabulation analysis was used to compare forest-cover maps. This analysis was implemented using the LCM change analysis procedure.

2.2.2. Selection of Spatial Variables

Spatial variables were selected based on the availability of reliable data and the ability to express the data as a spatially explicit variable. The spatial variables expected to compose a considerable share of the factors driving past and future forest cover changes in the area. The statistical summary and spatial distribution of the variables are presented in Table 1 and Figure 4. These variables are often highlighted in deforestation studies, such as in [26], and land-use change models, such as in [27,28].

Table 1. Statistical summary of spatial variables.

Spatial variable	**Mean**	**S.D.**	**Min.**	**Max.**
Elevation (m)	86	194	0	1,581
Slope (degree)	6.2	11.5	0	58
Proximity to road (m)	403	802	0	5,237
Proximity to water (m)	616	1,050	0	6,191
Proximity to primary forest in 2000 (m)	477	1,038	0	8,101
Proximity to primary forest in 2007 (m)	770	1,673	0	10,040
Proximity to secondary forest in 2000 (m)	146	406	0	4,248
Proximity to secondary forest in 2007 (m)	246	696	0	6,598
Proximity to settlement in 2000 (m)	1,169	1,818	0	8,517
Proximity to settlement in 2007 (m)	1,113	1,747	0	8,489
Proximity to cropland in 2000 (m)	122	392	0	3,506
Proximity to cropland in 2007 (m)	130	288	0	3,586

The conversion of forest often relates to physical accessibility variables. Accessibility to a road is a significant factor of deforestation. For example, the role of road access was highlighted in predicting the location of deforestation in many areas, such as the Basho Valley, Northern Pakistan [29], Northern Thailand [30] and the Congo Basin [31]. The location of water affects to the location of cultivation; therefore, the proximity to water is closely related to deforestation. Permanent cultivation in the area seemed to be concentrated close to water.

In addition to road and water access, forest conversion also depends on the type of land-use in the neighborhood. For instance, Ludeke *et al.* [32] found a strong relationship between deforestation and proximity to forest edge in a given period in Honduras. In this study, several of these variables were included: proximity to primary forest, proximity to secondary forest and proximity to settlement. The proximity to primary forest, secondary forest and settlement was measured as the shortest distance from each location to the nearest primary forest, secondary forest and settlement, respectively. Furthermore, we included the proximity to cropland, which was measured as the shortest distance from each location to the nearest cropland. Some studies found a strong relationship between deforestation and the expansion of cultivation in the mountains of northern Vietnam [9,33].

Topography often influences the spread and extent of forest conversion. For example, a case study in Costa Rica [34] found that as the slope gradient increased, deforestation decreased. In this study, topographic variables, including elevation and slope, were created from a contour map with a scale of 1:50,000 and contour interval of 20 m. This map was collected from the TDNP office.

The issue of correlated variables and data redundancy is minor because the neural network is good at solving these problems [27]. In this study, we examined the nature of the association between observed forest changes and spatial variables using Cramer's V coefficient [20]. The quantitative variables were binned into 256 categories to conduct the test [20] (Table 2). A Cramer's value close to 1 indicates a higher potential explanatory value of the variable; however, it does not guarantee a strong performance because it cannot account for the mathematical requirements and the complexity of the relationship. However, a variable can be discarded if the Cramer's V coefficient is less than 0.15 [20].

2.2.3. Forest Conversion Potential Estimation

We trained the MLPNN as a network with the three layers: an input layer with the number of nodes equal to the number of spatial variables; a hidden layer with the same number of nodes; and an output layer with one node representing a conversion potential map (Figure 3). The neural network is trained to derive the appropriate connection weights between the input layer and hidden layer and between the hidden layer and the output layer for classifying unknown pixels. The training process starts by iteratively presenting input data to the network. The connection weights are adjusted during network training to minimize the difference (error) between the network output and the desired output [35].

Figure 4. Spatial variables.

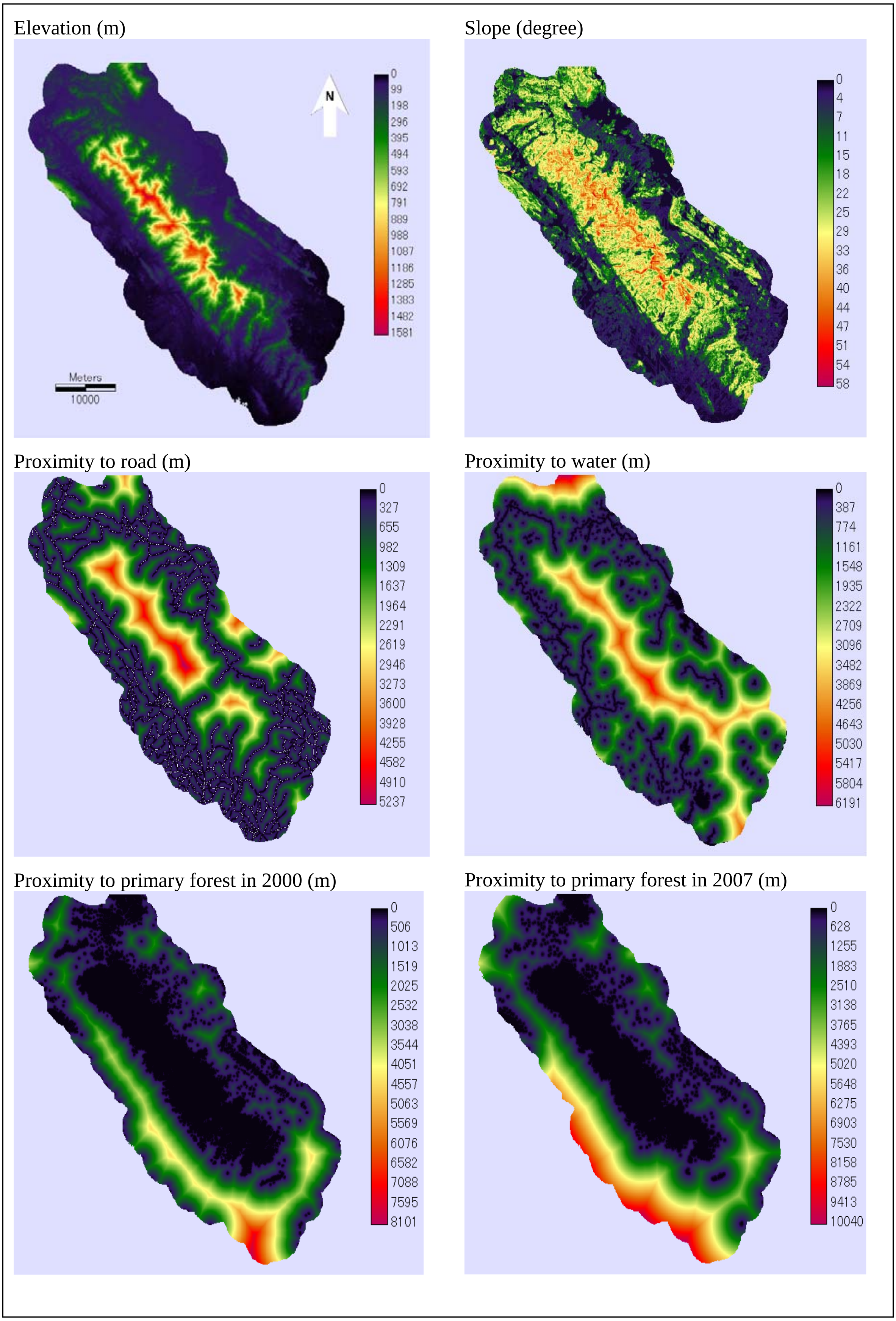
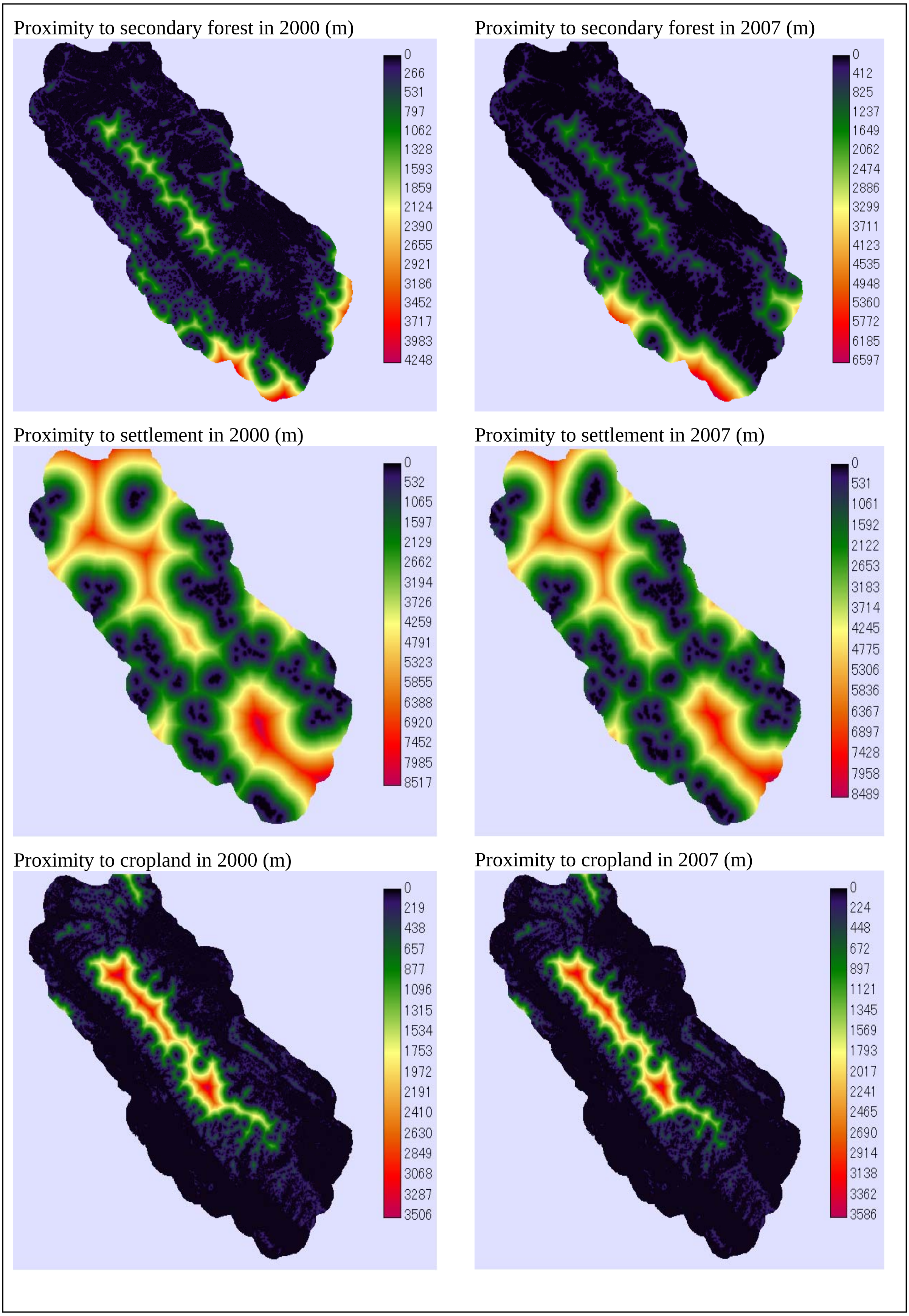


Figure 4. *Cont.*



In the study area, selective logging directly converts primary forest into secondary forest. Another pathway is the conversion of primary forest into cropland by shifting cultivation. The third way is the conversion of secondary forest into cropland. Therefore, we estimated three forest conversion potential maps for the prediction of forest cover. Each of the three conversions was trained individually. Then, we estimated the 2007 conversion potential maps for the prediction of forest cover in 2007 (model validation) and the conversion potential maps for the prediction of forest cover in 2014 and 2021. For the 2007 forest conversion potential maps, elevation, slope, proximity to road, proximity to water and the dynamic variables (proximity to primary forest, proximity to secondary forest, proximity to settlement and proximity to cropland) for the year 2000 were presented to the MLPNN for training as independent variables while the 1993–2000 forest changes were presented as the dependent variables (Table 2). With the same procedure, spatial variables and the 2000–2007 forest changes were presented to the network for training to estimate the 2014 and 2021 forest conversion potential maps. The dynamic variables were recalculated for the years 2007 and 2014. We followed the MLPNN automatic dynamic training mode where all training parameters were automatically changed to better model the data. A detailed of the MPL training procedure can be found in [20].

In general, the training results indicated a quick decline in the root mean square (RMS) error after 1,000 iterations, and the RMS error was mostly stable from 3,000 to 5,000 iterations. The RMS error flattened with little decline after 5,000 iterations; therefore, we stopped the training of the network after 5,000 iterations with a minimum loss of accuracy. According to [20], the accuracy rate of training should be achieved in the vicinity of 80%. Therefore, we terminated network training when the accuracy rate exceeded the minimum level. Once the network was trained, new data could be run through it.

2.2.4. Prediction of Forest Conversion for Identifying Vulnerable Areas

The prediction procedure used by the IDRISI's LCM is based on a competitive land allocation procedure similar to the MOLA [20]. The MOLA combines the predictions of the location and the quantity of land cover change. For the prediction of the 2007 forest cover, the MOLA looks through the three forest conversion potential maps from 2000 to 2007 and the quantity of area for each conversion. These forest conversion potential maps were produced by MLPNN. The quantities of area were estimated using Markov chain analysis. The purpose of using the Markov chain is to determine the amount of change that may occur to some point in the future. A Markovian process is one in which the state of a land-cover is identified by knowing its previous state and the probability of conversion from each state to another [20]. During the MOLA process, IDRISI's Markov module was employed to produce the 1993–2000 forest conversion probability matrix (Table 4) based on the forest-cover maps of 1993 and 2000. In the matrix, the diagonal represents the self-replacement probabilities, whereas the off-diagonal values show the probability of a change occurring from one land cover to another. The MOLA allocated land for each category. For example, in order to allocate the primary forest to cropland, the MOLA used both the conversion potential map from the primary forest to cropland and the quantity of the conversion. Using this conversion potential map, the MOLA allocated the pixels with the highest potential to cropland according to the amount. Other forest conversions were done in the same way. Finally, the predicted forest cover map of 2007 was generated by overlaying all results of the MOLA procedure. By using the same prediction procedure, the forest cover maps of 2014 and 2021 were predicted. The forest cover map of 2014 was predicted using the forest conversion potential maps from 2007 to 2014 and the 2000–2007 forest conversion probabilities (Table 6). The forest cover map of 2021 was predicted using the forest conversion potential maps from 2014 to 2021 and the 2000–2007 forest conversion probabilities.

Table 2. The relationship between observed forest changes and spatial variables.

1993–2000	**Cramer's V**	**2000–2007**	**Cramer's V**
Conversion from primary forest to secondary forest			
Proximity to settlement in 2000	0.3459	Proximity to settlement in 2007	0.3302
Proximity to water	0.5903	Proximity to water	0.6431
Slope	0.7053	Slope	0.6843
Elevation	0.7161	Elevation	0.7680
Proximity to road	0.8082	Proximity to road	0.8582
Proximity to primary forest in 2000	0.9132	Proximity to primary forest in 2007	0.9347
Conversion from primary forest to cropland			
Proximity to settlement in 2000	0.2911	Proximity to settlement in 2007	0.2525
Proximity to road	0.3204	Proximity to road	0.2750
Elevation	0.4289	Elevation	0.4471
Slope	0.5014	Slope	0.4938
Proximity to water	0.5700	Proximity to water	0.5701
Proximity to cropland in 2000	0.6552	Proximity to cropland in 2007	0.6986
Proximity to primary forest in 2000	0.8139	Proximity to primary forest in 2007	0.8087
Conversion from secondary forest to cropland			
Proximity to settlement in 2000	0.3811	Proximity to settlement in 2007	0.3536
Proximity to road	0.4101	Proximity to road	0.3652
Elevation	0.5089	Elevation	0.5473
Slope	0.6012	Slope	0.5835
Proximity to water	0.6803	Proximity to water	0.6903
Proximity to cropland in 2000	0.7554	Proximity to cropland in 2007	0.7961
Proximity to secondary forest in 2000	0.8935	Proximity to secondary forest in 2007	0.8743

Notes: The test was conducted in the LCM of IDRISI Taiga. The Cramer's V coefficients were tested with the p value of less than 0.05.

In order to apply the MLPNN-M model for the prediction of forest cover in the study area, the model needs to be validated. The purpose of model validation is to assess the predictive ability of the model for predicting changes in forest cover in the study area. The calibration data were separated from the validation data. The 1993–2000 forest cover maps and the 2000 spatial variables were used to calibrate the model. The 2007 actual forest cover map was only used for model validation. After the model was validated, forest cover scenarios were then predicted for the years 2014 and 2021 based on the assumption of forest conversions following the 2000–2007 Markovian dynamics. These prediction maps of future forest cover were used to identify areas vulnerable to forest conversions.

3. Results

3.1. Observed Changes in Forest Cover

The Landsat images for the years 1993, 2000 and 2007 were classified into primary forest, secondary forest, rain-fed agriculture, paddy rice, settlement and water (Figure 5). The overall accuracy of the classified maps for the years 1993, 2000 and 2007 ranged from 86.67% to 90.01%, and Kappa indices varied from 0.83 and 0.87. In this study, we focused on forecasting forest conversions; therefore, these classified maps were aggregated into primary forest, secondary forest and non-forest areas (Figures 6 and 7). Figure 6 shows the spatial patterns of forest changes for the periods of 1993–2000 and 2000–2007. The total primary forest loss for the period of 1993–2000 was 7,870 ha, equivalent to 20.59% of the primary forest area in 1993. For the period of 2000–2007, the primary forest loss was 4,893 ha, equivalent to 16.12% of the primary forest area in 2000. Some primary forest was converted into secondary forest. As a result, secondary forest for the first period increased by 3,970 ha, equivalent to 9.51% of the secondary forest area in 1993. In the second period, secondary forest increased by 385 ha, equivalent to 0.88 % of the secondary forest area in 2000 because the conversion of primary forest into secondary forest was reduced substantially. The low conversion may be attributable to better management of the primary forest. As a result of the conversion of primary and secondary forest into non-forest areas, non-forest areas increased over the periods. The increase in non-forest areas for 1993–2000 and 2000–2007 were 4,080 ha and 4,508 ha, respectively.

Figure 5. Land-use maps derived from Landsat in 1993, 2000 and 2007.

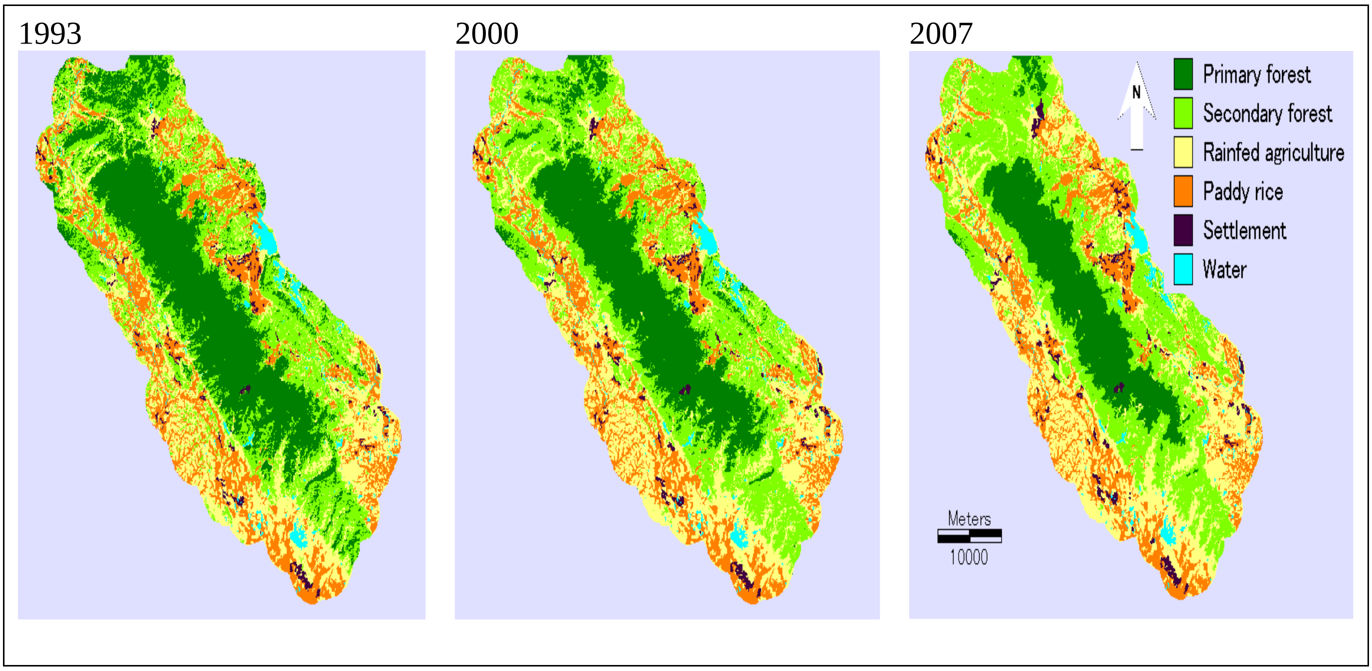


Figure 6. Forest persistence and change for the periods of 1993–2000 and 2000–2007.

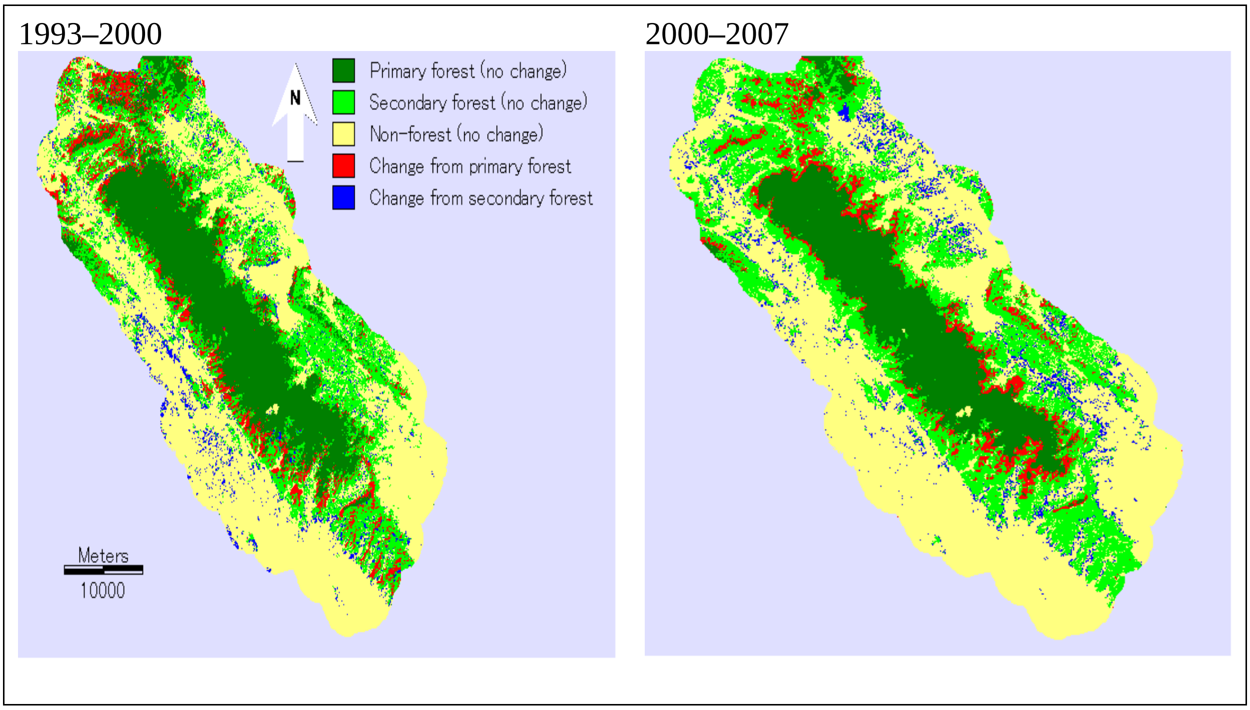
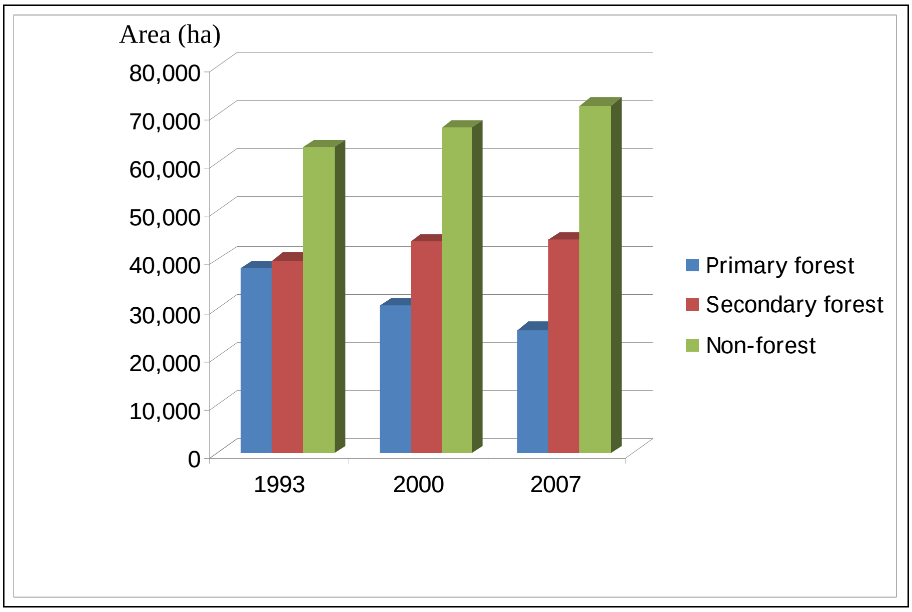


Figure 7. Areas of primary forest, secondary forest and non-forest.



3.2. Model Validation

Figure 8 shows the results of the training and the projection of the conversion potential maps for the year 2007. A forest conversion potential map consists of pixels with continuous scores varying from 0 to 1. A higher score pixel indicates a higher potential for forest change for that pixel. The higher potential areas for primary forest conversion are visible across the primary forest edges within the park and the surrounding areas. Similarly, the higher potential areas for secondary forest conversion are visible on the edges of the existing secondary forest segments. The forest conversion probability matrix was then estimated using the maps of forest cover for 1993–2000 (Table 4). Figure 9 presents the predicted map of forest cover in 2007 using the 2007 forest conversion potential maps and the 1993–2000 Markovian conversion probabilities. This output was used for model validation.

A validation technique that compares a predicted model with a null model was applied for model validation [36]. Basically, this technique considers the agreement between two pairs of maps according to percent correct criterion. In this study, the first comparison was between the 2000 actual forest cover map and the 2007 actual forest cover map (the null model). The second comparison was between the 2007 predicted forest cover map and the 2007 actual forest cover map (the predicted model). Finally, the predicted model was compared with the null model. The components of agreement and disagreement of the two models were calculated using the Validate Module within the IDRISI software (Table 3).

For the agreement components, both the two models have some similar characteristics. The largest component of agreement was due to location, followed by due to chance and due to quantity. Overall, the percent correct of the predicted model (96%) was greater than the percent correct of the null model (92%). Therefore, the prediction model performed better than the null model at the 30-meter resolution. According to [36], a prediction model should be used in an area where the model predicts as well as or better than the null model. Therefore, the model can be used for predicting forest cover in the region. By individual class, the non-forest class had the best agreement, followed by the primary forest and the secondary forest (Figure 10). The model appeared to predict contiguous patterns better than fragmented patterns. Both the non-forest and primary forest were characterized by contiguous patterns, but the secondary forest showed fragmented patterns. These characteristics may explain why the accuracy of the predicted secondary forest is less than the others.

Table 3. Agreement and disagreement of the null and predicted models at 30-meter resolution (percent of the landscape).

Components of agreement and disagreement	The null model	The predicted model
Agreement due to chance	33	33
Agreement due to quantity	6	7
Agreement due to location	53	56
Disagreement due to location	3	3
Disagreement due to quantity	5	1

The disagreement due to location and quantity is important in evaluating the accuracy in quantity and location of the predicted forest cover. In particular, these components help to improve the prediction. For the null model, the disagreement due to quantity was greater than the disagreement due to location. On the other hand, for the prediction model, the disagreement due to quantity was less than the disagreement due to location. This result showed that the MLPNN-M model was more accurate at predicting the quantity than the location of forest cover in the region. The disagreement due to location can be improved by enhancing the forest conversion potential maps because the forest conversion potential maps alone determine the location of forest conversion. This can be undertaken by considering additional explanatory variables. For example, soil variables such as soil organic carbon and soil fertility may improve the forest conversion potential maps because forest is mainly converted into agricultural land in the region. However, soil data are not available in the area.

The success of the model in predicting the location and the quantity of forest cover can be explained separately. With respect to the prediction of the location, selected spatial variables proved to be a considerable part of the variables driving the forest cover change in the area; therefore, the model was accurate at predicting the location of forest cover change. For the conversion from primary forest to secondary forest, the proximity to road and slope was found to be more important than the others. For the conversion of primary and secondary forest into cropland, the proximity to cropland, proximity to water and slope were determined to be more important than the others. These variables were also found to be important drivers of forest conversion in other areas such as in [13,40]. For the prediction of the quantity, the trends of forest conversion were conservative for the periods 1993–2000 and 2000–2007. This may explain the success of the prediction of the quantity of forest cover in the area. However, increasing demand for agricultural land driven by population pressure may affect to forest conversion. Population pressure may accelerate in the future; therefore, it is hard to infer whether the model predicts the correct quantity in the future.

Table 4. Forest conversion probability matrix for 1993–2000.

Category	Primary forest	Secondary forest	Non-forest
Primary forest	0.7941	0.1959	0.0100
Secondary forest	-	0.9072	0.0928
Non-forest	-	-	1.0000

3.3. Areas Vulnerable to Future Forest Conversions

The forest conversion potential maps for the years 2014 and 2021 are presented in Figure 8. Table 5 indicates the estimations of the forest conversion probabilities for 2000–2007. These inputs were combined within the model to simulate the forest cover patterns up to 2014 and 2021 (Figure 11). Within the study area, the MLPNN-M model predicts that the remaining primary forest will decrease from 18.03% in 2007 to 15.10% in 2014 and 12.66% in 2021. The secondary forest areas will decline only slightly from 31.17% in 2007 to 30.88% in 2014 and 30.18% in 2021 because a large portion of primary forest is converted into secondary forest. The non-forest areas increase from 50.81% in 2007 to 54.01% in 2014 and 57.16% in 2021 as a result of the conversion of both primary and secondary forest into these areas (Table 6).

Table 5. Forest conversion probability matrix 2000–2007.

Category	Primary forest	Secondary forest	Non-forest
Primary forest	0.8379	0.1527	0.0094
Secondary forest	-	0.9026	0.0974
Non-forest	-	-	1.0000

Figure 8. Forest conversion potential maps consisting of pixels with continuous scores varying from 0 to 1 (the legend is the same in all conversion potential maps).

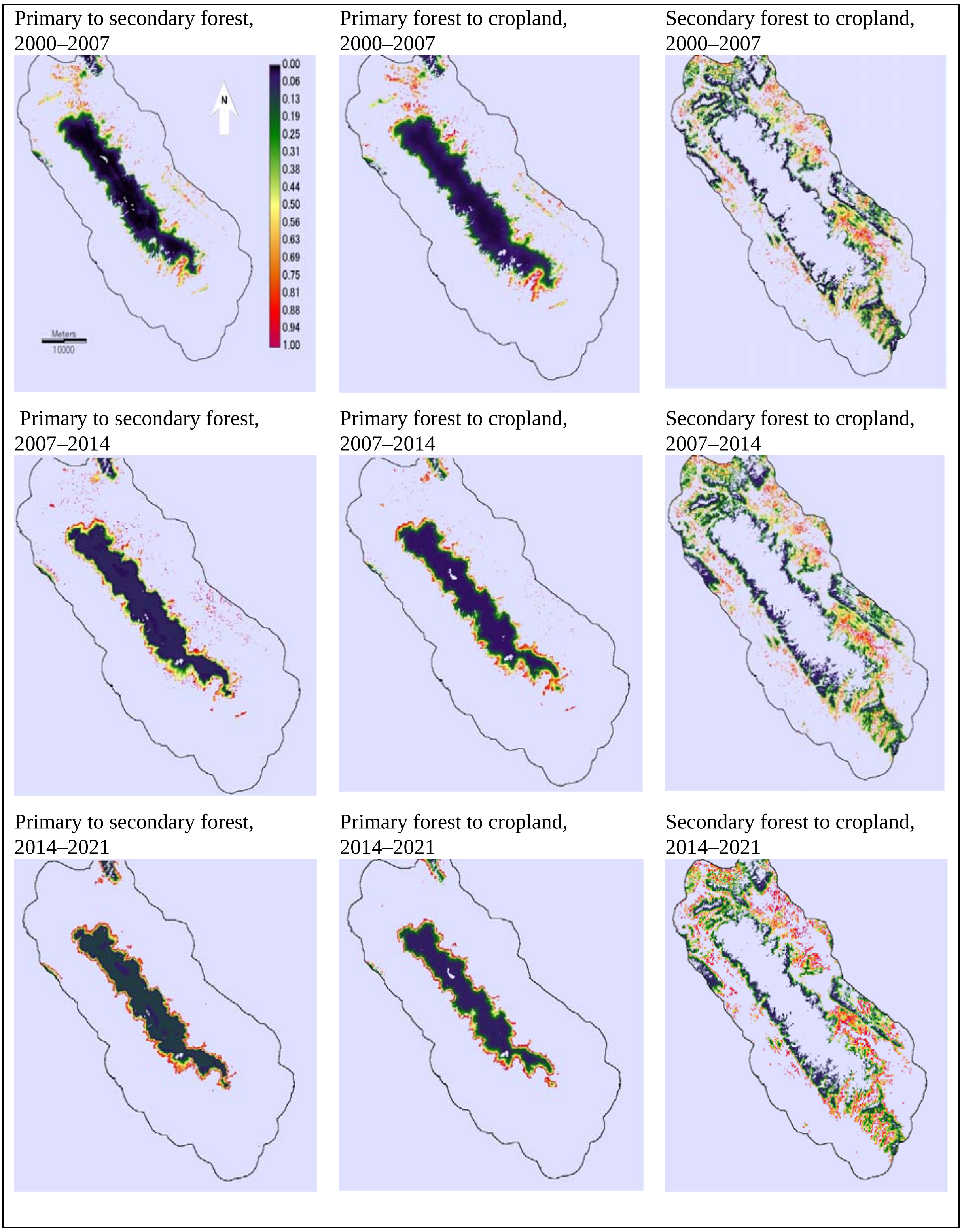


Figure 9. Actual *versus* predicted forest cover in 2007.

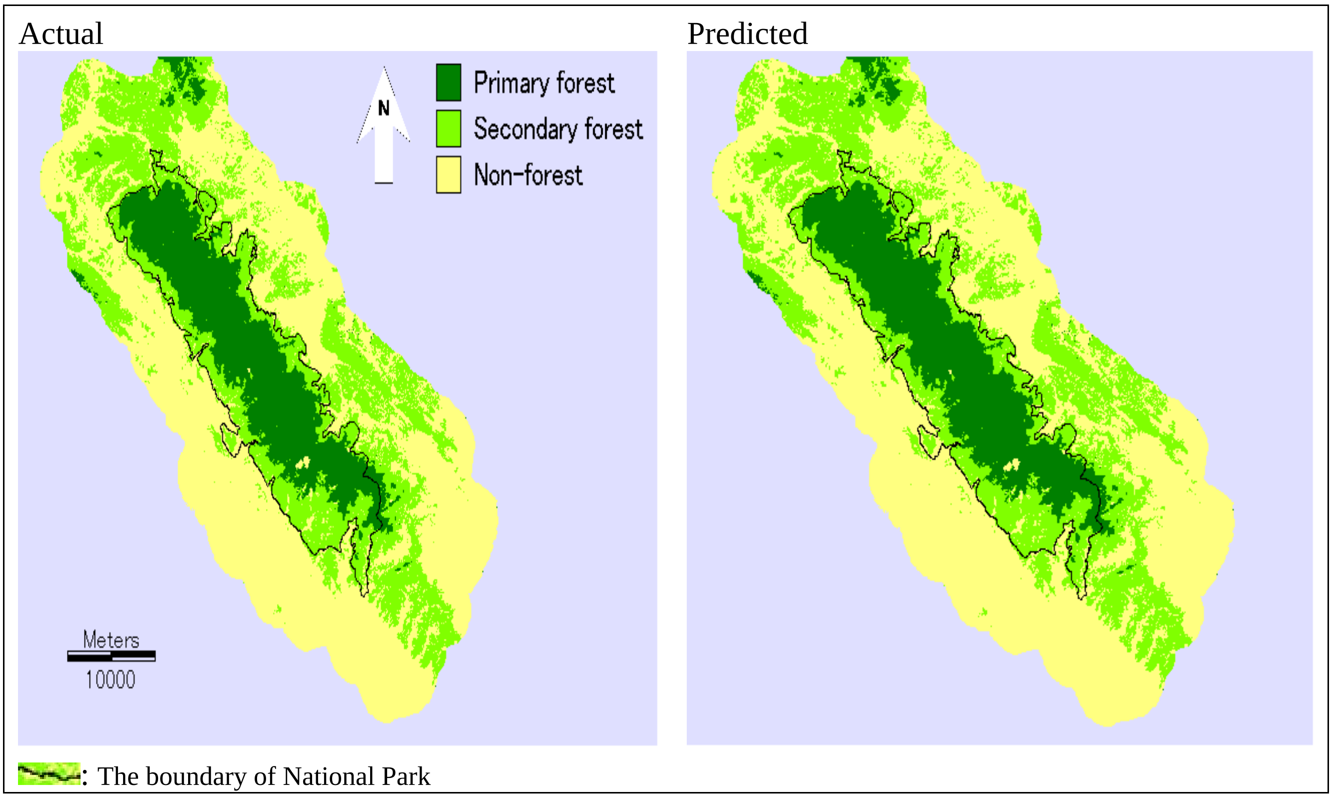
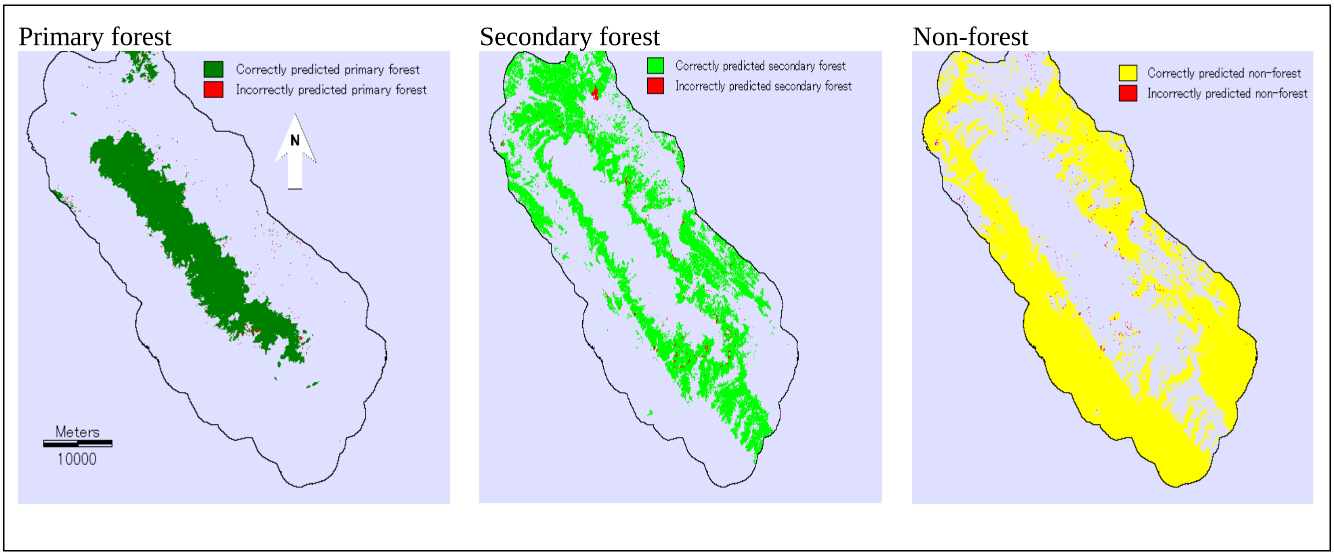


Figure 10. Correctly and incorrectly predicted areas of the predicted forest cover map in 2007.



In order to visualize the spatial patterns of forest changes, overlay analysis was conducted to highlight such areas. The forest change patterns are shown in Figure 11. The decline in primary forest is projected to be 4,127 ha in 2014 and 7,585 ha in 2021, equivalent to 16.21% and 29.79% of the 2007 remaining primary forest, respectively. The conversion of secondary forest into non-forest areas (cropland) is predicted to be 4,287 ha in 2014 and 8,535 ha in 2021, equivalent to 9.74% and 19.39% of the secondary forest in 2007, respectively. Many areas within the park appear to be vulnerable to conversion. This area may require intensified protection measures if the remaining primary forest is to be maintained in the future. The areas susceptible to secondary forest conversion often overlay with the areas near the edges of secondary forest in the buffer zone.

Figure 11. Predicted forest cover and areas vulnerable to forest changes in 2014 and 2021.

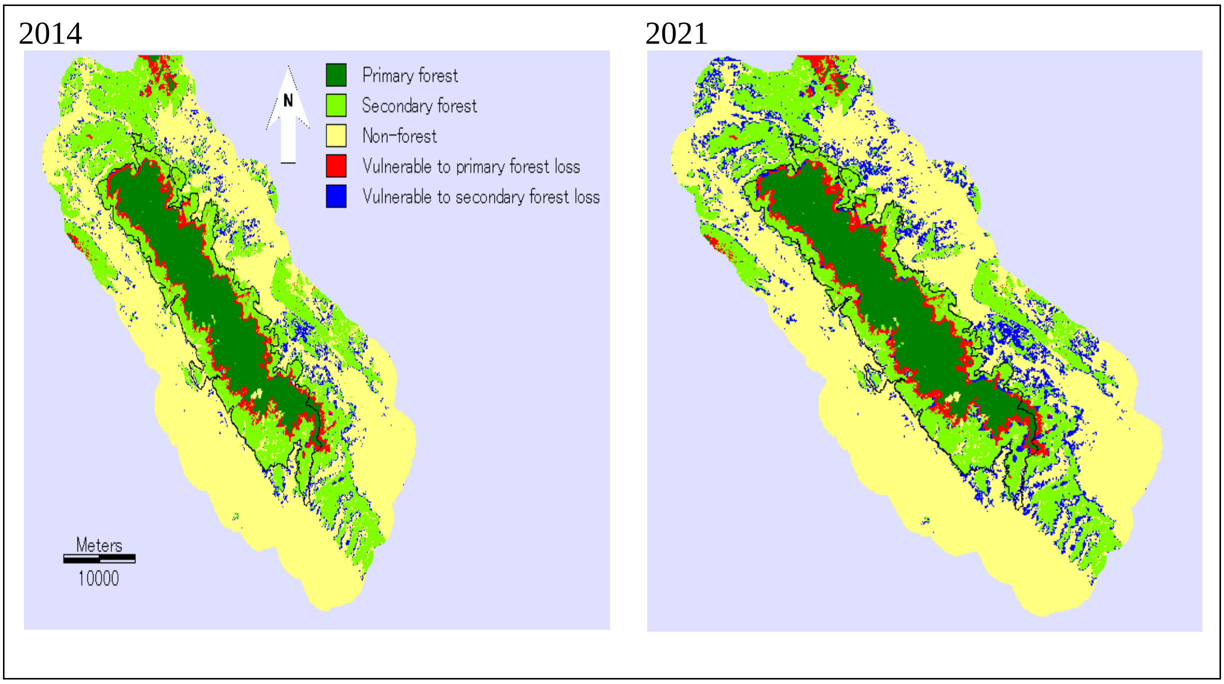


Table 6. Forest cover for 1993–2007 and predicted forest cover in 2014 and 2021 (percentages).

Category	**1993**	**2000**	**2007 (Real)**	**2007 (Predicted)**	**2014**	**2021**
Primary forest	27.06	21.49	18.03	16.82	15.10	12.66
Secondary forest	28.21	30.89	31.17	32.60	30.88	30.18
Non-forest	44.73	47.62	50.81	50.58	54.01	57.16

4. Discussion

The conversion of primary and secondary forest for the periods from 1993–2000 and 2000–2007 was observed within the strictly protected primary forest and the buffer zone. The primary forest loss for 1993–2000 was bigger than that for 2000–2007. Thus, primary forest loss still continues by illegal forest logging [12]. Similarly, a considerable primary forest loss was observed across the country during the period from 1990 to 2005 [6]. This conversion is a common trend in tropical forests [37,38]. The conversion of secondary forest to non-forest during the first period may be linked to a 1993 land law that provided land-use rights to individual households. Furthermore, government agricultural production input subsidies, such as crop varieties and fertilizers and improved access to credit and markets could contribute to this conversion trend. Similar conversions have been observed in other protected areas [11] and mountainous areas of Vietnam [33], and they have occurred in many other countries, particularly in developing countries. For example, [39] found that deforestation was strongly correlated with the extension of cropland area in Asia and Latin America.

There may be many driving factors of forest conversion, and they may vary from place to place. In our case study, selected spatial variables composed a considerable share of the factors driving forest changes. In particular, the accessibility variables seemed to be more important than the topographical ones. Many of these factors have been found to be important in other areas. For example, [40] identified proximity to road, town and forest/non-forest edge as important drivers of forest change in southern Cameroon. Elevation and proximity to road were highlighted as important factors of forest change in the lowlands of Sumatra, Indonesia [13]. Elevation, slope, proximity to road, settlement and proximity to forest/non-forest edge were the key factors of forest change in southeast Mexico [19]. Aside from these biophysical factors, socio-economic factors are often recognized as underlying driving forces of forest cover changes [39,41] and also play an important role in changing landscape. Although these underlying factors are the main pressures on forest conversions, their effect frequently comes from outside the forested areas. For example, the population in the secondary forest edge may have less influence on the conversion of secondary forest to tea plantations than populations outside these areas. This conversion may be caused by tea demand that originates from places further away. Therefore, our empirical analysis was based solely on the site factors of forest conversions.

The predicted forest changes are based on the assumption that forest changes will follow the 2000–2007 Markovian dynamics. In this area, the trends used in our predictions were largely driven by population pressure, and may be conservative. Increasing population, the high incidence of poverty, and the poor awareness of conservation among local residents have contributed to the loss of the primary forest and the conversion of secondary forest into cropland [12]. Forest conversion tended to occur in land suitable for agriculture. Shifting cultivation and commercial tea plantations were causes of cropland expansion into primary and secondary forest areas in the past. In particular, commercial tea plantations exist within the boundary of the park. Tea plantations may continue to extend into the primary forest area in the future because the area is highly suitable for tea plantations.

The identification of the areas vulnerable to forest changes is fundamental in the TDNP and has important implications for biodiversity conservation in the region. One of the most important applications would be to relate the spatial patterns of forest changes to the spatial distribution of species. This is particularly important for large protected areas. Surveys on the distribution of plant species in the area showed that the remaining primary forest within the park is the most structurally complex and richest in plant species composition, particularly in the areas from 350 to 800 meters above mean sea level [42]. According to our predictions, forest loss is likely to occur within this range of elevation. The loss of the remaining primary forest will threatens the survival of many species in the region. In particular, cultivation within primary forest areas drastically altered the composition and abundance of plant species [24]. In addition, the conversion of secondary forest into cropland indicates increasing pressure on the steep land areas in the surrounding areas, and may cause severe land degradation in the future due to soil erosion. Continuing soil degradation may pose a threat to the natural resource-based local economy.

From a protected area management perspective, the prediction maps of forest change patterns can help protected area managers identify where conservation and forest management efforts should be focused. This approach is particularly significant in Vietnam because limited finance resources for protected areas require focused efforts for conservation. Most of the government funding for protected areas is spent on salaries of forest rangers and not on development activities for affected populations.

At a larger scale, the prediction of forest change patterns can aid long-term sustainable forest management.

5. Conclusions

This study investigated the conversion of primary and secondary forest using remote sensing and the MLPNN-M model in Vietnam's TDNP region. We parameterized the MLPNN-M model to simulate the conversion of primary forest and secondary forest in the near future. The rates and driving factors of forest changes were identified using remote sensing data. Then, these data were used to calibrate the model for projecting forest change patterns. The results of model validation showed that selected spatial variable proved to be a considerable part of the variables driving forest conversion in the area; therefore, the model was accurate at predicting the location of forest cover in 2007. However, the more successful component of the model was its prediction of the quantity of forest cover in 2007. Based on the 2007 model validation scenario, the forest cover in 2014 and 2021 was simulated to identify areas that are vulnerable to conversion of primary and secondary forest. According to our model predictions, a considerable portion of primary forest within the park is threatened by forest clearance, which indicates that intensified protection measures are required to prevent further loss of primary forest. The secondary forest in the steep areas in the buffer zone of the park is likely to be converted into agricultural land, and these areas are susceptible to soil erosion. The methodology and results produced in this study can be a vital tool for monitoring the remaining primary and secondary forest in the TDNP region. The monitoring process can be implemented by regularly updating Landsat-derived maps of forest cover and predicting forest change patterns. Moreover, the prediction maps can be used to focus biological conservation efforts. The methodology can also be used more widely for conservation planning and management in other protected areas that are experiencing forest changes in Vietnam.

The model predicted quite reasonably the spatial patterns of forest changes in the study area; however, reforestation was not taken into account. Recently, deforestation and reforestation has been occurring simultaneously in the TDNP region. Therefore, future studies should attempt to include the reforestation process in order to further understand the dynamics as well as the patterns of forest changes in this area.

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References and Notes

1. Vitousek, P.M. Beyond global warming: ecology and global change. *Ecology* **1994**, *75*, 1861-1876.
2. Walker, R. Theorizing land-cover and land-use change: the case of tropical deforestation. *Int. Reg. Sci. Rev.* **2004**, *27*, 247-270.
3. Haines-Young, R. Land use and biodiversity relationships. *Land Use Policy* **2009**, *26*, 178-186.

4. Sala, O.E.; Chapin, F.S., III; Armesto, J.J.; Berlow, E.; Bloomfield, J.; Dirzo, R.; Huber-Sanwald, E.; Huenneke, L.F.; Jackson, R.B.; Kinzig, A.; Leemans, R.; Lodge, D.M.; Mooney, H. A.; Oesterheld, M.; Poff, N.L.; Sykes, M.T.; Walker, B.H.; Walker, M.; Wall, D.H. Global biodiversity scenarios for the year 2100. *Science* **2000**, *287*, 1770-1774.
5. Myers, N.; Mittermeier, R.A.; Mittermeier, C.G.; da Fonseca, G.A.B.; Kent, J. Biodiversity hotspots for conservation priorities. *Nature* **2000**, *403*, 853-858.
6. FAO (Food and Agriculture Organization of the United Nations). *Global Forest Resources Assessment 2005: Progress toward Sustainable Forest Management*; FAO: Rome, Italy, 2006; Available online: http://www.fao.org/DOCREP/008/a0400e/a0400e00.htm (accessed on 25 September 2008).
7. Poffenberger, M.; Nguyen, H.P. *Stewards of Vietnam's Upland Forests*. Center for Southeast Asia Studies: Berkeley, CA, USA, 1998; pp. 1-18; Available online: http://www.mekonginfo.org/mrc_en/doclib.nsf/0/E5E0A84E9B42A19F80256690003862FB/$FILE/FULLTEXT.html (accessed on 20 September 2008).
8. Do Dinh Sam. *Shifting Cultivation in Vietnam: Social, Economic and Environmental Values Relative to Alternative Land Use*; International Institute for Environment and Development: London, UK, 1994; pp. 3-15.
9. Meyfroidt, P.; Lambin, F.E. The causes of the reforestation in Vietnam. *Land Use Policy* **2008**, *25*, 182-197.
10. World Bank. *World Development Report 1992: Development and the Environment*. Oxford University Press: Madison, NY, USA, 1992; p. 200; Available online: http://econ.worldbank.org/external/default/main?pagePK=64165259&theSitePK=469372&piPK=64165421&menuPK=64166093&entityID=000178830_9810191106175 (accessed on 12 June, 2009).
11. ICEM (International Centre for Environmental Management). V*ietnam National Report on Protected Areas and Development*. ICEM: Indooroopilly, Queensland, Australia, 2003; pp. 19-47.
12. TDMP (Tam Dao National Park and Buffer Zone Management Project). *Rural Household Economics Baseline Survey*; Tam Dao National Park: Vietnam; Available online: http://tamdaonp.com.vn/ (accessed on 15 October 2009).
13. Linkie, M.; Smith, R.J.; Leader-Williams, N. Mapping and predicting deforestation patterns in the lowlands of Sumatra. *Biodivers. Conserv.* **2004**, *13*, 1809-1818.
14. Giriraj, A.; Irfan-Ullah, M.; Murthy, M.S.A.; Beierkuhnlein, A. Modelling spatial and temporal forest cover change patterns (1973–2020): A case study from South Western Ghats (India). *Sensors* **2008**, *8*, 6132-6153.
15. Turner, W.; Spector, S.; Gardiner, N.; Fladeland, M.; Sterling, E.; Steininger, M. Remote sensing for biodiversity science and conservation. *Trends Ecol. Evol.* **2003**, *18*, 306-314.
16. Lambin, E.F. Modelling and monitoring land-cover change processes in tropical regions. *Prog. Phys. Geog.* **1997**, *21*, 375-393.
17. Khang, N.D.; Hoe, H.; Duc, H.D.; Thin, N.N.; Tien, D.D.; Lanh, V.L.; Huyen, T.H. *Tam Dao National Park*. Agricultural Publishing House: Hanoi, Vietnam, 2007; pp. 9-56 (in Vietnamese).
18. Lambin, E.F. *Modelling Deforestation Processes: A Review*; TREES Series B: Research Report No. 1; EUR 15744 EN, European Commission: Luxembourg, 1994.

19. Mas, J.F.; Puig, H.; Palacio, J.L.; Lopez, A.S. Modelling deforestation using GIS and artificial neural networks. *Environ. Model. Software* **2004**, *19*, 461-471.
20. Eastman, J.R. *IDRISI Taiga, Guide to GIS and Remote Processing*; Clark University: Worcester, MA, USA, 2009; pp. 234-256.
21. Lek, S.; Delacoste, M.; Baran, P.; Dimopoulos, I.; Lauga, J.; Aulanier, S. Application of neural networks to modelling non-linear relationships in ecology. *Ecol. Model.* **1996**, *90*, 39-52.
22. Yuan, H.; Van Der Wiele, C.F.; Khorram, S. An automated artificial neural network system for land use/land cover classification from Landsat TM imagery. *Remote Sens.* **2009**, *1*, 243-265.
23. Zhou, J.; Civco, D. Using genetic learning neural networks for spatial decision making in GIS. *Photogramm. Eng. Remote Sens.* **1996**, *62*, 1287-1295.
24. Ghazoul, J. *Tam Dao Nature Reserve: Results of a Biological Survey*; Society for Environmental Exploration, UK and Xuan Mai Forestry College: Hanoi, Vietnam, 1994.
25. Eastman, J.R.; Jin, W.; Kyem, P.A.K.; Toledano, R. Raster procedures for multi-criteria/ multi-objective decisions. *Photogramm. Eng. Remote Sens.* **1995**, *61*, 539-547.
26. Pijanowski, B.C.; Brown, D.G.; Shellito, B.A.; Manik, G.A. Using neural networks and GIS to forescast land use changes: a land transformation model. *Comput. Environ. Urban.* **2002**, *26*, 553-575.
27. Li, X.; Yeh, A.G.O. Neural-network-based cellular automata for simulating multiple land use changes using GIS. *Int. J. Geogr. Inf. Sci.* **2002**, *16*, 323-343.
28. Dendoncker, N.; Roundsevell, M.; Bogaert, P. Spatial analysis and modeling of land use distributions in Belgium. *Comput. Environ. Urban.* **2007**, *31*, 188-205.
29. Ali, J.; Benjaminsen, A.T.; Hammad, A.A.; Dick, B.O. The road to deforestation: An assessment of forest loss and its causes in Basho Valley, Nothern Pakistan. *Global Environ. Change* **2005**, *15*, 370-380.
30. Cropper, M.; Puri, J.; Griffiths, C. Predicting the location of deforestation: the role of roads and protected areas in North Thailand. *Land Econ.* **2001**, *77*, 172-186.
31. Wilkie, D.; Shaw, E.; Rotberg, F.; Morelli, G.; Auzel, P. Roads, development, and conservation in the Congo Basin. *Conserv. Biol.* **2000**, *14*, 1614-1622.
32. Ludeke, A.K.; Maggio, R.C.; Reid, L.M. An analysis of anthropogenic deforestation using logistic regression and GIS. *J. Environ. Manag*. **1990**, *1*, 247-259.
33. De Koninck, R. *Deforestation in Vietnam*; International Development Research Center: Ottawa, Canada, 1999; Available online: http://www.idrc.ca/en/ev-9318-201-1-DO_TOPIC.html (accessed on 15 September 2008).
34. Sader, S.A.; Joyce, A.T. Deforestation rates and trends in Costa Rica, 1940–1983. *Biotropica* **1998**, *20*, 11-19.
35. Kanellopoulos, I.; Wilkinson, G.G. Strategies and best practice for neural network image classification. *Int. J. Remote Sens.* **1997**, *18*, 711-725.
36. Pontius, R.G; Huffaker, D; Denman, K. Useful techniques of validation for spatially explicit land change models. *Eco.Model*. **2004**, *179*, 445-461.
37. Brown, S.; Lugo, A.E. Tropical secondary forests. *J. Trop. Ecol.* **1990**, *6*, 1-32.
38. Wright, S.J. Tropical forests in a changing environment. *Trends Ecol. Evol.* **2005**, *20*, 553-560.

39. Bawa, K.S.; Dayanandan, S. Socioeconomic factors and tropical deforestation. *Nature* **1997**, *386*, 562-563.
40. Merten, B.; Lambin, E.F. Spatial modeling of tropical deforestation in southern Cameroon: spatial disaggregation of diverse deforestation processes. *Appl. Geog.* **1997**, *17*, 143-162.
41. Geist, H.J.; Lambin, E.F. Proximate causes and underlying driving forces of tropical deforestation. *BioScience* **2002**, *52*, 143-150.
42. Kuznetsov, A.N. *Rapid Botanical Assessment of Tam Dao National Park: Detailed Botanical Survey Final Report*; Tam Dao National Park: Tam Dao, Vietnam, 2005.

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